Sensor–based Feedback for Coordination Training on the Sensopro

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PhD Thesis submitted by

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Abstract

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The incidence of coordination problems and poor balance in the general population is at least partly associated with a lack of physical activity linked to the modern sedentary lifestyle, and the recent trends in digitalization may further exacerbate these issues in the future. Balance and coordination training on the Sensopro may constitute one promising tool to mitigate these problems: While performing exercises on the Sensopro, users stand on an unstable base of support that requires continual adjustments to maintain balance, which provides a challenging environment that, thanks to available safety features, allows risk-free training conditions even for people with diminished mobility. An automated sensor-based feedback system could provide additional training incentives through gamification and progress tracking, in addition to guiding users to better movement solutions to facilitate motor learning during autonomous training. However, the Sensopro previously only supported video instructions without augmented feedback. Consequently, the development of an automated sensor-based feedback system that provides relevant feedback during Sensopro exercises could improve motivation, training adherence, and training outcomes.

The goal of this project was therefore to develop a feedback system for the Sensopro in order to improve motivational aspects and training outcomes. First, a scoping review of the existing literature informed the design of the subsequent system, but it also revealed some potential gaps in the research that prevented the establishment of more general guidelines. Next, the training data gathered in a cross-sectional study of eight basis exercises on the Sensopro served as a reference for functional movement analyses and provided a training set for neural network models. Furthermore, a validation study demonstrated that the developed measurement system produces adequate tape kinematic data, including foot placement and orientation estimations. All these building blocks were then combined to develop algorithms that are able to produce relevant and understandable performance metrics. Finally, a longitudinal study was planned with the objective of empirically verifying the desired long-term benefits provided by the developed feedback system.

We thus successfully developed an automated sensor-based feedback system capable of providing relevant performance metrics for balance and coordination exercises on the Sensopro. Future research may include an empirical assessment of the expected benefits in a longitudinal study, improvements to the measurement capabilities by examining key aspects of the measurement setup in more detail, generalizing the measurement system to other unstable bases of support, and a systematic investigation of the effects of different feedback properties in complex movement tasks on the Sensopro.

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Contents

Introduction

1.1 Problem Statement

The increasing digitalization and the modern sedentary lifestyle are responsible for a growing concern regarding the incidence of balance and coordination problems in youth and adults, which can lead to a reduction in quality of life and a higher risk of falls in old age [1, 2, 3]. Furthermore, poor balance may, in extreme cases, lead to fear of falling and in turn additionally hinder physical activity [4]. Balance and coordination training on the Sensopro may mitigate these issues [5, 6, 7] through challenging exercises on an unstable base of support that are suitable for all age ranges [8]. Thanks to the available safety and comfort adjustments, Sensopro training could be a viable option for improving high-level mobility in high-risk populations as well, including older adults and stroke patients or patients suffering from neurodegenerative diseases [9, 10]. Despite being well suited for sensor-based feedback due to providing a semi-enclosed, static environment and already featuring a built-in tablet computer for video instructions, the Sensopro currently does not offer any automated measurements or augmented feedback. Yet, an automated feedback system could further support Sensopro training, for example, with progress tracking options for individualized training reminders or with gamification strategies to induce additional incentives for physical activity [11, 12]. Such a system could therefore encourage and guide users, leading to better training adherence, training compliance, and overall outcomes — hence improving balance, aiding efforts for fall risk prevention, and improving quality of life for users [13].

In the long term, such a feedback system would offer a great opportunity to establish a full online-feedback system that includes services for training data processing and storage in addition to the localized feedback on a single Sensopro device. This would establish a direct relationship between Sensopro AG and the end user, making the synchronization of training history data between different Sensopro devices possible and opening the door for individualized training feedback based on long-term training data. The Sensopro Luna is already used in therapy, rehabilitation, fitness, and professional sports, and newer Sensopro models may also increasingly enter home and work environments. With minor adjustments for the different models, the feedback system and its benefits could thus affect an extensive user base in all of these sectors. Additionally, the capability to measure and store individual training data would conceivably open up new avenues for further research regarding balance and coordination training on the Sensopro. This could include, for example, systematic research on the effects of different feedback regimes, with the Sensopro representing a fairly consistent environment for the investigation of complex yet comparable movement tasks. Moreover, the growing user base training on Sensopros with an automatic measurement system would also expand the pool of potentially motivated participants for large-scale observational or longitudinal field studies with manageable additional effort and cost. This may eventually lead to better individualized training recommendations and a deeper understanding of the general mechanisms and effects of feedback and coordination training on unstable bases of support.

The main goal of this project is to improve training outcomes and training experiences in the short and long term for a large variety of potential users by extending the functionality of the Sensopro with a sensor-based feedback system. The objective is therefore to inform and support the development of an online feedback system for the Sensopro in accordance with the requirements and constraints established in the associated Innosuisse project (see Section 1.2). In order to provide meaningful feedback that increases engagement and maximizes desirable behavior conducive to motor learning, we first need to gain insight into the properties of augmented feedback systems by examining the existing literature. However, relevant and intuitive feedback content is also a key factor in guiding users to better solutions for the specific movement tasks and thereby improving motor learning progress. Hence, we also need to examine and appraise movement patterns on the Sensopro so that we can operationalize key performance indicators and develop an appropriate measurement system, culminating in a system capable of producing relevant and accurate feedback during or after training. The main objective has thus been refined into the following specific research aims:

Aim 1: Establish evidence-based guidelines for the design of feedback regimes.

Aim 2: Contrast biomechanical data with functional movement analyses to facilitate the investigation of movement patterns and the establishment of baselines.

Aim 3: Design and validate the measurement system.

Aim 4: Develop algorithms that are responsible for deriving relevant and understandable metrics from the available measurement system output.

Aim 5: Assess the benefits of the developed feedback system.

These aims and the corresponding aspects of the overall project are not strictly hierarchical but rather interdependent, so the thesis structure presented in the following paragraph is merely a stratification of an iterative and occasionally parallelized design process. This interdependence is broadly illustrated in Figure 1.1.

To achieve these aims in a way that allows the adaption of the resulting system on regular Sensopro devices in rehabilitation and fitness environments, it is essential to first understand certain constraints from the implementation partner and the training equipment we are working with. Section 1.2 therefore offers a more detailed explanation of the Innosuisse project that this PhD thesis is embedded in, including a more detailed list of requirements for the desired feedback system, followed by Section 1.3 that provides a brief overview of the different Sensopro models. Then, the different aspects related to the design of a sensor-based feedback system for the Sensopro are examined in Chapter 2, with each section loosely corresponding to one of the five research aims. To address Aim 1, Section 2.1 briefly introduces the theoretical background of feedback design and the results of a scoping review on sensor-based augmented feedback. Next, Aim 2 was fulfilled by providing a biomechanical reference dataset of Sensopro exercise executions and corresponding performance criteria — Section 2.2 explains how this was achieved by first presenting related research on unstable bases of support and introducing the basis exercises on the Sensopro before describing the cross-sectional study that delivered the biomechanical dataset and facilitated the corresponding functional movement analyses. Then, to elucidate the design choices and compromises regarding the

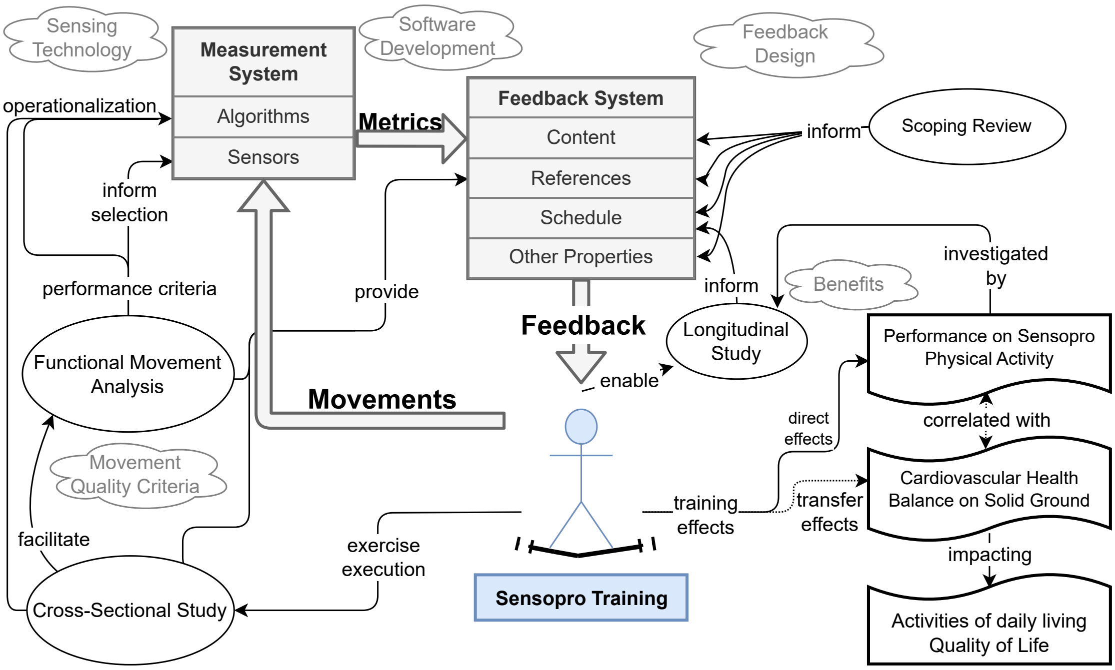

FIGURE 1.1: Project overview: Aim 1 concerns feedback design, Aim 2 the movement quality criteria, and Aim 3 combines sensing technology and software development. Aim 4 concerns algorithms to produce the metrics, but it needs to observe all other aspects to construct a beneficial feedback system, with Aim 5 finally evaluating these benefits.

basic measurement system for Aim 3, Section 2.3 discusses different sensor options, the necessary technical background on Inertial Measurement Units (IMUs), the resulting IMU-based measurement system, and the validation study assessing the accuracy of the derived tape kinematic data. Aim 4 necessitates operationalizing and incorporating the results of Aims 1-3 for the development of high-level algorithms that are tasked with supplying the feedback content by deriving meaningful yet understandable metrics from the tape kinematic data produced by the basic measurement system — Section 2.4 thus outlines the algorithms that resulted from this process so far. Finally, Section 2.5 describes past field tests and the planned longitudinal study that will address Aim 5 by evaluating the effects of feedback on the Sensopro, possibly contributing to adjustments to the feedback system and hopefully verifying its benefits for sensorimotor training.

1.2 Innosuisse Project: Sensopro

This PhD thesis is part of the Innosuisse project "Online-Feedback-System (OFS) for coordination diagnostics and training on the Sensopro in fitness and therapy" (Grant No. 38795.1 IP-LS). Innosuisse is the Swiss Innovation Agency and has the explicit goal of promoting science-based innovation by supporting small- and medium-sized enterprises in their research and development activities. This project is a collaboration between the Institute of Sport Science at the University of Bern and the implementation partner Sensopro AG. The goal of the project is to develop a feedback system for coordination training on Sensopro products. This entails that the topics treated in this thesis are intrinsically linked to the practical and economic needs of the implementation partner, who in turn supported this research with equipment, software development, and recommendations to ensure that research and business interests align and that the end product is economically viable as well as scientifically sound. However, the research itself is independent in the sense that the funders and the implementation partner had no role in the collection, analysis, and interpretation of the data.

The main objective in this project is the design of a feedback system that benefits the end user — depending on the use case, this can imply supporting motor learning, providing performance scores, conveying meaningful markers for the quality of exercise execution, or simply amplifying incentives for increased physical activity and adherence to a training schedule. For Sensopro AG, the developed Online-Feedback-System would also achieve several economic goals: Bolstering its market position by expanding their product portfolio, bringing existing trends in digitalization to the coordination training sector with gamification and biofeedback options, strengthening the relationship of the user with the training equipment through individualized instructions and feedback, and adding diagnostic utility to the Sensopros in therapy settings by providing meaningful performance and progress indicators.

Furthermore, the process of developing and validating said system includes endeavors that offer several opportunities for interesting scientific contributions:

- Analyze existing literature on augmented feedback in complex movement tasks to identify research gaps and ultimately expand the existing knowledge on guidance.
- Develop a simple measurement system on the Sensopro that could later be adapted to other unstable bases of support.
- Investigate movement patterns on unstable bases of support to find and operationalize markers for exercise execution quality.
- Explore the potential of advanced algorithms for estimating body kinematics from tape kinematics.
- Expand on the existing research regarding the effects of feedback on motor learning in complex movement tasks.

As a consequence of differing priorities in research and industry, this project must address various requirements in different areas. First, the project must contribute to the existing body of research by adhering to the expected scientific rigor and making results of experiments available through publications. Second, the developed system should be unobtrusive and easy to use to make it appealing for applications in different environments without adding unnecessary steps to the training experience. Third, safety and privacy protections need to be upheld in laboratory and field settings before and after deployment. Fourth, the design of performance metrics should observe human biomechanics to ensure that the feedback is conducive to functional movement patterns. Fifth, the visualizations should be simple enough to be understandable for users during and after exercises yet allow for optional access to more intricate metrics by interested users, coaches, and therapists. Last but not least, hardware and software should be cost-effective and compatible with existing products to make deployment economically viable.

In addition to their advisory role and their support with software development, contacting experts, and the procurement of hardware, the implementation partner also covered many of the above design tasks that are not related to research, specifically considerations regarding economical aspects and deployment. These tasks are not the direct topic of this thesis and will not be addressed in more detail here. However, these considerations still defined the scope of the project and influenced several decisions, especially the choice of exercises and equipment to investigate.

FIGURE 1.2: The Sensopro Luna with a fixed (left) or released (right) swingboard.
Copyright 2025 by Sensopro AG [14].

1.3 Sensopro Training Equipment

There are currently four available Sensopro models: Luna Fitness, Luna Physio, Casa, and Piccolo. The Luna Physio is a medically certified version of the Luna Fitness. The Casa is a smaller variant intended for home training. Finally, the Piccolo is a tiny variant intended for incorporating physical activity in office environments. All models consist of a metal frame and two non-stretchable canvases suspended by metal springs or elastic cords. Contrary to the Luna models, the Casa and Piccolo have no swingboard or elastic tubes, and the Piccolo does not have metal guardrails either. Due to the similarities between the bases of support in the different models, the results from one model should generalize to the other models with only small parameter adjustments (primarily tape length, spring length, and spring coefficient). Therefore, setting the focus on only one model is warranted to reduce the problem complexity for this project. Due to having the complete list of features as well as being the common model in fitness centers, the Luna Fitness has been chosen as the standard model for this project.

The Sensopro Luna Fitness is a stationary exercise device (approx. 2.5m x 1.4m x 2.35m) intended for coordination training in fitness and therapy. It consists of a large metal frame, two side rails, a video kit presenting exercise instructions in the front, and a swingboard with two tapes. Each tape consists of a non-stretchable canvas that is mounted on the swingboard in the front and back with either metal springs or elastic cords. The swingboard can remain firmly attached during exercise, or, if its retainers are released, it can rotate about the longitudinal axis through the swiveling holders in the front and back. The two tapes always form an unstable base of support for the user to stand on, so releasing the retainers simply adds an extra degree of freedom to make the base of support even less stable and the task more challenging. Spring guards in the front and back cover the springs and facilitate mounting and dismounting the Sensopro via a step behind the swingboard. Hereafter, the term *Sensopro* without further specification refers to the Sensopro Luna Fitness. The namesake company is referred to as *Sensopro AG*.

Aspects of Feedback System Design

2.1 Feedback Design Guidelines

2.1.1 Feedback Terminology and Background

Augmented feedback is external information that an athlete receives about their performance, for example, from a coach or an electronic device. This stands in contrast to intrinsic feedback that directly stems from the athlete's senses [15]. Since intrinsic feedback is outside the scope of this project, the term *feedback* will hereafter denote augmented feedback unless stated otherwise. Furthermore, this project is mainly concerned with automated, sensor-based evaluations rather than verbal assessments from coaches or therapists. The feedback system is intended to help these professionals in their tasks, e.g., by giving them access to otherwise difficult-to-perceive metrics or by delivering training data afterwards so that they do not necessarily have to watch the exercise in progress. It is important to keep in mind that the sensor-based feedback system is definitely not suitable for replacing individualized coaching, nor is it intended to do so. The augmented feedback should convey performance metrics, support motor learning, and add incentives for encouraging physical activity and adhering to established training schedules [16]. The measurement system is fundamental for the evaluations because it produces the metrics required for a fair rating of a performance. This rating advances the above goals in several ways, depending on the use case: it permits juxtaposition of different athletes' performances, furthering competition; it allows for comparisons with previous performances of oneself, empowering the users by increasing their sense of self-efficacy through a clear visualization of motor learning progress; and finally, it makes contrasting a performance with a baseline possible, facilitating the identification of peculiarities or weaknesses by a coach, therapist, or the users on their own. At the same time, the feedback system is constrained by the provided quantities and the precision of the measurement system.

All these considerations affect the trade-offs involved in the choices for different properties of the feedback regime, including its modality, content (metrics), timing, schedule, and other related design options. Visual feedback is the obvious choice with regard to the modality on the Sensopro because the required screen is readily available thanks to the video kit and because other modalities, such as auditory feedback, are more likely to disturb other people around the Sensopro in fitness centers. Visual feedback has the added advantage that users are likely accustomed to a wide variety of graphical representations for different kinds of information, which should make the task of designing accessible graphics relatively straightforward. On the other hand, what information these graphics should present, i.e., the feedback content, is more difficult to pin down. Performance metrics for coordination training exercises are arguably harder to establish compared to cardiovascular or strength training, because coordination tasks require complex motor skills needed to manage the elaborate interplay of multiple body parts to achieve the desired result. Therefore, the result itself, as well as the steps to achieve it, may be less quantifiable and less generalizable to other movement tasks. In contrast, cardiovascular and strength training metrics can rely on relatively common measures such as heart rate, speed, endurance, hypertrophy, and training volume. In the literature, the feedback content is often categorized by whether it conveys Knowledge of Performance (KP) or Knowledge of Results (KR), which correspond to assessments of the quality of task executions or assessments of task outcomes, respectively [17]. This is not to be confused with the timing of the feedback, which refers to whether it is given during the exercise as concurrent feedback or whether it is given after the completion of the exercise as terminal feedback. The exact timing may have profound consequences for the encoding of motor memories [18]. Finally, the feedback schedule defines when or under what conditions information is displayed. Giving the maximum amount of guidance all the time may incur an inordinate reliance on the evaluations shown, which is known as the guidance effect [19, 20]. Specifically, if such information is continuously available under training conditions, it may lead to worse performance under test conditions or field conditions, for example, when trying to apply the learned skill in activities of daily living or sports competitions. Careful structuring of the feedback schedule by employing fading strategies, which entail a gradual reduction of feedback frequency over time, may help avoid these adverse effects [21, 17]. Although this negative effect is well established for simple movement tasks, it is unclear if and how this generalizes to complex movement tasks like the basis exercises on the Sensopro [22, 23, 24]. Thus, a closer investigation into the possible effects of different feedback regime choices in complex movement tasks is warranted to better inform the design of the feedback system on the Sensopro.

2.1.2 Sensor-based Visual Feedback — A Scoping Review

The following scoping review consolidated the investigated feedback regimes and corresponding recommendations from the pertinent literature into an overview of possible feedback characteristics and associated benefits. This allowed us to make informed decisions about various aspects of the feedback system, thus at least partially addressing Aim 1 in the context of this project. However, despite limiting the included articles to studies of visual feedback in exercises that, like the exercises on the Sensopro, squarely fall into the realm of complex movement tasks, the resulting study pool exhibited considerable heterogeneity in exercise types, study methodology, participants, and properties of the feedback regime. Due to this multifaceted heterogeneity and the concerns revealed in the risk of bias assessments, the results of the included studies were incommensurable [25], even when split into several subcategories. As a regrettable consequence of this, the question of a conceivable partial generalizability of the guidance hypothesis [19, 26, 23] has thus still not been answered satisfactorily. This leaves open the possibility that detrimental effects from excessive guidance are simply delayed in complex movements, leading to diminished motor learning progress after the initial stage of motor learning.

The following abstract belongs to a peer-reviewed article published in Frontiers in Sports and Active Living [27]. The full article is in Appendix A.1

Sensor-based augmented visual feedback for coordination training in healthy adults: a scoping review

Introduction: Recent advances in sensor technology demonstrate the potential to enhance training regimes with sensor-based augmented visual feedback training systems for complex movement tasks in sports. Sensorimotor learning requires feedback that guides the learning process towards an optimal solution for the task to be learned, while considering relevant aspects of the individual control system — a process which can be summarized as learning or improving coordination. Sensorimotor learning can be fostered significantly by coaches or therapists providing additional external feedback, which can be incorporated very effectively into the sensorimotor learning process when chosen carefully and administered well. Sensor technology can complement existing measures and therefore improve the feedback provided by the coach or therapist. Ultimately, this sensor technology constitutes a means for autonomous training by giving augmented feedback based on physiological, kinetic, or kinematic data, both in real-time and after training. This requires that the key aspects of feedback administration that prevent excessive guidance can also be successfully automated and incorporated into such electronic devices.

Methods: After setting the stage from a computational perspective on motor control and learning, we provided a scoping review of the findings on sensor-based augmented visual feedback in complex sensorimotor tasks occurring in sports-related settings. To increase homogeneity and comparability of the results, we excluded studies focusing on modalities other than visual feedback and employed strict inclusion criteria regarding movement task complexity and health status of participants.

Results: We reviewed 26 studies that investigated visual feedback in training regimes involving healthy adults aged 18-65. We extracted relevant data regarding the chosen feedback and intervention designs, measured outcomes, and summarized recommendations from the literature.

Discussion: Based on these finding and the theoretical background on motor learning, we compiled a set of considerations and recommendations for the development and evaluation of future sensor-based augmented feedback systems in the interim. However, high heterogeneity and high risk of bias prevent a meaningful statistical synthesis for an evidence-based feedback design guidance. Stronger study design and reporting guidelines are necessary for future research in the context of complex skill acquisition.

In their 2013 narrative review [28], Sigrist et al. provided an overview of feedback research into the effects of different feedback modalities relative to task complexity, concluding that a systematic evaluation of feedback design within movement classes and specific modalities is needed before comparing the effectiveness of specific modalities to each other. They also mention the challenge associated with such studies due to the required technical effort, and they subsequently started a series of studies investigating feedback in a rowing simulator [29, 30, 31, 32]. Incidentally, the Sensopro could also be well-suited for such a systematic evaluation, which will be discussed in more detail in Section 3.3.3. The same 2013 review by Sigrist et al. also discussed the benefits of abstract visualizations to represent key movement features and the benefits of using concurrent (in addition to terminal) feedback to guide users to optimal movements without causing dependency on the feedback. Research into the effects of the exact moment when contextual cues are given further underpins the relevance of the timing of concurrent visual feedback in the formation of motor memories [18]. These considerations help to further delineate a strategy for the initial feedback system design.

2.1.3 Desired Feedback System on the Sensopro

While the scoping review indicated that the recent research on sensor-based visual feedback does not conclusively determine the role of guidance in complex movement tasks, the feedback system is likely not in grave danger of negatively impacting motor learning to a high degree, because strong negative effects of excessive guidance would presumably have been apparent in the literature. Nevertheless, there is an argument to be made for self-selection or, if available, coach-selection of feedback frequency and type, because self-selection has been associated with positive effects on self-efficacy [33] and both self- and coach-selection of feedback may still help detect and avoid potentially detrimental feedback. A fully automated fading schedule, however, is not warranted.

The strategy of combining abstract visualizations with concurrent and terminal feedback is suitable for the Sensopro feedback system in principle, but concurrent feedback may lead to challenges with regard to hardware limitations. Nonetheless, the next step is an analysis of movement patterns in Sensopro exercises to elucidate key features and the notion of optimality in that context, so that the system can indeed guide the users towards optimal movement patterns.

2.2 Performance Indicators for Sensopro Exercises

2.2.1 Movement Features on Unstable Bases of Support

It is essential to bear in mind that all exercises on the Sensopro are exercises on an unstable base of support. On one hand, the unstable base constitutes a challenging training environment that, together with the many variations of exercises on the video kit, could improve motor learning outcomes [34]. On the other hand, motor learning of balance and coordination skills is thought to be specific to the corresponding movement patterns, and therefore it is not immediately clear whether training on the Sensopro would produce a measurable transfer effect to balance and coordination tasks on hard ground, with both positive and negative examples existing in the literature [35, 36, 37, 38]. For this reason, the experts designing the exercise instructions on the Sensopro apply functional movement analyses and focus on functional movement tasks that closely mimic the (real-life) tasks the users train for [39]. The feedback system should likewise follow this theoretical background by emphasizing a task-specific understanding of movement patterns, necessitating an in-depth analysis of the movement patterns on the Sensopro.

The different step detection definitions and strategies discussed in Section 2.4.2 are corroborative of the difference between movements on solid ground and the Sensopro, i.e., stable and unstable bases of support. While related literature on measurement systems for exercises on unstable bases of support is available for slacklines, trampolines, and other devices [40, 41, 42, 43, 44], the Sensopro itself is a relatively novel field of investigation. Moreover, contrary to Sensopro exercises, walking on a slackline usually involves changes in foot placement along the slackline, so step detection strategies on slacklines are likely different from the required step detection approach on the Sensopro, where changes in foot placement during the exercise are less common. On trampolines and especially mini-trampolines, the stepping pattern may be similar to the stepping patterns observed on the Sensopro. Nevertheless, the fact that the base of support of trampolines resembles a plane rather than a tape likely leads to different step detection strategies as well. Since the strategies for a task as simple as step detection are already different on Sensopros, slacklines, and trampolines, it stands to reason that other, more complex tasks will also differ. An investigation of the potential strategies for detecting movement features on the Sensopro is therefore warranted.

2.2.2 Basis Exercises

Users can select the desired exercise from a large library of video instructions available on the video kit. Since there are too many different exercises on the Sensopro to consider each one of them separately, the focus is instead on eight basis exercises that cover different types of basic tape movements. The results from these exercises should broadly generalize to other exercises with similar tape kinematic patterns. As discussed in Section 2.3.1, inertial measurement units on the tapes will form the central building block for the measurement system. To assess the capabilities of the measurement system without interference from elements that cannot be measured, the deliberate choice was made to exclude all elastic tubes from the basis exercises. To further simplify the task at hand, the swingboard function is also not considered. Finally, touching the metal guardrails is discouraged but not prohibited due to safety concerns.

The following movement tasks were chosen as the eight basis exercises:

- One-Leg Stand: An asymmetrical balance task in which the athlete tries to stand on one leg for as long as possible. The unstable base of support makes it difficult to hold the pose for an extended time, so athletes often have to temporarily grab onto the handrails or set down the other foot in order to re-establish balance.
- Sideways: A balance task in which the athlete tries to keep the two tapes at a similar height while facing sideways (right or left) instead of forwards. The feet are shoulder-width apart and on different tapes, resulting in asymmetrical anteroposterior and lateral foot positions.
- Lunges: A slow, asymmetrical stability task similar to lunges on stable ground. Athletes position one foot towards the front and one foot towards the back, then they try to maintain mediolateral and anteroposterior balance while repeatedly going from upright into a lunge position and back, without lifting the feet.
- Squats: A slow, symmetrical stability task similar to squats on stable ground. Athletes try to keep the tapes at a similar height while repeatedly going from upright into a squatting position and back.
- Step: An asymmetrical rhythm task with medium speed. This involves shifting the weight between the left and the right leg. The movement is similar to walking in place, but the toes generally remain on the tape throughout the exercise.
- Bouncing: A symmetrical rhythm task with medium speed. Athletes rhythmically move the tapes up and down by slightly engaging the knees without lifting the feet off the tape.
- Sprint: A fast-paced, asymmetrical exercise, mimicking sprinting movements without moving forward. The toes may or may not remain in contact with the tape throughout the exercise.
- Waves: A fast-paced, symmetrical exercise in which the athlete tries to quickly move the tapes up and down while keeping them parallel.

In all exercises except sideways, the athletes are facing the video kit in front of them.

2.2.3 Movement Analysis

For a more detailed examination of the specific movement patterns during these basis exercises, a cross-sectional study was carried out to address Aim 2. Participants performed the eight basis exercises on the Sensopro, resulting in 65 datasets after exclusion due to measurement errors. Using a ten-camera motion tracking system (Vicon T20, 2MP, Vicon Nexus 2.12, Vicon Motion Systems Ltd., Oxford, UK), body kinematics of participants and tape kinematics of the Sensopro were recorded simultaneously. Participants were also filmed from the back and the right side using Blackmagic Pocket Cinema Camera 4K (Blackmagic Design Pty Ltd, South Melbourne, Australia). Finally, two types of 9-axis IMUs were attached to the tapes: the SFM2 (Sensor Maestros LLC, Denver, CO, USA) as a consumer-grade option and the Blue Trident (Vicon Motion Systems Ltd., Oxford, UK). A pilot study was conducted beforehand in the scope of a Bachelor's thesis [45] to refine the study methodology. Additional details regarding the cross-sectional study can be found in Appendix A.3.

The cross-sectional study did not yet lead to a separate publication, but the anthropometric, IMU, and motion capture data aided the development and testing of algorithms, and may serve as a baseline for feedback with a reference in the future (see [27] for examples of references in related research). The dataset was also used for training and evaluating neural networks (see Section 2.4.3). The resulting recordings were integral for expert questionnaires that led to functional movement analyses in a Bachelor's Thesis [46], which resulted in the selection of performance criteria for the Sensopro exercises.

The experts broadly agreed on the different performance criteria for each movement task, though sometimes with different thresholds for what constitutes a good or bad performance. The following key quality criteria were listed: avoid valgus or varus alignment in legs; maintain symmetrical posture (if applicable); keep center of mass centered above the base of support (except in step and sprint); distribute the weight equally on both tapes; keep the hip horizontal; hold an upright posture with a straight spine; relax shoulders; maintain a constant rhythm; and execute the movements consistently and calmly (except in sprint and waves). Thus, the performance criteria mentioned by experts mostly concerned correct posture, rhythm, symmetry, and consistency. During all exercises except for the one-leg stand and sideways, participants were usually able to refrain from touching the rails. Standing on one leg for longer than a couple of seconds proved to be exceptionally difficult for all participants, indicating that properly measuring performance in that exercise would likely require a sensor system capable of detecting rail touches, unless the difficulty is reduced by instructing users to hold onto the elastic tubes throughout the exercise. However, even if it may not be possible for the measurement system to detect all relevant movement features, they may still prove useful for the feedback system, for example, by simply scheduling pertinent cues that remind the user to guide their attention to these criteria.

Finally, interviews with physiotherapists by Sensopro AG revealed that motivational aspects of the feedback system are not just important for recreational applications, but also a core priority in rehabilitation and therapy. Since experts can supply metrics themselves by simply watching their patients, a precise measurement of clinically relevant movement features may not be strictly necessary. From this perspective, the focus should be on usability and on supplying gamification elements to engage users, thus encouraging them to adhere to the training schedule and to comply with exercise instructions. This means that even less functionally relevant movement features may be considered for feedback, as long as it succeeds in motivating the users.

However, we still strive to give meaningful feedback for four reasons: First, overly inaccurate or irrelevant feedback might demotivate inquisitive users. Second, as mentioned before, the ability to consistently record performance indicators may be instrumental in future field studies on motor learning. Third, the same performance criteria may be used in the future for commensurable performance scores to allow individual progress tracking and to foster competition between users. Lastly, even if the experts do not need the training recordings when they can observe the exercise execution, the system may still aid coaches and therapists by recording unsupervised training sessions for further evaluation. This may give coaches and therapists a tool to better assess progress [47], e.g., during the recovery after an accident or in training of motor skills. It is important to note that in this context, gamification strategies on the Sensopro may not necessarily only serve a motivational role: Serious games have found applications in many areas, including motor learning [48], and gamification elements were also previously employed for diagnostic purposes in an associated project that investigated pareidolia production in stroke patients [49].

2.3 Measurement System

2.3.1 Sensing Technology for Human Motion Analysis

To generate feedback about the performance, a measurement system must reliably supply information about the exercise execution. The selection of available sensor systems for measuring human motion is too large to consider each option separately [50], so it first needs to be narrowed down to a few candidates before addressing Aim 3. Inertial measurement units on the tapes are a promising candidate for detecting tape kinematics because they are often used for step detection on solid ground [51] and because of their ability to measure acceleration and rotation speed directly, without complex computations or assumptions on the surrounding environment. Therefore, IMUs will be the main sensors of interest for the measurement system, despite the disadvantage that they cannot directly detect information related to posture. This disadvantage could be remedied by extending the measurement system with other sensors.

A passive optical system would be one possible extension for obtaining information related to posture. Video cameras are ubiquitous due to the proliferation of smartphones, which explains the relatively cheap hardware and a broad range of available algorithms for interpreting large amounts of video data, including solutions for segmentation and pose estimation. Conversely, it faces challenges with respect to camera placement, privacy protections of user data, differentiating between the user and other people within the field of view, and potential privacy concerns from people in the surrounding area who did not agree to be recorded. The immediate transformation from video into abstract pose data could ameliorate some of these issues. Moreover, various range imaging technologies could further enhance the usually 2-dimensional recording with depth information for more accurate 3-dimensional estimations. The technical capabilities of a possible extension of the measurement system with consumer-grade cameras was investigated in a Master's Thesis on 3D human pose estimation [52]. The thesis results indicated that a camera-based measurement system may be sufficient for detecting movement cycles in slow exercises like squats or lunges, but it would encounter difficulties because of imprecise depth recognition and erroneous joint angle estimations during rapid movements or movements in an unfavorable direction. These results, together with the aforementioned practical concerns, led to this line of investigation being put on hold. Despite that, such a system could be considered again in the future, either with custom optical flow approaches for depth estimation [53] or with depth cameras using infrared projectors that could produce more accurate 3D data, thus simplifying pose estimation and making background removal trivial but requiring more expensive hardware.

Another option would be a radar (radio detection and ranging) or lidar (light detection and ranging) system that could provide position and velocity data, including information on posture. However, there are concerns regarding algorithm complexity, computational complexity, secure placement of the sensors, and interference from the surrounding environment. Other possible extensions of the measurement system could detect usage of other Sensopro components, like detection of contact with the side rails (e.g., using light barriers or capacitance) or kinematics and kinetics of the flexible tubes, although these features were not deemed important enough to be included in the current measurement system. All wearable options (including marker-based tracking, IMUs, electromyography, and electrocardiography) are excluded on the basis that putting on and taking off equipment for every training session would be cumbersome and raise hygiene concerns.

For these reasons, the proposed measurement system is only based on IMUs providing tape kinematic data. Future investigations may reevaluate possible active or passive camera-based extensions to supplement the feedback system with postural information.

2.3.2 Inertial Measurement Units and Sensor Fusion

Inertial measurement units come in different varieties, but the main components relevant to this project are the accelerometer, the gyroscope, and the magnetometer. Other components like pressure or temperature sensors may be internally important for making the readings of the main components more accurate, but these are of no further consequence here. Each of the three main components could theoretically cover between one and three spatial axes, but it makes sense to disregard options that are limited to one or two axes because all three spatial dimensions are significant for tape kinematics. The two main variants of interest are 6-axis IMUs, which only include accelerometer and gyroscope data, and 9-axis IMUs, which also include magnetometer data. When an IMU is attached to the tape, the accelerometer and gyroscope readings give immediate information about the tape's acceleration and angular velocity. By combining the accelerometer, gyroscope, and magnetometer readings in a process called sensor fusion, it is possible to obtain orientation information as well.

Orientations can be regarded as rotations relative to a reference coordinate system. Orientations can thus be represented by unit quaternions (versors), which are convenient for calculations due to their computational efficiency, numerical stability, as well as the absence of a gimbal lock. In this project, the w-component of a quaternion denotes the real part, while x, y, and z are the imaginary parts corresponding to the longitudinal (X), lateral (Y), and vertical (Z) axes, respectively. The positive axes directions are defined as follows: X forward; Y left; Z upwards. All kinematic data produced throughout this project adhered to this axis convention. The main disadvantage of quaternions is that they are largely unknown and hard to understand for laypeople. On the other hand, Tait-Bryan angles have computational disadvantages, but their linear relationship with rotations along the three spatial axes allows for quicker, more intuitive interpretation of visualizations (at least for the relatively small rotations observed in Sensopro tapes; combinations of larger rotations may be less intuitive). For this reason, both quaternions (for calculations) and Tait-Bryan angles (for metrics and visualizations) have been used in this project. Throughout the project, Tait–Bryan angles followed the XYZ intrinsic rotation convention to determine roll, pitch, and yaw. Roll refers to a rotation about the longitudinal tape axis (X), pitch refers to a rotation about the lateral axis (Y), and yaw refers to a rotation about the vertical axis (Z).

A caveat of unit quaternions, which likely had an impact on the IMU assessment discussed in Section 2.3.3, is that they are isomorphic to the special unitary group $SU(2)$, which covers the $3D$ rotation group $SO(3)$ twice over. This means that for every orientation in three-dimensional space, there are two ways to represent that rotation as quaternions. A intuitive way to see this is to consider the relationship of quaternions with axis-angle representations: a quaternion $q = (w, x, y, z)$ corresponds to a rotation of $\theta = 2 \times \arccos(r)$ degrees about the (x, y, z)-axis (only the axis direction is needed, and if $w = 1$, then there is no rotation and the axis is irrelevant). Now, since a rotation of θ about the (x, y, z) axis is the same as a rotation of $-\theta$ about the $(-x, -y, -z)$ axis, it is clear that q and $-q$ represent the same orientation in three dimensional space. This is troublesome because this may lead to inadvertently treating equivalent rotations as dissimilar, especially when applying naive algorithms for interpolation between orientations or for differentiating orientations to get angular velocities. On account of these problems, quaternions are often limited by imposing the condition that $w \geq 0$ to ensure consistent behavior, replacing q with $-q$ if this is not the case [54, 55].

Sensor fusion combines the readings from multiple components to achieve different or more accurate measurements. The orientation is estimated for each time step by integrating the angular velocity and adding the resulting rotation to the last orientation estimate. Without corrections from the other components, this estimate would exhibit integration drift, so it would continuously accumulate errors due to noise in the measurements and due to digitization (the process of converting analog quantities into digital formats). Fortunately, gravity and the earth's magnetic field offer a reference that can be used to correct this drift — provided these references are not made indiscernible by movements or electromagnetic interference. Note that an IMU measures proper acceleration, i.e., acceleration relative to free fall: there is no measured acceleration in free fall, and the measured acceleration vector at rest is pointing upwards with vector norm $1g$ (standard gravity, approximately $9.81 m/s^2$). When at rest, this gravitational acceleration vector can be compared against the expected upward direction in the current orientation to find the error in inclination (roll or pitch in Tait-Bryan angles). The magnetometer reading provides an estimate for the direction of true north, thereby providing a reference for the orientation in the horizontal plane (yaw in Tait-Bryan angles). The magnetometer reading is influenced by nearby devices and structures with different magnetic permeability, which unfortunately includes the surrounding metal frame of the Sensopro and the cables of the IMUs, making the horizontal orientation less reliable.

2.3.3 IMU-based Measurement Systems

As a result of the considerations in the previous two sections, the planned measurement system is based on IMUs attached to the Sensopro tapes, thus providing acceleration, angular velocity, and orientation data. In order to fulfill usability and safety requirements, the IMUs are attached to the underside of the tapes, with cables being guided towards the joint of the swingboard to allow normal operation without interfering with exercise execution on the Sensopro.

A Bachelor's Thesis assessed SFM2 IMUs regarding accuracy and stability [56] properties that would influence their potential use on the Sensopro. This first assessment warranted further laboratory tests, resulting in the observation that the integrated sensor fusion algorithm may have stability issues causing small discreet jumps in the orientation estimation when the IMU is rotated 180° from the default zero orientation, with the zero orientation corresponding to (X, Y, Z) axes aligned with (east, north, up) directions. After conferring with the IMU manufacturer and observing similar patterns in Blue Trident IMUs as well, we surmised that this may be a consequence of the quaternion being constrained to positive scalar values in the integrated sensor fusion library. If this is indeed the case, then this problem would likely affect many IMUs with integrated sensor fusion capabilities. One potential solution to this problem is to allow negative scalar components in quaternions and simply smooth the orientation output by detecting and correcting abrupt sign switching, thereby avoiding a discontinuous jump, but we lacked the resources to test this in an onboard sensor fusion library. Since taring did not affect this behavior, the only alternative to prevent this issue was to avoid problematic orientations during tests in the laboratory, which meant that IMUs were placed with the Z-axis pointing upward and the X-axis not pointing east. However, this constraint would certainly be too restrictive for the deployment of the measurement system for Sensopro customers. This issue was one of several reasons that ultimately led Sensopro AG to commission a custom IMU system, thus enabling them to adjust the employed sensor fusion algorithm as needed.

At first, a measurement system using only one IMU per tape was considered, with IMUs attached under the middle tape segments to directly record kinematic data of the area the users are most often standing on. However, this would diminish the value of the recorded data in exercises with different foot placement, such as lunges. Furthermore, in contrast to applications on solid ground [51], the dampening effect of the Sensopro tapes obscures the stepping patterns in the accelerometer data, thus hindering the reliable detection of relevant movement features. Sensopro AG consequently opted for a system with two IMUs per tape, attached to the front and rear segments, facilitating tape position estimations from IMU data as explained in Section 2.3.4. Yet, the commissioned sensor system is based on 6-axis IMUs that are not capable of recording magnetometer data, which means that yaw data is also not available. This is mostly a cost-saving measure, which is justified by the relatively small yaw angles observed during Sensopro training and by magnetic interference in real-life settings potentially leading to stability and accuracy issues. Nevertheless, depending on the outcome of ongoing investigations on advanced movement feature detection algorithms (see Section 2.4.3), a future expansion of the measurement system may be warranted — for example including magnetometers or adding a third IMU underneath the middle segment of the tape, provided that the subsequent feedback capabilities would justify the additional hardware cost.

2.3.4 A Simple Model for Estimating Tape Kinematics

The following abstract belongs to a peer-reviewed article published in Sensors [57]. The full article is in Appendix A.2

A Simple Model for Estimating the Kinematics of Tape-like Unstable Bases from Angular Measurements near Anchor Points

Sensorimotor training on an unstable base of support is considered to lead to improvements in balance and coordination tasks. Here, we intend to lay the groundwork for generating cost-effective real-time kinematic feedback for coordination training on devices with an unstable base of support, such as Sensopros or slacklines, by establishing a model for estimating relevant tape kinematic data from angle measurements alone. To assess the accuracy of the model in a real-world setting, we record a convenience sample of three people performing ten exercises on the Sensopro Luna and compare the model predictions to motion capture data of the tape. The measured accuracy is reported for each target measure separately, namely the roll angle and XYZ-position of the tape segment directly below the foot. After the initial assessment of the model in its general form, we also propose how to adjust the model parameters based on preliminary measurements to adapt it to a specific setting and further improve its accuracy. The results show that the proposed method is viable for recording tape kinematic data in real-world settings, and may therefore serve as performance indicator directly or form the basis for estimating posture and other measures related to human motor control in a more intricate training feedback system.

The article above describes a simple method for estimating tape kinematics based on orientation data recorded near anchor points. Consequently, the proposed measurement system may now use orientation data from IMUs to derive position and rotation data of the tape segment that the foot is placed on, albeit with currently limited accuracy for sideways displacement and rotation angles. Since this method does not rely on a specific placement of the feet on the tapes, it can be used for a large variety of Sensopro exercises, including lunges. One limitation is that the swingboard was not released during testing, so the potential effects of its use on accuracy or the expected range of sideways displacements is unknown. Nonetheless, this is a promising approach, and future research on generalizations of this method to slacklines or trampolines may not only broaden the range of possible applications, but it may also lead to higher accuracy for roll angle and sideways displacement estimations on the Sensopro.

The IMU-based tests indicated that drift may become an issue in Sensopro exercises with continuous movements, because these movements obscure the acceleration due to gravity and the orientation relative to the magnetic field, which prevents reliable drift corrections without resting periods. This predicament reinforces the need for a custom sensor fusion solution: the limited range of possible orientations achievable by Sensopro tapes could allow for the detection and correction of drift during exercise executions, irrespective of resting periods.

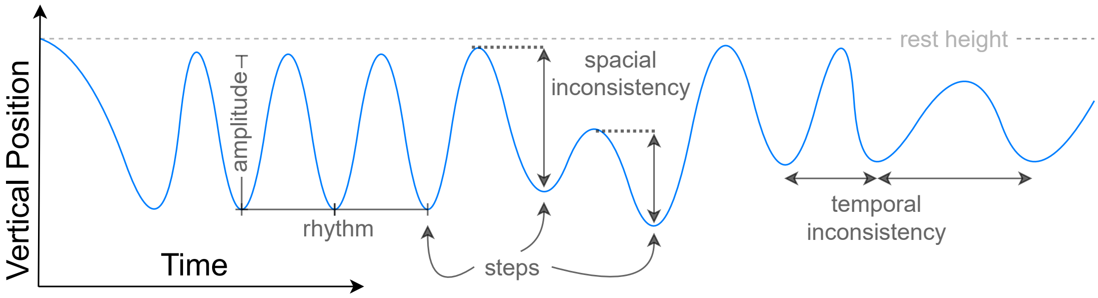

FIGURE 2.1: Step features defined by vertical tape position and time.

2.4 From Tape Kinematics to Relevant Movement Metrics

2.4.1 Basic Algorithms for Basis Exercises

The feedback system includes algorithms that are tasked with transforming the tape kinematic data from the measurement system into human-understandable metrics for visual feedback (Aim 4). Whether this concerns concurrent gamification elements or terminal progress scores, the derived metrics should still focus on relevant movement features and be consistent (as explained in Section 2.2.3), otherwise, users may be discouraged by irrelevant scores or when they notice inconsistencies, which they may even misattribute to a lack of training progress on their part.

The most straightforward metrics consist of movement features that are directly related to quantities recorded by the measurement system, such as roll angles, jitter, or tape heights. The roll angle of the tape, for example, could serve as an adequate measure for a balanced stance, since big roll angles of the tape imply either off-center foot placement or roll (i.e., supination or pronation) of the foot. In exercises like the one-leg stand while holding onto tubes, high roll angles may be part of a functional strategy for maintaining balance, so scores based on roll angle deviations would mostly offer an additional challenge. In exercises like squats, keeping a small roll angle may be a suitable performance indicator, but its relevance may depend on the specific use case and instructions from therapists (e.g., in rehabilitation). As opposed to roll angles, jitter is relatively ambiguous, as it simply refers to quick, uncontrolled shaking of the tape. Jitter scores could therefore be built on some trivial aggregation of tape acceleration, like the root mean square of the absolute acceleration vector, thus penalizing rapid changes in velocity. While this may be of interest in some exercises that would ideally be performed calmly, like lunges or the one-leg stand, its ambiguous definition means that its value lies mostly in broad comparisons between exercise executions. Compared to jitter, the difference between tape heights is a more versatile metric, as it provides information about lateral stability and symmetry that could be relevant in exercises like squats, lunges, sideways, waves, and bouncing. If the tape height is compared between the same phases of different movement cycles instead of just subtracting it between the tapes for every point in time, this would constitute an indicator of spatial consistency that would also be relevant for step and sprint exercises. This leads us to the importance of algorithms for step detection on the Sensopro.

2.4.2 Step Detection

Step counters based on micro-electromechanical systems are quite popular in exercise on solid ground and for measuring physical activity in general [58], which is beneficial both because there is a broad research base to rely on and because users may already be

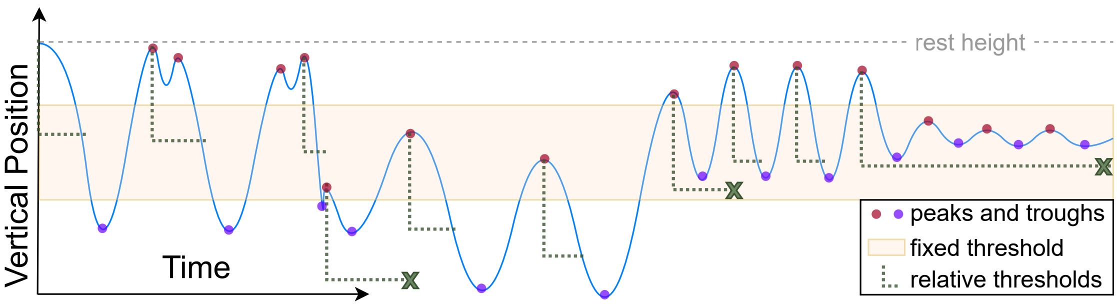

FIGURE 2.2: Step detection approaches based on signal peaks, a fixed tape height threshold, and relative height thresholds, leading to different points at which step events are detected.

accustomed to steps as a metric. If the measurement system can reliably detect when a step occurs, then basic metrics related to the rhythm of the movement cycles follow immediately. If the vertical range covered during a single step is available too, then spatial consistency metrics can be derived as well (see Figure 2.1), which may also lead to more accurate energy expenditure metrics. Steps can be operationalized in several ways, possibly involving assumptions regarding distance traveled as well as the movement pattern typical for human ambulation [59, 60, 61]. For example, in elderly people with reduced mobility, a shuffling gait pattern may be the main method for walking to reduce the risk of falls. Such a gait pattern would not necessarily involve lifting the moving foot off the ground or fully putting the entire weight on the other foot. Therefore, said definitions may depend on the specific problem at hand.

On the Sensopro, we are interested in movements that mimic walking on solid ground, but without traveling any distance. A step therefore simply involves shifting the weight partly or entirely onto one foot, thereby lowering that respective tape and lifting the other foot upwards — which may involve lifting that foot partly or entirely off the tape. Additionally, it is helpful for the generalizability to different kinds of exercise to define steps even more broadly to allow for singular, one-sided steps. Specifically, a left-leg step just means clearing a certain vertical threshold over a movement cycle with the left leg, without stipulating what the other leg does in the meantime. With this definition, a symmetrical bouncing exercise and an asymmetrical stepping exercise can both use the same step-detection algorithm: the first would simply require left and right steps to happen at more or less the same time, while the second would require left-right alternated steps. Algorithmically, the difference between bouncing and stepping exercises then becomes a question of phase-shift between the left and right movement cycles. Different exercises still require different parametrizations, such as the minimum required vertical clearance (i.e., the amplitude) that needs to be much larger in step cycles than in sprint cycles.

During initial trials on the Sensopro, acceleration data on its own proved insufficient for reliably detecting step events. The feedback system therefore relies on positional data for different step detection modules shown in Figure 2.2: First, an appropriately tuned peak-detection algorithm can accurately detect peaks and troughs in the vertical tape position. While this is useful for determining the amplitude and timing of a cycle, such a module struggles with providing concurrent feedback on its own due to signal noise and duplicative counting of twin peaks. Second, a fixed tape height threshold for each step cycle constitutes a constant measure to enforce a required minimum amplitude, but such a module would need individualized tuning to avoid putting users with decreased flexibility or different weight ranges at a disadvantage. Third, a relative tape height threshold would allow adaptive adjustments of the required peak or trough heights, thus being more equitable for different users yet potentially leading to less consistent exercise executions. Furthermore, both threshold-based approaches are unable to detect the precise reversal point, so employing them for concurrent feedback may incentivize users to clear the required range as narrowly as possible, which may or may not be desirable. Finally, the most versatile approach is to simply combine an appropriate threshold-based module with peak detection to compensate for the associated disadvantages. For example, clearing the lower bound of the threshold could prime the peak detection module so that a step event is triggered at the next reversal point, after which step detection is blocked until the upper bound of the threshold is cleared again.

2.4.3 Neural Network Models for Center of Mass Kinematics

The following abstract belongs to an unfinished article in preparation for publication in Sports Engineering. See Appendix A.3 for the full draft.

Prediction of Center of Mass Kinematics of Sensopro Exercises with Neural Network Models [In Preparation]

Augmented feedback supplements autonomous coordination training, ensuring correct exercise execution and enhancing self-efficacy by scoring and tracking performance indicators. We intend to develop a practical, cost-effective measurement system to provide center of mass predictions based on tape kinematics for advanced postural feedback in three balance and coordination exercises on an unstable base of support. In a cross-sectional study, 65 participants performed exercises on the Sensopro Luna, while a marker-based motion capture system recorded tape and body kinematics. These recordings were split into training and test data sets for several neural network models. To predict the center of mass position in all three dimensions from tape kinematics, we implemented models based on a convolutional and a variational auto-encoder neural network architecture. Preliminary results based on a subset of the data and a smaller convolutional neural network architecture showed good accuracy. Therefore, further experiments with different exercises, deeper models, and a more complex architecture are warranted.

By leveraging a deep neural network's capability of considering many interdependent parameters without the need to specify the underlying logic, it may be possible to obtain Center of Mass (CoM) information from tape kinematics without first deriving a biomechanical model and finding a way to handle noisy and possibly biased input data. With the CoM position, key performance indicators related to posture may be approximated, thus potentially offsetting some of the weaknesses of the current feedback system. For example, the lateral CoM displacement during waves or squats exercises could indicate asymmetrical posture, while the overall CoM sway may be an indicator of consistency and stability during exercise execution.

Concretely, the dataset from the cross-sectional study offers an opportunity to train exercise-specific neural network models that predict CoM displacement based on tape segment orientation, acceleration, and angular velocity, all of which may also be collected by IMUs. Preliminary results indicate that even simple neural networks are able to produce CoM data with adequate accuracy, provided the movements do not deviate too much from the movement patterns observed in the training set. However, the article merely serves as a proof of concept, demonstrating the prospects of an advanced measurement system consisting of high-precision orientation data of three tape segments as well as acceleration and angular velocity. If these tests produce promising results, later investigations could evaluate possible concessions in the input data that

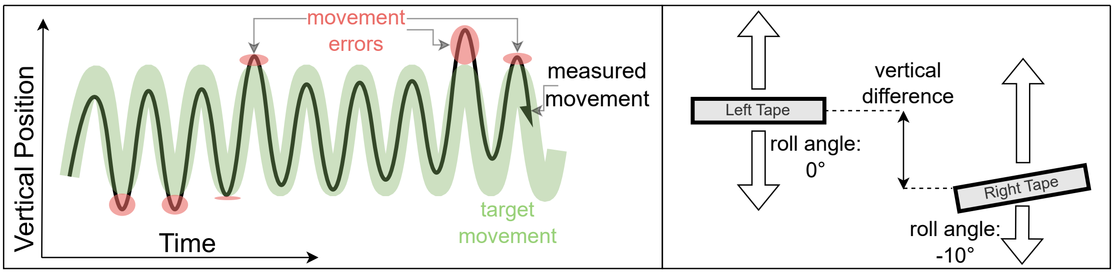

FIGURE 2.3: Illustrations of possible visualizations, e.g., for waves our bouncing exercises. Left: a line plot suited for spatial consistency feedback. Right: Beams corresponding to left and right tape heights for symmetry feedback, including tape roll angles.

would still allow an adequate prediction of CoM displacement. This additional investigation would likely result in adjustments to the measurement system (e.g., with an additional IMU) or neural network models that could handle data obtained from the current measurement system.

2.5 Feedback System Evaluation

2.5.1 Preliminary Assessments

The goal of the feedback system evaluation is to verify that the feedback system is indeed beneficial for Sensopro users (Aim 5). These benefits may encompass both enhanced motor learning progress and motivational aspects. Preliminary supervised field tests were performed in a fitness center, where users could experiment with a prototype system that provided concurrent and terminal visual feedback. The available visualizations at the time comprised abstract line plots, numbers, step event indicators, and horizontal beams indicating tape lateral balance (see Figure 2.3). These field tests were also an opportunity to test the configuration and recruit prospective participants for the planned longitudinal study. Sensopro users generally responded positively to the feedback system, with many responses including ideas for possible new features or adjustments to the visualizations to improve usability. However, the field tests also uncovered stability issues in the prototype system, at least partly caused by the much greater operating times compared to previous tests. The system was not designed to handle the resulting delays in the input data, leading to inaccurate feedback that impacted the training experience.

As one key consequence of the preliminary field tests, Sensopro AG eventually decided to transition towards only providing terminal feedback for the initial launch of the feedback system, thereby avoiding potential stability issues associated with the real-time processing required for concurrent feedback. This leads to a more stable user experience and less troubleshooting, but also entails scant opportunities for gamification elements and a smaller potential impact of the provided feedback on motor learning progress and motivation [18, 23]. For the current system to operate robustly on the video kit, it would need to be capable of dynamically dealing with delays caused by other processes running in the background, possibly in a resource-insufficient environment [62] that may lead to some data being dropped. However, the video kit is currently not designed for real-time scheduling, so it is preferable to outsource some of this computation to other hardware to guarantee the clear processing budget needed for concurrent feedback with static scheduling. The new hardware included in the custom IMU system commissioned by Sensopro AG may fulfill these requirements, so this problem may resolve itself. If this is not the case, additional hardware may be needed for the longitudinal study to ensure that the desired feedback is given consistently. The longitudinal study has subsequently been put on hold until this issue is resolved. Unfortunately, this means that there is no empirical data to verify the benefits of the developed feedback system. Instead, the next section will briefly explain the study protocol.

2.5.2 Longitudinal Study

To assess the long-term effects of feedback during Sensopro training on motivation and motor learning, a longitudinal study under field conditions is required. Following our advice from the scoping review (see Section 2.1.2), the study should consist of three groups: one wait list control group, one classical Sensopro training group without feedback, and one feedback training group. Training interventions should ideally consist of two or three training sessions per week over eight weeks, using a cross-over study design where participants switch between feedback and no-feedback conditions after four weeks. In the best case scenario, the intervention group starting without feedback will train in a different fitness center than the group with feedback, thereby preventing them from learning about the other intervention group (with the control group being split between the two sites). However, the total number of participants and the number of intervention sites may depend on how many volunteers sign up to participate in the study. By selecting participants from people who already train in a gym multiple times a week and by instructing them to use the intervention as a warm-up for their regular training, we hope to decrease the rate of attrition and the dropout rate. One training session lasts approximately 12 minutes and consists of a subset of basis exercises (e.g., step, sprint, bouncing, waves, and squats).

To assess the effects of the different interventions, pre-tests, tests just before the cross-over after four weeks, and post-tests are performed under laboratory conditions. The primary retention tests would consist of one training session on the Sensopro, but without feedback for all intervention groups. The dependent variables are the spatial and temporal consistency of the movement cycles, an assessment of the form during each exercise, and the total number of cycles in sprints and waves. Motivational aspects are assessed with questionnaires and overall training adherence. Transfer effects to exercises on solid ground are of secondary importance for this study, but a Y-excursion test and squats or repeated jumps on a force plate (measuring rhythm, symmetry, and consistency of ground reaction force patterns) may be included for exploratory purposes. Were the study to proceed as planned, we would thus not only be able to evaluate the benefits of the developed feedback system during Sensopro training, but also gain insights into the effect size of Sensopro training without feedback while simultaneously exploring potential transfer effects for future studies.

General Discussion

3.1 Synthesis of Findings

Balance and coordination training may provide an important tool to combat issues related to sedentary lifestyles, such as poor motor skills or increased risk of falls, thus affecting overall quality of life [2, 5, 7, 6]. The different Sensopro models offer an opportunity for challenging exercises to maintain and improve high-level mobility [10, 3] in diverse segments of the population without compromising on safety, thanks to the available safeguards. The goal of this project was therefore to promote training adherence, quality of movement, and overall motor learning progress on the Sensopro by developing a feedback system that can provide gamification elements as well as meaningful performance scores. While some aims towards that goal have not been fully realized, the work presented here constitutes a significant step towards extending the current functionality of the Sensopro Luna with a fully integrated feedback system for sensorimotor training on an unstable base of support.

The scoping review in Section 2.1.2 provided an appropriate overview of feedback properties and their various purported advantages (Aim 1), but it also demonstrated a gap in the available literature that largely precludes generalizations of these findings based on empirical evidence, most notably the open questions regarding long-term effects of excessive guidance and different fading strategies in complex movements [23, 28]. Instead, an adequate interim solution is to offer self-selection or coach-selection features in place of a fixed regime, thus reaping the associated benefits [33] as well as leaving the option of removing feedback in the eventuality that negative effects are suspected. Next, interviews with experts indicated that motivational aspects of feedback should not be neglected, with the actual biomechanical or medical relevance of the feedback taking on a secondary role in some rehabilitation and therapy settings. Yet, irrelevant or overly inaccurate feedback would likely confuse and disparage users, so the feedback system must still achieve a certain standard despite not needing high accuracy and stability for clinical settings. The cross-sectional study addressed the need for a reference dataset comprising exercise executions for the eight basis exercises, which now can supply baselines for the feedback system (Aim 2). The corresponding performance criteria obtained from the functional movement analyses and the expert questionnaires largely fall into two categories: postural or tape kinematic (or both). The developed IMU-based measurement system (Aim 3) is well suited for detecting movement features that are closely related to the tapes, such as rhythm or step depth consistency. However, a camera-based system, which could complement the IMU system with postural information, is not yet ready for deployment due to systematic errors in the pose estimations in addition to the privacy concerns and the increased computational cost. Overall, it was possible to at least partially transform the somewhat abstract performance criteria from Aim 2 into a few concrete metrics (Aim 4) that can be derived from the measurement system output. Although preliminary results look promising, the exploration of a center of mass prediction system in 2.4.3 has not yet concluded at the time of writing, so it remains unclear whether this approach could accurately provide some basic postural information without requiring cameras. If this exploration should not lead to satisfying results, a deeper exploration of different sensors (e.g., lidar or radar) or a combination of multiple sensors may still yield more accurate postural data. However, the demand for such a complicated system is not guaranteed, especially since it is possible that customers are already satisfied with the capabilities of the current IMU system.

Aims 1- 4 have therefore been achieved with varying degrees of success and completeness. In the meantime, Sensopro AG has started to deploy an initial version of the IMU-based measurement system that is able to provide terminal feedback, with ongoing monitoring and further development efforts likely leading to further adjustments in the near future. Finally, regarding Aim 5, preliminary observations during field tests have been presented in Section 2.5.1, and the study protocol for the planned longitudinal study is briefly discussed in Section 2.5. While motivational benefits and usability aspects will likely become apparent through customer responses over time, which in turn may lead to improvements to the feedback system that could facilitate a future in-depth investigation, a more rigorous longitudinal study would be needed in further research to empirically prove the benefits of the feedback with regard to optimized motor learning. However, on a theoretical basis, it stands to reason that an appropriate application of the feedback system is expected to benefit motor learning, purely based on the related research on the connections between motor learning and motivation [63], and especially considering the existing evidence that concurrent feedback may improve performance at least momentarily [20], which can in turn increase the perception of competence, task interest, enjoyment, and thereby ultimately also the effectiveness of motor learning [64]. These deliberations notwithstanding, the best general strategy regarding feedback design on the Sensopro may lie in openly relying on coaches and therapists to bring the displayed feedback into perspective for the users, thus entrusting the decision of its usefulness in each particular case to them. An automated feedback system such as this is simply incapable of fully accounting for the many individualized parameters influencing relevance of performance indicators, with priorities likely changing depending on age, motor skill proficiency, health, and training goals.

3.2 Limitations

Naturally, the main limitation is the lack of a longitudinal study that examines the long-term effects of the developed feedback system on sensorimotor training outcomes on the Sensopro (see Section 2.5). While there is some practical and theoretical evidence indicating that the feedback system may have an overall positive influence on the training experience and motor learning progress, it is still possible that empirical evidence would uncover some aspect that we have yet to sufficiently account for. Furthermore, the lack of concurrent feedback, which is one of the reasons why the longitudinal study was delayed, may limit the potential benefits of the feedback system, both due to a reduction in prospective gamification options as well as due to a the connection between concurrent feedback and motor skill learning [18]. However, thanks to the addition of new hardware in the custom sensor system, there may already be a solution for this problem, so a renewed exploration of concurrent feedback running on that hardware instead of running directly on the integrated video kit may resolve this limitation within the foreseeable future.

While the scoping review has yielded some practical results that affected the design of this feedback system (see Section 2.1.2), it was unfortunately not possible to compile evidence-based guidelines for the design of visual feedback regimes in general. While this may not impact the application of this system anymore, the unclear picture of the effects of augmented feedback on motor learning and motor adaptions has potentially profound implications in a variety of training scenarios related to complex motor tasks (see Section 3.3.3). Another small limitation concern the fact that the measurement system has only been tested on the Sensopro Luna with metal springs, this is, however, consistent with the project plan and it should be fairly straightforward to adapt the measurement system to models with elastic cords, possibly including the Sensopro Casa and the Sensopro Piccolo, if desired. Moreover, the investigations into models for tape roll angles, lateral tape displacement, the relationship between predicted longitudinal position and center of pressure, and the AI-based center of mass position estimation are all incomplete (see Section 2.3.4 and Section 2.4.3). However, this may also be regarded as a strength, seeing as this leaves many potential avenues open for further improvements regarding the accuracy and number of available metrics for feedback on the Sensopro.

3.3 Outlook

3.3.1 Sensopro Training Effects

The obvious next step is to conduct the planned longitudinal study (see Section 2.5) to resolve the main limitation mentioned in the previous section. This could not only verify the benefits of the current feedback system, but it could also encompass a small exploration of possible transfer effects regarding balance and coordination tasks on solid ground. Metrics of interest could include, e.g., plyometric jumps or squats on a force platform, with a focus on left-right symmetry. This could also help inform future studies, e.g., on the potential use of Sensopro training (with or without feedback) in the treatment of gross motor symptoms of neurological disorders such as ataxia [65]. Preliminary tests indicated that, given the right safety precautions and professional support, training on the Sensopro would indeed be feasible for patients suffering from this disorder, even in the presence of gait abnormalities that would prevent unaided upright walking.

Moreover, a prototype software system providing services for concurrent data analysis and storage was developed in an associated project [66], operating with cloud or on-premise storage solutions and suitable for integrating additional measurement devices if needed. Applying such a software system could not only be of interest to Sensopro users and their coaches or therapists (because it allows sharing information between Sensopro devices and different training sites without impacting the training experience), but it could also prove to be a powerful tool for combining the existing measurement system with laboratory setups for more sophisticated tests that are directly comparable to training sessions in the field. Integrating such a software solution on the Sensopro may therefore aid future studies by facilitating the consolidation of long-term observational data with field and laboratory data gathered with the same measurement system.

3.3.2 Advanced Tape Kinematic Measurements

Several possible paths for further research have been identified in the article on the simple trigonometric model for estimating tape kinematics (see Section 2.3.4): First, it would be interesting to apply a similar model to slacklines, not just to make IMU-based measurements viable for slackline training, but also because it could be helpful to investigate roll angles and lateral displacements in a system that only consists of one material (as opposed to the spring and canvas on the Sensopro). Second, possibly aided by the insights gained from slacklines, roll angle and lateral displacement estimation accuracy could be improved on the Sensopro by appropriately accounting for the different resistance to deformations in the canvas and the metal springs (resp. the elastic cords in other models). Third, an analysis of the exact center of pressure position on the tape in relation to the IMU-based sagittal position estimation may reveal a possible connection between the two, which could account for some of the observed differences between measured and estimated position. Fourth, taking advantage of the kinematic constraints present on the Sensopro tapes to detect and adjust for drift in the sensor fusion algorithm could lead to more accurate IMU-based orientation estimations, thereby improving the accuracy of all metrics that are derived from that (including vertical displacement and roll). Fifth, after a potential adaption of the existing measurement system to Sensopro models with elastic cords, an additional validation study may be warranted. Sixth, in order to adequately support swingboard operation with the current measurement system, an additional investigation into the effects of swingboard use on measurement accuracy may be required — if the current measurement system proves unsuitable for estimating the swingboard tilt angle, an extension to the measurement system with one additional IMU attached to the swingboard may be warranted. Lastly, a 3D IMU-based measurement system could be developed for trampolines, thus providing a similar feedback system for trampolines.

3.3.3 On Guidance

On a more tangential note, by applying the task-space model for motor learning [34] to past results on feedback timing, a reinterpretation with an interesting potential application emerges: Howard et al. provided evidence that the representation of sensorimotor states in motor memory depends on the exact timing of visual cues, i.e., with effects from visual cues decaying over time [18]. Considering that the visual cue is only one of many aspects of the sensorimotor state during task space exploration, it may be possible to extend the duration of such effects by coupling the information provided by the visual cues with a change in the sensorimotor state. For example, when instructing Sensopro users to shift the weight a little more towards the left during squats (e.g., in rehabilitation after an injury to the left leg), pairing some visual feedback with the instruction to make a non-functional adjustment to the movement to remind them of that feedback (e.g., by making a fist with the left hand) may serve as an alternative to continuous visual feedback. The proprioceptive change in the sensorimotor state due to that non-functional adjustment could therefore extend the duration of the effects of the initial visual feedback, even without consciously keeping the attention on that adjustment, because the task-space is persistently altered until the instruction is rescinded. Other than presenting an avenue for further research investigating the effects of feedback timing, such instructions may also bridge the gap between haptic feedback and visual feedback on the Sensopro, thereby potentially providing some limited advantages of haptic feedback during Sensopro training without additional hardware. While the feedback system on the Sensopro currently only considers unimodal visual feedback, it would also be possible for specific studies to extend the feedback system with sonification or haptic feedback, allowing further research into these modalities as well as multimodal feedback later on. Such experiments may be warranted despite the associated practical challenges (see Section 2.3.1), because previous research indicated that the underlying mechanisms may differ fundamentally between different feedback modalities [28], thus potentially leading to additional benefits for Sensopro training.

Finally, and perhaps most interestingly, the limitation regarding the results of the scoping review mentioned in Section 3.2 also introduces an opportunity for tackling the issue of guidance in complex movement tasks. Specifically, there is still a need for a concerted, systematic investigation into the exact function and effects of different augmented feedback properties with regard to motor learning in complex movement tasks. This general sentiment has been voiced several times before [23, 28, 67, 68]. Elucidating the role of augmented feedback in motor learning and motor adaptions could have far-reaching consequences on training of complex motor tasks, possibly even in training scenarios beyond sports or sports-adjacent settings. As mentioned in Section 2.1.2, the feedback system on the Sensopro may also present an ideal opportunity to study different feedback regimes, analogously to an existing series of rowing studies initiated by Sigrist et al. [29, 30, 31, 32]. Given the non-invasive measurement system combined with a wide variety of available full-body exercises for balance and coordination training within the fixed space provided by the Sensopro frame, it is difficult to imagine a more appropriate training device for studying the effects of feedback in complex motor tasks. Contrary to the rowing studies, feedback studies on the Sensopro could also be conducted under field conditions, with comparatively little additional effort thanks to the system being deployed in a variety of settings where Sensopros are already in use. This may allow studying long-term effects with a large pool of potential participants, which, in combination with the relatively homogeneous training setting provided by the Sensopro, would be likely to lead to more commensurable results.

3.4 Conclusion

After considering the available research on feedback design and investigating key performance indicators for eight basis exercises on the Sensopro Luna, we developed a feedback system that is capable of providing feedback of relevant performance metrics, with sufficient accuracy levels for movement features that are related to tape kinematics on the Sensopro. In principle, the feedback system may thus promote balance and coordination training by boosting engagement through gamification elements and by supporting automated performance tracking features that help users discern performance progress. This may further encourage physical activity, training adherence, and training compliance in applications such as exergaming, rehabilitation, and therapy. At the same time, the deployment of this system may lead to many opportunities for future research concerning further improvements to the system, the role of augmented feedback in motor learning of complex motor tasks, and the potential health benefits of training on unstable bases of support, especially with regard to the prevention or treatment of neurodegenerative and age-related diseases.

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Appendix: Publications

A.1 Sensor-based Visual Feedback — A Scoping Review

Sensor-based augmented visual feedback for coordination training in healthy adults: a scoping review

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Sensor-based augmented visual feedback for coordination training in healthy adults: a scoping review

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Introduction: Recent advances in sensor technology demonstrate the potential to enhance training regimes with sensor-based augmented visual feedback training systems for complex movement tasks in sports. Sensorimotor learning requires feedback that guides the learning process towards an optimal solution for the task to be learned, while considering relevant aspects of the individual control system—a process that can be summarized as learning or improving coordination. Sensorimotor learning can be fostered significantly by coaches or therapists providing additional external feedback, which can be incorporated very effectively into the sensorimotor learning process when chosen carefully and administered well. Sensor technology can complement existing measures and therefore improve the feedback provided by the coach or therapist. Ultimately, this sensor technology constitutes a means for autonomous training by giving augmented feedback based on physiological, kinetic, or kinematic data, both in real-time and after training. This requires that the key aspects of feedback administration that prevent excessive guidance can also be successfully automated and incorporated into such electronic devices.
Methods: After setting the stage from a computational perspective on motor control and learning, we provided a scoping review of the findings on sensor-based augmented visual feedback in complex sensorimotor tasks occurring in sports-related settings. To increase homogeneity and comparability of the results, we excluded studies focusing on modalities other than visual feedback and employed strict inclusion criteria regarding movement task complexity and health status of participants.
Results: We reviewed 26 studies that investigated visual feedback in training regimes involving healthy adults aged 18-65. We extracted relevant data regarding the chosen feedback and intervention designs, measured outcomes, and summarized recommendations from the literature.
Discussion: Based on these findings and the theoretical background on motor learning, we compiled a set of considerations and recommendations for the development and evaluation of future sensor-based augmented feedback systems in the interim. However, high heterogeneity and high risk of bias prevent a meaningful statistical synthesis for an evidence-based feedback design guidance. Stronger study design and reporting guidelines are necessary for future research in the context of complex skill acquisition.

KEYWORDS
sensor-based, augmented feedback, visual feedback, motor learning, coordination training, autonomous training, design guideline

Introduction

In the last decades, technological progress has brought about a multitude of competitively priced sensor devices for recording and analyzing human movement in real time. In the context of sports and exercise, this development led to a variety of commercial products leveraging sensor-based augmented feedback applied in domains ranging from physical activity monitoring to classical strength and endurance training to exergaming and even motor-skill learning (1). Such autonomous technological solutions promise to be an efficient and (cost-)effective complement to classical instructor-led interventions and are therefore marketed aggressively for home training, but also for fitness centers and even for clinical use in physical therapy and rehabilitation. The prevalence of human trainers and their obvious benefits in all kinds of sport training alone form strong indicators that such sensor-based augmented feedback training (SAFT) systems may also provide advantages in the aforementioned domains while tackling already prevailing and in the future intensifying cost and personnel capacity issues. Therefore, further investigation of potential benefits but also harms of sensor-based augmented feedback seems necessary.

In general, SAFT systems are intended to foster sensorimotor learning, a process which brings about a relatively permanent improvement in the capability of a person to perform a sensorimotor skill (2). From a theoretical perspective on motor control and learning, four principal sensorimotor learning mechanisms can be distinguished, which extend Newell's well-known task-space landscape metaphor (3) and were first elaborated by Hossner, Kredel, and Franklin (4)—namely, task-space formation, differentiation, exploration and (de-) composition. It quickly becomes apparent that SAFT systems can foster sensorimotor learning during all these stages. First, SAFT systems can assist novices during task-space formation, where learners need to identify basic functional task structures. As Hossner and Zahno (5) state, this process can be enhanced by (i) providing task-goal related instructions, (ii) following appropriate schedules, or (iii) introducing part-whole training. Not only can SAFT systems provide this information in a reliable and systematic manner, moreover, they can analyze the learner's compliance based on the gathered sensor data and adapt to potential deviations. Second, during task-space differentiation, learners start paying attention to less salient task parameters, thus increasing the dimensionality of the task-space. SAFT systems can support this process by inducing controlled amounts of variance, e.g., by increasing difficulty or augmenting errors. This contributes to optimally structured learning contexts that promote the identification of additional task-relevant control variables while, at the same time, assuring the exploration of the continuously evolving task subspaces. Third, SAFT systems allow to point the learner towards better task solutions during task-space exploration and therewith promote a systematic escape from local optima. According to Hossner, Kredel, and Franklin (4), this can be achieved by avoiding repetitive, blocked practice of task variants, which fosters a stronger representation in memory [cf. the reconstruction hypothesis (6)] and facilitates an interpolation of the explored support points of the task space [cf. the elaboration hypothesis (7)]. Fourth, such a well-explored task space can be expected to allow for a better transfer of sub-spaces containing movement structures into the context of different tasks. Consequently, during task-space (de-)composition, learners need to be supported in identifying functional (sub-)structures in their task spaces that can be potentially applied outside the current motor task (5). Applying the above reasoning again, as SAFT systems allow for a systematic variation of specific, functionally relevant control variables while keeping others constant, their application can promote structure detection and therefore (sub-)space identification. Moreover, decomposing a task into such transferrable sub-structures may allow to train those in isolation, increasing the quality of the building blocks independent from training the whole task (4). Functionally relevant task-space decomposition would additionally allow to start task-space exploration with a well-educated guess, consequently changing the learning of completely novel tasks to a transfer of functionally fitting subspaces from previous experience (5). With its fine granularity on sensory motor learning mechanisms, this theoretical framework has the potential to guide the conceptual design of SAFT systems to ultimately benefit sensorimotor learning.

Despite all potential benefits, a major challenge remains for a successful application of SAFT systems to sensorimotor learning: Finding appropriate approaches to guide the learner to specific regions of the task space, in other words, defining the optimal type and amount of instruction and feedback for the current experience level of the individual learner. Well established approaches in sports practice can be differentiated by the amount of structure provided during the learning process. They form a continuum between unsupervised and supervised learning regimes.

On one end of the continuum, and like unsupervised learning, (unguided) discovery learning builds on the self-organized search behavior by the learners, assuming that they can find their optimal task solution better than any external observer [e.g., Vereijken and Whiting (8)]. When targeting specific mechanisms of motor learning as sketched above, this approach seems particularly suited to exploit inherent variability, while a systematic addressing of specific regions of the task space seems limited.

Applying a rather prescriptive approach, located at the other end of the continuum, those specific regions might be targeted more easily by explicitly instructing the learner, ideally in the form of desired sensory consequences. Those instructions are thought to generate sensorimotor imagery together with the desired action consequences and therefore provide sufficient input to the motor system to parametrize the movement (4). While older research found larger detrimental effects due to raised psychological demands for explicitly learned skills (9), in a recent review, Kal et al. (10) did not find clear disadvantages in their descriptive synthesis. They therefore explicitly encourage employing both approaches in practice based on their appropriateness for the task and learning challenge at hand. Nevertheless, applying instructions and feedback excessively may introduce artificial feedback-specific dimensions to the task space which provide highly precise information for movement parametrization. From a Bayesian perspective, the estimations throughout the learning process would be dominated by those artificial dimensions over noisier, task-relevant dimensions. However as soon as feedback is removed, the artificial dimensions do not provide meaningful information anymore, preventing the sensorimotor system from finding a good solution. This phenomenon is known as the guidance effect (11, 12). Even if this effect does not necessarily generalize to more complex tasks [e.g., (13–16)], considering the general mechanism seems sensible.

In their 2002 review, Wulf and Shea (14) concluded that principles derived from simple skill learning do not necessarily generalize and more intensive research on complex skills is required to advance motor learning theory and to adequately inform practice. Since then, most research has been investigating augmented feedback very broadly [cf. Sigrist et al. (17)]. Neglecting given instructions and experience levels while including multiple modalities, mixed populations, and simpler movement tasks in medical settings generally results in a very heterogenous set of outcomes not allowing for a clear-cut synthesis of the results. The combination of these factors may have contributed to the ambiguous result patterns in prior research on augmented feedback in motor skill learning.

In this review, an approach involving a restrictive search purview has been employed to increase the homogeneity of the included research. Diminished health, older age, or different levels of motor development may affect motor learning and the optimality of developed strategies, so we restricted target population to healthy, non-elderly adults. When it comes to the task complexity-dependent effect of feedback, it is still unclear whether it should be regarded as a binary question of simple movements vs. complex movements, or rather as a spectrum. We thus opted for a conservative definition of complex movements that involves postural control and multi-joint movements, further limiting the considered experiments to sports-related coordination training interventions with such complex movement tasks. A previous review on the potential impact of different feedback modalities and parameters has concluded that vision was the most investigated modality (17), which can be enforced from an implementational viewpoint due to the ubiquity of electronic screens in digital technologies and existing training devices. By focusing on visual feedback as the largest body of evidence only, we expect to maximize the review's synthesis potential. To sum up, the objective of our scoping literature review is thus to provide the basis for informed feedback design and to provide guidelines for the development of future autonomous visual SAFT systems for sports-related settings to maximize the training benefits derived from such feedback. More specifically, we approach this objective by addressing the following goals:

i. Aggregate results pertaining to similar feedback regimes to provide an overview of the findings in relation to these choices.
ii. Outline what visual feedback regimes have been considered in sports-related research.
iii. Compile the recommendations made in these studies regarding visual feedback regimes.

Methods

We followed the PRISMA Extension for Scoping Reviews (PRISMA-ScR) (18) without prior registration of a formal review protocol. A research librarian advised the investigators in the selection of the databases and the formulation of the search strings. In accordance with the recommendations of the Interim Guidance from the Cochrane Rapid Reviews Methods Group (19), the three electronic databases Embase, PubMed, and Cochrane Central were searched to cover a comprehensive basis of the available literature. The last search on each database was carried out on the 17th of October 2022 by one investigator. The search strings consisted of a conjunction of disjunctions, grouped into the following four inclusion criteria (with *NEAR/10* meaning that the respective keywords need to be closer than ten words):

- **Feedback:** *("knowledge of performance" OR "knowledge of results" OR ((augment* OR external OR extrinsic OR kinetic* OR kinematic* OR motion) NEAR/10 (feedback OR biofeedback)))*
- **Coordination:** *(performance OR motor OR movement OR skill* OR coordination OR neuromuscular OR techni* OR athlet* OR sport*)*
- **Training:** *(training OR acquisition OR improvement OR learning OR athlet* OR sport*)*
- **Visual:** *(visual* OR display* OR screen OR perceptual*)*

The search was limited to articles published in peer-reviewed journals and always covered abstracts. If the database interface permitted a combined search with titles and keywords, then these were also included. Where possible, filters were set to exclude reviews and study registrations and to only consider intervention studies. If this was not possible, the filtering process was performed manually in the screening phase. There was no restriction to sensor-based feedback in the search terms because such specifics of the methodology may be missing in the abstract.

The screening procedure consisted of two phases: The first phase was based on abstracts, titles, and keywords, while the second phase considered the full-text articles. In both phases, two screeners read all records. After the first phase, 52 items had conflicting verdicts, which were then discussed on a one-by-one basis until a consensus was reached between both screeners. After the second phase, all results were discussed to verify the final selection. Studies in languages other than English were excluded, as well as studies older than 30 years (publication year 1991 or earlier) as sensor-based real-time feedback was practically unavailable before. Studies were excluded if they did not include a complex sports-related coordination task with sensor-based visual feedback or did not have at least one group of healthy, non-elderly adult participants. The general rationale behind these criteria was mostly based on the theoretical aspects that were discussed in the introduction. A practical explanation with the resulting concrete differentiations in the screening procedure is given here:

- Sensor-based feedback:
  Our goal was to restrict the purview to feedback that was generated in an automatic and objective manner, as opposed

to, e.g., human augmented feedback from coaches or peers. This decision has some unintuitive consequences: Video-feedback was included, because it is technically a sensor, while other visual feedback generated by electronic devices such as laser pointers was not included.

- Visual feedback:
  By focusing on one feedback modality, we hope to attain more consistent results. However, we still included studies that added other feedback modalities to the provided visual feedback if the visual feedback was clearly in the focus. Other intervention groups with different feedback modalities or no feedback at all were considered as control groups for the data extraction.
- Healthy, adult, non-elderly population:
  Disorders, diseases, and age could affect motor learning mechanisms, because these factors might alter the optimality of specific movement solutions and because cognitive maturity or decline might affect motor learning. Thus, as a rather conservative boundary, we only considered participants that are between 18 and 65 years. If a study involved at least one group of participants that fully satisfies these criteria, then the study was included even if other groups were considered in the study. In that case, all groups not satisfying these criteria were ignored during the data extraction.
- Sports-related, complex sensorimotor tasks:
  We expected participants to have a different mindset in sports-related training compared to medical settings. Compared to sports, interventions targeting activities of daily living (ADL) generally have a different focus, and, in turn, a potentially different feedback objective. Therefore, we excluded ADL and simple balancing tasks.

  We purposefully drew the line between simple and complex tasks rather conservatively so that any study lying between clearly complex and clearly simple tasks was excluded as well. This should ensure that possible negative outcomes stemming from tasks that were not quite complex enough are fully avoided in the synthesis of outcomes, but it is in no way meant as a definition for what constitutes a complex movement task. Tasks which required active control of only one single joint were excluded, as well as bimanual tasks such as reaching, pointing, or sequencing. On the other hand, rowing studies were included despite the seated position if the correct execution of the task required coordination of leg, hip, and trunk movements in addition to the movement of the arms.

After the full-text screening, included studies were categorized into three distinct groups according to the applicability of their results for a potential synthesis. First, if a study reported on the difference between pre- and post-tests for intervention and comparable control groups, with all participants satisfying our population inclusion criteria, then it was categorized as reporting a *training effect*. This category has the potential to indicate how visual feedback design affect retention effects.

For the control group to be considered as comparable, we required that it was different from the intervention group, both regarding participants (i.e., a distinct set of people) and the provided feedback: the control must have either no feedback, a different feedback modality, or also visual feedback but with a relevant change to the way it is designed or administered. Furthermore, the feedback must be withdrawn during testing for all groups to ensure that the measured effects stem from changes in the motor skill in the original task. The measured effect must therefore constitute actual learning and not just a temporary effect caused by the task difference brought about by the given feedback. Second, a study that compares feedback trials with no-feedback trials was categorized as reporting *immediate effect* of feedback. The control can again consist of no-feedback, a different modality, or visual feedback with some aspects changed. Contrary to the first category, these studies must necessarily include tests or measurements with feedback. The control group can either be a different group of participants like in the first category, or alternatively the same group under different feedback conditions in a within-subject design. Therefore, whereas the first category required at least two groups of participants satisfying our population inclusion criteria, one such group was enough to categorize the study as reporting on immediate effects. Third, all other studies were only deemed relevant from a *design-only* perspective, with the focus on the design choices rather than their results. To be included in this category, studies still had to satisfy our inclusion criteria, but they either had exactly one participant group satisfying our population criteria and no within-subject design, or they had multiple participant groups that were not comparable because they did not differ in the administration of the visual feedback (for example only differing in other feedback modalities administered in conjunction with visual feedback).

For the structured data extraction, two investigators extracted information and co-edited the results into a table. Conflicting table entries were discussed until a consensus was reached. The table was then stratified so that all entries follow common nomenclature, and further condensed into the two final, more concise tables presented in this article. The study characteristics were summarized in a first table (**Table 1**), where the columns broadly describe the category, the task and its goal, the intervention, and the participants for each study. A second table (**Table 2**) was split into the three study categories (training effect, immediate effect, design-only) by horizontal lines, using multiple rows for reports including multiple studies, depicting details of the outcomes and the visual feedback regimes for each study. For each main outcome of the studies in the training effect category, at most one post-test (PT) directly following the last intervention session, one short-term retention test (RT1) at least 1 day after the last intervention session, and one long-term retention test (RT2) were considered, each of which is represented in a different column. Potential additional retention tests were discarded because they would only describe the pattern of depreciation over time in more detail. Since the time effect of the interventions in these studies cannot be clearly separated from the immediate effect of the feedback, measurements during the intervention phase were not considered for this study category. Conversely, such immediate tests (IT) were considered

TABLE 1 Overview of tasks, goals, interventions, and population characteristics.

Identifier	Type	Task	Goal	Duration	Sessions	Groups	*N*	Age	Sex	Experience
Benjaminse et al. (20)	TE	Sidestep	Reduce peak knee forces	1	1	3	90	24.6 ± 4.4*	X	Advanced
Chan et al. (21)	TE	Treadmill Running	Soften footfalls	14	8	2	320	18–50	X	Intermediate*
Ericksen et al. (22)	TE	Jumping	Stick the landing	1	1	3	36	20.7 ± 2.3*	F	Beginner
Gilgen-Ammann et al. (23)	TE	Running	Reduce ground contact time	28	8	3	30	31.0 ± 7.5	X	Advanced
Mononen et al. (24)	TE	Shooting	Maximize accuracy	28	12	4	34	20.4 ± 1.8	M	Intermediate
Mulloy et al. (25)	TE	Fencing Lunge	Maximize propulsion, keep sequencing	180	6	2	32	18–40	X	Novice
Nagata et al. (26)	TE	Jump Squats	Increase lifting velocity	28	7	4	37	19–22	M	Advanced
Nekar et al. (27)	TE	Squats	Maintain proper form	28	12	4	48	18–35	M	Beginner
Post et al. (28)	TE	Golf Chipping	Hit target, maintain form	1	1	2	44	21.8 ± 1.3	X	Novice
Rauter et al. (29)	TE	Rowing	Follow reference	2	2	5	40	19–32	X	Novice
Rauter et al. (30)	TE	Rowing	Match target movement	2	2	2	16	27.7 ± 1.9	X	Novice
Rucci and Tomporowski (31)	TE	Hang Power Clean	Maximize power output	28	7	3	17	18–22	F	Intermediate
Sigrist et al. (32)	TE	Rowing	Match target movement	3	3	4	35	28 ± 3.7	X	Novice
Todorov et al. S1 (33)	TE	Table Tennis Return	Hit target through barrier	1	1	3	42	NA	X	Novice
Todorov et al. S2 (33)	TE	Table Tennis Return	Hit target through barrier	3	3	2	18	NA	X	Novice
Viitasalo et al. (34)	TE	Shooting	Maximize accuracy	84	36	4	30	37.5 ± 11.3*	M	Beginner
Anson et al. (35)	IE	Treadmill Walking	Reduce trunk variability	1	1	1*	10*	22.6 ± 4.9	X	Intermediate
Eriksson et al. (36)	IE	Treadmill Running	Adjust running technique	1	1	1	20	28.4 ± 6.4	X	Advanced
Hamacher et al. (37)	IE	Walking	Achieve a balanced gait in frontal plane	1	1	1*	15*	45–65	F	Intermediate
Jones et al. (38)	IE	Ergometer Cycling	Increase performance	21	4	2	20	35.5 ± 6.5*	M	Advanced
Koritnik et al. (39)	IE	Stepping	Match reference	1	1	2	23	23–30	X	Intermediate
Washabaugh et al. (40)	IE	Treadmill Walking	Use full range of motion of knee joint	1	1	1	13	21.0 ± 2.5	X	Intermediate
Weakley et al. (41)	IE	Back Squat	Maximize concentric power	14	4	1	12	21.8 ± 0.9	M	Intermediate
Sigrist et al. (42)	DO	Rowing	Match target movement	2	2	3	24	26.1 ± 3.0	X	Novice
Teng et al. (43)	DO	Treadmill Running	Increase trunk flexion	28	4	1	12	23.3 ± 3.8	X	Intermediate
Teran-Yengle et al. (44)	DO	Treadmill Walking	Avoid knee hyper-extension	1	1	1	17	26.6 ± 5	F	Intermediate

The studies are specified by category (type: TE, training effect; IE, immediate effect; DO, design-only), task, goal, characteristics of the intervention (duration in days, sessions, groups), and population: N = number of participants, age (years, either as range or as $M \pm$ SD), sex (M, male; F, female; X, mixed), and experience. NA means not available. *Adjusted by review authors (only counting healthy, adult, and not elderly participant groups; aggregated age; different definitions for experience levels).

for the studies in the immediate effect category, where the focus is not on the effect of the intervention over time but rather on how the feedback affects performance at the instant when it is applied. Finally, no outcome measures were reported for the design-only category because these studies are only relevant for the overview of feedback regimes in the literature, i.e., goal (ii) of this review. The outcomes were represented by arrows indicating whether participants in the visual feedback intervention performed significantly better (⇑), significantly worse (⇓), or not significantly different (⇔) when compared to the control group. For the training effect category, these reported effects always refer to the learning rates or the change from baseline to post- or retention tests (PT, RT1, RT2), in other words group-by-time interaction effects. Conversely, immediate effect studies always refer to the group effects measured (IT), while potential time effects were discarded. Other tests in the respective categories were not reported in the table. In case of differing outcomes, effects for multiple main outcomes were represented separately by splitting them into multiple lines while comparisons to multiple control groups were separated by commas. Multiple visual intervention groups were addressed by prefixing these comparisons with a letter assigned to the different groups (for more details on the chosen nomenclature, refer to the note below Table 2). The chosen intervention groups could have multimodal feedback, but visual-only groups were preferred if available, in which case additional multimodal groups would be disregarded in the reporting of outcomes.

Study populations were classified according to our estimation of their experience in performing the specific movement task. This classification does not necessarily coincide with the one used in the corresponding reports, which were usually based on levels of competition of the recruited participants instead. We classified participants as *Novice* if they had likely no prior experience with the task. Further, *Beginner*, *Intermediate*, and *Advanced* refer to some experience, regular experience, and expert-level experience with the task, respectively.

The qualitative extraction of the recommendations made in the literature was a less structured process. The discussion and conclusion sections of the included studies were screened for statements that we deemed relevant and generalizable for informing future feedback design. Such statements were only extracted if they satisfied two additional conditions: they were based on the results found in the study (as opposed to other referenced research), and they went beyond descriptions and explanations of the outcomes. Two reviewers marked potential candidate passages in the text, and one reviewer then made the decision whether they should be picked up in the result section of this review. The intention was to include only the most important statements in a concise overview.

Finally, one investigator performed a risk of bias assessment using the risk-of-bias tool for randomized trials (ROB 2) (45) for each study in the training effect category. The rationale for this assessment was to evaluate the strength of evidence that a potential meta-analysis could provide in a systematic review of this research topic.

TABLE 2 Overview of dependent variables, applicable effects, and feedback regimes.

Identifier	CG	Outcome Measures	IT	PT	RT1	RT2	Feedback Measures	Content	KP	KR	C	T	R	F [%]
Benjaminse et al. (20)	Coach, No	Segment Angle (Trunk) Biomechanical Measures	NA	–	⇑, ⇔ ⇔	–	Scene^{T}	Video	X	–	–	X	X	100
Chan et al. (21)	No	Ground Reaction Force Injury Occurrence	NA	⇑ –	–	– ⇑	Force^{T}	Plot	X	–	X	–	–	≈67^{fH}
Ericksen et al. (22)	Coach^{M}, No	Joint Angles (Hip, Knee) Ground Reaction Force	NA	⇔, ⇑	–	–	Segment Position^{T}	Segments + Line^{M}	X	–	X	X	X	100
Gilgen-Ammann et al. (23)	No	Ground Contact Time	NA	–	⇑	–	Mean Time	Bar + Num.	X	–	–	X	X	100H
Mononen et al. (24)	Visual	Score + Score Variability Directional Errors	NA	–	F: ⇑; P: ⇔ ⇔	⇔	Aiming-Point^{T} & Position + Score	Target + Trace & Target + Num.	X –	– X	–	X	– X	F: 100; P: ≈50 100
Mulloy et al. (25)	No	Angular Velocities (Hip, Knee, Ankle)	NA	–	⇔	–	Maximum Angular Velocity + Timing	Color Bar Chart	X	–	–	X	X	≈70
Nagata et al. (26)	No, Coach	Barbell Velocity	NA	⇔	–	⇔	Scene^{T} Mean Velocity	KP: Video; KR: Num.	X –	– X	–	X	–	100
Nekar et al. (27)	Coach^{M}, Visual, No	Knee Extension + Balance Knee Flexion Flexibility	NA	⇔, ⇑, ⇑ ⇔, ⇔, ⇑ ⇔	–	–	Scene^{T}	AR^{M}	X	–	–	X	X	100
Post et al. (28)	Visual^{Y}	Accuracy Form Score	NA	–	⇔	Transfer: ⇑	Scene^{T}	Slow-Motion Video + Video	X	–	–	X	X	100^{S}
Rauter et al. (29)*	Haptic	Spatial Error Velocity Error	NA	–	⇔	–	Position^{T}	Oar Trace	X X	– –	X –	– X	X X	≈70
Rauter et al. (30)	Visual^{Y}	Spatial Errors	NA	–	⇔	–	Position^{T}	Trace^{M}	X	–	X	–	X	≈70E
Rucci and Tomporowski (31)	Verbal	Strength + Power Form Score	NA	⇔ ⇓	–	–	Scene^{T}	Video	X	–	–	X	–	100
Sigrist et al. (32)	Haptic, Audio	Absolute Angular Error Scaling Error Rotation Error Velocity Error Movement Variability	NA	–	⇔ ⇔ C: ⇔; T: ⇑ C: ⇔; T: ⇔, ⇑ C: ⇔, ⇑; T: ⇔	C: ⇔; T: ⇔, ⇑ ⇔ ⇔, ⇑ ⇔ ⇔	Position^{T} + Orientation^{T}	C: Oar; T: Oar + Trace	X	–	X –	– X	X	C: 72 T: ≈72^{S}
Todorov et al. S1 (33)	Coach^{M}	Accuracy Score	NA	⇑	–	–	Position^{T} & Score	Trace & Num.	X X	– –	X –	– X	X X	100
Todorov et al. S2 (33)	Coach	Accuracy Score Trajectory-Distance Score	NA	⇑	–	–	Position^{T}	Trace & Num.	X	–	X	X	X	≈33
Viitasalo et al. (34)	Visual, Coach^{M}	Accuracy	NA	⇔	–	–	Aiming-Point^{T} & Forces & Scene^{T} & Position + Score	Target + Trace & Num. & Video^{M} & Target + Num.	X X –	– – X	– – –	X X X	– X –	≈14 ≈17 100
Anson et al. (35)	No	Low-Frequency- Translational Variance Various Gait Parameters	⇑ ⇔	NA	NA	NA	Position^{T}	Target + Dot	X	–	X	–	–	100
Eriksson et al. (36)	Audio^{W}	Vertical Displacement Step Frequency	⇔	NA	NA	NA	Positions^{T} + Mechanical Power^{T}	Bar Chart	X	–	X	–	X	100
Hamacher et al. (37)	No^{W}	RoM, Inclination (Pelvis) RoM, Inclination (Trunk)	⇔ ⇑	NA	NA	NA	Segment Angles^{T}	Avatar + Axes	X	–	X	–	X	100
Jones et al. (38)	Visual^{W}, Visual	Time, Speed, Power, Perceptual and Physiological Measures	⇑, ⇔	NA	NA	NA	Position^{T} Distance^{T}	Avatars Num.	X	X	X	–	X	100
Koritnik et al. (39)	Visual	Spatial & Temporal Adaptation	⇑	NA	NA	NA	Joint Angles^{T}	Avatar	X	–	X	–	X	100
Washabaugh et al. (40)	No^{W}	Joint Angle + Aftereffects (Knee), Muscle Activation	⇑	NA	NA	NA	Joint Angles^{T}	Bar Chart	X	–	X	–	X	100

(*continued*)

TABLE 2 Continued

Identifier	CG	Outcome Measures	IT	PT	RT1	RT2	Feedback Measures	Content	KP	KR	C	T	R	F [%]
Weakley et al. (41)	Coach^{W}, Coach^{W}, No^{W}	Barbell Velocity	⇔, ⇔, ⇑	NA	NA	NA	Mean Velocity	Num.	X	–	–	X	–	100
Sigrist et al. (42)*	NA^{W}	Spatial & Temporal Errors (Angle + Angular Velocity)	NA	NA	NA	NA	Position^{T}	Oar^{M} Trace^{M}	X X	– –	X –	– X	X X	≈70^{E}
Teng et al. (43)	NA^{W}	Kinematics (Trunk), Joint Kinetics (Hip, Ankle), Automaticity	NA	NA	NA	NA	Segment Angle^{T} Score	Dots Num.	X X	– –	X –	– X	X –	≈50^{fH}
Teran-Yengle et al. (44)	NA^{W}	Joint Angle (Knee)	NA	NA	NA	NA	Joint Angle^{T}	Plot	X	–	X	–	X	≈50

The studies are categorized by horizontal lines into types (first training effects, then immediate effects, then design-only, see Table 1). Columns specify the type of control groups (instruction/feedback conditions: No, Visual, Haptic, Audio, Coach, ^{M} = multimodal, ^{Y} = yoked control group, ^{W} = within-subject comparison) and outcome measures. Interaction effects of feedback for immediate testing (IT), post-test (PT), first retention test (RT1), and last retention test (RT2) are shown by arrows. ⇔: no significant difference between intervention group (IG) and control group (CG); ⇑: IG significantly better, ⇓: IG significantly worse; if effects are identical for multiple outcome measures and/or control group comparisons they are summarized by one arrow, in case of differing effects: ',' splits control groups, ';' splits feedback groups, letters are assigned if multiple visual feedback regimes were applied (F, full; P, partial; C, concurrent; T, terminal). NA means not applicable or not reported. ^{M} indicates that the feedback was multimodal, ^{T} that feedback measure had a time-component. In addition to feedback measure and graphical content of the visual feedback display (properties are linked by "+" if presented simultaneously, while "&" links multiple quantities separately shown), the following properties of the feedback regime are shown: knowledge of performance (KP), knowledge of results (KR), concurrent (C) or terminal (T) feedback and whether a reference (R) was available (X = applied, – = not used), feedback frequency (F in %) as fixed percentage of trials/time or overall average percentage for fading (^{f}) resp. maximum allowed percentage for self-selected (^{S}) and error-based (^{E}) regimes without considering reported additional home-exercise (^{H}).

*Rauter et al. (29) utilized the same visual feedback group's data as the unimodal visual group in Sigrist et al. (42), so their feedback regime was clearly without adding to the available evidence. We instead listed the multimodal audiovisual feedback group for Sigrist et al. (42).

Results

Study selection and data extraction

The initial literature search identified 892 records from three databases (Figure 1) (46). After removing 224 duplicates, 668 distinct records remained. From these, we excluded all records that did not satisfy the criteria specified in the methods section: 588 records were excluded in the abstract screening stage and 55 reports during the full-text screening, leading to 25 reports included in the final dataset. 15 of these 25 reports measured training effects of visual feedback, but one report consisted of two empirical studies, so in total 16 studies were assigned to the training effect studies. The remaining 10 reports were not eligible for the training effect category because some only had one intervention group satisfying our population criteria (7 reports), no post-intervention tests without feedback were performed (2 reports), or because the control groups differed in other feedback modalities without affecting attributes of the visual feedback (1 report). Of these 10 reports, seven measured performance under different visual feedback conditions and were thus eligible for the immediate effect category, featuring five within-subject designs, one between-subject design, and one with both within- and between-subject comparisons. The remaining three reports did not compare immediate performance under different visual feedback conditions, but instead reported training effects over time for a single group (2 reports) or had control groups that all received the same visual feedback (1 report). All 26 studies of the 25 reports and their characteristics deemed relevant for this review are summarized in Table 1 (population and intervention) and Table 2 (dependent variables and feedback).

Several small adjustments were made during the data extraction process. Two studies incorporated groups of participants that did not match our population criteria (35, 37), these groups were subsequently ignored in the data extraction. Multimodal groups receiving visual feedback were disregarded in three studies (31, 39, 42) in Table 2 because visual-only intervention groups and non-visual control groups were available. Rauter et al. (29) designated the visual feedback group as control group, but for our purposes this constitutes the intervention group, with the haptic feedback groups serving as control instead. In three studies (23, 24, 34), one "true" control group, in which the participants received no intervention at all, was disregarded in Table 2. An item of concern was that Rauter et al. (29) and Sigrist et al. (42) seemed to share the same visual-only feedback group, i.e., only one unique dataset was gathered for both studies. The visual-only feedback group is therefore counted twice in the columns of Table 1 that concern study participants. This group was assigned to Rauter et al. (29) as the main intervention group in Table 2 so that it could be counted for group comparisons in the training effect outcomes. Because Sigrist et al. (42) is in the design-only category, the same group is not relevant for group comparisons here, so this group was ignored for this study in Table 2 to avoid over-representation of the same feedback regime. Instead, the otherwise similar multimodal group was considered as the main intervention group in Sigrist et al. (42).

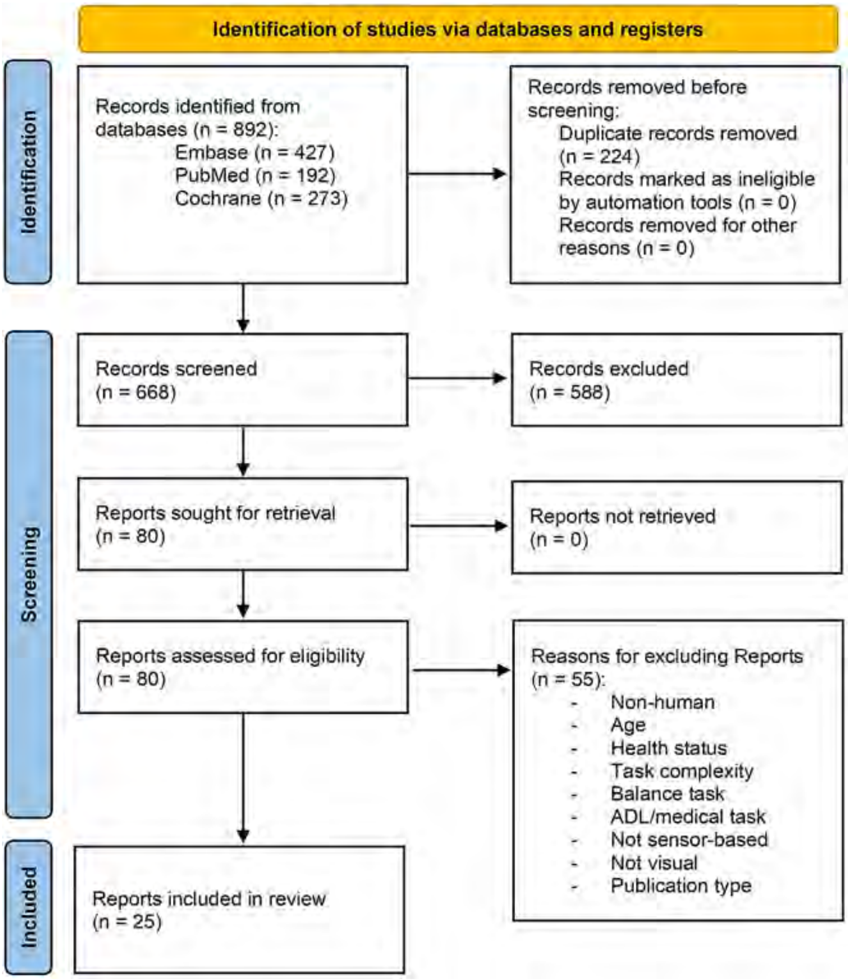

FIGURE 1
PRISMA 2020 (46) flow diagram: overview of the study selection process consisting of database searches, abstract screening, and full-text assessment.

Populations and intervention formats

Most studies (18 out of 26) had a relatively small group size with less than 15 participants per intervention arm (**Table 1** columns “Groups” and “N”). The exceptions were Benjaminse et al. (20) with 30, Chan et al. (21) with 160, Mulloy et al. (25) with 16, Post et al. (28) with 22, Eriksson et al. (36) with 20, Hamacher et al. (37) with 15, and Teran-Yengle et al. (44) with 17.

Instructions were often implicit to the task, e.g., trying to hit a target implicitly conveys the desire to increase accuracy, which was the goal in 5 out of 26 studies. Increasing physiological power output was the objective in 5 studies. More nuanced instructions consisted of following a target movement (5 studies), reducing joint strain (2 studies), or a direct adjustment to the movement technique (11 studies). Two studies explicitly combined the performance goal with the demand to maintain proper technique.

When classifying the studies according to their intervention schedule, 10 studies lasted for less than 1 day, encompassing a single session, while 5 studies lasted between 2 and 3 days with 2–3 sessions. Nine studies lasted between 2 and 4 weeks with 4–12 sessions; the remaining 2 studies lasted 12 weeks with 36 sessions and 6 months with 6 sessions, respectively.

Utilized visual feedback regimes

The quantities used for the feedback mostly consisted of positions, joint angles, or forces relevant to the movement task, often coinciding with one of the dependent variables (cf. “Feedback Measures” and “Outcome Measures” in **Table 2**). These quantities were mostly measured using motion capture systems, cameras, force plates, and inertial measurement units. Todorov et al. (33) used an electromagnetic sensor to track paddle position and orientation. Nekar et al. (27) employed a mobile AR device. The rowing studies (29, 30, 32, 42) all utilized the same rowing simulator, which incorporated rope robots, motion capture, and wire potentiometers. The shooting studies (24, 34) employed an optoelectronic shooting system to detect the shot and to determine the relevant performance metrics. The shooting studies also included a trace of the point where the shooter was aiming at. Nagata et al. (26) used an optical encoder system to measure lifting velocity. In Eriksson et al. (36) and Weakley et al. (41), a position transducer measured the displacements and velocities, respectively. In Jones et al. (38), participants trained on a cycle ergometer. Participants in Washabaugh et al. (40) wore an exoskeleton that measured joint angles (while also applying the resistance for the movement task). Teng et al. (43) included the percentage of time spent in the desired parameter range as terminal feedback in addition to the concurrent joint angles measured by a motion capture system.

Knowledge of Performance (KP) feedback was given in every study, with four studies additionally including Knowledge of Results (KR) in the augmented feedback, but the timing of KP and KR feedback varied between studies. For KP, concurrent and terminal feedback was approximately equally common (in 16 and 17 studies respectively, shown in columns “C” and “T” of **Table 2**). One study, Sigrist et al. (32), reported a deliberate delay of terminal KP feedback during the trials: After feedback was requested by the participant, there was a 10 s delay, after which feedback was shown for the last 18 s of the movement. KR was given as terminal feedback in 3 of 4 studies, with only Jones et al. (38) giving concurrent KR feedback during their trials by displaying the total distance covered.

In 21 studies, some form of reference was incorporated to the visual feedback (as indicated in column “R” of **Table 2**). Possible forms of reference were ideal values or ranges (e.g., given as a line), a virtual avatar or a reference-oar performing the correct movement, or a split-screen video with another performance. Hamacher et al. (37) provided a reference by showing the current joint angles with the desired ranges overlaid on a virtual avatar of the participant. The data for the provided references was either sourced *a priori* (e.g., from recommendations or from experts showing the correct movements) or generated during the study from a participants’ previous performances.

According to the following classification into four groups (plots, numerical, video, complex graphics), the 26 studies featured a total of 38 occurrences of graphical feedback visualizations (see column “Content” in **Table 2**). These visualizations varied in terms of graphical complexity and abstraction level, but no study tried to graphically convey more than three quantities at once and no study reported issues with the understandability of the graphics. In 12 studies the feedback was visualized by plotting it on a 2-dimensional plane. This was achieved with linked motion-capture marker-models (1 study), showing the trace of the movement on a plane (5 studies) or in a 3D virtual environment (2 studies), quantity-time plots (2 studies), dots on quantity-quantity plots (1 study), and markings on virtual bulls-eye targets (3 studies, two of which included aiming-traces). In 11 studies, numbers were represented as numerical values or vertical bars. A video recording of the participant was used in 6 studies, one of which involved augmented reality with graphical movement guidance. More complex graphical representations (9 studies) involved virtual avatars, a virtual copy of the training environment to show the trace in, or a virtual rowing simulator that included a virtual representation of the oar and other modalities (e.g., traces). In Jones et al. (38), the avatar was set on a virtual cycling track that graphically simulated a movement through space dependent on their cycling performance. Five studies (22, 27, 30, 34, 42) applied additional non-visual feedback in the visual feedback group, so the participants received multimodal feedback. Audio resulting from the simulation of water in the rowing studies (29, 30, 32, 42) were considered part of the immersion and not specifically marked as multimodal feedback in the table. Analogously, the virtual extension of the oar was not treated as visual feedback. All groups in all rowing studies received this audio and visual feedback.

A form of summary feedback (i.e., feedback that is not specific to a single movement execution) was used in Nagata et al. (26) by averaging over the whole set, and in Gilgen-Ammann et al. (23) by providing only the mean ground contact time over each interval run. Jones et al. (38) was the only instance where participants were deliberately deceived about the nature of the provided feedback: One group was told in one trial that the pacer (the reference avatar) showed their own performance from a baseline trial, without telling them that its speed was increased by 2%.

The reported frequency of each feedback schedule refers to the percentage of trials or time during the intervention phase in which participants had the opportunity to receive feedback (**Table 2** column “F”). Test trials without feedback were treated the same as training trials without feedback if they consisted of the same movements. For the instantaneous effect studies, the frequency was generally 100% because there was no meaningful intervention phase to average over. The only possible exception is Jones et al. (38), which received a + 2% and a + 0% pacer as feedback for 25% of the time each, with the remaining 50% of the total time being reserved for baseline tests without pacer. In 18 studies, the feedback schedule was completely predetermined for at least one visual feedback group. In 8 studies, at least one group received visual feedback with other scheduling strategies. Fading feedback (a gradually decreasing frequency over the intervention duration) was used in Chan et al. (21) and Teng et al. (43). Self-selected feedback (providing feedback only upon request by the participant) was used in Sigrist et al. (32) and Post et al. (28). Self-selection led to variable feedback frequencies considerably different from the maximum possible frequencies, e.g., resulting in a mean frequency of 9% (range 2%–37%) compared to 100% possible in Post et al. (28). Error-based feedback (no or reduced visual feedback when performing below a certain error threshold) was used in three of the four rowing studies (29, 30, 42). Specifically, the trace was only drawn above the error threshold in Rauter et al. (29) and Sigrist et al. (42), and the transparency of the reference oar was increased with decreasing error, making it harder or even impossible to see. In Rauter et al. (30), visual feedback was provided if the spatial error was the dominant error, otherwise an auditive feedback was given for the velocity error instead. Three studies (21, 23, 43) explicitly reported that participants continued training outside the intervention sessions during the intervention period, at home or elsewhere. For these studies, the reported frequencies only refer to the training during the trials, other training (at home without feedback) was not taken into account.

Effect of visual feedback on intervention outcomes

Using a vote counting approach, it is evident that the reported effectiveness of feedback varies a lot between studies (see **Table 2**, where votes are indicated by arrows). When interpreting these outcomes, it is crucial to also consider what exactly the intervention groups were compared against: Even the control groups showed high heterogeneity, which makes a fair comparison impossible. Only one study, Rucci and Tomporowski (31), reported that the visual feedback group showed worse outcomes than their control group, which received verbal feedback. Positive and no benefits are approximately equally common in the feedback and no-feedback conditions of the training effect studies. Even when looking only at the studies with the biggest group-sizes, the outcomes are mixed: Chan et al. (21) (160/group with fading) shows a clear benefit, Benjaminse et al. (20) (30/group with 100% feedback) and Mulloy et al. (25) (16/group with 70% feedback) show no benefit compared to no-feedback control groups, and Post et al. (28) (22/group) only shows a clear benefit in a transfer test. This pattern does not continue in the immediate effect studies, where feedback groups always outperformed no-feedback groups in at least one outcome measure. Otherwise, no clear pattern is visible regarding the time at which the tests were administered ("IT", "PT", "RT1", and "RT2" in **Table 2**) or regarding specific feedback regime parameters. While the studies in the immediate effect category yielded proportionally more positive results than the training effect studies, this was not statistically tested either and no risk of bias assessment was performed for this category, so this may be due to publication bias. The tendencies shown in the tests of the training effect category are further relativized by the concerns shown in the risk of bias assessment.

Because of the high risk of bias and because the included studies are too heterogenous in their design and especially their outcome measures, a statistical synthesis of the findings was not conducted. The risk of bias assessment revealed high concerns for all experiments in the training effect category except for Ericksen et al. (22) (some concerns) and Nekar et al. (27) (low concerns). Chan et al. (21) was considered to have high concerns with regard to feedback effectivity since the control group did not receive instructions to "run softer" in the intervention (effectively resulting in no intervention instead of a no-feedback intervention). All other high concern evaluations are already determined by domain 1 (underspecified randomization process) and domain 5 (no information due to lack of prespecified analysis plan). Any synthesis based on these results would therefore suffer from a very low strength of evidence. Attributing outcomes (positive or non-significant) to movement tasks, experience levels, or specific feedback parameter choices is not warranted, since any purported effect could be attributed to random chance or bias (induced by the specific selection or grouping criteria) rather than a generalizable property of motor learning.

Feedback regime recommendations from the literature

While **Table 2** may serve as a basis to find similar research to consider in future SAFT studies, the remainder of this section is devoted to summarizing recommendations made by the authors of included studies. These recommendations are not necessarily based on hard evidence, i.e., significant study results with a low risk of bias, and instead represent a collection of informed opinions to pay attention to in the future scientific investigation of SAFT.

Benjaminse et al. (20) concluded that the ideal feedback modality might depend on gender, with males in their study benefiting from visual feedback, whereas females instead might benefit from different feedback modes. Anson et al. (35) further mentioned that visual processing is slower and therefore more amenable to slow movements when compared to other modalities. Additionally, larger movements may be easier to detect with visual feedback than smaller movement details. Sigrist et al. (32) suggested that the effectiveness of concurrent feedback may not only depend on the complexity of the movement task, but also the complexity of understanding the task requirements. They stressed that different feedback modalities have different strengths, and further explain that concurrent visual feedback may be more suitable for instructing complex movement, whereas haptic feedback should be used instead for temporal guidance. Sigrist et al. (42) also discussed modality-dependent benefits (sonification for temporal aspects, visual feedback for spatial aspects). However, no significant benefit of multimodal over unimodal feedback was found in the study. They concluded that the selective advantages may be determined by the exact design of the feedback rather than being inherent to the modality itself.

Benjaminse et al. (20) also mentioned that providing subject views from multiple angles might improve the outcome, but that feedback with high complexity can be detrimental. Post et al. (28), however, explicated that the instruction to focus on the (previously defined) critical features of the movement task may be sufficient to avoid overwhelming the learner with the information presented in video (even without offering a video-specific interpretation). Rucci and Tomporowski (31) corroborated other results according to which video feedback without additional cues has little effect on skill acquisition. They emphasized that regardless of the feedback modalities used to deliver feedback, it should provide information on how movement errors can be detected (instead of only directing the learners' attention to the error). This complements Mononen et al. (24), who argued that it might be difficult to establish a link between the received feedback and the corrections that should be made. Teran-Yengle et al. (44) mentioned that real-time feedback can provide the learner with specific information that is not available with intrinsic feedback, thus encouraging exploration and discovery of alternative movement solutions.

Jones et al. (38) concluded that the practical effects of challenging correct feedback as opposed to threatening deceptive conditions should be further explored, and that their effects may ultimately depend on the performance of the learner as well. Washabaugh et al. (40) emphasized the importance of using external motivational tools, such as feedback, to increase both learning and training intensity when intrinsic motivation is lacking. Weakley et al. (41) stressed the importance of providing encouragement and feedback during resistance training, and further noted that the extent of the benefit and the most successful way of providing such encouragement may also depend on individual characteristics, particularly the degree of conscientiousness. In this line of argumentation, Rauter et al. (29) suggested that future studies should tailor feedback to the experience of the participants, that feedback should be changed over the intervention time to prevent studies from becoming monotonous, and, moreover, that such changes have the potential to reduce the induced feedback-dependency (Note that these recommendations specifically concern the planning of feedback in studies and may not be meant as a direct recommendation for feedback in practice). Also, Sigrist et al. (32) recommended to combine multiple modes of feedback and to use an intelligent feedback strategy that individually tailors feedback to preferences, learning rates, error patterns, feedback susceptibility, and performance.

Ericksen et al. (22) explicitly cautioned against using the proposed feedback without first examining retention and transfer effects. Post et al. (28) mentioned that their study could represent an example where transfer may be a more sensitive test of learning, and that self-selected scheduling of split-screen feedback facilitates motor learning under the right circumstances. Todorov et al. (33) explained that the goal of their study was to show that augmented feedback can give an advantage in a difficult multi-joint movement, so the characteristics of augmented feedback in their study were chosen with that goal in mind. They stressed that this consequently does not constitute proof that all the choices made were required to achieve a significant performance benefit. In other words, the chosen conditions were deemed sufficient, but possibly not necessary.

The other reports only mentioned intervention effects and general explanations, but did not state explicit, generalizable feedback regime or study recommendations based on their results.

Discussion

Summary and limitations

We aggregated information about the intervention and visual feedback regimes utilized in 26 studies on training complex, sports-related sensorimotor tasks. We additionally presented the authors' recommendations concerning feedback regimes. In general, studies were practice-oriented and therefore compared considerably different interventions with various feedback regimes, without making generalizability of results for specific feedback parameters a priority. Despite our efforts to increase homogeneity by applying restrictive inclusion criteria, this remaining heterogeneity and the differences between the measured outcomes make it difficult to relate effects of single parameters changes over multiple studies. For the studies with multiple main outcomes, taking one as the main outcome for such a comparison would be an arbitrary choice with a high risk of introducing bias. Consequently, a statistical synthesis of the effectiveness of different feedback parameters was considered inadequate. There were no clear indications as to which specific sensorimotor tasks or target populations might benefit from visual feedback, and where it should be avoided. Therefore, this review reported current trends regarding visual feedback regimes and their effectiveness in the research literature, but it could not provide strong evidence concerning specific feedback parameters. Moreover, when assessing the strength of evidence for or against the specific feedback design used, most included studies had either high concern according to ROB 2 or consisted of relatively small sample sizes per intervention group. As such, the described results should not be taken as definitive evidence, but rather as indications to take into consideration for guiding future research or practical implementation. For these reasons, we cannot give specific recommendations for practical SAFT system design and will instead summarize general considerations based on the designs and recommendations in the literature as well as giving theoretical guidelines to inform future research on SAFT system design.

By employing a strict search procedure specifically narrowed to sensor-based visual feedback, we set out to reduce the breadth of the study scopes *a priori*. These restrictive definitions were intended to facilitate objective evaluation but do not constitute a theoretical consensus. The exclusion of bimanual tasks, for example, was not based on research showing that these movements are necessarily simple tasks, but instead was a result of conservatively avoiding potential interference when including semi-complex tasks. Also, the boundaries between some other reported categories (e.g., concerning experience levels) should only be interpreted as rough indicators. Finally, the restriction to sensor-based feedback excluded functionally identical but non-sensor-based designs. For example, applying body-mounted laser pointers does not utilize sensors but provides the exact same information as a motion sensor and a display [cf. Stien et al. (47)]. On the other hand, raw video replay was included [e.g., Benjaminse et al. (20)] because of the camera sensor, which does not necessarily provide different information than a physical mirror [e.g., Roy et al. (48)].

While we believe we have covered the most important parameters in the design of visual feedback, there may be other important design variations in the remaining body of research beyond our search parameters and the three searched databases, especially in databases more related to sports. Based on the results shown here, we would not expect subsets with sufficient homogeneity to allow generalizable quantification of the benefits of specific feedback parameters even with a larger set of included studies. Including simple movement tasks, which tend to have more standardized testing and outcome measures, would not help with our main research question either because previous research has shown that the effects of feedback do not generalize to complex tasks (13–16). Be that as it may, our sample consisted of various settings in which visual feedback was used effectively, indicating that further usage and study of visual feedback seems warranted: In certain settings, visual feedback can have a positive impact, both on the immediate effects during training and on the learning and retention of complex sensorimotor tasks over longer periods of time.

Feedback regimes in the literature

We have seen a strong focus on knowledge of performance rather than knowledge of results. This may be explained by the fact that knowledge of results is often readily available (e.g., by looking at the point where a thrown ball has landed), so SAFT systems are not required in these cases. Moreover, designing concurrent knowledge of results may be more difficult and may not even make sense in non-continuous tasks. Indeed, the only case where we have seen concurrent knowledge of results was a cycling task where the result (total distance covered) is continuously updated. The benefits of KR or KP feedback have been discussed extensively in the literature, suggesting that it is a crucial aspect and that it should be considered when comparing one feedback intervention to another (49). However, there may be task goals and feedback regimes where the distinction is not so clear, particularly when execution of a prescribed movement without spatial error is the desired result [e.g., Koritnik et al. (39)].

Regarding the timing of feedback, we have seen little variation in feedback delay, with most feedback being simply described as concurrent or terminal. Sigrist et al. (17) concluded in their review that concurrent feedback is more beneficial as task complexity increases, so this could serve as a guiding principle. Anson et al. (35) argued that visual feedback is better for slow movements because visual processes take longer compared to proprioception. From this perspective, feedback delay is a spectrum rather than a binary property. This seems to be in contrast with the prevailing definition of concurrent or terminal feedback. We also note that in both concurrent and terminal feedback, delays in feedback could theoretically be added to encourage independent self-assessment and error prediction by the learner.

We found that feedback frequency was sometimes not reported, or at least not as a deliberate choice. As mentioned before, a reduced frequency could also be the result of tests during the intervention period. This, of course, should be taken into account when interpreting a feedback intervention from a study or using it in practice, as a different efficacy might be observed if the feedback training is not interspersed with non-feedback tests. In addition, strategies such as self-selected or error-based feedback could lead to an implicit, individualized fading mechanism, that promotes, for example, higher involvement and better transfer (50). If increased competence in the movement task through learning leads to fewer feedback requests or fewer errors exceeding the defined threshold, then this will effectively lead to less feedback received over time, as indicated by the vast discrepancies between average and maximum feedback frequencies in these regimes [e.g., in Post et al. (28)].

Feedback can be presented at different levels of abstraction and reliability. This may include, for example, ambiguities in representation, rounding of scores, combining multiple scores into one score, or over time (i.e., changing the resolution or specificity of the feedback). This can make it more difficult for the subject to interpret the results, introduce a threshold below which errors are imperceptible, or otherwise weaken the link between the measured quantity and the information conveyed to the subject. An example of deceptive feedback was given in Jones et al. (38), which is also a good example of using two different levels of abstraction: In addition to the more precise performance feedback provided by displaying distance traveled as a number, increased speed was also encoded in a complex graphical representation by moving an avatar faster through the environment. Taken in isolation, such complex feedback would not allow accurate differentiation of small changes in speed over time.

Finally, the most versatile parameter for visual feedback is the content of the graphical representation itself. We saw some complex graphics, but many of the included studies had relatively simple representations such as numbers, bars, and plots. The choice of visual feedback display format (such as plots, avatars, videos, etc.) seems to matter little. We would have expected much more variance in this area because it is becoming easier to develop such complex graphics and because commercial products with such graphics are ubiquitous, including exergames or virtual and augmented reality devices. This discrepancy could be explained by visual feedback becoming too complex for the learner to interpret effectively, or by potential confounding factors introduced with complex graphical representations that encode multiple variables simultaneously. Having said that, we have not seen any cases where the authors explicitly stated that the feedback was too hard to understand for the participants. None of the graphical representations were deemed too complex, and none of the quantities too abstract for the participants. As a result, we do not see a reason to restrict these parameters *a priori*. However, we should point out that the number of parameters conveyed at once were always rather small (i.e., at most three). It is not quite clear whether this was a purely scientific decision to control what the participants focus on, or whether this is a feedback design decision because participants may not be able to process or select from too much information at once. We would only expect the latter point to play a big role for concurrent feedback, since in the case of terminal feedback, there is ample time for the participant to study the information and select the most relevant parts in the terminal condition. A possible exception to the generally low number of parameters is present in video feedback: Depending on one's perspective, the scene can be interpreted as one parameter conveying the general silhouette or posture of the whole body, or it can be interpreted as containing a plethora of parameters including limb positions and joint angles. This might also explain the recommendations to guide the participants' focus with appropriate instructions, as this would affect the effective numbers of parameters to interpret.

We should also point out that the main goal of SAFT systems is to be beneficial for overall training, and comprehensibility of the provided feedback is only one aspect of this. It is unclear to what extent the feedback needs to be cognitively processed at all for it to help with the operationalization of certain movement parameters. After all, even if subjects find the visual feedback confusing or do not quite understand it, the feedback could in principle still have a positive effect because some (negative) patterns are still recognizable. This is more apparent in sonification, where understanding the parameterization may be more difficult than hearing when something about the movement is out of the ordinary. Another possible explanation for the relatively low diversity in the graphical content of the feedback are the rather uniform objectives of the feedback regimes we encountered: The feedback regimes were generally focused on direct error correction (with the error in question being directly related to the study outcome measures). Other possible objectives of feedback, such as guided exploration of the task-space through targeted variation of task and feedback parameters, remain largely uncharted. A more in-depth theoretical analysis of the movement tasks and training goals according to the four task-space learning mechanisms could encourage the examination of other feedback objectives.

Implications for the practical application of SAFT systems and future research

Implications for the application of SAFT systems in practice remain largely speculative. The main challenge to practically apply SAFT systems lies in identifying effective feedback regimes for specific sensorimotor tasks, and specific populations at specific stages of learning. The effectiveness of concurrent feedback may depend on the complexity of the movement as well as the complexity of understanding the task requirements. The optimal modality may depend on gender, speed of movement, and how large a movement is (i.e., visual discernability). There is some evidence that visual feedback is better suited for spatial task aspects (as opposed to temporal tasks), but Sigrist et al. (42) mentioned that this may be an artefact of simplicity of feedback design. In other words, designing intuitive feedback may be more straightforward if it has the same modality as the movement aspect, but that does not mean that otherwise a good design is impossible to find or that this feedback is inherently more effective. There may also be a tradeoff between feedback simplicity and the amount of information conveyed. Video feedback in particular may be too complex for the user, so additional, carefully formulated instruction is required. This guidance should ideally direct the user to correct the error and not just give information about the error, which necessitates a comprehensive understanding of the task and the involved control parameters. Finally, feedback can encourage the user to increase performance, but the effectiveness of this may be highly dependent on the user's preferences or skill level. The feedback should thus ideally be highly individualized and adaptive. When the motivational aspect is the main goal of the feedback, then the feedback regime might be regarded as successful even if it does not affect the overall training efficiency, as long as it does not hinder progress either.

In our opinion, the current research on feedback for complex skill learning does not support any sweeping statement for or against specific feedback regime parameters in practice. In this regard, not much has changed since the call for more intensive research on complex skill learning from Wulf and Shea (14) in 2002. It looks like visual feedback for complex movements at least does not lead to worse learning outcomes in most cases even if no explicit fading was implemented, provided that this is not due to publication bias. This lack of negative outcomes stands in contrast to feedback on simple movements [cf. the guidance hypothesis (11, 12)], which we interpret as corroborating Wulf and Shea's warning against using results from feedback studies with simple movement tasks to inform the feedback design for complex skills.

Whether visual feedback shows a significant positive effect or no significant effect at all seems to depend on the situation—how much this concerns the design of the feedback regime, the movement task, or the characteristics of the participant cannot be said with any certainty based on the current scientific literature. To better explain and predict the effectiveness of feedback in certain settings, standardized evidence is needed, so that a statistical meta-analysis that compares similar settings with low risk of bias becomes feasible. To this end, we call for future research to focus on obtaining clear definitions on what constitutes a complex coordination task and ideally finding task-category-dependent standardized coordination tests that can be utilized as main outcome parameters in different studies. After establishing a solid basis to build upon, systematic experiments varying only single parameters of the provided feedback for specific tasks would have the potential to produce prescriptive feedback design recommendations. Furthermore, generalizability of results from one outcome of interest to others in the context of augmented feedback training should be investigated: For example, it is not clear at the moment whether specific feedback design parameters, such as a reduced feedback frequency, would have the same effect in training for better endurance-running economy and training for increased weight-lifting performance. Interestingly, this need for more uniform, fundamental research on complex movement task learning with feedback mirrors the conclusion reached by Kal et al. (10) in a systematic review comparing the benefits of the implicit and explicit motor learning. This is a clear indication that this problem is not confined to feedback design studies, but rather points to a systematic issue with the design of trials investigating complex movement tasks in general, specifically the lack of trial and reporting guidelines as suggested by Kal et al. While there are useful reporting checklists for exercise studies, such as the Consensus on Exercise Reporting Template (CERT) (51), these checklists are not specific to feedback studies and only cover the reporting rather than the design of studies.

Theoretical considerations

In the absence of evidence-based guidance, we fall back on the theoretical background to inform future SAFT research to the best possible extent. First and foremost, it should be kept in mind that SAFT systems cannot be designed without considering the characteristics of the task and the instruction regime. Even if no explicit instructions are given to the learner, the way the feedback is presented during or after task execution potentially influences the learner's (implicit or explicit) task goals. As outlined in the introduction, SAFT system designers need to be aware of the subtleties of the well-established and researched motor learning approaches that lie between discovery learning and prescriptive, explicitly instructed learning. Only then can the designer leverage the real potential of systems to systematically assist motor learning during task space formation, exploration, differentiation, and (de-) composition. This is particularly important because instructions and feedback can cause shifts in attentional focus and influence learner motivation, triggering or hindering the learning of task specifics [e.g., compensatory effects (52)]. Unfortunately, the complexity of retrieving the correct instruction and feedback rises with the complexity of the task space. To tackle this issue, a structured approach to task understanding seems necessary. Naturally, domain specific knowledge, e.g., from experts in the field, in addition to evidence from similar previous research could provide a good basis for potentially fruitful feedback regimes. Complementary, functional task analysis (53) seems to be a well-suited approach to guide the identification of structure and functionally relevant features of the sensorimotor task without forcing the user to adopt a specific theoretical stance. Even if naturally the focus, functional assignments for specific modalities of the task's (sub-)actions are not limited to the biomechanical domain but can also be derived from anatomical, physiological, coordinative, perceptual, mental, or tactical perspectives on the sensorimotor task. As Hossner et al. (53) noted, these further functional justifications are based on the fact that a learner's perceptual-motor skills and psychological competencies shape individual task spaces. Hence, functional task analysis seems particularly suitable for the design of SAFT systems, as it automatically distinguishes (functionally irrelevant) style aspects from (functionally relevant) errors in the individual task solution. Both can be incorporated into the design of feedback—the latter as feedback that should be given to ensure correct and functional task solutions, the former as feedback that should be avoided to keep individual freedom and compensation potential high for the motor system and increase its robustness. Once the task space and relevant control variables are identified, the designer can begin to define the intended objectives of the feedback and instructions.

To define the intended objectives of the SAFT, a broad examination and prioritization of the potential benefits of feedback in the target setting is required. We describe some of these potential benefits for visual feedback here, but this list is by no means exhaustive. First, feedback can provide benefits simply by reducing monotony or making the learner more aware of their learning progress, which can, in turn, increase motivation (54). Second, feedback can be used to alter the goal-specifications or shift attentional focus (55). For example, adding an accuracy score in a throwing task might shift the learner's goal: Instead of trying to maximize the power output, the desired result might become movement precision or correct form, guiding the learner closer to an optimal solution. Such feedback may be necessary to guide the learner out of a local optimum in the task-space (4) or to encode variables related to injury risk in the optimization of a movement solution. Third, feedback could focus only on its immediate effect and not on lasting improvements. For example, correct posture and movement execution may be important factors for safety during strength and endurance training. In this case, it may even be beneficial to provide feedback to improve these parameters during each single training session, provided that the exerciser never has to perform these tasks without feedback, and they rather serve as basic building blocks for other skills. Fourth, visual feedback can be easily ignored by looking away, even if this is obviously not considered its primary intent. This may, however, be an advantage of visual feedback over other feedback modalities, as it allows for a form of self-selection that has been reported to increase the effectiveness of feedback and motivation (50). For an even more detailed discussion of the effectiveness of different types of feedback, we refer the reader to the pertinent review by Sigrist et al. (17). Since the intended objective of a feedback is critical for the design of the feedback regime, we additionally refer the reader to **Table 1** in Hossner and Zahno (5), where the specific roles of variance in different motor learning mechanisms are summarized.

There is not necessarily a fixed feedback regime that is optimal for all individuals. The optimal feedback strategy might even depend on the individual's daily mood, motivation, or physical condition, and it might change over a single training session with the level of fatigue. In addition, different aspects of the same task may be optimized in different ways, and tradeoffs could occur. For example, injury-prevention, speed, and jump height in volley spikes may be mutually contradicting goals that result in different optimal movement executions depending on the importance placed on each aspect.

Once a promising solution is found, a well-designed intervention study with fair controls is recommended to validate the effectiveness of the feedback intervention. If motivation is a primary objective of the feedback, even a null effect on learning rates may be considered a positive outcome, as it could mean that the motivational benefits can be reaped without impeding training progress. On the other hand, if the feedback-guided intervention is aimed at learning real-world skills in a training setting, transfer tests are needed to validate the effectiveness of the designed intervention, or at least, according to Teran-Yengle et al. (44), some sort of formal documentation of carry-over to normal life. When testing a novel training intervention with feedback, we strongly recommend three intervention groups: One with the novel training intervention with feedback, one with the novel training intervention but without feedback, and one as a classical control (no intervention or reference intervention). With such a design, the study can not only validate the effectiveness of the intervention, but it may also show the extent to which the outcome was influenced by the feedback provided.

Proposed strategy for SAFT system design in future research

Based on the literature reviewed and the theoretical considerations, we propose the following general strategy for designing SAFT systems in a scientific setting: First, clearly define the intended objectives of the SAFT. Second, conduct a functional task analysis to clearly identify functionally relevant control variables and error mechanisms. Third, determine options for initial feedback solutions based on prior research and domain-specific knowledge. Fourth, if needed to make an evidence-based decision, conduct small pilot studies to choose among different parameter options. Fifth, conduct a well-designed comparative study that includes transfer testing and a single clear main outcome measure. For novel training interventions with feedback, two control groups may be optimal: one with the training intervention without feedback, and one that does not receive the intervention. For established training interventions with novel feedback, a single control group getting the same intervention without feedback is sufficient. In both cases, we do not recommend designating a group receiving different feedback as the control group, unless the utilized feedback can be regarded as the gold standard in that setting. This procedure should support investigation of the potential benefits of a developed feedback intervention in practice as well as answering the question whether the feedback itself made a significant positive contribution to the overall outcome.

Conclusion

We compiled significant findings, utilized feedback regimes, and recommendations from a set of 26 studies on visual feedback in complex sensorimotor tasks with healthy adults. Although the current evidence base is insufficient to derive clear rules for or against the use of specific feedback regimes in complex sensorimotor tasks, the findings outlined in this review and the referenced research can serve as a basis for the initial steps in the process of developing a feedback regime for learning sports-related skills. Consideration of the properties of the sensorimotor task, the task instructions, the feedback regime, and the intended objectives of the feedback is critical. Because the evidence in the literature does not form a strong basis for an evidence-based feedback design guidance, the proposed strategy for future sensor-based augmented feedback training research is instead based on statements in the literature as well as the theoretical background. These considerations are only meant to inform feedback intervention studies in the interim. Standardized study design and reporting guidelines for motor learning research on complex movements, compiled by experts on motor control, are needed to direct future research in a way that will lead to a stronger scientific foundation that can adequately inform design decisions for sensor-based augmented feedback systems in practice.

Author contributions

HH and RK developed the research question. HH searched the databases. HH and JH reviewed the records in both phases and performed the data extraction. JH conducted the risk of bias assessment. HH drafted the first version of the manuscript, RK added the theoretical conceptualization. All authors provided critical feedback and corrections, contributing significantly to the research, analysis, and manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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A.2 A Simple Model for Estimating Tape Kinematics

A Simple Model for Estimating the Kinematics of Tape-like Unstable Bases from Angular Measurements near Anchor Points

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Article

A Simple Model for Estimating the Kinematics of Tape-like Unstable Bases from Angular Measurements near Anchor Points

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Abstract: Sensorimotor training on an unstable base of support is considered to lead to improvements in balance and coordination tasks. Here, we intend to lay the groundwork for generating cost-effective real-time kinematic feedback for coordination training on devices with an unstable base of support, such as Sensopros or slacklines, by establishing a model for estimating relevant tape kinematic data from angle measurements alone. To assess the accuracy of the model in a real-world setting, we record a convenience sample of three people performing ten exercises on the Sensopro Luna and compare the model predictions to motion capture data of the tape. The measured accuracy is reported for each target measure separately, namely the roll angle and XYZ-position of the tape segment directly below the foot. After the initial assessment of the model in its general form, we also propose how to adjust the model parameters based on preliminary measurements to adapt it to a specific setting and further improve its accuracy. The results show that the proposed method is viable for recording tape kinematic data in real-world settings, and may therefore serve as a performance indicator directly or form the basis for estimating posture and other measures related to human motor control in a more intricate training feedback system.

Keywords: sensor-based; kinematics; augmented feedback; dynamic exercise; unstable surface; balance training; inertial measurement unit

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1. Introduction

Physical exercise on unstable bases of support is associated with cognitive, cardiovascular, and performance benefits in coordination and balance tasks [1–8] (although the transfer of sensorimotor capabilities to tasks on stable surfaces may be limited [9–11]). Training on unstable bases of support can be supported by training feedback systems that provide performance indicators for coaches, augment individual, autonomous training with feedback on execution parameters; or serve as an input device for the gamification of such training scenarios [12]. Importantly, measurement systems used in such environments should not increase the complexity of using the training equipment, but rather integrate seamlessly into the training experience, while still providing relevant feedback on execution or task performance. To that end, our goal here is to lay the foundation for a cost-effective and versatile diagnostic and training feedback system capable of estimating performance-related movement characteristics. The objective is therefore to estimate performance parameters, e.g., the kinematics of the unstable support base or the dynamics of human posture, with device-mounted sensors rather than wearable sensors. While camera-based measurement systems [13,14] might offer the highest flexibility for such a task, they are associated with significant hardware costs for the image sensors and the CPUand/or GPU-based analysis units. On top of potentially raising privacy concerns, they are further limited by their intrinsic susceptibility to artifacts introduced by varying lighting conditions, occlusions, additional persons in the field-of-view, and geometric constraints to capture the whole scene. Inertial sensors, e.g., attached to the unstable support bases and capable of directly estimating their kinematics, seem to be a more viable approach. Instead of relying on a camera-based measurement system, we therefore intend to derive these kinematics in a way that is also compatible with versatile and cost-effective device-mounted Inertial Measurement Units (IMUs). However, it is not entirely clear which postural information or performance measures [15] can be accurately derived from such kinematics alone. For more complex postural estimates, such as knee positioning or center-of-mass information, a more detailed investigation of the relationship between the support base and body kinematics could be required. Irrespective of other relevant characteristics that are not directly related to the kinematics of the support bases due to multi-joint biomechanics, these kinematics should at least correspond well with the kinematics of the feet. As such, support base kinematics can provide the necessary data for basic applications such as step counters and various other simple performance metrics in tape exercises, as well as a rudimentary control to ensure correct exercise execution.

Systems for estimating performance-related movement features on stable bases founded on accelerometers have previously been developed [16,17]. However, these systems do not work well in settings with irregular steps [18], so direct transfer to unstable support bases is impaired. Other research tackled the task of developing measurement systems for unstable bases [13,15,19–21], some of which also included IMUs [22–24]. However, deriving position data can be challenging on unstable bases, since double integration of acceleration data suffers from strong drift [25], which cannot be tared in regular intervals because there are no extended rest phases [26] between steps. We propose estimating the position of the support base by other means. To the best of our knowledge, the approach presented here has not been disseminated previously.

Specifically, our proposed setup leverages a specific constraint of slacklines and training devices with similar geometries, such as the Sensopro Luna, which consists of a metal frame and two slackline-like tapes that the exercising person is standing on (see Figure 1). Independently of whether the tape under consideration is a flexible slackline or a more rigid tape with springs on a Sensopro Luna, the tape can only take up tension (i.e., pulling forces in the direction of the tape), and so its geometry aligns with the direction of the pulling forces. The tape can thus be modeled as an idealized rope with only longitudinal geometric extension, so that one can derive the position of the contact point of a mass on the tape (which exerts another force on the rope) by only measuring the angles of the tape near the anchor points, provided the positions of the anchor points are known. So, in order to derive the position and roll angle of the tape segment directly below the mass, our model only needs the static geometric constraints of the setup and angular measurements near the tape anchor points (estimated, e.g., by IMU sensors) while deliberately ignoring potentially available measurements from segments close to the acting mass (e.g., the feet of the exercising person).

(**a**) (**b**)

Figure 1. The tapes of the Sensopro Luna during a sideways exercise (**a**) and at rest (**b**), with green markings indicating the IMU positions. Blue plastic covers are screwed onto the tape, hiding the springs. The anchor points are below the black platforms at the front and back.

From the various potential kinematic measures of the tape, the focus in this article is on tape segment orientation and position, particularly the segment in contact with the mass. Functionally, the orientation and position axes on the tape have fundamentally different significance in tape exercises. Firstly, the longitudinal position has two potential functions: The longitudinal position of the lowest tape point approximates the foot position along the tape, which may help to ensure correct foot positioning for specific exercises. Additionally, changes in the longitudinal position of the lowest point over short periods of time might correlate to changes in pitch angle. Therefore, they also have potential for estimating the relative changes in the longitudinal position of the center of pressure (CoP) resulting from the foot pitch angle, even though the absolute pitch angle of the tape segment or foot cannot be determined in this way (a change in pitch results in a change in the longitudinal CoP position, just like moving the foot would also move the CoP position, which makes distinguishing these two effects difficult). Secondly, the lateral displacement of the support base can be utilized as a proxy for lateral CoP movement [27] and is therefore indicative of performance in balancing tasks [28]. However, depending on the geometric constraints of the training devices, it only has a very low magnitude and is consequently strongly affected by measurement noise. Even though our chosen experimental setup strongly limits its magnitude, we still include it in the analysis because of its functional relevance for lateral CoP changes and its expected larger role in slacklines due to their higher magnitude of lateral displacement. Thirdly, the vertical displacement is the most important measure for exercises with a stepping motion, since step count, intensity, and rhythm are directly derived from vertical displacement over time. Fourthly and lastly, the roll, pitch, and yaw angles of the tape segment close to the foot are related to posture and foot placement on the tape, so these angles may provide important information to correct improper exercise execution. Even if all of these angles could be measured without the model presented here by attaching an IMU sensor to the tape segment below the foot, such a setup would limit supported foot placements to a small area on the tape and increase prediction errors due to higher accelerations compared to the placement of the measurement devices close to the anchor points.

The goal of this validation study is to present a novel model for estimating tape kinematics and to assess its accuracy. After describing the proposed general model in detail and discussing a basic parameterization to further adjust it, we analyze its accuracy with both input from a motion capture system under laboratory conditions and an example IMU input that could be used under field conditions.

2. Materials and Methods

2.1. Nomenclature and Coordinate System on the Luna

To carry out our experiments, we used the Sensopro model Luna Fitness (Sensopro AG, Münsingen, Switzerland), an exercise device primarily designed for coordination training and commonly found in fitness and rehabilitation centers (see Figure 1). The Luna Fitness can be described as follows: When training on the Sensopro, users stand on two unstable tapes while receiving exercise instructions from a touch screen in front of them. Each tape consists of a rectangular non-stretchable canvas connected to two sets of four springs that are attached to the front and back anchor points on the surrounding metal frame. The total length between the front and back anchor points is 1726 mm, and the unloaded, initial length of the springs is approximately 200 mm.

We define the coordinate system as follows: The origin is in the exact center of the anchor points, between the two tapes. The X-axis points forwards, parallel to the long tape axis. The Y-axis points to the left and the Z-axis points upward. Roll, pitch, and yaw correspond to rotations about the X-, Y-, and Z-axes, respectively, using Euler angles, or, more specifically, Tait–Bryan angles following the XYZ intrinsic rotation convention. In this application, the restricted range of possible rotations of Luna tapes keeps the resulting angles similar to the corresponding axis-angle representation (which are used internally for motion capture post-processing) and helps avoid the mathematical limitations associated with Tait–Bryan angles. However, this may not be the case in other settings and should be verified before employing the same algorithm on slacklines, for example.

2.2. Tape Kinematics Model

We consider each tape separately as an ideal rope that connects the two fixed anchor points at $(\pm 863, 0, 0)$ in the sagittal plane, as shown in Figure 2. The general model only requires one setting-specific parameter, namely the rest length L, measured from the back anchor point to the front anchor point. It treats the foot as a single point (X, Z) on the tape that causes the maximum Z-displacement d_M. This point is computed from the front and back angles α and β, which result in pitch-angle-based model predictions for the vertical position (Z) and the longitudinal position (X_Z). Note that the obtained input pitch angle values are normalized so that both the front and back angles are positive when the tape is displaced downwards; in the proper physical frame of reference, the front pitch would be negative instead. Equations (1) and (2) based on ray intersection and trigonometry, respectively, show the mathematically equivalent formulations (we noted both formulations because they can have different performance and stability properties depending on the exact implementation and system).

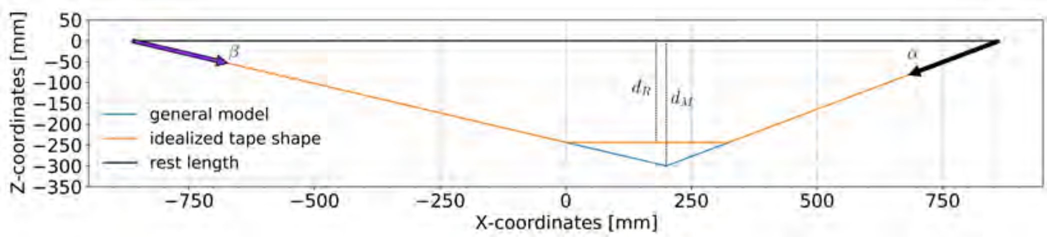


Figure 2. The general model for the X-position and Z-displacement d_M compared to the actual tape displacement approximated by d_R. The black and purple arrows correspond to the front and back tape segments that determine the input angles α and β, respectively.

$$t = \cos(\alpha) + \sin(\alpha)\frac{\cos(\beta)}{\sin(\beta)} \qquad Z = -\sin(\alpha)\frac{L}{t} \qquad X_Z = \cos(\alpha)\frac{L}{t} \tag{1}$$

$$Z = \frac{-L}{\frac{1}{\tan(\alpha)} + \frac{1}{\tan(\beta)}} \qquad X_Z = \frac{|Z|}{\tan(\alpha)} \tag{2}$$

The general model output assumes that $Z = d_M$ (as shown in Figure 2) and thus overestimates the actual displacement of the tape (d_R) because the foot is not a point mass. The difference between d_M and d_R depends on the size of the shoe, the position of the foot on the tape, the flexibility of the shoe and the foot, and the flexibility of the tape around the shoe. For example, assuming a flat segment of a length of $L_F = 260$ mm results in a 0.85-ratio for d_R/d_M (applying the intercept theorem results in $d_R/d_M = L_F/L$), which yields an alternative, parameterized model output Z_{R85}. Note that the longitudinal position (X) is not affected by this parameterization, but the correct X-position of d_R could be anywhere below the shoe.

We use the same basic model in the horizontal plane to infer the yaw-angle-based model predictions for the lateral displacement (Y) and the longitudinal foot position (X_Y). For the yaw-angle-based model, however, we do not include an alternative parameterization correcting the foot segment length because only small Y-displacements are possible on the Sensopro Luna, and so the absolute error remains small, too. An additional property that the model does not consider is the fact that the springs of the Sensopro Luna can have different resistance to lateral displacement from the rest of the tape, resulting in different yaw angles along the longitudinal tape axis. Similarly, the roll rotation angle can also be modeled as increasing linearly along the X-axis, but suffers from the same issue because the spring segment has different resistance to angular deformation than the tapes. Contrary to the yaw-based lateral displacement, this effect is too large to ignore for the roll angles. Therefore, the following four modeling variants are included in the analysis for comparison:

- A non-configurable model expecting linearly increasing roll (R_M);
- A model with spring-coefficient parameterization expecting the rotation in the spring segment to be a fixed multiple of the rotation in the tape (R_S);
- A model with the same spring-coefficient parameterization as in R_S but with an additional weighted sum based on the longitudinal foot position (X_Z) to rely more on the measured input roll from the sensor that is closer to the foot (R_{WS});
- A trivial approach that simply adds the measured front and back roll angles, ignoring the contribution of the remaining tape segments altogether (R_A).

Overall, the model outputs are labeled as follows: X_Z and X_Y denote the X-position predictions obtained from the Z and Y models, respectively. Y and Z describe the general (non-parameterized) model predictions for the lateral and vertical displacement, respectively. Z_{R85} refers to the Z-prediction optimized using the 0.85-ratio parameterization obtained from the theoretical shoe-correction and the synthetic recordings, while Z_{R82} refers to the 0.82-ratio parameterization obtained from the full dataset recorded in this validation study (the 0.82-ratio is only included to show how demographic-specific parameterization could further improve the output, but it is possible that it constitutes overfitting).

2.3. Validation Study

We conducted an exploratory assessment with a convenience sample of three participants, denoted as A, B, and C, with shoe sizes between 42.5 and 45 (EUR shoe sizes, with shoe lengths measured at 28 cm to 32 cm and shoe widths at 11 cm to 12 cm). Each participant performed the following ten exercises on the Sensopro Luna: (01) stepping in place; (02) strong steps; (03) sprinting; (04) symmetrical bouncing; (05) one-leg stand; (06) walking back and forth; (07) walk with roll variation; (08) walk with yaw variation; (09) stepping with variation in lateral foot positioning (Y); (10) standing sideways (facing to the right) and stepping (Figure 1a shows the left-facing version of this exercise). Exercises 01–05 and 10 were similar to standard Sensopro exercises, but focused on variation in movements instead of consistency. Exercises 06–09 were not typical exercises, but ensured coverage of a bigger range of possible states. The exercises were performed for 60 s each, but the recordings were longer to allow for start-up and shutdown sequences. Directly after the start-up sequence and before the start of the exercise, participants jumped onto the tapes to facilitate temporal alignment of the IMU and motion capture data streams during post-processing.

A Vicon optical motion capture system (10 Vicon T20s cameras, 2 MP, 500 Hz, Vicon Nexus 2.13, Vicon Motion Systems Ltd., Oxford, UK) tracked foot and tape movement by means of reflective markers (14 mm diameter). We attached three markers to each foot and eleven markers to the inner (five markers) and outer (six markers) edges of each tape, as shown in Figure 3.

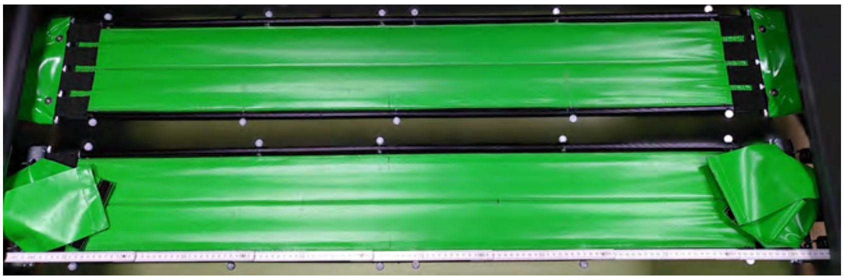


Figure 3. Reflective marker on the tapes (with the front on the right hand side). The plastic covers on the right tape have been loosened to partially expose the metal springs.

The markers were grouped into eight pairs per tape, with the inner edge marker in the middle of each tape belonging to two pairs. These pairs split the tape into seven sections, with each marker pair being the border between two sections. This way, each tape section had three (middle section) or four (other sections) markers defining the section position and rotation, with the exception of the front and back sections that connected the two tape markers with the anchor points (the view of the anchor points was obstructed by the metal frame of the Luna, so the anchor point positions had to be reconstructed from static measurements and markers on the metal frame tracking potential shifts). The Tait–Bryan angles (up to this point in the calculation, angle-axis and quaternion representations were used internally for the transformations) of the front and back sections later served as inputs for the different kinematic model functions. Additionally, one IMU (SFM2, Sensor Maestros LLC, Denver, CO, USA) was attached to the bottom side of the front and back sections of each tape (four IMUs in total). Using sensor fusion of accelerometer, gyroscope, and magnetometer data, these sensors estimated the front and back section roll, pitch, and yaw angles. This setup serves as an example of a cost-effective orientation measurement system.

A third-order 100 Hz low-pass Butterworth filter was applied to the data before resampling and interpolating it from 500 Hz (resp. about 400 Hz for IMU data) down to 200 Hz, so that the resulting motion capture and IMU data shared the same timestamps. The coordinate system was then transformed to ensure that the longitudinal tape axis was exactly aligned with the X-axis. As a next step, the relative translations and rotations of each tape section were computed using the same transformation (these transformations were found by applying the align_vector method in the scipy.spatial.transform.Rotation class [29], which internally applies the Kabsch algorithm [30]). To improve numerical stability, our implementation of the model defaulted to zero predictions (i.e., no displacement, X in the center) when given small input angles (less than 0.1°). Data points where the center of the foot segment was at least 70mm above the center of the tape segment were excluded from the subsequent analyses, because this indicates that the foot was almost or entirely removed from the tape (this threshold was determined from the height of foot markers when standing still; it is still possible for the foot to be in partial contact with the tape above that threshold, for example, by tiptoeing). Similarly, data points where both feet were on the same tape, which only happened in trial 10, were also excluded. A total of 30 trials were processed for both tapes, resulting in 60 single-tape recordings. One trial (B08) was cut to only approximately 56 s instead of the regular 60 s due to a technical issue causing a delay in the IMU start-up sequence. All other trials were cut to exactly 60 s of exercise time.

2.4. Statistical Evaluation

For the statistical analysis, we first checked the applicability of the model and obtained a rough estimate for the application-specific model parameterization by analyzing data from separate trials where the tape had been manipulated in a more synthetic manner by hand (Z-displacements without roll, Y-displacements without Z-displacements, and roll without Z- or Y-displacements). This yielded the required parameters for R_S, $R_W S$, and Z_{R85}. Then, we assessed the accuracy of each model output, first for motion capture-based input angles and then for IMU-based input angles, by comparing the model predictions to the reference values, defined as follows: For each point in time, the reference Y-, and Z-displacements were taken from the tape segment with the highest absolute Z-displacement. The reference X-position was obtained from the motion capture markers attached to the foot and the reference roll angle was taken from the tape section with the highest absolute roll (this might be different from the section with the highest Z-displacement because the foot can be in contact with several tape sections).

For the motion capture-based input angles, we visualized the prediction error with a modified box plot, compiled a table showing the Root-Mean-Squared Error (RMSE) for each trial, and generated more detailed plots showing the effect that X and Z position have on the prediction error of key outputs (X_Z, Y, Z_{R85}, and R_{WS}). For the IMU-based input angles, we first plotted the difference between IMU- and motion capture-based angles for a single trial. Because of the systematic bias in pitch drift, we then applied a simple drift adjustment for pitch by shifting negative values up before visualizing the overall IMU-based prediction errors with a modified box plot again.

3. Results

3.1. Applicability of the Model

Because post-processing was kept to a minimum for the synthetic checks, the measured marker coordinates in the figures were not corrected for slight axis-misalignment, marker placing inaccuracies, or marker jitter, which might sometimes result in a few millimeters of difference between the recorded frame marker positions and anchor point coordinates.

Figure 4 shows a consistent pitch for tape segments that are not near the foot position, as would be expected based on the simple rope model. The model output overshoots the actual Z-position, which is ameliorated when employing the 0.85 shoe length factor. A similar plot is shown for lateral displacement (Y) in Figure 5. Note that the maximal lateral displacement is much smaller than the vertical displacement shown in Figure 4, and some markers do not lie on a straight line. The yaw angles are larger in the first and last segment compared to the more central segments. Furthermore, the model prediction near the back (i.e., the left tape in Figure 5) shows a substantially larger overshoot than the model prediction towards the center (right tape), despite similar absolute Y-displacements in the measured data. Finally, Figure 6 shows how the tape roll develops along the longitudinal axis (X), with the non-parameterized model strongly overestimating the maximum roll angle.

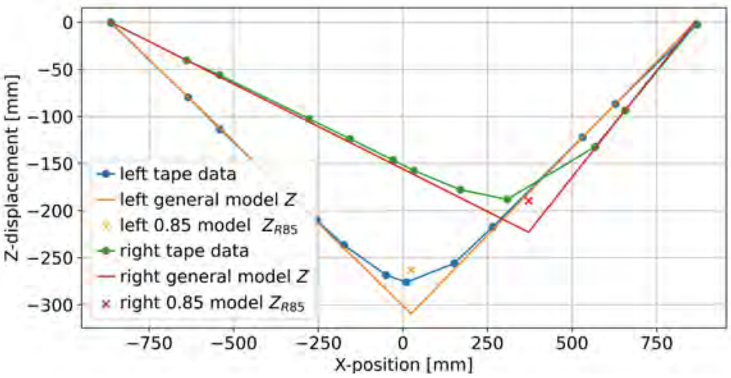


Figure 4. One data point of the left and right tapes in the sagittal plane (as seen from the side).

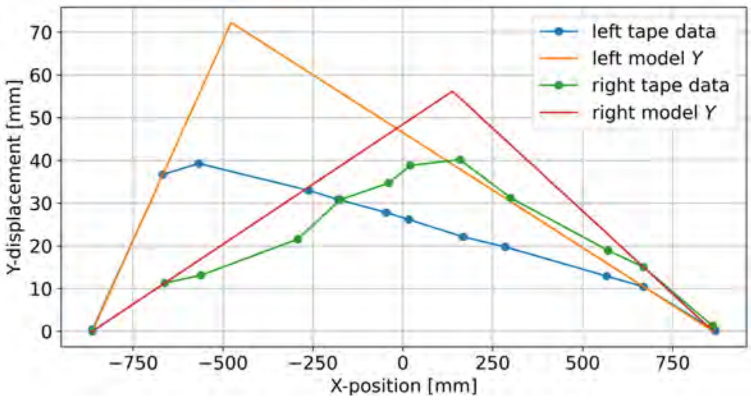


Figure 5. One data point of the left and right tapes in the transversal plane (as seen from above).

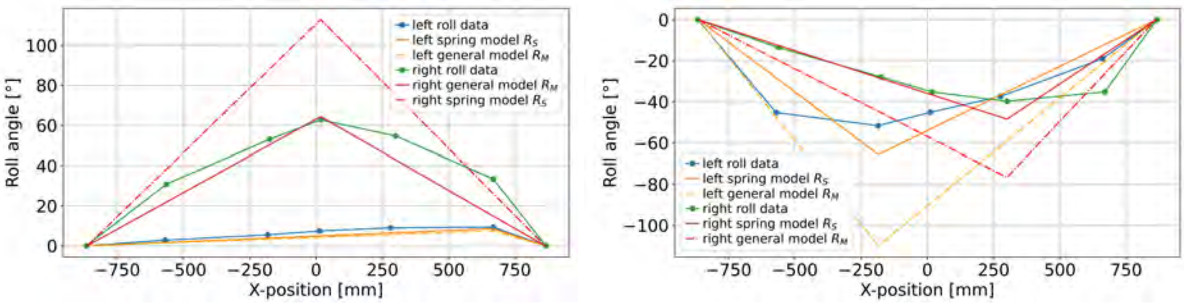


Figure 6. Variation in roll angle along tape axis compared to non-parameterized (R_M) and parameterized (R_S) model outputs.

3.2. Model Accuracy

3.2.1. Descriptive Statistics

A total of 359,211 data points were recorded, covering 1796 seconds of exercise time. Due to the foot being removed from the tape, 54,781 and 52,916 of these samples were excluded from the following analysis for the left and right tapes, respectively. Consequently, the analysis included 304,430 and 306,295 samples for the left and right tapes.

Figure 7 shows the accuracy of the different model outputs. Most ($\pm 2\sigma$, i.e., 96%) pitch-based predictions (X_Z) lie within $[-4\text{ cm}, +14\text{ cm}]$ of the measured X-position of the foot, but the yaw-based predictions (X_Y) are spread out to $[-36\text{ cm}, +45\text{ cm}]$. Both X-predictions also have notable outliers exceeding ± 40 cm (an interval that covers more than half the tape length). Most predictions for lateral displacement (Y) are within an error margin of ± 8 mm (note, however, that the maximum observed lateral displacements in these trials were only ± 70 mm). For the vertical displacements, the parameterized solutions resulted in more accurate predictions than the non-parameterized model (Z). The median of the prediction error for the 0.82-ratio is closer to zero compared to the 0.85-ratio, but the variation remains similar: for Z_{R85}, more than 96% of predicted positions are within -8 ± 12 mm of the actual displacement, while Z_{R82} moves that interval to 2 ± 12 mm. Finally, the spring-corrected model predictions (R_S) lie within $\pm 8.5°$, except for outliers, which is also more accurate than the non-parameterized roll angle model output (R_M). Adding weights based on the reference X-position has a small positive effect, with the weighted spring-corrected roll predictions (R_{WS}) lying within $\pm 7°$ of the reference for over 96% of all data points. The simple approach R_A is only slightly less accurate, with $\pm 9°$. Similarly, half of all predictions lie within $\pm 1.9°$ of the reference for R_S and R_{WS}, while the same proportion covers the interval $[-2.2°, +2.0°]$ for R_A.

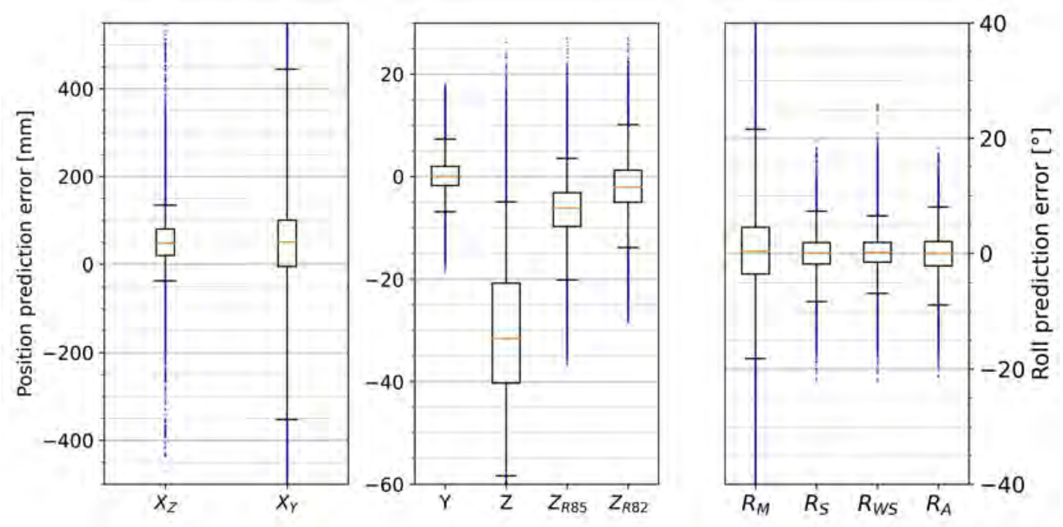
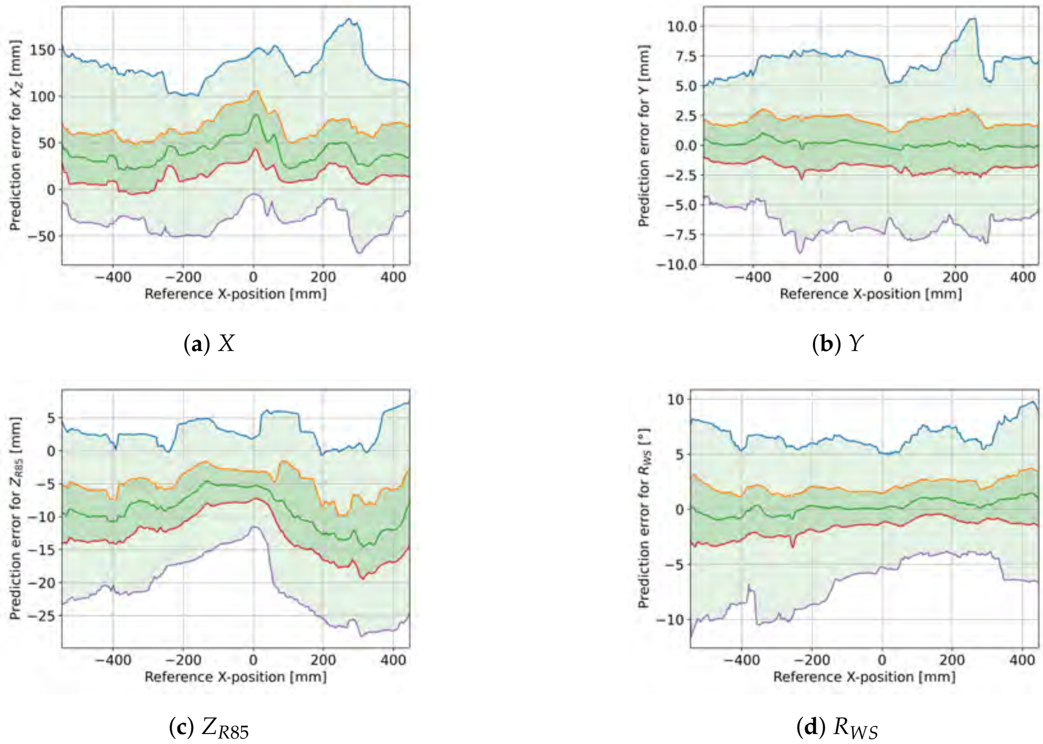


Figure 7. Modified box plots of the prediction errors in all samples. The whiskers range from the 2nd to the 98th percentile, and the boxes cover the 25th to 75th percentile. The median is shown as an orange line, and all outliers (highest and lowest two percentiles) are marked in blue.

3.2.2. Effect of Position on Accuracy

Figure 8 shows how the different model outputs are affected by the foot position along the tape axis. The spring-corrected roll angle displays a tendency to have smaller prediction errors towards the center of the tape. A similar pattern emerges in Z_{R85}, but less pronounced. The predictions for longitudinal (X) and lateral (Y) displacements both show variations with no clear pattern. Figure 9 similarly shows the effect of the downward displacement of the tape. Other than at small ($\leq$5 cm) and at very big ($\geq$30 cm) displacements, there seems to be little effect on the prediction error, except some curvature in Z_{R85}.

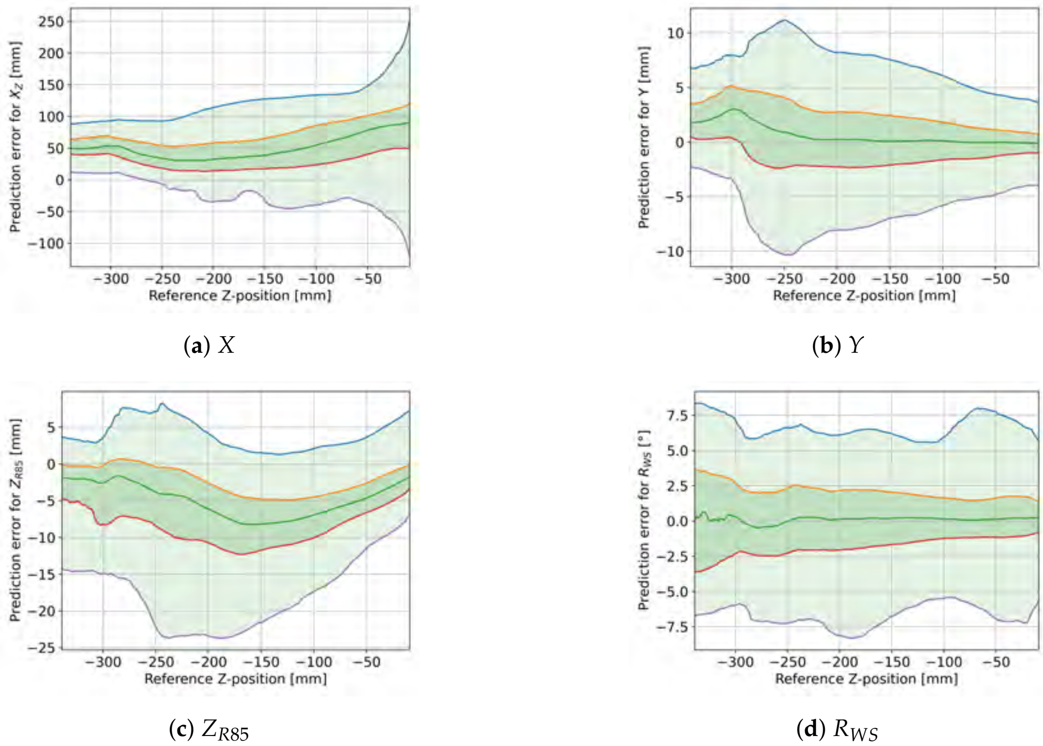
Table 1 shows how the accuracy is affected by different exercises. Notably, the RMSE of the longitudinal position prediction X_Z is lower in sideways trials and highest in sprinting trials. The lateral (Y) and vertical (Z) displacement outputs show largely consistent performance over the different trials, except for increased RMSE for Z_{R85} and Z_{R82} in the walking trials with increased X-position variation (trials 06–08). The roll angle predictions also seem to have higher RMSE in these walking trials, but they also have higher RMSE in trials 04 and 05 (bouncing and one-leg stand), with trial 10 (sideways) only having an above average RMSE for R_M and R_{WS}.



(**a**) X (**b**) Y

(**c**) Z_{R85} (**d**) R_{WS}

Figure 8. Effect of X-position on prediction error for X, Y, Z_{R85}, and R_{WS}. The green line is the median, the dark green area covers the 25th to 75th percentiles, and the light green area covers the 2nd to 98th percentiles (96% of all data points). The blue, orange, red, and purple lines correspond to the 98th, 75th, 25th, and 2nd percentiles, respectively.



(**a**) X (**b**) Y

(**c**) Z_{R85} (**d**) R_{WS}

Figure 9. Effect of Z-position on prediction error for X, Y, Z_{R85}, and R_{WS}. The green line is the median, the dark green area covers the 25th to 75th percentiles, and the light green area covers the 2nd to 98th percentiles (96% of all data points). The blue, orange, red, and purple lines correspond to the 98th, 75th, 25th, and 2nd percentiles, respectively.

Table 1. RMSE of prediction error for each exercise.

Exercise	X_Z (mm)	X_Y (mm)	Y (mm)	Z (mm)	Z_{R85} (mm)	Z_{R82} (mm)	R_M (°)	R_S (°)	R_{WS} (°)	R_A (°)
01	80.7	94.7	2.5	30.1	5.0	4.6	4.8	2.2	1.8	2.7
02	79.0	108.1	2.2	33.3	5.5	5.2	4.3	1.8	2.1	2.0
03	90.3	115.0	2.7	32.7	7.1	3.7	4.4	1.7	2.1	1.9
04	58.8	103.5	3.7	33.7	9.0	4.7	6.6	5.0	3.3	5.5
05	60.0	112.6	3.3	36.8	8.5	5.1	7.0	4.8	3.5	5.5
06	65.5	205.8	2.9	38.5	12.0	7.8	8.4	2.5	2.6	2.5
07	64.8	203.1	3.8	33.8	11.5	7.8	12.2	3.7	3.6	3.9
08	56.8	196.7	3.4	35.2	11.4	7.6	13.4	4.3	4.0	4.6
09	59.9	117.5	4.3	33.0	6.7	4.4	8.3	4.0	3.4	4.7
10	23.6	179.4	3.0	30.3	7.0	5.7	10.9	2.5	3.2	2.4
all	66.6	148.8	3.3	33.7	8.7	5.8	8.6	3.5	3.0	3.8

3.3. Model Accuracy on IMU Data

Figure 10 shows that the IMU pitch and yaw angles used as inputs for the model predictions drift away from the reference angles recorded by the motion capture system, but this is not the case for the roll angles. Figure 11 shows that the IMU-based predictions for X, Y, and Z are much less accurate than the ones obtained from the motion capture system. The roll predictions are similar to the one based on motion capture data. Note that the prediction error after the drift for pitch angles was corrected with the assumption that the tape cannot exceed its rest height, i.e., that the input angle for Z and X_Z is always positive. Compared to the motion capture based model output, the 96% prediction error interval increased as follows: from $[-4\text{ cm}, +14\text{ cm}]$ to $[-14\text{ cm}, +24\text{ cm}]$ for X_Z; from ± 8 mm to $[-5\text{ cm}, +4\text{ cm}]$ for Y; from -8 ± 12 mm to $[-53\text{ mm}, 27\text{ mm}]$ for Z_{R85}; and from $\pm 7°$ to $[-10°, +11°]$ for R_S, R_{WS}, and R_A. Notably, R_{WS} had a larger prediction error than R_A and R_S, which was not the case for the predictions based on motion capture data.

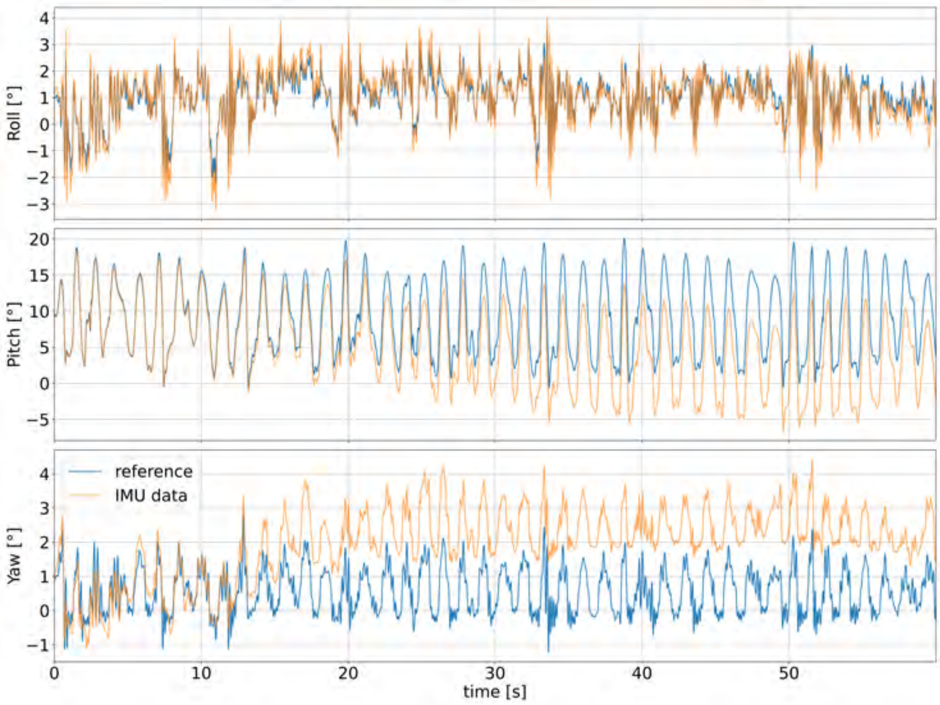


Figure 10. Comparison between IMU angles and reference motion capture data for a single trial (C02).

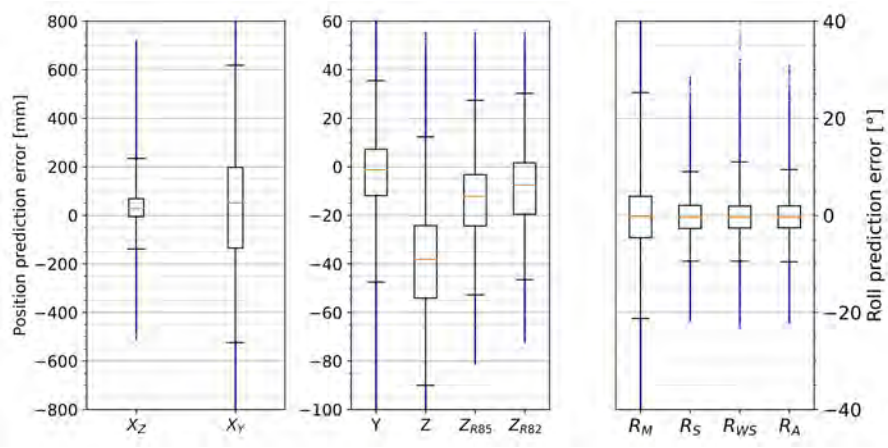


Figure 11. Modified box plots of prediction errors using IMU input data. The whiskers range from the 2nd to the 98th percentile.

4. Discussion

4.1. Summary of Findings

The proposed model for estimating relevant kinematic data for exercises on tapes was successfully applied to the Sensopro Luna Fitness, including a simple parameterization for foot-size adjustments. With near-perfect input angles from the motion capture system, the model achieved a prediction error within a few centimeters of the reference measurements for lateral (Y) and vertical (Z) displacements (see Figure 7). Since the tape is wide enough to wrap around the foot and the reference system could only measure marker positions near the edges of the tape, this may at least partially lie within the measurement error for the reference data. Similarly, the error range for the longitudinal position (X, excluding 4% of data points as possible outliers) is smaller than the length of the foot. While this seems like a large variation at first, the following aspect needs to be taken into account before evaluation: by shifting the center of pressure forward and backward, the theoretically perfect X measurement (i.e., the CoP position) would also shift while barely affecting the reference X-position that is only based on the foot markers. This interpretation is supported by the fact that the sideways trial (exercise 10) had a noticeably smaller RMSE than the other trials (see Table 1). The same model does not perform as well for roll angle predictions; even the parameterized and weighted versions are not substantially more accurate (see Figure 7) than a simple addition of roll angles measured at the front and back. Finally, while the estimation based on IMU measurements showed higher prediction errors than the motion capture-based predictions, the accuracy would probably suffice for some applications, such as gamification. However, there is still room for further improvements in several areas.

4.2. IMU Drift

Drift in the IMU angles could be mitigated in several ways. One simple adjustment was already included here, namely prohibiting negative pitch input angles. This brought the Z_{R85} prediction error down from $[-35\ \text{mm}, 61\ \text{mm}]$ to the $[-53\ \text{mm}, 27\ \text{mm}]$ shown in Figure 11, and reduced X_Z from $[-33\ \text{cm}, 42\ \text{cm}]$ to $[-14\ \text{cm}, 24\ \text{cm}]$. Another strategy would be to detrend the signal to mitigate the effects of drift (from short experiments, a third-order 0.001 Hz high-pass Butterworth filter seems to work well for pitch angles; similarly, a 0.01 Hz high-pass filter seems adequate for roll angles), but this has the downside of hiding long-term shifts in movement patterns over the exercise duration. When additional information about the intended exercise is provided (e.g., by linking the data collection and algorithms to the selected exercise or by implementing an automatic classification system similar to [24]), this could be used to impose more specific constraints on the input data. For example, in symmetrical exercises where the whole weight is on the tapes, the displacement averaged over a time window of several seconds should remain more or less constant. Furthermore, some part of the pitch angle drift seems to be caused by the repeated up and down movements during regular exercise or the tape swinging freely in its natural frequency. The one-sidedness of the observed pitch drift patterns could therefore be explained by the general sensor fusion algorithm considering accelerations near 1G as resting points for the internal drift correction. This would lead to the inclusion of time frames with 1G downward accelerations (in addition to the 1G upward accelerations expected at rest). Overall, it would likely be beneficial to implement a specialized sensor fusion algorithm that would estimate the input angles based on the raw accelerometer, gyroscope, and magnetometer data. By adapting the sensor fusion algorithm to the specific setting, in which the state space of possible angles is severely restricted, such drift patterns could potentially be detected and avoided. For example, when the foot contact is suddenly removed, Sensopro Luna tapes show fairly regular oscillation frequencies that could be filtered in the measured input angles to avoid drift and increase reliability.

4.3. Outlier Detection

In addition to these possible improvements to the IMU input, the outliers could be detected independently of the orientation measurement system. Our model currently only considers each time frame separately. Generally, temporal coherence conditions can be enforced on X, Y, and Z to reject at least some of the observed outliers, because these values should change smoothly. Also, since the model outputs two variables for each data point ((X_Z, Z) or (X_Y, Y)), we can infer information about the reliability of one by using the other. Low Z values generally lead to unreliable X_Z estimations, and the same is true for Y and X_Y. Conversely, moving the foot in the X direction usually involves lifting the foot off the tape. So, large changes in X-predictions (i.e., larger than the foot length) without an intermediate foot-lift-off phase are likely inaccurate (unless for exercises where both feet are on the same tape).

The biggest outliers for the X-position tend to happen when the tape is not under load, because then, even little changes in input angles can have big effects on the predicted X_Z. When removing the foot from the tape, it quickly oscillates up and down in a range of about ± 4 cm. It would be best to detect idle or oscillating tape conditions and handle them separately to avoid these issues. For a similar reason, the yaw-angle-based longitudinal position estimation (X_Y) does not seem to be a viable option for the Sensopro Luna; displacements in the Y direction are in the range of a few centimeters, and small perturbations in the input will therefore have a big effect on the predicted X_Y-position. For this reason, slight marker shifts and tape deformations during recording are also sufficient for explaining the chaotic lines observed in Figure 5, since the marker positions only deviate a few millimeters from a straight line (excluding the first and last segments). When using IMUs for tape angle measurements, the predicted Y and X_Y positions would be even less accurate because the yaw angle required as n input is more susceptible to drift and fluctuations (contrary to pitch and roll, the sensor fusion for yaw angles cannot use gravitational acceleration for drift correction and must rely on magnetometer data instead). These issues can generally be mitigated by rejecting measurements with small angles altogether. This is a reasonable procedure under real-world conditions since the X-position is a meaningless measure when the foot is removed from the tape and since we are not interested in the vertical and lateral tape positions when unloaded.

4.4. Effects of X- and Z-Position on Accuracy

The effects of the X- and Z-positions on the different model outputs shown in Figures 8 and 9 have a few different possible explanations:

- Generally, more data samples are gathered near the center of the tape (i.e., X near 0), because the standard exercises in the first five trials have little X-variation. It is possible that the movement in the latter five trials with more X-variation is also more erratic, which would generally increase the prediction error. Furthermore, the motion capture markers are closer together near the center of the tape, so the reference measurements might be less accurate in the front and back sections for all variables other than the X-positions.
- The longitudinal position prediction X_Z defaults back to the center of the tape when the tape is not under load, which would explain the larger variations for small Z-values and possible smaller variations when the X-reference is near zero. Since the variation is mostly within a $[-10\text{ cm}, +20\text{ cm}]$ interval around the reference X-position, it is possible that this variation is not due to prediction errors at all: the distances of heel-markers and toe-markers to the foot-center position are also about 10 cm and 20 cm, respectively, so this could be due to changes in the center-of-pressure position (which is what the model actually tries to predict) relative to the foot-center position.
- Larger Y-variation can be achieved by the user when positioned near the center of the tape (X near zero) and with increased downward force applied to the tape, at least up to a point, since extreme Z-displacements are difficult to achieve when there is additional sideways displacement. With larger real Y variation, larger prediction errors are to be expected.
- There is less variation in Z_{R85} prediction error near the center of the tape (see Figure 8c), but the pattern is not symmetrical, so this could be an instance where the more erratic movements in the trials with more X-variation (i.e., trials 06–10) affect the prediction error. The curved form with increased Z-displacement up to -250 mm could be indicative of a non-linear error term that has not been included in the parameterized model, especially since the median error is affected the same way.
- The distribution of the roll angle prediction error seems to be more spread out for smaller Z-displacements, but the 25th to 75th percentile ranges show the exact opposite effect. This can, again, be explained by smaller variations in roll angles for extreme Z-values. However, there is a much stronger dependency on the X-position: increased distance from the center leads to up to three times larger prediction errors. Consequently, the current implementation of the parameterized model is not suitable for X-positions near the very front and back of the tape.
- According to Figure 8, the prediction error is not symmetrical in the sagittal axis. This could be explained by the fact that in most trials, the feet were pointing forward, so that the toes would have a higher X-value than the heels. The only exception was trial number 10, where the feet were turned to the right, resulting in a smaller effective foot segment. Generally, the prediction error for Z_{R85} and R_{WS} seems to increase with larger distance from the center, but it is not clear whether this is due to a potential limitation of the model, due to the feet affecting the measured angles when closer to the anchor points, or just due to less regular movement patterns in the trials that also had large movements in the X-direction. However, if the different movement patterns are the actual reason for the increased prediction errors, we would expect a noticeable pattern in the trial RMSE in Table 1.

4.5. Limitations

The accuracy assessment conducted in this study is limited by the measurement setup in several ways, some of which have already been mentioned before. Here, we list the most pertinent caveats: First, the validation study is only meant as an assessment of the model accuracy, with a focus on covering basic exercises as well as a large variety of tape poses. It is by no means a representative study for making statements about general exercise patterns and human body kinematics during training. Furthermore, it is possible that the reported accuracy ranges exhibit specific biases, so additional setting- and exercise-specific validation with more participants is recommended before the model is used in practice. Second, only small Y-variations were achieved, potentially reducing the observed prediction error independently of the chosen model. Third, we used foot markers to detect and exclude measurements where the foot was not on the tape. Under real-world conditions, this would have to be detected algorithmically if these data points needed to be excluded. Finally, the theoretically ideal reference position would be the center of pressure, which cannot be determined directly in our setup—its position may be anywhere below the foot (with a larger range of lateral variation than in slacklines [27]). Moreover, marker positions and complex tape behavior further separate the measured values from the ideal CoP position. Nevertheless, these inaccuracies should lie in an inconsequential range for everything but the Y-variations, and so we believe that this validation setup is sufficient to show the usefulness of the model. Removing these unsystematic measurement errors in the data (if possible at all) could affect the estimated accuracy in both directions, so it is not clear whether it would increase or decrease the estimated accuracy ranges.

One general limitation of the model presented here is that we expect the tape to be loaded, which is not always the case. When the mass is quickly removed from the tape, this can lead to complex oscillations that affect the orientation at the front and back. These oscillations can even lead to the inputs having different signs, which leads to numerical instability for all model outputs. Even if both angles have the same sign, it is possible that the two 3D rays resulting from tape angle measurements do not intersect. Our proposed method looks at the XZ and the XY 2D-planes separately to determine the (X_Z, Z) and (X_Y, Y) intersection positions, respectively. If there is no 3D ray intersection, then this will result in $X_Z \neq X_Y$, which could serve as an indicator for inaccurate measurements. However, the Y displacements we observed here were not large enough to make use of this. Generally, if IMU measurements result in a discrepancy between X_Z and X_Y, we suggest giving more weight to the (X_Z, Z) position due to the yaw angle being less reliable.

The model also does not account for the change in spring length under load, which affects the exact X-position at which the roll angle is measured. Therefore, the exact factor relating measured roll to foot segment roll may change with increased pitch (although we would expect a more clearly visible pattern in Figure 9d if this effect was strong).

4.6. Future Research

Future research should try to replicate these accuracy assessments for slacklines. The observable parameter ranges are severely restricted by the Sensopro Luna as follows: Y is within ± 7 cm, Z is between 0 cm and 38 cm, and roll is between $-30°$ and $30°$. An assessment in slacklines would therefore be especially important for the Y-displacement, but potentially benefit the other parameters as well since it would allow for larger displacements in all directions (e.g., [20] used a slackline of 3 m length and 5 cm width, compared to the 1.73 m long and 20 cm wide tapes used here). Additionally, a slackline would have one homogeneous material throughout the full length of the elastic ribbon, so it may be beneficial to investigate the potentially simpler relationship of these quantities with measurements in slacklines, too. For example, given a yaw and roll angle estimation formula on slacklines that is parameterized with length and rotational stiffness constants, another candidate for computations on Sensopro tapes could be found by applying that same formula twice (with different parameter values on the spring and tape segments). Alternatively, setting-specific heuristic approaches like the one applied in R_A could already be sufficient, but those likely also benefit from data-driven adjustments.

Another interesting topic for further investigation is the relationship between model output and kinetic features, specifically between foot pitch, center of pressure, and predicted X-position. We expect that some variation in the X_Z prediction can be explained by changes in posture affecting the exact center-of-pressure position beneath the foot and, consequently, the position of the lowest point of the tape, rather than solely being due to measurement or model errors. If that is the case, it would be possible that the pitch or the center-of-pressure X-position could be predicted if the exact foot placement on the tape is given. The feet are generally not completely removed during typical exercises, so the X-position of each foot should be fixed in some sense, which would make these relative variations useful in practice. While we already saw some correlation between small X-variations and foot pitch variation in this dataset, a different measurement setup would be required to identify a direct relationship between these quantities with certainty. For example, leveraging in-sole pressure measurement devices or employing a full-body motion capture system with biomechanical modeling, one could potentially relate variations in model predictions to center-of-mass and center-of-pressure movements.

Finally, although we focused on the tapes of the Sensopro Luna in the accuracy assessments and proposed further adjustments based on slackline measurements, we see the simplicity of the general model as a potential strength in the sense that it could already be applied to other Sensopro models and slacklines as-is, even without a more detailed investigation into the best possible setting-specific parameterization. Nevertheless, we recommend a previous application-oriented validation in order to obtain pertinent accuracy ranges and updated parameter values, since the accuracy reported here may otherwise not apply due to population biases and different exercise sets. It would also be interesting to see how such a model would perform for trampolines, where several input angles could be measured at different positions. It may be possible to adapt this approach to trampolines by either treating them as several overlapping two-dimensional rope models or by expanding the approach to a full three-dimensional model of unstable bases of support.

5. Conclusions

The general model provides a rough estimate of the most relevant kinematic parameters, sufficient for gamification applications. Adjusting the model with a few tape-specific parameters greatly reduces bias and improves the accuracy of the model. With these adjustments, generating feedback for coordination training based on the output of this model seems possible. Our results show moderate accuracy for sagittal foot positioning along the tape and high accuracy for vertical displacement, while lateral displacements, roll angles, and potential kinetic relationships may require further investigation. IMU-based measurements suffer from drift over time, but appropriate drift corrections can mitigate this issue. Promising related applications of the proposed model include slacklines and trampolines.

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Conflicts of Interest: This study was funded as part of an InnoSuisse project with Sensopro AG. Innosuisse projects have the explicit goal of promoting science-based innovations. Therefore, the proposed model was discussed with Sensopro AG to ensure that IMU-based feedback, in general, is a viable option on the Luna. The funders had no role in the collection, analysis, or interpretation of the data.

Abbreviations

The following abbreviations are used in this manuscript:

IMU	Inertial Measurement Unit
CoP	Center of pressure
RMSE	Root-Mean-Squared Error

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A.3 Neural Network Models for Center of Mass Kinematics [In Preparation]

Prediction of Center of Mass Kinematics of Sensopro Exercises with Neural Network Models

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This draft will undergo revision after acquiring all results, possibly involving small changes to the methodology.

Prediction of Center of Mass Kinematics of Sensopro Exercises with Neural Network Models *[preliminary draft]*

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Abstract

Augmented feedback supplements autonomous coordination training, ensuring correct exercise execution and enhancing self-efficacy by scoring and tracking performance indicators. We intend to develop a practical, cost-effective measurement system to provide center of mass predictions based on tape kinematics for advanced postural feedback in three balance and coordination exercises on an unstable base of support. In a cross-sectional study, 65 participants performed exercises on the Sensopro Luna, while a marker-based motion capture system recorded tape and body kinematics. These recordings were split into training and test data sets for several neural network models. To predict the center of mass position in all three dimensions from tape kinematics, we implemented models based on a convolutional and a variational auto-encoder neural network architecture. Preliminary results based on a subset of the data and a smaller convolutional neural network architecture showed good accuracy. Therefore, further experiments with different exercises, deeper models, and a more complex architecture are warranted

Keywords: Coordination Training, Augmented Feedback, Model Prediction, Time-Series Analysis

1 Introduction

The Center of Mass (CoM) plays an important role in assessments of postural control[4, 5, 8]. Postural control is also a central aspect of balance and coordination training, making the CoM an interesting candidate for performance assessments or augmented feedback on unstable bases of support[7] such as the unstable tapes of the Sensopro Luna. While existing methods of estimating the CoM position with optical motion capture systems have high accuracy[1], they require expert supervision and expensive camera systems that are not suitable for field conditions. Hence, alternative measurement systems based on wearable Inertial Measurement Units (IMUs) have been proposed[2, 4]. In contrast to these efforts, we use kinematic measurements of the unstable base of support to predict CoM displacement without the use of wearables, thus avoiding complex user-setup or calibrations. This should be possible in theory because the reaction forces on the unstable base of support are intrinsically linked to the forces applied to the CoM and therefore to changes in CoM kinematics[6] as long as the unstable base is the only contact point. Furthermore, by training different neural network models with different sets of input kinematics, we intend to assess the potential viability of potential CoM prediction systems based on tape kinematics derived from IMUs attached to Sensopro tapes[3]. Such a system would make cost-effective tracking of features related to postural control attainable under field conditions, thereby facilitating automated postural feedback and performance tracking for autonomous balance and coordination training in therapy and fitness centers. To that end, we compare the accuracy of three exercise-specific models to gain insight into the relative difficulty of CoM prediction for different exercises on the Sensopro. For each exercise, both a convolutional neural network and variational autoencoder architectures are tested and compared to gauge the potential of deeper and more complex models. Finally, we analyze and discuss these results for each axis separately, with the main focus on the mediolateral CoM displacement accuracy because this would be the most relevant direction for most forward-facing exercises on the Sensopro.

The objectives of this article are therefore (1) to demonstrate that center of mass position can be predicted from tape kinematics with neural network models, (2) to compare the relative accuracy of these models for different Sensopro exercises in all three principal spatial axes, and (3) to compare the accuracy of predictions made by model architectures of different complexities.

2 Material and Methods

2.1 Participants

Participants for the cross-sectional study were recruited from sport science students (18 to 24 years old). In order to avoid systematic biases due to fatigue and asymmetrical exercises, participants were evenly allocated into eight groups that differed in the order in which the exercises were executed and in leg placements for asymmetric exercises. The initial goal was to collect at least eight full recordings for each of the eight groups, but 12 recordings had to be excluded from the dataset due to issues with the recorded data (missing markers, recording errors, system errors). Consequently,

Fig. 1: The Sensopro Luna during a sideways exercise (left) and tapes (right) showing marker and IMU placement. *Copyright 2025 by Sensopro AG.*

additional invitations were sent out until all of the 64 slots were filled by complete recordings, with at least 4 female and 4 male participants for each of the 8 groups. In total, 77 participants were invited over the span of six months, resulting in 65 full recordings (including one additional participant that was recorded as a reserve).

The study was carried out in accordance with the Declaration of Helsinki and was approved by the Institutional Ethics Committee of the Faculty of Human Sciences at the University of Bern (approval number: 2019-08-00004). Written informed consent was obtained from all individual participants included in the study.

2.2 Devices and Setup

Exercises were performed on a Sensopro model Luna Fitness (Sensopro AG, Switzerland), shown in Figure 1. Tape motion and body kinematics were recorded with a marker-based motion tracking system (10 Vicon T20s cameras, 2MP, 500Hz, Vicon Nexus 2.12). Tape kinematics were also recorded using two inertial measurement units (Blue Trident IMUs, 500Hz, Vicon), attached to the center of each tape (see Figure **??**). Anthropometric data was gathered for each participant before completing static and dynamic calibration recordings for the full-body marker model (Vicon Plug-in Gait full-body model).

The motion capture system provided the CoM data (three values, one value for each axis), which constituted the desired output. The full input for the models comprised orientation of the front and rear tape segments, IMU data, trigonometric position estimates for the lowest point on each tape, and the estimated height difference between tape. Each IMU measured acceleration, angular velocity, and orientation data (using sensor fusion) of the middle segment (nine values per tape). The motion capture system recorded the orientation data for the front and rear segments (three values each). The tape segment orientations were then used to derive lowest tape point XYZ-position estimates (three values for each tape) using the trigonometric formula from [3]. Finally, the difference of the vertical position estimates was added to the input too, for a total of 37 input values and three output values.

2.3 Exercises

Participants first performed each of the eight base exercises for 30 seconds as a warm-up. After the warm-up phase, each exercise was repeated four times for 45 seconds each, with a break of at least 20 seconds between each exercise (participants could request longer breaks if necessary). Representatives from Sensopro AG advised us in the choice of exercises to ensure that they were fairly representative for exercises on the Sensopro Luna in general, with the restriction that they should not involve complex hand movements or other elements of the Sensopro (e.g., not holding onto elastic tubes or metal rails unless for safety reasons). Of the eight recorded exercise types, only the following three exercises were chosen for training the neural network models in this study: 1) stepping in place (slow, asymmetrical movement); 2) waves (fast, symmetrical movements); 3) single leg stance (difficult balancing task, with participant frequently grabbing the metal rails for support).

2.4 Data Processing

The inbuilt functions in the Vicon Nexus software were used to first fill gaps in the marker trajectories and then generate the reference CoM data. Trials with less than 20 seconds of CoM data were excluded from training and testing sets. (This could happen when the posture of the participant resulted in a marker being covered throughout the exercise.) The orientation data from front tape segments, rear tape segments, and IMUs was tared using the static recordings of each participant. A third-order 100Hz low-pass Butterworth filter was applied to all recordings before resampling to 200Hz. The orientation was converted to roll, pitch, and yaw following the intrinsic XYZ convention for Tait-Bryan angles. Then, the position estimates for the lowest point on both tapes, as well as the height difference between the tapes, were derived from the orientation data of the respective front and rear segments. Finally, all these values were combined together with the resampled raw data from the IMUs to form the input and reference for training and testing of models. The trivial reference model did not require training and simply used the estimated lowest points weighted by left-right height difference to derive a CoM prediction (the lower tape tends to have more weight on it, so the CoM displacement is predicted to be closer to the lower foot displacement).

2.5 Preliminary Tests

Disclamer: This section and the corresponding preliminary results and discussion will be removed after the analysis of the more complex neural network models is complete.

To gauge the potential of CoM-prediction based on tape kinematics, we first checked whether a smaller neural network would achieve promising results by using the recorded tape kinematics for the prediction of CoM_Y. The training set for these tests consisted of stepping trials from 16 participants, and the test set consisted of 45 stepping trials from the other participants that were not included in the training set. Trials were not yet fully processed, so the recordings were not yet downsampled from 500Hz. For the analysis, the difference between predicted and measured COM_Y-positions was summarized with short descriptive statistics while the overall distribution was visualized with a boxplot and a Bland-Altman plot.

2.6 Neural Network Models

The same convolutional neural network architecture was used to train three baseline models, one specific for each exercise. The absolute vertical CoM position is not attainable through tape kinematics alone, as it depends on the height and posture of the participant. Therefore, each model was instead tasked to predict the relative

CoM position, i.e., the CoM displacement, based on the full set of the 37 possible input parameters. Similarly, a more complex model based on a variational autoencoder architecture, consisting of the above CNN in conjunction with an LSTM and a decoder, was trained for each exercise to compare the accuracy and reliability of the more complex architecture with the simple convolutional neural network.

In order to train the models, the complete dataset is split into a test set and a training (and validation) set. For each exercise, one trial from each participant is chosen at random for the test set, and the other three trials were moved to the training set. The randomization was necessary to avoid a systematic bias due to increasing fatigue.

2.7 Network Architecture

A convolutional neural network (CNN) was developed to predict the lateral displacement of the body's center of mass (CoM_{XYZ}) displacement from fixed-length sequences of multivariate sensor data. The input to the network consisted of preprocessed time-series signals. These signals were normalized and shaped into tensors of size $[N, 1, F]$, where N is the number of samples and F is the number of extracted features per frame (in this case, 37 input channels). The network architecture comprises three successive 1D convolutional layers with increasing filter depths (8, 16, and 32 channels), each using a kernel size of 3 with a padding of 1. Each convolutional block is followed by a ReLU activation and a max-pooling operation (kernel size = 2), reducing the sequence length from 8 to 1 across the three pooling stages. The output of the final convolutional layer is flattened and passed through two fully connected layers with 64 and 32 neurons, respectively, using ReLU activations. This is followed by a final linear output layer that yields a single scalar value representing the predicted CoM_Y. The model was trained using the Adam optimizer with a learning rate of 0.001. Mean squared error (MSE) was used as the loss function to minimize the regression error. The dataset (excluding test set trials) was split into training (80%) and validation (20%) subsets, and training was performed over 25 epochs with a batch size of 256.

In a next step, the same convolutional network was combined with a bidirectional long short-term memory (LSTM) architecture to realize a variational auto-encoder topology.

2.8 Statistical Analysis

We compute the RMSE of the difference between predicted and expected displacements to evaluate the overall accuracy of the 6 neural network models and compare them to the accuracy of the trivial reference model. The position-dependent variability is explored with plots showing error quantiles against CoM displacements. Potential accuracy differences between participants are shown using a confusion matrix.

3 Results

Three wave trials had to be excluded due to missing CoM data. The full dataset therefore included a total of 260 step trials, 257 wave trials, and 260 single leg trials.

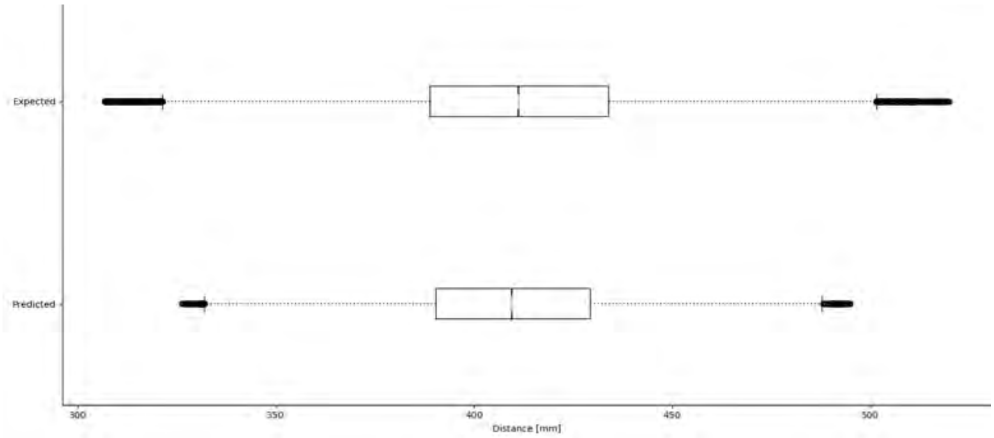

Fig. 2: A boxplot showing the distribution of the lateral CoM position measured by the motion capture system (top) and predicted by a simple neural network model (bottom).

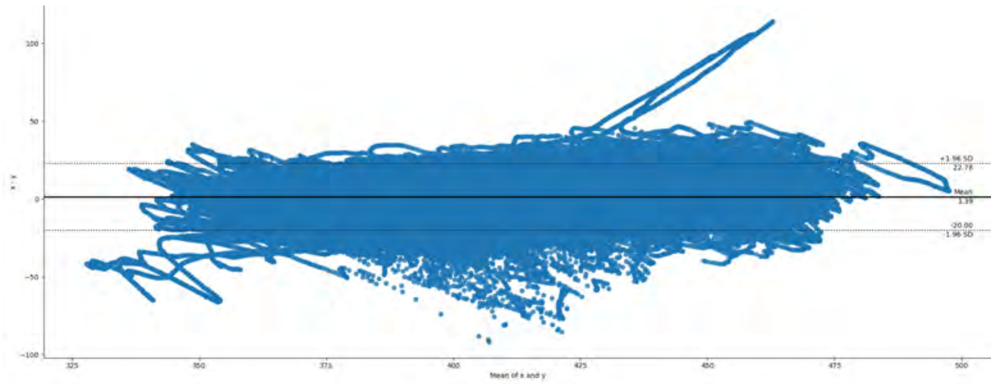

Fig. 3: A Bland-Altman plot showing the variability of lateral CoM position measurements and predictions.

Furthermore, three participants had to be excluded from the preliminary tests due to improper setup of the IMUs. The test set thus consisted of 45 trials, resulting in N= 958 664 test samples. The median difference between predicted and measured CoM_Y-positions was $1.6mm$ (M= $1.4mm$, SD= $10.9mm$). The boxplot and Bland-Altman plot of the spatial distribution are shown in Figure 2 and Figure 3, respectively.

4 Discussion

The preliminary results look promising overall. The low (less than two millimeters) mean and median imply a low general bias in samples that were not in the training set. If the model was overfitted and only applicable to participants that it was trained

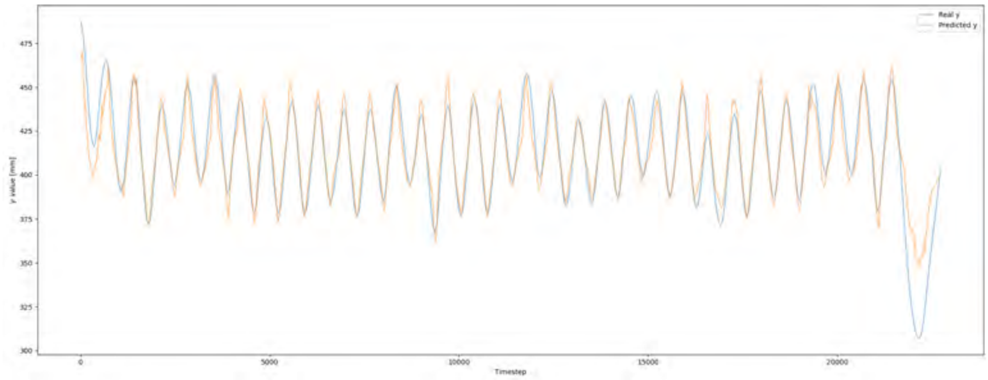

Fig. 4: An example stepping trial showing that the model underestimates large displacements.

on, then we would expect higher offsets there. Likewise, the standard deviation of $10.9mm$ is also acceptable, considering that it is comparable to the observed standard deviations of other IMU-based CoM measurements (e.g., the sway tasks in [2]). Figure 2 shows that predicted CoM_Y covers a smaller range of Y-positions than the measurements, which indicates a systematic underestimation of large displacements. However, this pattern is barely visible on the Bland-Altman plot, so it is not clear whether this may cause an issue in some cases. Figure 4 has therefore been included here to compare the measurements and predictions for a single trial. While small underestimations are visible in almost every peak, the most salient underestimations are at the start and at the end of that trial. One likely reason is that the participant was still getting into position in the beginning, but started leaning further to one side to get into a more comfortable position at the end. If this is correct, then the issue mostly concerns movements that are not part of the regular exercise executions of the training set and the planned cutting of the trials would therefore further improve the average predictions by reducing the test set to trained movement patterns.

Since the preliminary tests were successful, further investigation is warranted. Post-processing and recalibration of the IMU data using static measurements is expected to lead to more consistent training data and allow for the inclusion of all 65 participants. The planned training and analysis of CNN and VAC models for three exercises could eventually lead to the development of an IMU-based CoM feedback system on the Sensopro. If successful, this may aid balance and coordination training by offering postural feedback without additional user-setup that would be required for wearables, thereby hopefully increasing engagement, motivation, and training adherence in fitness, rehabilitation, and therapy settings.

5 Conclusion

The preliminary tests show that a convolutional neural network may be capable of predicting center of mass positions from tape kinematics during Sensopro exercises, provided the movements are similar to previously trained exercise executions. Further exploration of different exercises using a reduced set of tape kinematics with a deeper convolutional neural network is therefore warranted. Another line of investigation is the training and testing of a deep neural network based on a variational autoencoder architecture.

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Statements and Declarations

5.1 Funding

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5.2 Competing Interests

This study was funded as part of an InnoSuisse project with Sensopro AG. Since Innosuisse projects have the explicit goal of promoting science-based innovations, the authors were in contact with and advised by representatives of Sensopro AG during the planing phase of the study, which specifically affected the choice of included exercises. The funders had no role in the collection, analysis, or interpretation of the data. The authors have no relevant financial or non-financial interests to disclose.

5.3 Ethics Approval and Consent to Participate

The study was carried out in accordance with the Declaration of Helsinki and was approved by the Institutional Ethics Committee of the Faculty of Human Sciences at the University of Bern (approval number: 2019-08-00004). Written informed consent was obtained from all individual participants included in the study.

5.4 Consent for publication

Not applicable.

5.5 Data availability

Study data and code that support the findings of this study are available from the corresponding author upon reasonable request.

5.6 Materials availability

Not applicable.

5.7 Code availability

Both the code for the neural network models as well as the corresponding weights will be made available on an online repository.

5.8 Author contribution

Conceptualization: HH, MS, RK; Methodology: HH, MS, RK; Formal analysis and investigation: HH; Writing - original draft preparation: HH; Writing - review and editing: MS, RK, TN; Funding acquisition: RK, TN; Resources: RK, TN; Supervision: RK

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