GymSoles: Improving Squats and Dead-Lifts by Visualizing the User's Center of Pressure

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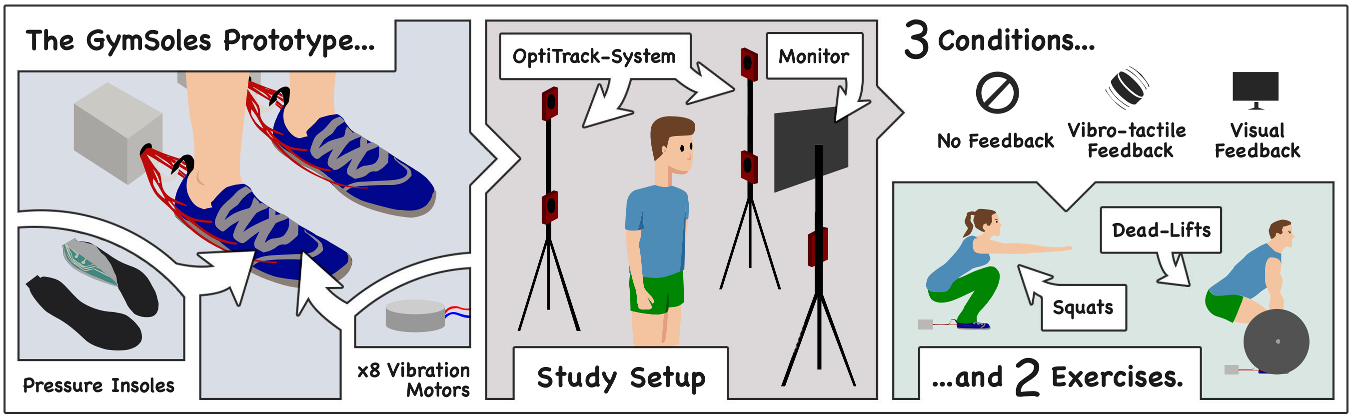

Figure 1: We developed GymSoles, a proof of concept prototype consisting of a pressure sensitive insole used to calculate the Centre of Pressure (CoP). Moreover, it incorporates eight vibration motors mounted on the shoe's walls providing vibrotactile feedback. We conducted a controlled study to evaluate workout exercises, such as squats and dead-lifts under three conditions: no feedback, vibrotactile feedback, visual feedback. It has shown that GymSoles helps improve body posture.

ABSTRACT
The correct execution of exercises, such as squats and dead-lifts, is essential to prevent various bodily injuries. Existing solutions either rely on expensive motion tracking or multiple Inertial Measurement Units (IMU) systems require an extensive set-up and individual calibration. This paper introduces a proof of concept, GymSoles, an insole prototype that provides feedback on the Centre of Pressure (CoP) at the feet to assist users with maintaining the correct body posture, while performing squats and dead-lifts. GymSoles was evaluated with 13 users in three conditions: 1) no feedback, 2) vibrotactile feedback, and 3) visual feedback. It has shown that solely providing feedback on the current CoP, results in a significantly improved body posture.

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CCS CONCEPTS
• **Human-centered computing → Ubiquitous and mobile computing systems and tools**;

KEYWORDS
Smart Insoles, Improving Body Posture, Workout Performance, Squats, Dead-Lifts, Centre of Pressure, Vibrotactile Feedback, Visual Feedback

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1 INTRODUCTION
The proper execution of exercises is important to achieve the desired training results and to prevent the occurrence of various injuries. Exercises, such as squats and dead-lifts, are elemental full body exercises [11, 90] and contribute to a healthy body when executed properly. Existing assistive systems to evaluate exercises, such as squats and dead-lifts, usually rely on expensive motion tracking systems [10], or on multiple Inertial Measurement Unit (IMU) systems [43]. These solutions have significant limitations in a gym setting,

as they are highly obtrusive and require extensive calibration. Alternative approaches, such as force plates are bulky and generally developed for laboratory use. We see a smart insole to provide a valuable solution. Currently, commercial smart insoles, such as Nike+ [2] and Adidas MiCoach [38], are already available for training. These track a user's step counts and stride. While these metrics may be useful, the lack of immediate feedback severely limits their usability in a gym. A recent work, MuscleMemory [56], explored the scope of wearable technology in high-intensity exercise communities and developed a wearable bend sensor based on PTviz [3]. The authors visualize knee bends for squat exercises, to help athletes and coaches to better understand the exercise's quality in a group-based training setting.

Inspired by MuscleMemory [56], we also aim to assist with immediate feedback aiming to improve exercise posture in a typical gym setting. In our research, GymSoles, we selected an insole based approach for its wearable and unobtrusive properties. Our approach is similar to FootStriker [32], which improves the workout performance for running exercises while providing feedback at the foot. We also utilize foot pressure data, however, with the focus to improve body posture during squats and dead-lift exercises. We identified the user's needs and possible system requirements by conducting expert interviews with four professional trainers. Consequently, a proof of concept system was developed and user studies were carried out to gain valuable insights on potential renditions for future designs. In particular, we focused on evaluating feedback types visualizing the Centre of Pressure (CoP) that resulted in an improved body posture.

To summarize, the main contributions of this paper are:

- Expert interviews with trainers providing insights on the importance of squats and dead-lifts, as well as on commonly used assessment methods.
- A proof-of-concept system which displays the CoP using visual or vibrotactile feedback to significantly improve body posture with squats and dead-lifts.
- Insights for researchers and practitioners for designing a future gym assistant based on CoP visualization.

2 RELATED WORK

Optical Motion Tracking

The two most commonly used systems in the motion tracking domain are: Vicon [87] and OptiTrack [4]. Both methods are considered highly efficient for tracking in bio-mechanics [9], sports science [9], and exercise science [10]. The tracking accuracy is the main advantage of these systems. However, these systems are immobile, requiring carefully attached optical markers at important anatomical positions, such as the user's joint angles. An improper placement and unfavourable lighting conditions will substantially reduce the accuracy. The Coach's Eye [23] can overcome some of these limitations. It is a mobile application that handles videos from multiple cameras to enable an analysis of movements, such as squats, weight lifting, aerobics etc. [37]. As an alternative, researchers also use a goniometer-based single camera system, which do not require optical markers to evaluate exercises [13, 72, 92]. Only minimal or no calibration is required, which makes it fairly applicable in clinics or in a gym facility. However, camera-based systems may create privacy concerns.

Activity Tracking by Inertial Measurement Units

Inertial Measurement Units (IMU)-based tracking systems were originally introduced as a low cost and portable solution for motion tracking [43]. IMUs incorporate a multi-axis accelerometer, gyroscopes, and magnetometers. In academic research, IMUs are commonly used for activity recognition [1, 31, 91], gait analysis [16, 34, 44], rehabilitation [44, 49] etc. In activity recognition, a single IMU is often sufficient to identify a certain activity by merely looking at motion specific features. For instance, RectoFit [52] utilizes an arm-worm IMU to recognize, and count repetitive exercises. For actual applications, such as gait analysis and rehabilitation applications, it is necessary to calculate the exact Range of Motion of certain joint angles [75, 84]. This has been widely explored by previous research, which utilized a joint angle measurement for gait analysis [14, 41, 85] and rehabilitation [6, 18, 62]. Still, there are few works specifically focusing on exercise training [76, 82, 89]. Among current work, a personalized exercise trainer for the elderly [82] was proposed. Another work particularly focuses on accurate exercise performance classification by solely relying on IMU data [89]. Another recent work specifically focused on looking at squat sonification for people who struggle with physical activities. The authors utilized the inbuilt IMU of a mobile phone to track squat exercises [53]. However, IMU also yield drawbacks, as an extensive calibration [35], a thoughtful sensor placement to minimize skin movement [26], and a careful segment-to-body alignment [75] are necessary. Contrary to rather "simple" activity recognition, measuring accurate postures require multiple IMU distributed on the body. As IMUs are already deployed with smartwatches, it has been used to track exercise performance in the gym [78] . Still, tracking body postures accurately are not yet possible with smartwatches.

Exercise Tracking with Force-Plates

In literature, laboratory grade force plates are used with applications requiring an analysis of impact forces in the gait cycle, performance monitoring in sports science, and also applications in balance studying for rehabilitation and exercise, etc. [51, 64]. AMTI [58] , Kistler [8], Hawking Dynamics [19], and Pasco Scientifics [61] provide some of the most commonly used laboratory grade force plates to analyze balance and foot dynamics. These devices measure the ground reaction force and displacement of the Center of Pressure (CoP). An inexpensive alternative pressure plate is provided by Nintendo's Wii Balance Board [12]. Moreover, in academia there are developments of low-cost force-plates, namely for biomechanical parameter analysis [81]. While high accuracy is the main advantage of these platforms, the lack of portability limits their usage.

Insoles in Motion Analysis

The main purpose underpinning smart insole use, compared to other tracking technologies, is unobtrusiveness. The use of foot interfaces, in particular pressure sensitive insoles, has been explored within previous decades [20, 70, 71]. Previous research has largely focused on a few applications. The major applications analyze the gait for rehabilitation purposes [7, 55, 60, 63, 93] and measure performances in sports, dancing, etc [29, 59, 65]. Commercially available pressure sensitive insoles [15, 17, 22, 25, 66, 74, 77, 83] have also been used in research [21, 30, 40, 54, 67, 88], namely to track steps, count strides, analyze the gait, and for activity recognition. As some of these solutions are solely based on pressure sensors, other solutions also incorporate IMUs. A recent work, ClimbingAssist [24] uses a pressure sensitive insole and provides instant feedback while climbing to improve climbing technique with beginners. Also, more recent trends explore implicit interactions with smart insoles, such as for user identification, detecting floor types, and body postures [48, 57]. Another recent work [57] demonstrates the possibility of recognizing postures and categorizing different motion patterns, such as bowing posture, posture when looking up, looking right, looking left, calf stretch etc. Moreover, other research [5, 45] on commercial products [69] uses smart insoles for balance assessment in rehabilitation.

In summary, posture detection and balance assessments can be enabled with pressure-sensitive insoles, as the upper body posture has a significant impact on the plantar pressure profile. The plantar pressure profile can be thus utilized to calculate the Centre of Pressure (CoP), which in our research is communicated to the user via vibrotactile or visual feedback.

3 EXPERT INTERVIEWS

We conducted semi-structured interviews with four professional trainers, each of whom had more than three years of experience as a trainer.They were sports science graduates and employed as full-time trainers. We asked a few predefined questions, in an open-talk in a 45 mins face-to-face session to understand the most challenging aspects an individual might encounter during their workout. The interviews were audio-taped and transcribed afterwards to better identify the insights described.

Full-body Exercises are Recommended for Beginners

All trainers mentioned that full-body exercises, particularly squats and dead-lifts, were the most essential for any beginner,which can be performed at home or at the gym. For example, one of the trainers indicated that "*Squats hit almost all of the muscle groups. So it is one of the best for burning body fat quickly. Also, dead-lifts strengthen the core and the back. Both are very good full body exercises*". Squats activate almost all of the entire body's muscle groups [28], including the core and lower body muscles. Similar to squats, the dead-lifts exercise strengthens the entire core, the back (spinal erectors), the glutes (gluteus maximus), the legs (quadriceps femoris, adductor magnus, hamstrings), and the shoulders (trapezius) - *see also Figure 2* [1].

Significance of CoP for Correcting Exercises

It is highly important to maintain a correct body posture while executing exercises. The expert trainers mentioned having a rule of thumb, which is to focus on the shift of the Centre of Pressure (CoP) on the foot. The CoP is regarded to be a good indicator and is used as a reference point to explain the correct execution of squats or dead-lifts with a proper body posture. For a correct squat execution, the plantar pressure should ideally be concentrated at the heel area, while the individual squats down. An incorrect technique, such as bending over the upper body, may cause the CoP to move to the distal foot, which can eventually result in critical injuries: *"When performing squats, usually we instruct them (the learners) to maintain the knees and prevent them from passing the toes. This allows them to keep their weight concentrated to the heel [...] bending the upper body over [will] move the weight more towards the distal foot and can results in knee injuries"* In dead-lifts, there is even a higher chance that the learners' posture significantly deviates from the correct execution technique. This occurs particularly with higher weights. According to the trainers, these deviations should be identifiable by looking at CoP.

[1] https://www.muscleandmotion.com

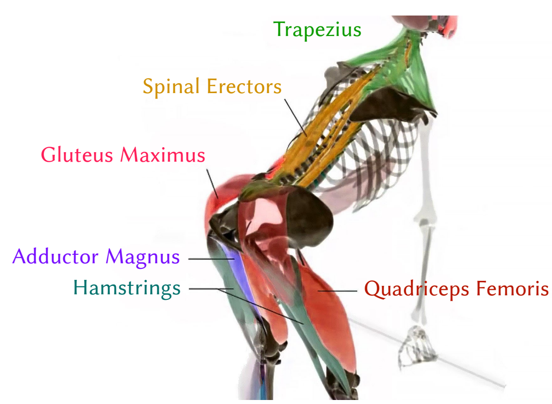


Figure 2: Displaying the major muscle groups being activated when executing dead-lift exercise.

Increased Challenge and Risk for Beginners

According to the expert trainers, the first step to educate a beginner is to demonstrate the correct execution technique. However, most beginners struggle to perform squats accurately on their first attempt. Performing the dead-lift in a correct way, is even more crucial when extra weights are added: "*Teaching them (the learners) the correct [squats and dead-lifts] technique is difficult at the beginning. [...] Even people who do know the correct technique will struggle to perform the correct technique when they increase the weight. So, I might have to correct the technique and [in particular] the posture by giving them further instructions*". The expert trainers mentioned that beginners are especially prone to sustaining injuries and focusing on this user group would be beneficial.

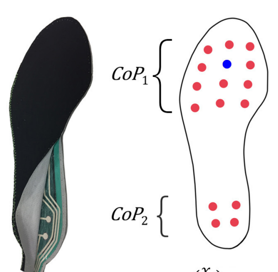
Gyms Lack of Evaluation Technology

In the gyms we visited, no technologies existed to assess the proper execution of exercises objectively. Interestingly, the current technique for exercise assessment is based on self or expert judgment: *"Usually the learners correct their posture by looking at the side mirrors or front mirrors."*. For beginners, it is important to have an expert trainer. The lack of technology used is due to three reasons: (1) Impracticability: a trainer mentioned that " *[...] we don't use any technology inside the gym to train squats or dead-lifts. In university labs, we have used force plates to understand balance and stability while performing exercises. But those devices are not practical to use inside a gym."* (2) Technical expertise required: Setting up current assistive technology is still complicated cannot be done easily by a trainer. Another reason for the lack of availability of evaluation technology is the fact that most of these are (3) very expensive [27] compared to the low budget of common gyms.

4 GYMSOLES

Requirements

Based on the expert interviews, we identified the following requirements necessary for a system to help improve the posture of squats and dead-lifts in a typical gym setup:



$$CoP_1 = \frac{1}{\sum_{i=1}^{12} p_i} \sum_{i=1}^{12} p_i S_i \qquad MP_1 = \frac{1}{12} \sum_{i=1}^{12} p_i$$

$$CoP_2 = \frac{1}{\sum_{i=13}^{16} p_i} \sum_{i=13}^{16} p_i S_i \qquad MP_2 = \frac{1}{4} \sum_{i=13}^{16} p_i$$

$$CoP = \frac{MP_1 CoP_1 + MP_2 CoP_2}{MP_1 + MP_2}$$

with $S_i = \binom{x_i}{y_i}$ the position and p_i the pressure of the i^{th} sensor

Figure 3: The Sensing.tex pressure sensitive insole features 16 pressure points. The Centre of Pressure (CoP) is calculated as depicted. The sensor point indicated in blue color considered as the centre of origin for calculating CoP.

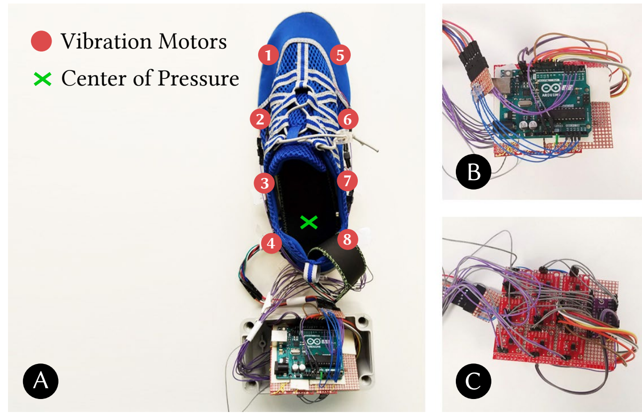


Figure 4: A) Vibration feedback system was developed with eight vibration motors. B) An Arduino Uno was used for control and communication. C) 8 haptic motor drivers (DRV2605L) by sparkfun and an I2C multiplexer from Adafruit (TCA9548AA) were used to control the motors.

(1) Appropriate sensing mechanism:
   - reflecting the body posture while exercising
   - not constraining body movements
   - no extensive calibration required

(2) Appropriate feedback mechanism:
   - displaying the CoP in real-time
   - recognizable in a gym setup where noise exists
   - unobtrusive and not bothering

Resulted Design and Prototype Implementation

The resulted design consists of an input component, which is a pressure sensitive insole, and a feedback component, which is the vibrotactile stimulus implemented into the shoe. Additionally, we developed a visual feedback for a screen.

Pressure Sensitive Insole. To collect pressure data, we used a commercially available pressure insole (UK size 10-11) from sensing.tex [46], which consisted of 16 force-sensitive pressure points, based on resistive technology. The insole and its sensor layout is depicted in *Figure 3*. The sensor placement somewhat aligns with critical pressure points discovered in previous work [33, 36, 80]. We developed a voltage divide circuit to enable interfacing the insole with an Arduino. We calculated the CoP as shown in *Figure 3*.

Vibrotactile Feedback (Shoe). In 2015, Ma et al. [42] investigated a vibrotactile feedback display for smart foot wear, mainly for gait correction. However, to display a shifting CoP, we took a different approach. Our vibrotactile display is based on eight motors (Yuesui Coin Type Vibration Motors), which were placed on the side walls of a sports shoe with a UK size of 10-11 *(see Figure 4)*. To control all vibration motors, we used eight Sparkfun Haptic Motor Drivers (DRV2605L). As all the drivers had the same fixed I2C address, they were interfaced to an Arduino by using an I2C multiplexer from Adafruit (TCA9548A). We have chosen this actuator layout

Figure 5: Java based software was developed to provide visual feedback.

based on suggestions from literature [50]. Moreover, Ben Shneiderman's theory [79] of providing feedback to the closest location where the input is generated, influenced the decision to select the foot to provide feedback. We mapped the CoP to the vibration motors in such a way that the vibration sensation was close to the CoP. For example, when the CoP shifts to the heel *(see green spot at the shoe in Figure 4)*, only motors No. 3, 4, 7, and 8 will be actuated. Additionally, the motors No. 8 and 4 will vibrate at a higher frequency than No. 3 and 7, since the CoP is closer to the heel. The vibration frequency was kept within the range of 200Hz and 400Hz, which is well within the vibrotactile perception range for the human skin [86]. All vibration motors were driven with max power to reduce the signal attenuation through the socks. In other words, we controlled the frequency only.

Visual Feedback (Monitor). The visual feedback system was an application developed in Java and ran on a monitor, which was placed in front of the user. A dot wandering between the heel and toe area was visualizing the foot's CoP, as shown in *Figure 5* (CoP is currently at the heel).

5 EVALUATION

We conducted a user study to evaluate whether CoP feedback will impact the posture while executing squats and dead-lifts exercises. Specifically, we focused on evaluating the following hypotheses:

H1 : Having feedback on center of plantar pressure distribution (CoP) will improve body posture during squats and dead-lifts exercises.

H2 : Users will prefer vibrotactile feedback, because it does not require visual attention while exercising.

Apparatus

The GymSoles prototype, placed on both feet, were controlled from a Macbook Pro via USB serial port. The calculation of the CoP, as well as the feedback (visual / vibtrotactile) were performed in real-time. To assure low latency, the data rate was sampled down to 20Hz, which is still sufficient for low-motion exercises. Additionally, an OptiTrack motion tracking system was used to collect additional ground truth motion and posture data.

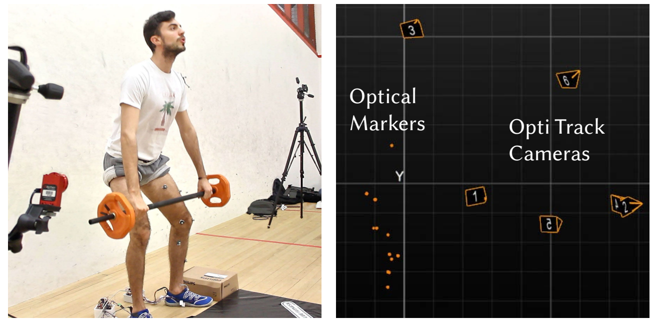


Figure 6: Twelve markers were attached to the leg, two markers were placed at the waist, and one marker was placed on the shoulder. OptiTrack motion capture system and Motive software was used to record marker data.

Participants

The power analysis revealed that we required at least 12 participants for a significance level of .05, the effect size of .5, power of .8, and 4 conditions. Therefore, we recruited three trainers (2 males and 1 female) aged 32, 28, and 23, as well as 13 participants (9 males and 4 females) aged between 20 – 31 (mean = 24.9; SD = 2.9). We selected the participants in accordance to their foot size, since matching the size to the shoe prototype, a UK size 10-11, was necessary.

Task and Procedure

Trainers. We collected the trainers' demographic data, the years of experience, and their confidence levels in performing squats and dead-lifts through a questionnaire, after signing the consent agreement. Then, the trainer had to wear the prototype, as we attached optical markers as shown in *Figure 6*. They were asked to perform squats and dead-lifts as accurately as possible. We recorded their pressure profile, as well as motion data using the OptiTrack system.

Participants. After the consent sheet was filled out, the participant was equipped with the GymSoles prototype, as we affixed optical markers to their bodies. During the study, a trainer was present to give instructions on how to perform squats and dead-lifts accurately. In addition, the trainer provided a demonstration. We conducted a within subject study, where the participant performed squats under three conditions, (1) no-feedback, (2) vibrotactile feedback, and (3) visual feedback. The sequence of the conditions were counterbalanced across all conditions to limit a possible learning effect. In each condition, the participant had to perform a complete set of squats with 10 repetitions. The same procedure applied to dead-lifts, but 10kg 20kg weights were incorporated. These weights were suggested by the expert trainers. At the end of the study, the participant was given a questionnaire to indicate the usefulness and preference of

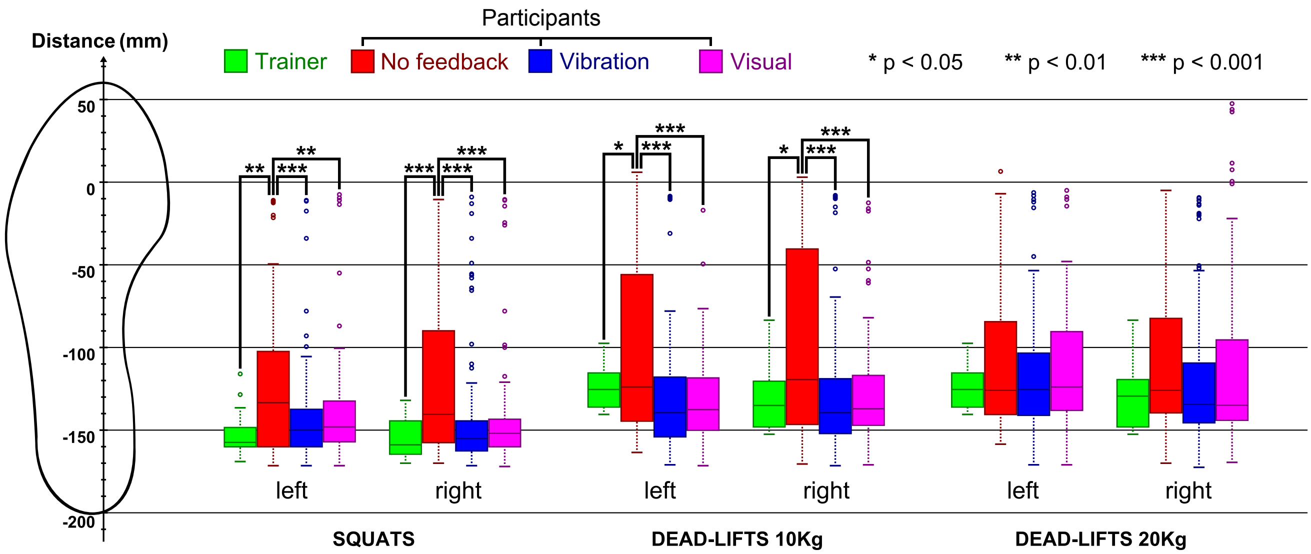


Figure 7: The figure shows turning point CoP profiles of the participants for Squats, Dead-lifts$_{10Kg}$, Dead-lifts$_{20Kg}$. The box plots are matched to actual distribution of the CoP, as depicted. The origin of the axis was taken as described in Figure 3. For Squats and Dead-lifts$_{10Kg}$ NFL-TL, NFL-VibL, NFL-VisL, NFR-VibR, NFR-VisR pairs gave significant difference. Dead-lifts$_{20Kg}$, did not have a significant difference between the trainers' and the participants' pressure profile for any of the three conditions.

the feedback types using a 5-pnt Likert scale. Moreover, we asked for previous experience in performing such exercises, their confidence in performing squats and dead-lifts, as well as an open-ended feedback opportunity to share their subjective opinion on the systems' current design and other useful suggestions.

Data Gathering

The trainer's CoP was collected and later used as the ground-truth. The CoP was logged as a time series. However, for the data analysis, we only took the 'CoP at a turning point'. The 'CoP at a turning point' is defined as the CoP value at the exact time when the trainer changes the direction of motion from squatting down to standing/lifting up. This approach was chosen, because the trainers mentioned the turning point as the most critical position in squats and dead-lifts. To analyze the posture, we considered the hip angle and the knee angle *(see Figure 8)* similar to previous studies [39]. As both angles are connected with body posture [73], we calculated the ratio between both angles: $R_{k:h}$, which we collected in addition to the CoP at the turning point.

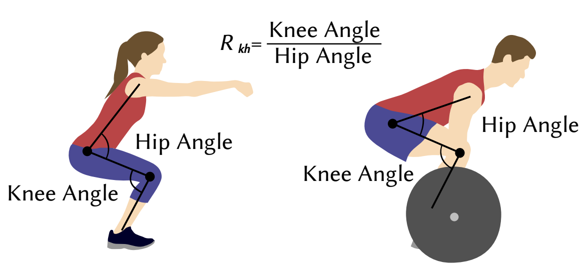


Figure 8: The hip angle and knee angle were calculated using the Motive software. Then, we calculated the ratio $R_{k:h}$ between those, as a measurement current body posture.

Results

We present results in two different aspects: 1) CoP profiles and 2) body posture using the angle ratio *($R_{k:h}$)*. We compared the trainers' data with the participants' data for all three conditions (no-feedback, vibrotactile feedback, and visual feedback) for all exercise scenarios (squats, dead-lifts$_{10Kg}$, and dead-lifts$_{20Kg}$).

CoP Profiles. A one-Way ANOVA for independent samples among both, squats ($F_{7,768}$=10.73, $p < .0001$) and dead-lifts$_{10Kg}$ ($F_{7,667}$=11.36, $p < .0001$) yielded a main effect. A post-hoc analysis using Tukey's HSD revealed that both the squats, as well the dead-lifts$_{10Kg}$, NFL-TL, NFL-VibL, NFL-VisL, NFR-TR,NFR-VibR, NFR-VisR pairs yielded a difference *(see Figure 7)*. There was no significant difference between VIBL-TL, VIBR-TR, VISL-TL, VISR-TR, VISL-VIBL, and VISR-VIBR. This shows that for squats, as well as dead-lifts$_{10KG}$, merely visualizing the CoP enables the participant have their actual CoP similar to that of a trainer, compared to having no feedback.

However, in dead-lifts$_{20KG}$ a one-way ANOVA did not show a main effect ($F_{7,621}$=1.86, $p > .05$). Due to the weights, some participants were not stable and could not control the exercises during the first few set repetitions. Also, 20kg was considered excessive for many participants. Hence, exhaustion occurred quickly, which in turn created inaccuracies in

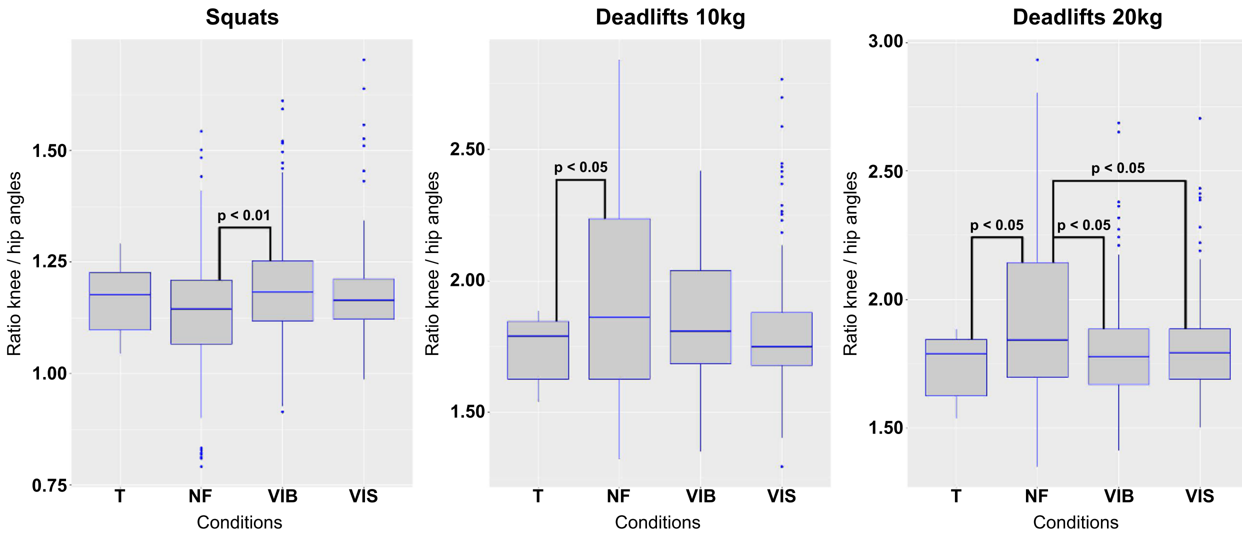


Figure 9: $R_{k:h}$ distributions for Squats, Dead-lifts$_{10Kg}$ and Dead-lifts$_{20Kg}$ for trainers and participants across all conditions. For squats, the significant difference only occurred between NF and VIB. For Dead-lifts$_{10Kg}$, significant difference was only between the pair T-NF. For Dead-lifts$_{20Kg}$, there was a significant difference between the three pairs, NF-T, NF-VIB and NF-VIS.

Figure 10: $R_{k:h}$ distributions of Squats, Dead-lifts$_{10Kg}$ and Dead-lifts$_{20Kg}$ for trainers and beginner level participants across all conditions. The significant difference was given by three pairs: NF-T, NF-VIB and NF-VIS.

execution styles and thus contributed to an increased randomness. This is evident in the increased standard deviation of the CoP *(see Figure 7)*.

Based on the feedback of the post-questionnaire (self-esteemed confidence), we could categorize our participants into two groups: advanced users (six participants) and beginners (seven participants). We then performed two separate one-way ANOVA tests for each user category. For both the beginners ($F_{7,355}$=1.417, p >.05) and the advanced users ($F_{7,1,281}$=11.36, p >.05), we did not see a main effect.

Body Posture ($R_{k:h}$). For the squats exercise, a one-way ANOVA for independent showed a main effect across all participants ($F_{3,334}$=3.701, p < .05). However, Tukey's HSD revealed that the difference was only between No-Feedback and Vibrotactile Feedback – *see Figure 9*.

To make more meaningful statements, we looked deeper into the data and divided the subjects into a beginner and an advanced user group once more. The one-way ANOVA showed main effects for beginners ($F_{3,168}$=13.36, p <.0001). A Tukey's HSD range test confirmed that the difference occurred between these pairs, NF-T, NF-VIB, NF-VIS *(see Figure 10)*. Furthermore, it indicated that no differences occurred between VIB-T, VIS-T and VIS-VIB, which supports our previous finding with CoP data. Providing a beginner with any type of feedback on the CoP enables them to perform the

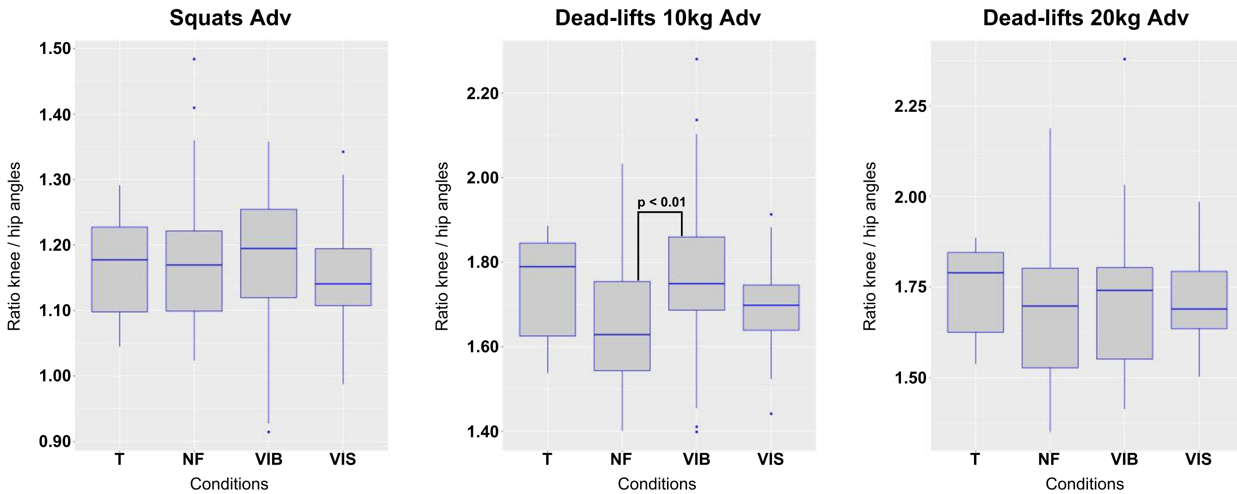


Figure 11: $R_{k:h}$ Distributions of Squats, Dead-lifts$_{10Kg}$ and Dead-lifts$_{20Kg}$ for trainers and advanced users across all conditions. Squats and Dead-lifts$_{20kg}$ did not show significant differences. A difference was found at Dead-lifts$_{10kg}$ at the NF-VIB pair.

squat exercise similar to a trainer (in terms of CoP profile and body posture). For advanced users, a one-way ANOVA did not show a main effect. ($F_{3,168}$=1.152, p>0.5) – *see Figure 11.*

For dead-lifts$_{10Kg}$, a one-way ANOVA showed a main effect for all participants ($F_{3,321}$=3.075, p<.05). A Tukey's HSD revealed the significant difference occurs between the T-NF pair *(see Figure 9)*. As previously performed, we again ran one-way ANOVA tests for the beginner group and the advanced group. The results were similar to the previous squat results, as the beginner group showed a main effect ($F_{3,180}$=10.66, p <.0001). A Tukey HSD test reveals the difference between the NF-T, NF-VIB, and NF-VIS pairs. *(see Figure10)*. There was no difference between the VIB-T, VIS-T, and VIS-VIB pairs. Once again, this supports our claim that any type of CoP feedback, vibrotactile or visual, for a beginner will improve the posture for dead-lifts with a low weight. Advanced users showed a main effect ($F_{3,157}$=4.101, p <.01), whereas Tukey's HSD reveals that the significant difference is only between NF-VIB *(see Figure 11)*.

The one-way ANOVA for dead-lifts$_{20Kg}$ showed a main effect ($F_{3,297}$=4.465, p <.01) for all participants *(see Figure 11)*. For the beginner group, again, a one-way ANOVA showed a main effect ($F_{3,172}$=12.47, p <.0001). A post-hoc analysis via the Tukey's HSD test showed the following pairs, NF-T, NF-VIB, NF-VIS *(see Figure 9 and Figure 10)*, to be significantly different. There was no significant difference between the pairs of VIB-T, VIS-T and VIS-VIB, which again confirms that providing feedback for beginners is important. The one-way ANOVA for advanced users did not show a main effect ($F_{3,144}$=1.44, p >.05). In general, we observed the $R_{k:h}$ to significantly increase for squats, while it significantly dropped for dead-lifts for beginners with correct execution. We suspect this is mainly due to the nature of the exercise.

Post Questionnaire

A summary of the subjectively rated usefulness on a 5-point Likert scale (1-very low, 5-very high) for each condition is depicted in *Figure 12*.

For squats, the highest mean in terms of usefulness was found for Visual Feedback (M=4.2; SD = .9) followed by Vibration (M=3.9; SD = .9) and No-Feedback (M=2.8; SD = .7). A one-way ANOVA test showed a main effect ($F_{2,36}$=10.09, p <.0001). A Tukey's HSD identified the difference at the pairs VIB-NF and VIS-NF. We found similar results for dead-lifts. With dead-lifts, the highest mean was again identified at Visual Feedback (M=4; SD = .9) followed by vibration (M=3.6; SD = .9), and no-feedback condition (M=2.7, SD = .8). Also, a one-way ANOVA showed a statistical main effect ($F_{2,36}$=8.18, p <.01). A Tukey's HSD test suggests differences to occur between the pairs VIB-NF and VIS-NF. Overall, we can state that both types of feedback were considered useful compared to no feedback.

In terms of user's preference *(see Figure 12)*, a pairwise t-test (p >.05) did not show any significant differences between vibration feedback – Vib (M = 3.7; SD = 1.315) and visual feedback – Vis (M = 3.9; SD = .9).

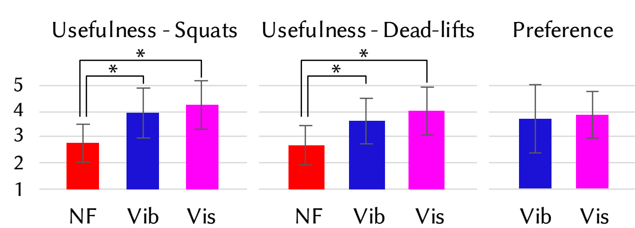


Figure 12: In both, squats and dead-lifts, users rated Vibration Feedback (VIB) and Visual Feedback (VIS) to be significantly more useful than No Feedback (NF). There is no preference for a vibrotactile and visual feedback

Answering Hypotheses

- **H1** : We *accept* this hypothesis. By solely visualizing the CoP (vibrotactile or visual feedback), the participants showed a significantly improved body posture ($R_{k:h}$) similar to the trainers for both exercises.
- **H2** : We *reject* this hypothesis because vibrotactile feedback was not significantly preferred over visual feedback. However, participants found visual and vibrotactile feedback to be more useful than no feedback.

6 DISCUSSION

Summary of Key Insights

Visualizing CoP Significantly Improves Body Posture. Our results evidence that users were able to improve their body posture ($R_{k:h}$) significantly when the CoP is visualized either via vibrotactile or visual feedback. Although we only focused on two exercises (squats & dead-lifts), we believe CoP visualization will also benefit a variety of other exercisers, such as weight-lifting, lunges, high knees, running, etc.

No Quantitative Difference in Feedback Type. In our quantitative analysis, we compared the CoP and the body posture ($R_{k:h}$) from the user in respect to the expert trainers. The collected data could not evidence a difference between vibrotactile and visual feedback. Therefore, selecting a suitable feedback type may be decided on other factors, such as personal preference etc.

No Qualitative Preference in Feedback Type. Asking the participants for their preferred feedback type and the perceived usefulness of the system, did not result in a significant difference between vibrotactile and visual feedback. However, participants favouring the vibrotactile feedback were more excited and providing additional feedback, such as: *P10: " Vibrotactile feedback is more subconscious and helped me to keep my correct posture (no angling down the neck to a specific position)", P4: "Visual feedback, while effective, requires the user to consistently look at a screen to gauge how well he or she is performing", P5: "The vibration system allows you to concentrate on your technique while getting subtle feedback, which I liked. The visual feedback made me concentrate too much on my centre of pressure, which could possibly make me forget about my overall technique".*

Visual Feedback Enables Greater Precision. Due to the nature of reduced haptic perception at the feet, visual feedback allows for more precise feedback. Therefore, some participants preferred visual feedback due to the higher resolution. P7: *"couldn't locate the vibrotactile feedback very well"*, P12: *"With visual feedback, I could track my center of pressure more as I found it encouraging to do it better."*, P3: *"the visual feedback was much more effective in terms of resolution."*

Level of Expertise Creates a Difference. The qualitative results support our quantitative findings in that for squats and dead-lifts, the beginners have improved their performance significantly with either visual or vibration feedback present. However, advanced users did not significantly experience an improvement or decrease in performance, with or without feedback. It became clear that there is a relationship between the users' experience of receiving CoP feedback and the level of expertise. An advanced user, who is greatly familiar with the execution of both exercises and regularly visits the gym stated: *"I actually prefer not having any feedback, this was disturbing me from paying attention to the correct execution." (P1).* Moreover, three out of six advanced users also mentioned that the vibration feedback created excessive disturbances at times. However, five out of seven beginners mostly preferred vibration feedback, as it was more perceivable subconsciously.

Limitations and Future Directions

Unobtrusive Feedback Design. In particular, the advanced user group explicitly stated that designing unobtrusive feedback is highly important, as they perceived vibrotactile feedback as too obtrusive.In addition, vibration is usually perceived as very alarming [68]. Therefore, we derive the design recommendation of only providing vibrational feedback when the user's CoP deviates from the correct pressure profile, such as getting out of the heel range. Also, in a realistic gym setup, vibrotactile feedback may be overlooked because of environmental vibrations, namely when people nearby drop weights. A solution could be relying on pressure feedback, such as Solenoid haptuator coils (ZHO-0420L). As the current system provides visual feedback, using a monitor situated in front of the user may create negative effects on body posture. If the display is located unfavourably, this forces the user to angle the head. Using a peripheral head mounted display [47], such as Google Glass, could overcome this limitation. Information on being still in the threshold-range of the correct CoP could be indicated in the peripheral vision and thus would not disturb the user or deviate attention.

Embedding the Trainers' Ground Truth Model. Currently, at the beginning of each session, the participants were educated and instructed to keep their CoP in a certain range while performing the exercises. This is a thumb-rule the trainers use to explain the exercise. However, we observed the trainers' CoP to also shift into certain ranges at certain stages of the exercises. Embedding such a time-space model of the CoP could possibly help advanced users to further improve their execution style and posture. However, implementing this is not entirely straightforward because tracking the user's exercise execution is necessary, before mapping the trainer's ground truth from the same state. This would require motion tracking, such as an optical tracker or a wearable system. Very recent investigations [78] show that using an IMU of a smartwatch could be used to accomplish this task. Moreover, machine learning may be advantageous to derive more sophisticated user recommendations based on the deviations from the trainers ground-truth model.

Miniaturized and Unobtrusive Hardware Design. GymSoles is still in a proof of concept stage, which is only ready for laboratory use. A future development must provide a miniaturized design that is wearable. We envision a tiny hardware add-on to be attached on top of the shoe and communicating with the insole as a viable solution. Merely making use of a single vibration motor may be sufficient if we map the spatial distribution of the CoP to a change of vibration frequency and amplitude.

7 CONCLUSION

We presented a novel insole prototype, GymSoles, which enables the user to significantly improve their body posture during squats and dead-lift exercises. The introduced solution is informed by expert interviews with four expert trainers. In particular, these interviews pointed out that full body exercises, such as squats and dead-lifts, are of high importance. Also, it is said that these exercises are often incorrectly executed and thus can potentially result in serious injuries. The trainer's rule of thumb is to maintain the Center of Pressure (CoP) at the heel of the foot. However, this is difficult for users to assess and internalize. An insole was used for tracking and calculating the user's CoP, which displayed it using vibrotactile feedback and visual feedback. GymSoles was evaluated with 13 participants. The results demonstrate that solely visualizing the user's CoP significantly improved body posture for both exercises, as the effect was clearer for beginners. To conclude, we envision a practical real-time feedback system, similar to GymSoles, to effectively assist individuals with properly executing daily exercises. In future, such a system would significantly contribute to an increased overall health and well-being.

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