FootStriker: An EMS-based Foot Strike Assistant for Running

MAHMOUD HASSAN, German Research Center for Artificial Intelligence (DFKI), Saarland Informatics Campus
FLORIAN DAIBER, German Research Center for Artificial Intelligence (DFKI), Saarland Informatics Campus
FREDERIK WIEHR, German Research Center for Artificial Intelligence (DFKI), Saarland Informatics Campus
FELIX KOSMALLA, German Research Center for Artificial Intelligence (DFKI), Saarland Informatics Campus
ANTONIO KRÜGER, German Research Center for Artificial Intelligence (DFKI), Saarland Informatics Campus

In running, knee-related injuries are very common. The main cause are high impact forces when striking the ground with the heel first. Mid- or forefoot running is generally known to reduce impact loads and to be a more efficient running style. In this paper, we introduce a wearable running assistant, consisting of an electrical muscle stimulation (EMS) device and an insole with force sensing resistors. It detects heel striking and actuates the calf muscles during the flight phase to control the foot angle before landing. We conducted a user study, in which we compared the classical coaching approach using slow motion video analysis as a terminal feedback to our proposed real-time EMS feedback. The results show that EMS actuation significantly outperforms traditional coaching, i.e., a decreased average heel striking rate, when using the system. As an implication, EMS feedback can generally be beneficial for the motor learning of complex, repetitive movements.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**; *Mobile devices*; *Empirical studies in ubiquitous and mobile computing*; • **Hardware** → Bio-embedded electronics;

Additional Key Words and Phrases: Electrical muscle stimulation, wearable devices, wearables, real-time feedback, motor skills, motor learning, sports training, running, in-situ feedback, online feedback, real-time assistance

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1 INTRODUCTION

Running is the most popular sport with regard to the number of active hobby athletes. According to Timex, 76% of the 1048 adults claimed in an online survey to exercise at least once a week, and the majority run without assistance or monitoring from a coach [4]. In 2015, more than 17 million runners finished competitions ranging from a 5km distance to the full marathon distance (42.195 km) in the United States alone[1]. The growing popularity of recreational sports has recently gained attention by the tech industry. In 2014, the sports and fitness

[1]www.runningusa.org/statistics

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Authors' addresses: M. Hassan and F. Daiber and F. Wiehr and F. Kosmalla and A. Krüger, German Research Center for Articial Intelligence (DFKI), Saarland Informatics Campus, Saarbrücken, Germany.

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Fig. 1. A runner wearing the FootStriker prototype.

performance wearable market was valued at $3.5 billion and is expected to reach $14.9 billions by 2021 [31]. The market used to be dominated by sports specialists (e.g., Adidas and Nike), but recently, big tech companies (e.g., Apple, Microsoft, and Samsung) have entered the industry. The currently available tools provide GPS tracking, speed, distance, and heart rate monitoring. Many users are motivated to upload their activities to gamified social networks specifically made for sports (e.g., Nike+, Runkeeper, or Strava) to share with friends, compete and collect badges [21].

The currently used measures are mostly quantitative, although some wearables also provide real-time qualitative data about the running style, such as ground contact time [29]. In this work, with qualitative training data we generally refer to data that directly provides a measure of the effectiveness of the running technique, e.g., at a given pace a shorter ground contact time usually is a direct indicator of a more economic running technique. In contrast, we describe training data as quantitative if it provides only a measure of running performance and thereby is only indirectly informative about the effectiveness of the running technique. For example, we refer to the pace as quantitative, as it could be increased either with more physical effort or with an improved running economy even if the physical effort is constant.

For recreational runners, it is often not easy to interpret the measured numbers, usually displayed on a small screen on a fast-moving wrist while running. Many factors influence adequate information representation and are not taken into account by current sports technologies [27]. An effective analysis of the running technique can therefore only be provided by professionals or expert coaches using slow motion videos.

As many amateur athletes do not have access to a coach, long distance running generally causes a high incidence of repetitive stress injuries per year, including stress fractures and knee problems. Approximately 56%

Fig. 2. An example highlighting the difference between heel striking (left) and forefoot striking (right)

of recreational runners sustain a running-related injury each year [28]. Other studies report a high correlation between long distance running and injuries [16].

Ideally, the initial foot contact (i.e. foot strike) should absorb the high impact forces, which is not the case when striking the ground with heel first. Heel striking is nevertheless natural for most runners as they learned it, i.e. adapted it form walking. It is the prevalent running style as it requires less physical effort at slow paces, but it becomes inefficient when running fast [1]. An example highlighting heel striking compared to forefoot running is shown in Figure 2.

There exist several bio-mechanical differences between forefoot strikes and heel strikes. With regard to injury prevention, the most important difference is the higher impact peak measured for the vertical ground reaction force. This generates a more rapid, high-impact peak when initially contacting the heel with the ground. Heel strikers have an overall injury rate that is approximately twice as high compared to forefoot runners [2]. On the other hand, a midfoot or forefoot strike pattern, contacting the ground with the midfoot first, can reduce the mechanical stress for the body. Transitioning to a midfoot strike pattern is accepted as a potential way to decrease impact [5].

Besides the decrease in the risk of injury, runners often have an intrinsic motivation to change their running style to mid- or forefoot running that results in a shorter stride length and a higher stride frequency. Rotschild surveyed 785 runners, of which 94.8% self-reported to be either recreational or amateur runners. When questioned about the most helpful resource for the transition, the participants most frequently mentioned supervised instruction by a coach or running professional (n = 208, 26.5%) [22]. Heel striking not only increases the chances of injuries but leads to a lower running efficiency and should thus be avoided [30]. Amateur athletes who want to become faster therefore want to change their running style to imitate professional athletes, as one-third of the elite runners in the world engage in midfoot running [8].

To address this issue, we propose *FootStriker*, a wearable system that detects the user's running style using force sensitive resistors (FSR) in the insole of a running shoe and uses electric muscle stimulation (EMS) as a real-time feedback channel to intuitively assist the runner in adopting a mid- or forefoot strike pattern (see Figure 1). The runners wearing *FootStriker* were not given any further instructions. In a between subject study with 18 participants, we compared this novel approach against classical running technique analysis that consisted of slow motion videos and verbal instructions. We measured the improvement of the running technique as the ratio between number of heel strikes and total number of steps (heel strike rate). We show that *FootStriker* leads to significantly lower heel strike rates compared to classical coaching after running with the device for three kilometers and then disabling the EMS actuation. By collecting qualitative feedback from the participants we prove that all participants developed active knowledge about their newly-learned running technique and could verbally express it only by using the device. In a third control group, we removed the actuation effect on the calf muscles and used the EMS signal only to alert the user if a heel strike was detected. At the same time, we ensured that the signal could still be perceived during running. As in this alert condition, we could not observe a significant effect, overall we show that EMS actuation actually was necessary to achieve the desired running style adaptation, and alerting the user was not sufficient.

2 RELATED WORK

Our work is related to previous studies on ubiquitous running technology and EMS actuation in HCI.

2.1 Ubiquitous Running Technology

Sports has recently received more attention in UbiComp and HCI. Running watches, wearable fitness trackers and other training tools are ubiquitous today [7, 27]. As surveyed in [17], one direction of work is concerned with how technology can help athletes in rehabilitation and generally to avoid injuries. Other themes include motivation for athletes through interactive computer games [15]. Jensen and Mueller [10] reviewed current technologies that are used for run training, and based on that, present a design space and initial guidelines for research and development of future run training interfaces. Our work complements the blind spot in their design space with a run-training technology that focuses on running technique and assistive feedback. Many wearable devices exist today that can be used to track and analyze running activities. However, most of them only provide assistance and feedback on running performance (for example distance, elevation, pace), not running technique [10].
While existing commercial products focus on performance, Wijnen et al. [29] aim to provide real time analysis of running technique. During actual field training, they measured technique-related parameters such as ground contact time, heel-off time, gait line, and pressure distribution during roll-off. However, this data was not provided to the athlete in real-time but sent wirelessly to a computer for post-training or post-race analysis. Harms et al. [6] used several miniature orientation sensors to measure motion and body posture and Stohrmann et al. [24] demonstrated the feasibility and comfort of using the inertial measurement unit (IMU) for assessment of kinematic parameters of running.

Existing approaches using wearables to improve running technique mostly provide post-analysis only. In contrast, our work provides real-time feedback on running technique using EMS. To the best of our knowledge this is the first application of EMS actuation to correct running technique. In the following we introduce general work on EMS actuation in HCI.

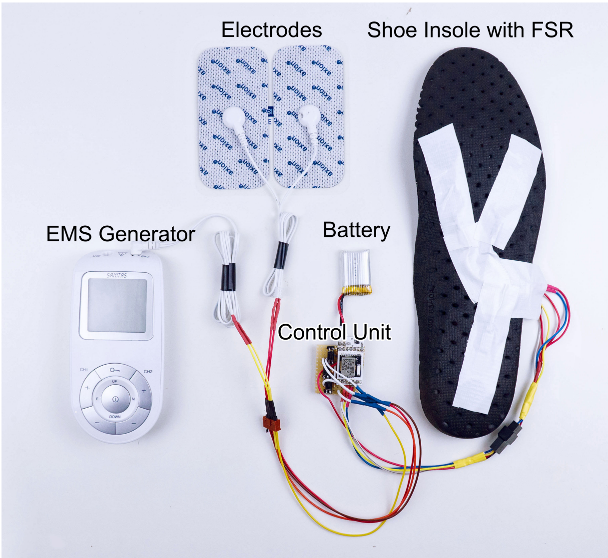

Fig. 3. Overview of the hardware components of the prototype.

Fig. 4. Placement of the EMS electrodes and wearable control unit.

2.2 EMS Actuation in HCI

Some research on EMS as an interface exists in HCI. Lopez and Baudisch [12] proposed an EMS interface for video games. In their approach a mobile game is controlled by tilting the device, and the EMS signal is sent to the player's arm to add a level of difficulty into the game. In [13], the physical impact of a virtual reality boxing game is simulated by actuating the arm in a similar movement to what actually happens in a physical boxing match. In [20], users could experience the feeling of the softness and hardness of virtual 3D objects on a computer. Affordance++ by Lopes et al. [14] is an extension to the physical affordance of everyday objects. Objects can communicate with users and tell them how they are supposed to be used. For example, a can of paint can direct the user to shake it before using it.

An approach that is closely related to our work is using EMS for pedestrian navigation [19] Typical GPS navigators rely mostly on visual and audio feedback. The EMS-based actuated navigation is a new kind of pedestrian navigation where the system could steer participants and change their walking direction by applying an EMS signal to the sartorius muscles in the upper legs.

Passive haptic learning allows the learning of a new motor skill while not keeping any attention on the learned task. In [23], users were able to acquire the keyboard typing skill passively while listening and focusing on audio. In [9], users learned to play the piano while engaging in everyday activities. In these two studies, users used tactile-enabled gloves with a vibrating motor for each finger. We follow a similar approach to passive haptic learning by using EMS to directly actuate muscles and thereby enable subconscious motor learning.

3 PROTOTYPE

The goal is to design a system that can reliably detect heel strikes, and can control the EMS signal on time. We design the system taking into consideration the technical engineering challenges:

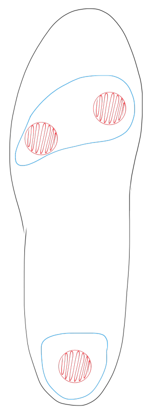

Fig. 5. Positions of the FSR on the shoe insole.

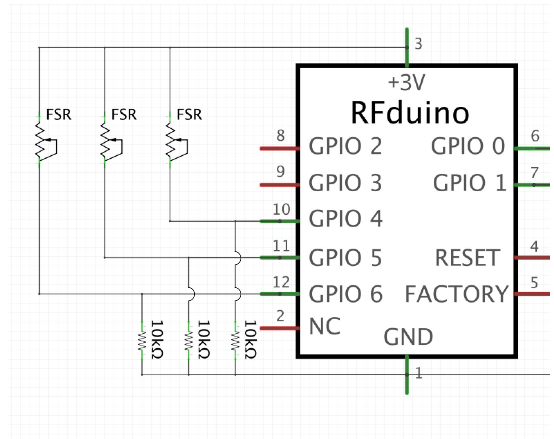

Fig. 6. Design of the detection circuit.

(1) During a foot strike, the duration between the heel touching the ground and the forefoot touching the ground is about 0.05 sec, which poses an engineering challenge to detect heel striking.
(2) With an average cadence of 100 strides/min, runners have a 0.60 sec duration per stride. That is 0.30 sec for the swing phase and 0.30 sec for the foot touching the ground. The EMS signal needs to be activated or disabled in these short intervals. To ensure safety, we use optocouplers to galvanically isolate the circuit of the commercial EMS device and the control unit.

The prototype consists of three main parts (see Figure 3): (1) a force-sensitive shoe insole to detect the running strike type, (2) a medically approved EMS generator[2], and (3) an Arduino-powered control unit that reads the data from the force sensors, sends the data to a computer for logging and controls the EMS signal.

3.1 Force-sensitive Shoe Insole

The shoe insole contains three force sensing resistors (FSR)[3], one on the heel area and two on the forefoot area, as denoted in Figure 5; there are two sensors in the forefoot area so that runners with foot pronation or supination are not neglected. Pronation and supination are the inward and outward roll of the foot while running. The FSR sensors are connected to the Arduino, as in Figure 6. The sensors change their electrical resistive value based on the force applied to them, and hence the voltage value read by the Arduino indicates the force applied at the corresponding sensor.

3.2 Arduino Unit

The Arduino unit reads the values from the sensors continuously, detects the foot strike, and activates the EMS control circuit in the case of heel striking. We use the Bluetooth-enabled RFduino board RFD22301 as the main microcontroller[4]. Desktop Python scripts are used to read the data sent via Bluetooth from the RFduino unit, to find the calibration thresholds (as shown in Figure 8), to log the data, and to visualize the results.

[2]Beurer Sanitas SEM 43 Digital EMS/TENS with Axion electrodes.
[3]Interlink model 402 FSR, 1.5cm-diameter.
[4]www.rfduino.com

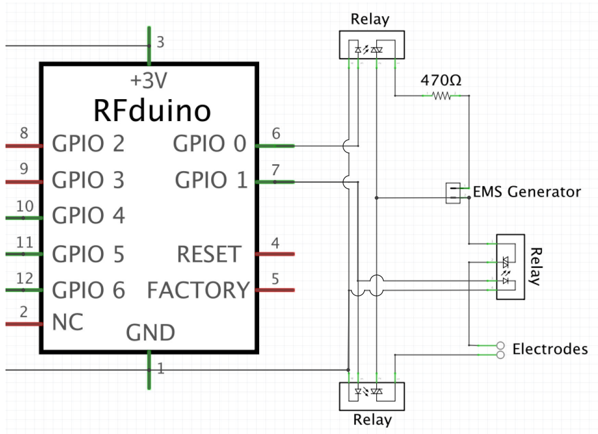

Fig. 7. Design of the EMS control circuit.

3.3 Control Circuit

The control circuit is based on the Let Your Body Move [18] toolkit. We implemented a simplified version of it (Figure 7) which contains only three electronic switches (relays) and a low resistance (470 ohms). The circuit will either direct the generated EMS signal to the user or to a small resistance and disconnect the user from the EMS circuit loop. The low resistance circuit is necessary as the EMS generator has a safety option to switch off once it is disconnected.

3.4 Calibration

Because the resistive values of the FSR sensors depend on the person's weight, the curvature of the foot and the stiffness of the shoe, a calibration is needed for each participant. For each sensor, two thresholds are used (see Figure 8): the higher threshold is the lowest value above which the sensor is considered ON, which means this part of the foot is touching the ground. The lower threshold is the highest value below which the sensor is considered OFF, which means this part of the foot is not touching the ground. We define three states of the foot during running, as shown in Figure 9:

(1) IN AIR: when all three sensors are off.
(2) LANDING: When only one sensor is on and its previous state is “IN AIR”.
(3) TAKING OFF: when a sensor's state is off while the previous state of the same sensor was on.

3.5 Heel Strike Detection

Heel-striking is defined by the state if the heel sensor is ON and the state is LANDING. The calibration and detection mechanism was developed during pilot-testing using a slow-motion video capture of different strike types. We compare the output of the Arduino which was sent via Bluetooth to a mobile phone with the actual foot-strike as it appeared in the video. During the experiments, we took a slow-motion video of participants and we achieved a recognition rate of 100%.

3.6 Portability

From a technical perspective, the prototype works outdoors as well, as it was designed to be very lightweight and uses wireless communication via BLE. It senses heel strikes and triggers the EMS actuation standalone without

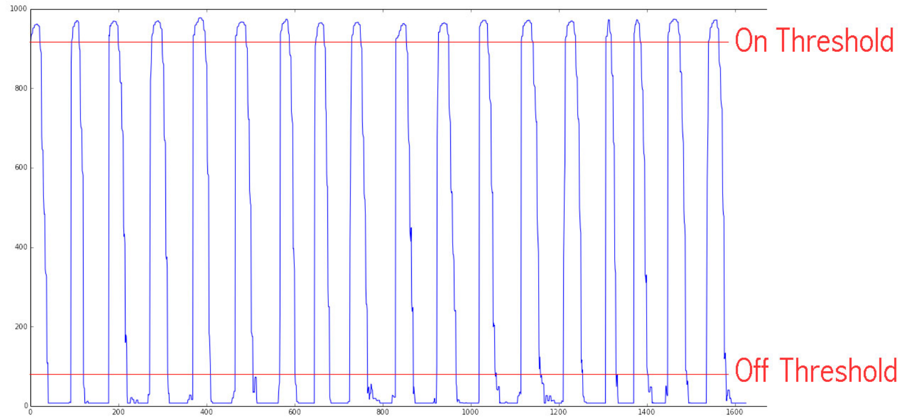

Fig. 8. Example of the calibration data and the corresponding thresholds.

the need for an additional host computer. The wireless data interface is used only to read out the statistics of the run. We took special care to keep the control unit, at only 42 grams, as light as possible. This unit is directly worn on the shoe and we thereby did not significantly increase the moving weight such that it would be noticeable to the runner.

4 EXPERIMENT

The goal of the experiment was to measure the improvement in running technique towards a mid- or forefoot running pattern (i.e. the avoidance of heel striking) using different feedback methods. The improvement is measured by the decrease in the heel strike rate. The experiment has been approved by the ethical review board of the Faculty of Mathematics and Computer Science of Saarland University. Informed and written consent has been provided freely by the participants. All participants were eplicitly told that they can stop the expiriment at any time without loosing benefits. They were compensated with 10 Euros per participation.

4.1 Conditions

Participants are divided into three groups that get different feedback (between-subjects): Classical, EMS actuation, and EMS alert.

Classical In the classical approach the participants are shown a 240fps slow-motion video capture of their first run highlighting the foot striking using a 9.7-inch tablet during the first break (i.e. after Block 1). Participants are given a verbal explanation of the danger of heel striking for long term injury avoidance as

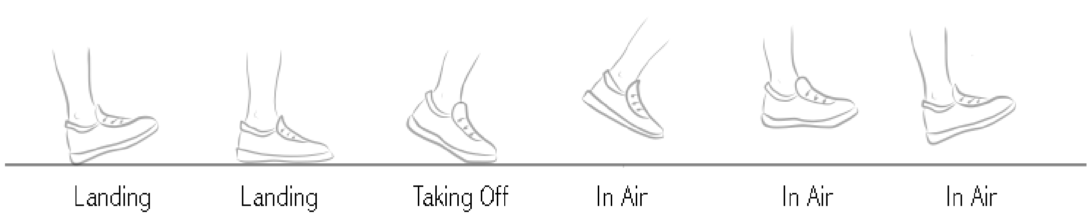

Fig. 9. The different defined states for the gait cycle.

well as its effect on performance. Participants are shown a side-by-side slow motion video of their running alongside a professional runner to emphasize the difference. Lastly, participants are given instructions to help with running on the mid- or forefoot by correcting the body posture and preventing over-striding (too long steps).

EMS Actuation During the first break, participants are given a general introduction about electrical muscle stimulation and are shown a live demo of using an EMS device to move the hand by putting the electrodes on the forearm. Then the EMS generator is connected to the control unit and to the electrodes which are on the participants' calf muscles, and the strength of the EMS signal is set to the max intensity at which the users still feel comfortable running with it. The max strength varied between participants (from 5 to 15), while the device allows a range from 0 to 30. In this group users are given no instruction or explanation about foot-striking or running technique in general. Only two pieces of information are given to them: (1) When you feel the signal, it means something is wrong, and when it is off it means you're running correctly; (2) The EMS signal is trying to correct your running, so you should be relaxed and try to work with the signal. Participants run their second 3km run with the EMS signal triggered when a heel strike is detected and active during the swing phase (while foot is in the IN AIR state).

EMS Alert In this condition, the EMS signal is used as a notification rather as an actuation or direct steering of the participants' movements. This is accomplished by applying the signal while the foot is on the ground (LANDING and TAKING_OFF states). This way the EMS signal can hardly actuate the muscle as EMS actuation is not strong enough to actuate the foot while it is on the ground.

The purpose of the second condition is to measure how much improvement (if any) this new type of feedback can have on learning a new running technique, and the short term effect of adopting the new learned technique after removing the device, so that we measure the dependence on the device. The rationale behind the third condition is that we want to investigate whether a possible improvement of the participant's running technique is due to the actual control of the participant's movement, as in the second condition, or only the alerting effect. We introduced this condition in order to exclude the possibility that the running technique adaptation in EMS actuation was due to its pure notification effect. Hypothetically, by testing only EMS actuation, it could have been concluded that the effect was introduced by its timing and side notification effect, not by the electrical stimulation and change of landing foot angle.

4.2 Participants

From a group of 21 recruited volunteers, 18 participants (15 males and 3 females) were considered, neglecting one overqualified participant (who already runs on the mid- or forefoot) and two outliers (their results varied significantly from the norm). Participants were aged between 24 to 36 years (M = 26.5, SD = 3.31). Their height ranged from 160 cm to 190 cm (M = 180.5, SD = 7.87) and their weight range was 52 kg to 92 kg (M = 74.5, SD = 12.41). Participants were recruited through a poster advertisement on a university campus asking for amateur/mid-level runners who run at least once a week and can run a 5km distance in 20 to 35 minutes on a treadmill.

After a participant arrived, he/she was assigned to one of the three conditions randomly while keeping the three conditions balanced. There was one participant who was overqualified. For this participant we did not measure any heel strike in the first run, and thus he was already a mid-/forefoot runner. After we were done with all the data points we noticed two outliers, one in the classical condition and the second in EMS actuation. These two participants had results that varied significantly from the other participants in the same condition. We omitted these two data points and recruited two more participants to fill in the missing data points and keep the number of participants per group balanced.

4.3 Task

Participants were divided into three groups; all three groups were asked to run 5km in three blocks (1km + 3km + 1km) with 5-minute breaks in between. Design A between-subjects design was used with feedback as the independent variable and heel strike rate as the dependent variable.

4.4 Procedure

After signing an informed consent statement, each participant was introduced to the experiment. After filling out a demographic questionnaire, the participant was equipped with the wearable device. During the whole experiment, all participants used the force-sensitive shoe insole and the RFduino unit to detect the heel strike rate and send the data via Bluetooth to a laptop to log the results. The calibration is done in a 5-minute warm-up run before the 5km main run. In the first 1km run, users are asked to run normally at their average 5km pace. The heel striking rate is collected and used as a baseline to measure how much improvement users will make. The second 3km run was conducted according to the different conditions. A third 1km run is used to investigate the learning effect, so only the detection mechanism is used for all participants in the three groups and no feedback of any form is given.

4.5 Apparatus

The apparatus consists of the wearable device, as introduced in the implementation section, and a treadmill. During the whole experiment, all participants used the force-sensitive shoe insole and the RFduino unit to detect the heel strike rate and send the data via Bluetooth to a laptop to log the results. Even though the prototype we built features out-of-lab portability, we decided to conduct the user study on the treadmill as we thereby assured a valid detection of heel strikes by backing up the data of the FSR sensors in the insole with slow-motion videos. However, a previous study [3] found out that there is a significant difference in running biomechanics between treadmill running and overground running at a speed faster than 17.46km/h, and no significant difference at a slower speed. In our study the fastest participant was running at 15km/h, so we expect there will not be a significant difference if the same experiment is done out-of-the-lab.

4.6 Hypotheses

Our hypotheses for the experiment are formulated as follows:

- **H1** Participants are able to learn mid-/forefoot running (i.e. avoid heel striking) using EMS actuation without further instruction.
- **H2** Participants are better able to learn mid-/forefoot running using EMS actuation feedback than with the classical approach.
- **H3** EMS alert feedback (without further instruction) is not sufficient to instruct the runner towards a correct mid-/forefoot running technique.

5 RESULTS

We evaluated our approach by measuring the effectiveness of the EMS feedback and additionally collected subjective feedback after completing the three-kilometer run.

5.1 The Effect of Feedback

The effectiveness of feedback (independent variable) was measured in heel strike rate (in percent) as the dependent variable. Heel strike rate determines the ratio of heel strikes to the total number of steps:

$$HeelStrikeRate = \frac{numberOfHeelStrikes}{totalNumberOfSteps}$$

Table 1. Heel strike rates (in percent) in each participant of the classical feedback group

Participant	**1st Block,1km**	**2nd Block,3km**	**3rd Block,1km**
P1	97.03	81.48	88.35
P2	100	96.40	99.39
P3	100	65.69	64.39
P4	89.51	85.58	81.53
P5	98.95	87.42	98.18
P6	96.8	73.64	91.75
MEAN	97.05	81.70	87.27
SD	3.95	10.82	12.99

Table 2. Heel strike rates (in percent) in each participant of the EMS actuation feedback group

Participant	**1st Block,1km**	**2nd Block,3km**	**3rd Block,1km**
P13	93.64	9.19	8.59
P14	84.1	29.92	24.02
P15	100	9.63	3.6
P16	98.13	3.19	2.69
P17	99.78	33.55	2.94
P18	98.1	9.48	4.71
MEAN	95.63	15.83	7.76
SD	6.09	12.61	8.25

Table 3. Heel strike rates (in percent) in each participant of the EMS alert feedback group.

Participant	**1st Block,1km**	**2nd Block,3km**	**3rd Block,1km**
P7	99.26	99.64	99.84
P8	99.68	99.96	100
P9	92.06	76.42	49.05
P10	100	96.96	99.78
P11	99.78	96.83	97.3
P12	97.56	97.15	98.51
MEAN	98.06	94.49	90.75
SD	3.07	8.96	20.45

Tables 1-3 show the heel strike rate for each participant in the three blocks. In the third block no feedback was provided and this run was used to measure the learning effect of each feedback approach.

In Block 1 all participants performed equally badly in all conditions, with a very high heel strike rate (M = 91.81, SD = 22.64). A one-way between-subjects ANOVA shows no significant effect of feedback on heel strike rate at the $p < .05$ level for the three conditions $[F(2, 15) = 0.43, p = 0.66]$. This result indicates that our sample represents the target population of heel strikers.

In Block 2 the participants' running technique was corrected using the different feedback approaches. A one-way between-subjects ANOVA was conducted to compare the effect of feedback on heel strike rate for classical, EMS actuation and EMS alerting conditions. There was a significant effect of feedback on heel strike rate at the

$p < .05$ level for the three conditions [$F(2, 15) = 90, p < .0001$]. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for the EMS actuation condition (M = 15.83, SD = 12.61) was significantly different than for the classical condition (M = 81.70, SD = 10.82) and the EMS alerting condition (M = 94.49, SD = 8.96). The classical condition did not significantly differ from the EMS alert conditions. These results (summarized in Figure 10) suggest that the EMS actuation approach really does have an effect on heel strike rate when used in runners. The results further suggest that EMS actuation significantly outperforms both the classical approach and the EMS alerting approach. Figures 11, 12 and 13 show the progress of each participant over time in Block 2. Participants of the classical condition started out very promising but quickly fell back into the bad habit of heel striking (see Figure 11). In the EMS actuation group the heel striking rate quickly drops for every participant and remains at at very low level (see Figure 12).

In Block 3 all participants ran without feedback. This run was used to measure the actual learning effect of different conditions. A one-way between-subjects ANOVA was conducted to compare the effect of feedback on heel strike rate for classical, EMS actuation and EMS alert. There was a significant effect of feedback on heel strike rate at the $p < .05$ level for the three conditions [$F(2, 15) = 60.53, p < .0001$]. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for the EMS actuation condition (M = 7.76, SD = 8.25) was significantly different than for the classical condition (M = 87.27, SD = 12.99) and the EMS alerting condition (M = 90.74, SD = 20.45). The classical condition did not significantly differ from the EMS alert conditions. Taken together, these results suggest that the EMS actuation approach really does have a learning effect on heel strike rate. Specifically, our results suggest that EMS actuation significantly outperforms both the classical approach and the EMS alerting approach.

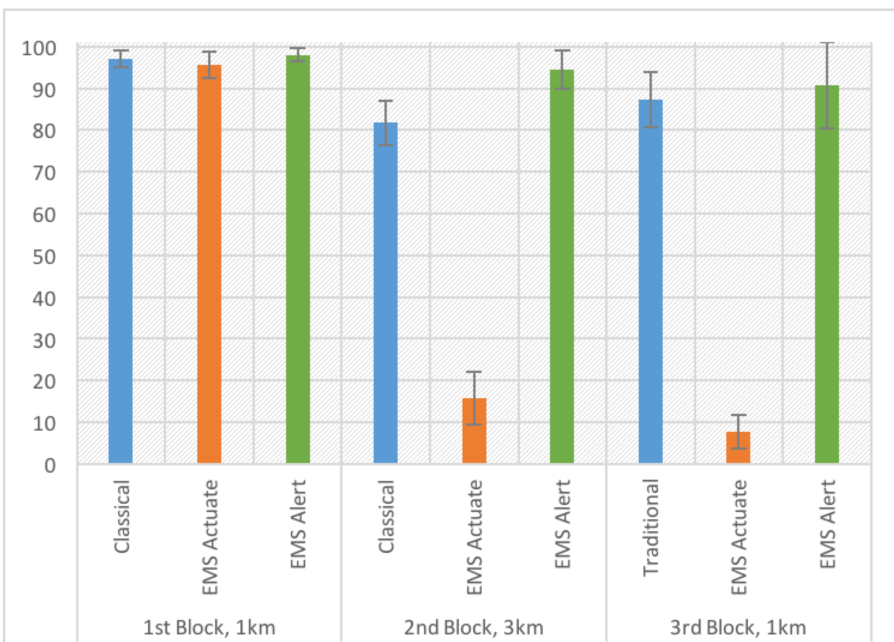

Fig. 10. The average and standard deviation of the heel strike rate (in percent) for the three groups in the three block runs.

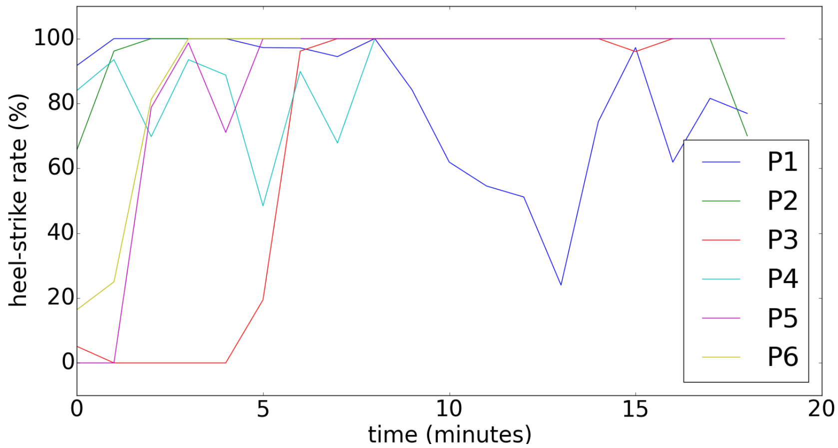

Fig. 11. Heel strike rate of the second block run of the classical feedback group over time.

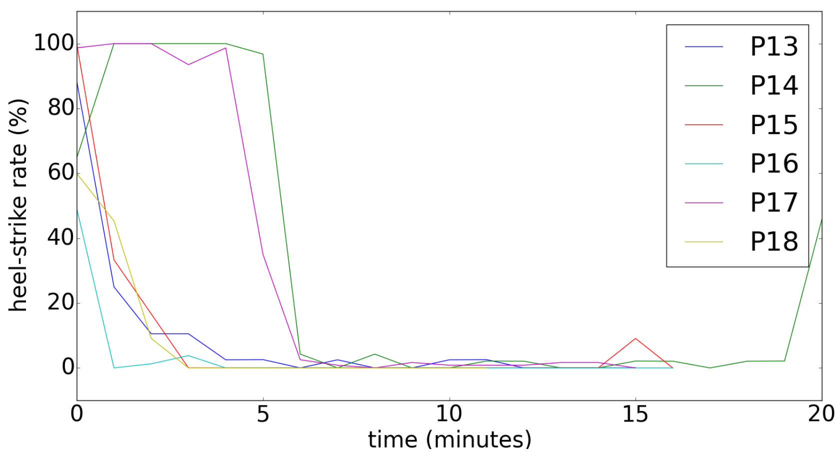

Fig. 12. Heel strike rate of the second block run of the EMS actuation feedback group over time.

5.2 Subjective Feedback and Observations

Subjective feedback was gathered after the experiment by a short questionnaire. The participants in the classical feedback group were asked how hard they had to work to adopt the new learned running technique. 3 of 6 found it physically harder specifically for the calf muscle and one participant found it harder to concentrate on adopting the new technique while running.

When asked about how much improvement they think they made, only one participant thought he did significantly better (P3); the others admitted it was hard to change the running style they have used for years. One participant said "I tried my best but it was hard to carry on" (P5). Another participant said "it is difficult to

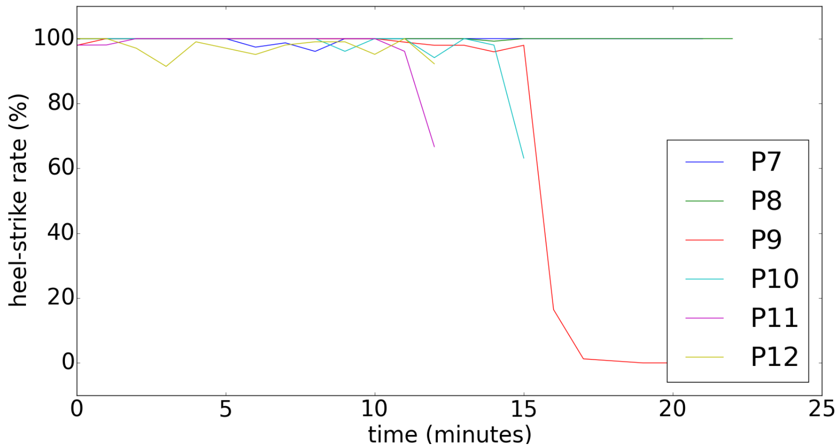

Fig. 13. Heel strike rate of the second block run of the EMS alert feedback group over time.

change running technique" (P6). Participants in the EMS actuation and EMS alert conditions were asked about what they thought the device was trying to make them do, and when it was triggered.

Every participant in EMS actuation was able to explain the effect after Block 2. In contrast, the EMS alert group participants were not able to explain the semantics of the EMS alert, except for one participant (P9). Being asked what they did to figure out the reason for the error alerts, they answered that tried out different strategies to find the error source (e.g. different cadence, running with high knees, faster speed, slower speed, landing on a different area of the treadmill (middle or the sides), the direction the feet were pointing (inward or outward), short and long strides).

Participants in EMS actuation and EMS alert groups were asked to assess the comfort of EMS as a wearable device based on the Comfort Rating Scales (CRS) [11]. Participants were asked to rate the following criterion on a scale from 0 to 10, 0 being very low and 10 very high.

Emotion I am worried about how I look when I'm wearing this device. I feel tense or on edge because of wearing the device.
Attachment I can feel the device on my body. I can feel the device moving.
Harm The device is causing me some harm. The device is painful to wear.
Perceived Change Wearing the device makes me feel physically different. I feel strange wearing the device.
Movement The device affects the way I move. The device inhibits or restricts my movements.
Anxiety I do not feel secure wearing the device.

6 DISCUSSION

In the experiment we evaluated our approach to use EMS actuation as a feedback technique to improve running technique. In the following we discuss the results of the experiment.

6.1 The Effect of Feedback on Motor Learning

The experiment reveals that runners are able to learn mid-/forefoot running (i.e. avoid heel striking) using EMS actuation without further instruction. The qualitative feedback from the participants of the EMS actuation group we received after completing the three-kilometer run implies that they were able to figure out what they learned,

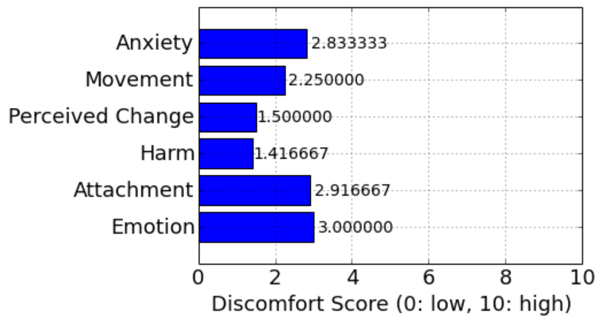

Fig. 14. The average scores on the Comfort Rating Scales.

since all participants correctly verbalized it. Thus, all participants were able to explain that they must not touch the ground with the heel first; we assumed that the device could correctly communicate the kind of movement, the correct direction and the time at which the movement had to be performed. They were then able to run with a low heel strike rate without feedback in Block 3, which already confirms H1.

However, this result couldn't be explained only by the fact that they figured out what they did wrong, because the classical group also was aware of the source of error, but they were not able to permanently avoid heel striking. The results of Block 3 suggest that EMS actuation feedback is significantly better than classical. This indicates that EMS actuation directly supports motor learning and is thus more effective than the classical approach (H2).

EMS alert only (without further instruction) was also not sufficient as feedback to guide the runner towards the error source. The results of Block 3 suggest that EMS actuation feedback is significantly better than EMS alert. This indicates that an EMS signal alone, that alerts but does not actuate the feet into the right pose, is not enough (H3). Looking at the total number of heel strikes of the EMS actuation group compared to EMS alert and the classical coaching approach, we can see that the runners had more time to practice the correct running technique, as they on average did pick up the correct technique earlier and did not fall back into incorrect behavior as in the classical approach. Thus, they would also have more total time to practice midfoot or forefoot running compared to the other two groups, which might be one explanation of why the EMS actuation group still did perform better even when the device was turned off during the last kilometer. From a physiological perspective, this explanation is in line with the current understanding of muscle memory, which increasingly develops over time with every correctly executed movement. The more correct repetitions are executed, the more likely this is to create long-term muscle memory, meaning that the movement could be correctly executed unconsciously.

6.2 Fatigue Effect

Figure 11 indicates a fatigue effect on participants who don't get real-time feedback. Participants started running relatively well with lower rates of heel strikes, but then the heel strike rate increases again. This is supported by the subjective feedback gathered after the experiment.

6.3 Learning Pattern with EMS actuation Feedback

Figure 12 shows a pattern where all participants started their second block run with a very high heel strike rate, but could quickly (maximum 6 minutes) learn and adopt the new foot striking technique. However, some spikes appear later in the curve. The reason for these spikes might be the fatigue effect, as in the classical feedback group. Unlike the classical feedback group, the issue of falling back to heel striking is instantly and continuously corrected. On the other hand, only one participant (P9) in the EMS alert feedback group (Figure 13) could find out how to correct the foot striking technique, but it was too late (after 16 minutes) compared to participants in the EMS actuation group. Moreover, this participant couldn't keep the new technique in the third run (49.05% heel strike rate) compared to the EMS actuation group where the average heel strike rate was 7.76%. Another explanation for the low but non zero heel strike rate after the six minutes mark would be a general inaccuracy of the movements, as the motor skill was still fresh and not completely internalized. In a long-term test, if this effect does not disappear, the system could be implemented with a certain degree of tolerance.

6.4 Perceived Comfort of EMS

The CRS scores suggest that our EMS-based system is considered comfortable to wear and run with. Perceived pain or harm got the lowest average score from participants, indicating that the strong EMS signal that was able to actuate user foot was not perceived as painful based on users' own rating.

6.5 Correlated Effects

Although we used the device only on one leg, we observed from the videos that participants who corrected their striking patters did so for both sides. Moreover, participants who changed their striking from heel striking to mid- or forefoot striking also changed their body posture and started using the more preferable falling forward body posture. Avoiding over-striding is also another correlated effect that was observed in that same group of participants who successfully started avoiding heel striking. This effects confirms the intuition of running biomechanics, that runners who do heel striking are more prone to have the less preferred very long strides technique (over-striding).

7 CONCLUSION

In this work, we demonstrated the potential of using EMS-based assistive feedback to trigger an unconscious motor learning process at the time of physical exercise. Our wearable system *FootStriker* detects the user's running strike pattern and provides real-time feedback via EMS to intuitively assist the runner in adapting to mid- or forefoot running. The runners wearing *FootStriker* were not given any further instructions, and accepted and felt comfortable using the device. We conducted a user study, in which we compared *FootStriker* against classical coaching. We could show that using EMS actuation, our systems significantly outperformed classical coaching. Subjective feedback from the participants indicates that all participants developed active knowledge about their newly-learned running technique and could verbally express it after completing the run. In a second control group (EMS alert), we removed the actuation effect on the calf muscles and used the EMS signal only to alert the user if a heel strike was detected. At the same time, we assured that the signal could still be perceived during running. As in this alert condition, we could not observe a significant effect, overall we show that EMS actuation actually was necessary to achieve the desired running style adaptation; alerting the user was not sufficient.

With a significant improvement over the classical coaching technique, showing technical feasibility and effectiveness in terms of motor skill learning, we laid the foundation for novel assistive wearable devices for sports. Previous work using haptic feedback as a notification could perform just as well as classical coaching techniques [25].

Still, running professionals and coaches cannot be replaced by our system, as their expert knowledge is required for the externalization of domain knowledge at the time of building or reprogramming the system. Actuating more complex movements requires accurate and timely orchestration of the muscles. Identifying those as well as sensing body postures correctly, together with the establishment of rules for connecting the sensors, is not trivial and requires knowledge about biomechanics. However, we think that our approach is generalizable to other areas, and EMS-based assistants for learning new motor skills can be beneficial, especially for amateur athletes. We envision that athletes who do not have constant access to professional coaches can in the future use the proposed class of wearable devices as an inner feedback loop to communicate with experts and receive qualitative feedback about their personal technique advancements.

8 FUTURE WORK

8.1 Long-Term Study for the Learning Effect

Our short experiment showed an overall significant improvement in adopting the new running technique using only a short three-kilometer run as the learning window and a one-kilometer run to test the learning effect. A future study could measure the long-term learning effect, measuring how long users can adopt the new technique they learned through EMS actuation feedback before falling back to the old heel striking technique. A clinical study [26] showed that using EMS can help people with foot-drop disability to learn the correct walking technique and users could sustain the new technique for at least three months. In our case, the target users are physically healthy and active, and the long-term effect is expected to last longer.

8.2 Muscle Coordination

In this study, we focused on only one running mistake (heel striking) and we stimulate only one muscle group (calf muscle). EMS actuation achieved a significant improvement over the classical coaching approach. A potential direction for future work is to study actuating multiple muscles to correct multiple mistakes, hence to learn a complex movement or help in synchronizing a specific required pattern. Muscle coordination is an important aspect in most sports, and teaching a complex movement requires a lot of practice time from coaches and athletes. EMS can provide a more intuitive interface for learning such patterns.

8.3 Out-of-the-Lab Study

The perception of the EMS feedback might be different outdoors. A future field study should be done out of the lab to investigate whether the improvement we measured using EMS as actuation also holds for outdoor running.

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