A Study on Real-Time Visualizations During Sports Activities on Smartwatches

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ABSTRACT

Nowadays, many wearable devices such as smartwatches exist that can be used to track and analyze sports activities. Generally, these devices are equipped with high-resolution screens, but most applications provide only textual status information as real-time visual feedback during the respective activities. This limited amount of information is particularly the case for running, which is among the most frequently tracked sports activities with wearable devices. So far, only a few products and prototypes provide assistance and feedback related to running technique and efficiency, but also predominantly by means of textual data representations.

This work investigates visualization approaches on the smartwatch for real-time feedback. We conducted two user studies in order to evaluate the feasibility and user acceptance of visualizations for running-technique training that assists the runner in implementing a forefoot running style. Despite frequent glances at the smartwatch, the results confirm that a runner's performance is not impaired in comparison to traditional training. Further, the results indicate that runners benefit from the visualizations in various ways: They feel more motivated and supported, improve their self-assessment, and have the certainty that they perform the new technique correctly. Most participants also took a very positive view on the intuitiveness of the visualizations.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**; *Mobile devices*; *Empirical studies in ubiquitous and mobile computing*; *Information visualization.*

KEYWORDS

Wearable devices, smartwatch, real-time feedback, visualization, sports training, running, real-time assistance, in-situ feedback, motor skills, motor learning

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1 INTRODUCTION

Running is the most popular outdoor activity by participation rate and by frequency of participation in the US since 2010 [91]. However, long-distance running generally causes a high incidence of repetitive stress injuries per year. Studies report that among distance runners the knee is the body part that is most affected by injuries [80, 95]. One of the reasons for the high knee injury rate is that up to 95% of runners land on their heel and that a runner's footfall pattern, which is defined by the part of the foot which strikes the ground first, plays a central role in lower extremity mechanics [21]. In general, foot strike patterns are classified into rear-, mid-, and forefoot striking, whereas the implications of midfoot striking are similar to forefoot striking and are subsumed in the following. The amount of running-related research in sports and health sciences is declining [50], but has not yet clearly answered the question about which of both foot striking styles is better from economical and injury prevention viewpoints. Concluding the two opposing standpoints on the optimal footfall pattern [21, 40], both agree that a forefoot striking pattern is associated with higher demands on the foot, ankle, and Achilles tendon, and that a rearfoot striking pattern exposes a greater demand on the knee. Current literature reviews also state that the lack of longitudinal and prospective studies with large sample sizes impedes a reliable statement on the risk of injuries depending on the foot strike type (FST) [21, 40, 68]. However, a retrospective study indicates that habitually forefoot strikers suffer from less injuries compared to rearfoot strikers [20]. Most recently, Chan et al. [14] published a prospective study with 320 novice runners that indicates 62% less running-related injuries in the foorefoot striking group. Despite controversial opinions in

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health and sport science on the benefits of transitioning from a rearfoot to a forefoot striking style, we decided to visualize a runner's FST in order to explore the user acceptance and utility of real-time visualizations on smartwatches during sports activities.

Technology-supported running is dominated by performance-oriented metrics [46], such as elapsed time, traveled distance, and pace. Currently, new wearable assistive technologies are introduced that give an insight on the runner's technique and can therefore contribute to improve the running economy and reduce injury risks [4, 57]. In general, concurrent visual motor feedback has proven to be a useful tool to learn complex tasks [85], such as gait retraining [1] which is expected to benefit from the emerging wearable technologies [69, 88]. Our approach complements studies that use more invasive modalities, e.g., electrical muscle stimulation (EMS), to assist runners in adopting a forefoot running technique [41]. This work proposes and evaluates a novel real-time visualization for smartwatches that assists runners in learning a new running technique. It combines and addresses several emerging or under-explored research topics:

- Real-time visualizations on smartwatches for sport activities are sparse and studies investigating smartwatch-based visualizations during exertion are missing [2, 9].
- Technique measurements and assistance is an emerging category for sport wearables [46].
- User acceptance and efficacy for self-serviced visual motor feedback beyond textual data representations on smartwatches is unknown.

2 RELATED WORK

2.1 HCI and Sports

Recent trends in mobile and wearable technology are particularly encouraging an increased research interest within the field of human-computer interaction (HCI) on designing interactive technologies for performing physical activities with a special focus on running. From a holistic point of view, Mueller et al. [63] provide a number of guidelines for the process of designing mobile running applications and highlight that individual phases of a run, e.g., preparation, jogging before and while fatigue, and cool down, are important and deserve explicit consideration as basis for a successful experience. Moreover, Woźniak et al. [102] promote the design of solutions for a broader scope that also include the runner's social environment and support communities for ambitious athletes.

Summarizing previous research and released products, Jensen and Mueller [46] conclude that there is a lack of assistive running technologies that support running technique improvements. In order to foster developments that address this shortage and further the field of research, special events [58–60] and tutorials [19] are organized on a regular basis. In addition to this clear call for novel approaches that assist runners in improving their running technique, Amini et al. [2] identified that users demand real-time visual feedback on smartwatches during fitness activities opposed to the widely implemented post-hoc analysis of fitness data with the help of smartphone devices. RunMerge [48] is a recent example that demonstrates and evaluates how to present complex running technique-related measurements after the workout.

2.2 Real-Time Feedback

In the following, ubiquitous running technology with a focus on real-time feedback is discussed. Since running technology does not exclusively rely on visual feedback, other modalities are briefly mentioned first.

Auditory feedback has been proven as an effective feedback modality for running by using music [22, 72], telephone calls between remote running partners [62, 64, 65, 71], and rhythmic pulse beats [5, 26].

Haptic sensation was also explored as a feedback channel for improving the arm movement [89], the breathing technique [94], and EMS feedback for learning forefoot running without instructions [41]. Based on the results by Hassan et al. [41], we decided to rely on the same task of transitioning a runner's FST in order to evaluate and investigate visual real-time feedback on smartwatches. Our approach can be regarded as less invasive and more versatile for regular use since it does not require EMS electrodes.

Visual feedback for running has been studied as well. TripleBeat [22] is the successor of the MPTrain system [72]. In addition to the music feedback, it features virtual competition with other runners and a novel glanceable user interface (UI) presented with a mobile phone. The glanceable UI allows to quickly obtain performance metrics including recommendations on how to improve the performance. By conducting a user study the authors highlight the utility and the unobtrusiveness of self-serviced visual feedback. The Runalyser system [100] is an early example for real-time capturing of numerous technique-related running metrics during a race. In contrast to most other systems, all recorded measures were displayed on a large TV screen and thus were not primarily intended for the instrumented runner during the race but the audience. The RunRight system [70] was designed to experience feedback on body movement while running and in other sport settings. Vertical and horizontal acceleration data was displayed on a smartphone by mapping each sensor reading to a glyph on a two-dimensional coordinate system. Seuter et al. [83] showed real-time feedback from inertial measurement units (IMUs) attached to a user's legs as simplified animated 3D bone-models on the user's smartphone and smartglasses in order to foster the body awareness. They conducted a small qualitative user study to assess the prototype's acceptance and feasibility. Participants also reported the unhandiness of the smartphone as mobile display and criticized the small display of the smartglasses. In another quantitative study Seuter et al. [84] attested that a smartwatch is better suited for interactions while running compared to a smartphone and smartglasses. JoggAR [90] followed an experience-first approach and transforms jogging with smartglasses to an exertion game in order to increase the enjoyment during workouts. The authors presented the augmented reality (AR) visuals on demand and provided audio feedback to limit the user's distraction from the real environment. Recently, Hamada et al. [39] also experimented with a see-through head-mounted display (HMD) to implement a virtual runner that acts like a pacemaker. The virtual runner was rendered transparent and solely visualized by its shoes and hands to minimize visibility restrictions of the real world for the user. Pacemakers were also implemented and investigated with real devices, such as quadcopters [36, 61] and driving robots [92] that escort the athlete. Tominaga et al. [92] attached a camera and screen to their robot that enabled video-mirroring and guidance of the user's movements in real-time for improved body self-monitoring. Ambient displays with LED strips mounted on shoes [17] and minimalistic dynamic textile patterns [30] were investigated to encode running data.

2.3 Glanceable Feedback and Visualization

Visual stimuli that are particularly intended to be perceived with a quick glance interface with research efforts in HCI, information visualization, and communication design. In the following, we introduce the concept of glanceable visualization in general. We then briefly discuss visualization research that focuses on small graphical data representations and particularly discuss small-scale visualizations on smartwatches.

Matthews et al. [55] define *glanceable* in the context of peripheral displays on computer screens as "quick and easy visual information uptake, which is equivalent to Mullet's *immediacy* principle for design [66]". This principle of "perceptual immediacy" states that "simple designs ... can be immediately recognized and understood wit a minimum of conscious effort" and "can be perceived during the span of a single glance" [66]. Matthews [54] further reviews and analyzes which concepts and theories, including attention and gestalt theory, lead to glanceable visuals. She proposes guidelines for effective glanceable displays based on abstraction techniques, design variables, and design characteristics. Additionally, the design implications are evaluated with regard to their cognitive demands and distractions from primary tasks in multitasking environments for learned and unlearned sets of stimuli. The visual stimuli are defined as renditions that also include textual data representations. The shorter the duration of a glance and peripheral vision time is, the better is the *glanceability* of a rendition. It was shown that renditions that feature high-symbolism or text improve the glanceability for unlearned conditions, but simpler and abstract renditions are better than text or renditions with higher symbolism when learned.

In general, definitions of glanceable feedback include visual stimuli designed for quick glances with limited attention and minimal interruptions from primary activities, but also ambient peripheral vision with almost unconscious perception. Implementations cover a wide spectrum that ranges from stationary physical sculptures that change their shape [44, 53], ambient installations that change the lighting environment [38, 53, 56], or large public screens [10] to personal wearables with few LEDs [25, 47] or small high-resolution screens [2, 23, 35]. Measured by the implementations' physical size and degree of mobility, guidance [16] and notifications [55] on desktop screens, tablet-based dashboards [24], and phone-based solutions [18, 22, 82] fall in between. Other important aspects that vary between glanceable feedback applications are the purpose, the targeted audience, privacy considerations by personalizing devices and abstracting the feedback, and the physical and perceived screen resolution. The latter defines the amount of information that can be encoded for a single glance. Today's smartwatches with high-resolution screens provide a fair foundation for rich glances with high information throughput. Pascoe and Thomson [74] emphasized early the importance of glanceability for smartwatches. The glanceable nature of smartwatches becomes evident when considering use cases that allow to replace smartphones [52].

2.3.1 *Small-Scale Visualizations.*

Blascheck et al. [9] recently reviewed small-scale visualization techniques in the context of glanceable visualizations on smartwatches and identified visualization research that previously addressed related issues. Data glyphs, word-sized graphics, and micro visualizations fall in this category.

Historically, research on data glyphs is the oldest field of research that considers small-scale visualization problems at its foundation. "Data glyphs are data-driven visual entities which make use of different visual channels to encode multiple attribute dimensions. They can be independently spatially arranged ...[,] vary in size" and they "are individual representations of multi-dimensional data points, often meant to be shown in small-multiple settings" [28]. In the course of the last 60 years, a multitude of glyph designs, data mappings, and placement strategies [96, 97] were proposed optimized for a variety of application domains, such as medical visualization [78, 79], flow visualization [49, 75, 77], and visualization of scientific three-dimensional fields in general [51]. Since documented and imaginable data encodings from data dimensions to visual glyph parameters seem to be countless [67], there are many surveys to guide researchers and practitioners. Recently, Borgo et al. [11] surveyed the comprehensive spectrum of glyph-based visualization approaches and included relevant fundamental concepts and theories from semiotics, perception, and cognition in the scope of their report. Most recently, Fuchs et al. [28] systematically reviewed empirical studies evaluating glyph designs and they did not encounter any study that investigated the effect of viewing time or display size in relation to glyph designs. Glyphs are generally not constrained in display size, but in practice, they are often assembled in large sets of many instances that are small in size [29]. Data glyphs can be regarded as a special case of the much younger and broader definition of word-sized graphics or micro visualizations, which renders small-scale visualizations applicable in any context and without restrictions. Glyph design guidelines often recommend to incorporate only limited auxiliary structures, e.g., labels, data axes, grid lines, or legends or to forego auxiliary structures [9].

Tufte [93] was the first to propose the concept of "small, high-resolution graphics usually embedded in a full context of words, numbers, [or] images". He named his approach "sparklines [which] are *datawords*: data-intense, design-simple, word-sized graphics". With sparklines being embedded in text he compared them with typography, which also contains iconic but non-data-driven graphics, such as emoticons. As diverse as the visual variety of typography, which also follows strict typographic rules, are similar definitions of data-driven word-scale or word-sized visualizations [8, 31–33] that can be summarized under the term micro visualizations [12, 34, 73]. Micro visualizations target explicitly small to medium-sized displayable areas but are also often designed for embeddings in larger layout ensembles. Further concrete examples for micro visualizations are: horizon graphs [81] that were evaluated and compared to line charts [42, 45], scented widgets [101], separation plots [37], gestaltlines [13], sportlines [76], and word-sized eye-tracking visualizations [6, 7]. Brandes [12] discussed in the context of visual analytics potential benefits of properly designed high-resolution micro visualizations that could facilitate seamless micro and macro readings. Macro readings are referred to as quick glances at a visualization that provides an overview to the recipient and micro readings reveal more detailed information at longer reading times but without "context discontinuities due to zooming" or other required interaction techniques.

In conclusion, glyph and micro visualization literature provides valuable information on designing effective small-scale visualizations but does not explicitly consider small physical wearable displays. So far, there are also no comprehensive and systematic guides that help to transfer the wealth of established visualizations targeted at desktop-grade display sizes to much smaller screens [9], such as wrist-worn displays. Other effects on perception of visualizations, e.g., the relation of color and the size of colored visual elements, have not yet conclusively been studied [87].

2.3.2 Visualizations on Smartwatches. Gouveia et al. [35] designed a variety of watch faces that visualize and highlight the user's physical activity levels. They further evaluated a subset of their designs in a user study in order to facilitate the understanding of how different forms of glanceable behavioral feedback influence the user's physical activity and engagement. They conclude that providing glanceable activity data strongly encourages users to be more active but effects of long-term use are not yet studied. Amini et al. [2] explored the design space of visual data representations for real-time exploration of performance-oriented fitness data on smartwatches. They clearly targeted a use case most similar to ours but did not consider technique-oriented feedback as we do and they did not evaluate their design proposals in a user study.

Apart from research that explicitly focuses on visualizing activity and health data on smartwatches, Chen [15] presented a visualization application tailored for smartwatches that allows interactive exploration of time-series data, but considers longer lasting interaction sequences beyond quick glances which does not favor concurrent primary tasks with physical exertion, e.g., running. Horak et al. [43] investigated how smartwatches can be used to support large scale visualizations on display walls with small personalized visualizations on the wrist related to specific data points on the immersive display setup. Similar to Chen [15], they targeted interaction sequences longer than short glances. Blascheck et al. [9] conducted extensive user studies in order to determine perceptual thresholds for the data comparison performance with bar charts, donut charts, and radial bar charts on smartwatches. They also varied the visual complexity in their experiments by visualizing different amounts of data values with the chosen chart types at constant physical display resolution and dimension of a smartwatch. Participants performed the data comparison task equally well for bar and donut charts when random data was tested. Radial bar charts performed significantly worse, especially when many data values were displayed at once.

3 PROTOTYPE

The objective of our wearable running assistance system for footfall technique training is identical to the prototype designed by Hassan et al. [41], but we are interested in exploring a different and less invasive feedback modality by employing visual feedback on a smartwatch instead of applying EMS feedback on the runner's calf muscles. The final prototype is shown in Figure 1.

Our solution for foot strike assistance consists of three main hardware parts: (1) Shoe insoles made of thin plastic sheets for the left and right foot. Each insole has installed three 0.5" force sensitive resistors (FSRs) at anatomical landmarks of the foot to detect if the foot touches the ground first with the heel or forefoot. (2) Control units are mounted on the laces of the running shoes and are wired to the insoles. They measure the voltage drop across the FSRs. Per foot, all three raw FSR sensor values are transmitted via Bluetooth at ~100 Hz to a connected client device. (3) A 42 mm Apple Watch Series 3 is connected to both micro controllers and receives the sensor data of both feet in real-time. Parallel to analyzing the runner's gait cycle, the computed data is visualized on demand for the user.

Since the hardware design of our smart insole is based on the FootStriker system [41], our foot strike detection algorithm follows also their proposed method. We verified our implementation in a short pilot study. Slow-motion video captures of short running sessions with varying FSTs confirmed an excellent FST recognition rate of approximately 100% as reported by Hassan et al. [41].

3.1 Visualization

For demonstration purposes [19, 98, 99] of the FootStriker wearable [41], the authors created a visualization designed for smartphones and intended for the audience. They defined the *current* heel strike rate (HSR) as the percentage of heel strikes in relation to the amount of strides over the last eight footsteps and visualized this value (y-axis) with a line plot over a period of the last 40 strides (x-axis). This graph essentially showed the binary FST, heel or forefoot strike, over time convoluted with a linear filter kernel. This method of data processing facilitates to assess the trend of the runner's foot striking technique but inhibits quick and glanceable feedback on the very recent foot strikes.

Providing clear and legible real-time feedback with low latency is important for a system intended for concurrent motor feedback [85]. Translating the line plot of the FST to a smartwatch screen resulted in suboptimal visualizations with low ratings of participants in early design studies. This was especially the case when emphasizing the legibility of individual steps by reducing the size of the filter kernel which ultimately led to potentially high oscillations of the line chart between the two extremes of the current HSR. Experimenting with other established chart types, such as area charts, did not yield satisfactory results but led in dialog with pilot testers of our system to the following user-centered design approach.

We propose a visualization that mimics the runner's real world environment and is designed to facilitate an intuitive translation of performed strides to visualized strides. Instead of following the conventional approach of mapping the time-related quantity on the x-axis of a chart-based data visualization, dedicating the y-axis to encode the time dimension exhibits a more appropriate mapping in our application context. The rationale behind this decision is that a runner who raises his arm in front of him to consult the visualization on a smartwatch display should get the impression of looking at his distance travelled. In order to achieve this effect we represent the distance travelled with a trace of footprints. Each footstep is visualized as a colored rectangle that appears at the top of the screen at the very moment the runner's foot touches the ground and moves after its appearance with constant speed to the bottom of the screen. The screen is divided in two halves. Footprints resulting from strides performed with the left foot are visualized on the left half of the screen and strides corresponding to the right foot

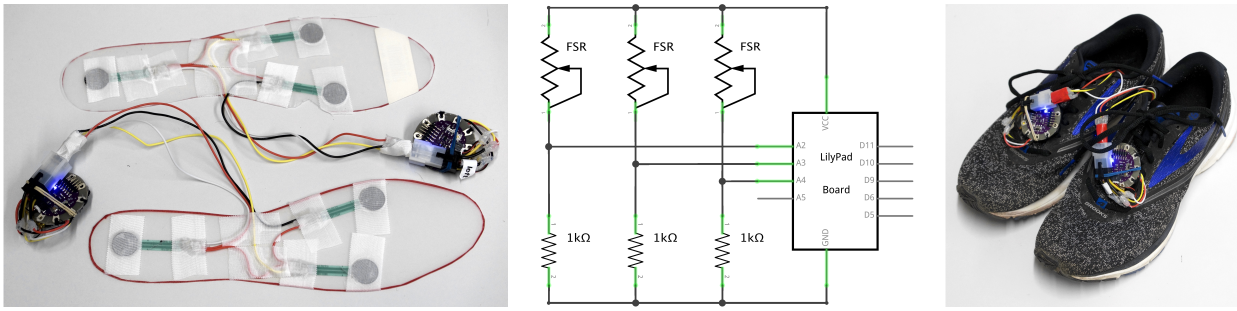

Figure 1: Force sensitive insoles with control units (left), its circuit design (middle), and instrumented running shoes (right).

(a) Graphical feedback with short time interval (5 s). **(b) Graphical feedback with long time interval (90 s).** **(c) Textual feedback based on short time interval (5 s).**

Figure 2: Animated graphical (a, b) and textual (c) real-time feedback visualizations. The screen is divided in two halves for the left and right foot. In Figure (a) and (b) red bars encode *heel strikes* and white bars encode *forefoot strikes*. Figure (c) displays the current *forefoot strike rate*.

are visualized accordingly on the right half. The animation speed and the height of the rectangles is defined by the time interval that is being visualized. Visualizing a short history of performed strides results in thick rectangles moving fast from top to bottom and displaying a longer trend results in thin and slowly moving bars. The base color of each stride encodes the captured FST. Since it is our objective to assist the runner in learning forefoot striking, red colored strides signal heel strikes that should be avoided and strides drawn in white represent successful forefoot strikes. Figure 2 depicts examples of our graphical visualization described above for two different time intervals and also shows a textual feedback screen that resembles current state of the art approaches to communicate running-related parameters.

In a small pre-study with three participants we explored an appropriate range of values for the visualized time interval by varying its length between the two extremes from displaying just a single stride on the whole screen of the smartwatch to displaying as many strides as possible. We limited this upper bound by the screen's native resolution with the result that a bar representing a stride can be drawn just as thin as a single line of pixels. The latter variant is demonstrated in Figure 2b. In the experiments, we assured that participants can still spot individual strides when the FST is altered. Interviews revealed that the visualization with the minimal time interval containing just the current stride exposed too little feedback for a smartwatch-based feedback method that is queried on demand. A covered time interval of five seconds as shown in Figure 2a was identified as the ideal lower bound that offers just enough information content and creates the impression of looking at the distance travelled. The maximum interval of 90 seconds was reported as useful to answer two questions. First, “How am I currently performing?” and second, “How did I perform over a longer period of time?”.

In the following experiments we decided to investigate the effect of the time interval parameter of our proposed visualization and the effectiveness of concurrent self-serviced visual feedback in general for learning forefoot running. Given the space constraints on a smartwatch display, the abstract, minimalistic, and compact design of our footprint visualization allows us to scale the time interval in a large range to maximize the effect of this parameter. Other design objectives might involve a more playful visualization of footprints that feature higher symbolism or a more iconic appearance closer to a stereotypical symbol of a footprint in order to represent a stride. We also envision to encode parameters in footprint glyphs other than the FST.

4 EXPERIMENT I

It was our goal to evaluate the utility of visual feedback for transitioning the running technique towards forefoot striking. The second objective was to evaluate the impact of the length of the visualized time interval on the usage of our proposed visualization design.

4.1 Hypotheses

For this experiment we defined the following research hypotheses:

H1 Learning forefoot running with self-serviced visual feedback yields better results than without visual feedback.

H2 Feedback that visualizes a long time interval is consulted less often than a visualization that covers a shorter interval.

4.2 Study Design and Task

We adopted the overall study design of the FootStriker experiment [41] with a total running distance of five kilometers which are split in three blocks with breaks in between.

1st Block (1 km) is meant for warm-up, for identifying the runner's target pace, and for measuring the runner's baseline running technique which allows us to exclude participants from the study that already pursue a forefoot running style.

- **2nd Block (3 km)** is the actual workout with the defined goal of implementing a forefoot running technique. Depending on the participant's assignment to the different groups, runners receive different forms of assistive feedback.
- **3rd Block (1 km)** is a short terminal run without any feedback for assessing the learning effect of the conditions.

Our study followed a between-subjects design with the feedback method being the independent variable and the measured HSR as the dependent variable for comparing running technique improvements. For the evaluation of the visualization's glanceability, the number of glances is the dependent variable.

4.3 Conditions

Participants were assigned to one of the following three experiment conditions that involved different levels and forms of feedback. All three groups were based on the classical coaching condition described by Hassan et al. [41] that was reported to exhibit poor running technique improvements. In contrast to invasive EMS feedback that can be applied without instructing the participants [41], our feedback methods require some instructions to create awareness and context for the purpose of our visualization.

Every condition received traditional forefoot running coaching implemented as follows. Each participant's habitual footfall pattern was captured with slow-motion video recordings at 240 Hz during the first running block of the experiment. During the break after the first block participant's were shown their slow-motion video recordings on a large 55" TV screen and their foot strike technique was highlighted and discussed. Proper forefoot striking was demonstrated to the participants by showing slow-motion videos of a professional runner that underlined the differences in execution. Finally, participants were verbally instructed on how to implement forefoot running by avoiding over-striding and by paying attention to their body posture.

Since it was our main objective to evaluate the utility of self-serviced visual feedback on smartwatches, we chose to equip all participants across all conditions with a smartwatch during the second and third block of the experiment in order to match the conditions as much as possible for measuring the impact of our visualization and excluding the effect of wearing a smartwatch. We configured the smartwatch for all conditions to signal the user each kilometer they ran as it is typically done by most running applications. This notification was implemented by playing a default auditive and haptic alert but without providing any special visual information since we reserved this modality for feedback on the FST for groups two and three which are defined in the following.

- **Group 1: Classical Coaching Only** Subjects received traditional coaching merely as described above. The only conceptual difference between this group and the control group reported by Hassan et al. [41] is the addition of our notifications for every completed kilometer in block two.
- **Group 2: Visualization (5 s)** In addition to classical coaching terminal to the first block and the running distance notifications introduced for group one, subjects were enabled to evaluate their running technique during the second block on demand by consulting the visualization of their footfall pattern over a short five-second time interval (Figure 2a).
- **Group 3: Visualization (90 s)** This group only differed from group two with respect to the length of the visualized time interval which was set to 90 seconds (Figure 2b).

4.4 Participants

We recruited in total 37 volunteers through social media channels, word of mouth, and poster advertisements on the university campus. Inclusion criteria were that participants are required to be recreational or amateur runners that are capable to complete a five-kilometer run in 20 to 35 minutes and that participants are not forefoot strikers.

Two participants were excluded after the first running block because they exhibited already a forefoot running style for their target pace. One participant felt very uncomfortable and cancelled the experiment during the second block. Furthermore, four trials were excluded because of wrong and missing FST detections. Finally, a group of 30 participants (19 male and 11 female) was included in this study. Participants were compensated with sweets and a voluntary participation in a lottery of two 25 Euro gift cards. The included participants reported their age between 22 and 49 years (M = 29.7, SD = 5.5), their weight between 54 and 98 kg (M = 77.1, SD = 10.4), and their body height between 163 and 196 cm (M = 179.5, SD = 9.2). Participants with visual impairment were asked to use their habitual vision aid during the experiment so that they can clearly read a wrist watch.

4.5 Procedure

Participants were welcomed, presented a written description of the experiment, and asked to sign an informed consent. While the participant's running shoes were instrumented with the FST-sensing prototype, the participants filled out an initial demographic questionnaire. The participants were instructed to complete the first running block with their habitual running technique and to select their competitive running speed based on their daily shape that would allow them to run five kilometers without decreasing their speed. After the first block, all participants underwent the classical forefoot running coaching procedure. Subsequently, all runners were equipped with the smartwatch and familiarized with the notification for completing a kilometer by providing an example alert. For participants in the control group, the display of the smartwatch did not show anything. Participants assigned to groups two or three received a short three-minute training session with their corresponding five-second or 90-second time interval visualization and they were introduced to the general handling of the smartwatch which included how to activate the display by raising the arm. Thereafter, the second running block was carried out according to the different conditions with each participant's target pace identified in the first block. After the second running block, all participants were asked to complete an intermediate questionnaire about their running experience regarding their task completion and their perceived influence of the kilometer-based notifications on the task of implementing a forefoot running style. Groups two and three were further asked to judge the quality and the utility of the provided visualization. Finally, the third running block was conducted without any feedback for all three groups. After completing the last running block, participants filled out a final questionnaire identical to all conditions and identical to the intermediate questionnaire not related to the notifications or the visualization in order to quantify changes in the running experience. The whole procedure took between 60 and 90 minutes.

4.6 Apparatus

We conducted the experiment in a laboratory on a consumer-level treadmill which allowed us to conveniently record the whole procedure on video and to maintain controlled experimental conditions.

All displays of the treadmill except the display of the current running speed were covered with a piece of cardboard to minimize distractions for the runner. From the beginning of the experiment, participants were equipped with the smart insole and after the classical coaching session they were equipped with the smartwatch. The raw data from the force sensors and the derived foot strikes were recorded on the smartwatch during the whole experiment. We captured a closeup of the participants' foot strike pattern in slow-motion which served as a basis for the classical coaching session after the first block and for post-hoc verification of the detected foot strikes. Glances were automatically detected by logging all display activations and deactivations of the smartwatch in our visualization application. Additionally, the participants' interactions with the smartwatch were recorded on video to validate the automatically identified glances.

4.7 Results

We evaluated the effectiveness of our proposed feedback method by analyzing the objective measurements of the FST and the glances.

Unless otherwise noted all hypothesis tests were computed with a significance level α of 0.05, the Shapiro-Wilk test was applied to assess if the data could be assumed to be normally distributed, and the homogeneity of variances was asserted by Levene's test.

4.7.1 Effect of Feedback on the Heel Strike Rate. The effect of the feedback method (independent variable) was assessed by the variations of each participant's FST over time measured by means of the HSRs (dependent variable).

Each participant's average HSRs for the first, second, and third running block are summarized in Figure 3. The HSR was normally distributed for all conditions in the first block ($p > 0.06$), but not for the remaining majority of cases ($p < 0.01$). The same applies to the assessment of the homogeneity of variances. Only the first running block exhibits equal variances ($p = 0.31$) and the variances of the other variables could not be assumed to be equal ($p < 0.001$). We applied the nonparametric Kruskal-Wallis test for independent samples to our data for all blocks. In addition to the medians (Mdns), the corresponding means (Ms) and standard deviations (SDs) are provided in the following evaluation to describe the data.

Very high HSRs with minimal deviations could be observed in the first running block across all participants and conditions (Mdn = 96.38, M = 96.31, SD = 2.49). For this first block, which assesses the runners' habitual running technique, there was no statistically significant difference in the HSRs for the three different feedback conditions, $\chi^2(2) = 1.24$, $p = 0.54$.

During the second running block, participants were asked to avoid heel strikes. They were assisted in implementing a forefoot running style by different types of feedback. A statistical significant effect of the feedback type on the HSR could be observed for the three feedback groups, $\chi^2(2) = 7.35$, $p = 0.03$. Dunn-Bonferroni post-hoc tests revealed that group one (Mdn = 6.99, M = 29.87, SD = 42.45) and three (Mdn = 0.34, M = 0.92, SD = 1.50) differed significantly ($z = 2.52$, $p = 0.04$) with a large effect size (Cohen's $r = 0.56$) [27]. There were no statistical differences for the other two pairwise comparisons, neither between group two (Mdn = 2.76, M = 5.60, SD = 8.42) and three ($p = 0.10$), nor between group one and two ($p = 1.00$). Compared to the study conducted by Hassan et al. [41] our participants across all conditions (Mdn = 1.04, M = 12.13, SD = 27.36) exhibited a notably low HSR. Even our control group, that differed conceptually only slightly from their condition, performed surprisingly well. Just three out of ten participants (P0, P6, P33) assigned to our control group showed a poor performance similar to the value range reported by Hassan et al. [41]. The others competed with the participants assisted with visual feedback methods. Nevertheless, the results suggest that the condition with self-serviced visual feedback based on a long visualized time interval significantly outperformed the condition without concurrent visual feedback.

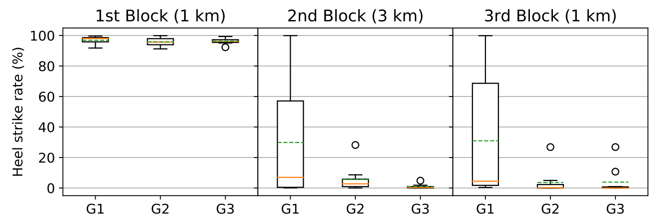

Figure 3: Box plots (orange line: median, green dashed line: mean) of the heel strike rates for groups (G) one to three.

The third running block was conducted without feedback for all conditions and was meant to assess the learning effect. The HSRs differed significantly between the conditions, $\chi^2(2) = 9.56$, $p = 0.01$. Post-hoc Dunn-Bonferroni tests showed also for this block a large significant effect ($z = 2.90$, $p = 0.01$, $r = 0.65$) for the pairwise comparison among group one (Mdn = 4.44, M = 30.96, SD = 44.04) and three (Mdn = 0.00, M = 3.87, SD = 8.74). Group two (Mdn = 0.19, M = 3.61, SD = 8.32) was not significantly different from group one ($p = 0.05$) and three ($p = 1.00$). These results suggest that only the visual feedback method that provides a visualization for the long time interval has a significant stronger learning effect on the HSR compared to the condition without concurrent visual feedback.

4.7.2 Effect of Feedback on the Glances. The effect of the self-serviced visual feedback method (independent variable) on the runner's glancing behavior was measured by the absolute number of glances (dependent variable).

Each automatically logged glance was manually verified and reviewed with synchronized video recordings showing the user's interaction sequences. On average, 11.47% of glances across all participants, assigned to either of the two visual feedback groups two or three, were removed due to unintended display activations without glances from the user at the smartwatch. These wrong detections, especially for participants with more than 30% of removed glances (P15, P31, P26), typically resulted from wiping away sweat or hair from the forehead with the arm wearing the smartwatch.

The data was normally distributed for both conditions ($p > 0.06$) but the homogeneity of variances could not be assumed to be equal ($p = 0.01$). We did not resort to a nonparametric test and conducted an unpaired t-Test. The total number of glances between group two (M = 26.10, SD = 10.31) and group three (M = 32.50, SD = 20.82) did not statistically differ, $t(13.16) = -0.87, p = 0.40$.

4.8 Discussion

The results lead to the conclusion that runners with self-serviced visual feedback are generally not more successful at learning forefoot running than runners without visual feedback. Only those runners with visual feedback with a long visualization interval performed significantly better than the comparative group one with classical coaching. Results of the second condition with a visualization based on a short interval did not significantly differ from the other two conditions. These quantitive results suggest to reject the first hypothesis (H1) because it could not be statistically shown that both conditions with visual feedback outperformed the classical coaching condition.

Furthermore, no statistically meaningful differences in the glancing behavior of the two extreme cases of our proposed visualization method could be observed. The glancing behavior of condition two with a short visualized time interval did not statistically differ from condition three with a long visualized interval. Thus, the second hypothesis (H2) was also rejected.

As a result of the experiment, it can be stated from an objective standpoint that recreational and amateur runners are able to perform and learn forefoot running without explicit assistive concurrent feedback. The majority of all participants achieved average HSRs clearly below 15%. These results are considerably different from the work by Hassan et al. [41]. The main difference between our and their control group was the notification on the smartwatch after every kilometer of running.

Results from the questionnaires conducted after the runs indicate that the visualizations were more useful to perform the forefoot running than the notifications. This is not surprising since both features, the notifications and the visualizations, were introduced to the participants for two distinct purposes of estimating the workout progress and for self-serviced forefoot running assistance. However, the participants' responses suggest that the mere notifications might have had a strong influence on the success rate of the participants since the notifications were used as a tool to stay focused on the primary task of forefoot running. Habitually, heel striking runners who try to implement a forefoot running style need to pay special attention to the forefoot running technique.

The subjective results of this experiment indicate that runners without visual feedback tend to miss concurrent feedback in order to validate their running technique and that runners with visual feedback welcome assistive technology for gaining confidence in correctly implementing forefoot running. Furthermore, the proposed visualization technique was described as an intuitive and effective tool that users would intend to use for future forefoot running workouts.

5 EXPERIMENT II

5.1 Research Questions

This second experiment was conducted for two reasons: firstly, in order to assess the runners' preferred visual feedback method and secondly, in order to evaluate the impact of the notifications on the runners ability to implement forefoot running.

5.2 Study Design and Conditions

In order to facilitate comparisons with the results of the previous experiment, the study design and conditions were kept as identical as possible to group one of Experiment I.

Group 0: Classical Coaching Only Without Notifications Subjects received traditional coaching as described in Section 4.3 but they were not equipped with a smartwatch during the first and second running block and they did not receive any notifications to signal their progress. Best efforts were taken to reproduce the same condition of the control group in the study conducted by Hassan et al. [41].

Exclusively the third running block of the study design of the first experiment was modified in order to pursue the first goal of this second experiment to evaluate the runner's feedback preferences.

Altered 3rd Block (1 km) During the course of this block subjects were asked to make use of all three visual feedback methods as depicted in Figure 2: the graphical feedback visualization with a short time interval (5 s), with a long time interval (90 s), and a textual visual feedback representation based on a short time interval (5 s).

The textual feedback method was added to represent the status quo of data representations on smartwatches during workouts.

5.3 Participants, Procedure, and Apparatus

Three months after the first experiment, eleven additional participants (9 male and 2 female) were recruited who had not participated in the previous experiment but met identical inclusion criteria. They were rewarded with sweets and a voluntary participation in a lottery of a single 25 Euro gift card. The runners reported their age between 22 and 29 years (M = 25.0, SD = 2.5), their weight between 59 and 97 kg (M = 83.1, SD = 12.3), and their body height between 166 and 187 cm (M = 177.6, SD = 7.2).

The experiment's procedure was altered insofar that the participants were equipped with the smartwatch and instructed with its purpose and use right before the new third running block. Participants were asked to change the visual feedback technique after every third of the third block. The order of presenting and using the three different visualization methods was randomized for every participant. Each visualization method was introduced to the runner right before the utilization. Finally, after the last running block semi-structured interviews were conducted with each runner in order to evaluate their experience and feedback preferences. The interview consisted of twelve questions to encourage the participants to reason about the advantages and disadvantages of the individual feedback methods, their utility, perceived intuitiveness, and choice of visualization parameters.

Due to a technical problem the captured data of a single participant (P43) could not be retrieved from the smartwatch. Thus, the data could not be used for statistical comparisons of the HSRs with the data obtained from Experiment I. Nevertheless, the participant's interview was included in the analysis.

The second experiment's apparatus was identical to the first experiment except that the participants were equipped with the smartwatch not until the altered third running block.

5.4 Results

We compiled the subjective answers in the semi-structured interviews to evaluate the preferred feedback method. Additionally, the impact of notifications was evaluated by analyzing the objective measurements of the FST.

5.4.1 Interviews and Feedback Preferences. The evaluation revealed that the visualization with the short time interval was the most preferred feedback method. It was considered the best method by five participants. Each of the other two feedback methods (visualization with long time interval and textual feedback) were preferred by two runners. A single participant would have had preferred a combination of the graphical feedback visualization with the short and long time interval and another participant did not have a preferred feedback method. Thus, ten out of eleven participants preferred visual feedback on a smartwatch over no feedback and considered the self-serviced concurrent feedback an assistive tool to implement forefoot running. Reasons for this consideration were mostly the provided feedback for successful self-monitoring, motivational aspects, and assistance to learn forefoot running.

As reported by the participants, the advantages of the visualization with the short time interval were predominantly an accurate symbolization of the completed strides, the simple graphical layout of the screen, and its clarity caused by a limited amount of presented information. The contrary was identified as one of the advantages of the visualization with the long time interval which included a high amount of details and provided a better summary of the error rate but this method was also often described as confusing. Simplicity was reported as the biggest advantage of the textual data representation. Participants concluded that the textual representation did not demand to interpret the data. Nevertheless, the most disadvantages were attributed to this feedback method, e.g., predominantly the shortage of information, the missing link to the run, and the lack of visible progress over time which made it more difficult for runners to judge whether their performance is improving or deteriorating.

Further, more than 60% of the participants preferred a visualization with the short interval over the long interval and the same percentage rated the visualization with the short interval as the most intuitive feedback variant. Three participants rated both visualizations with a short and long time interval as equal in this regard but better than the textual representation. Only a single participant rated the textual representation as most intuitive. Slightly more than half of the participants felt that they were able to interpret the textual data representation fastest. 27% chose the visualization with the short interval and two participants chose both graphical visualizations as fastest to read.

The feedback for the current stride was very important for seven out of eleven runners. The others did prefer to get feedback for the last couple of strides or for a longer period. The separation of the left and right foot was important for 90% of the participants.

5.4.2 Effect of Feedback on the Heel Strike Rate. Similar to Experiment I, the effect of the feedback method (independent variable) was assessed by the variations of each participant's FST over time measured by means of the HSRs (dependent variable).

This data complements the HSRs measured for the previous groups one to three in the first experiment. The HSR was normally distributed for all conditions (group zero to three) in the first running block ($p > 0.06$), but not for the second running block ($p < 0.01$). Only the first block exhibited equal variances ($p = 0.42$) and the variances of the HSR for the second block could not be assumed to be equal ($p < 0.001$). In accordance with the first experiment we conducted a Kruskal-Wallis test for independent samples. We did not include the third running block in this comparison with the other conditions since its procedure was significantly altered for this second experiment which does not allow for a statistical analysis with data obtained in the first experiment.

Again, very high HSRs with minimal deviations could be observed in the first running block across all participants and conditions (Mdn = 96.04, M = 96.09, SD = 2.42). For this first block, there was no statistically significant difference in the HSRs for the four different conditions, $\chi^2(3) = 2.17$, $p = 0.54$.

During the second running block, participants were asked to avoid heel strikes. A statistical significant effect of the feedback type on the HSR could be observed for the four groups, $\chi^2(3) = 11.03$, $p = 0.01$. Dunn-Bonferroni post-hoc tests revealed that group zero (Mdn = 5.90, M = 26.10, SD = 35.45) and three (Mdn = 0.34, M = 0.92, SD = 1.50) differed significantly ($z = 3.11$, $p = 0.01$) with a large effect size ($r = 0.70$). There were no statistical differences for the other five pairwise comparisons between group zero and one ($p = 1.00$), group zero and two ($p = 1.00$), group one and two ($p = 1.00$), group one and three ($p = 0.06$), and group two and three ($p = 0.26$). These results suggest that the condition with self-serviced visual feedback based on a long visualized time interval significantly outperformed the condition without concurrent visual feedback and without notifications.

5.5 Discussion

The statistical analysis of the resulting HSRs of the extended experiment with the data obtained from the first experiment leads to the conclusion that there is not enough evidence to state that runners are in general better in implementing forefoot running with concurrent feedback or notifications than without concurrent feedback or notifications. Only one significant difference could be observed between group zero and three. No statistical differences could be shown for the other pairwise comparisons. The applied nonparametric Kruskal-Wallis test analyzes differences of medians. The median of the HSRs of group zero was 5.56 units greater than the median of group three. Comparing the means of the HSRs would result in a difference of 25.18. Both differences are considerably lower than those observed by Hassan et al. [41] because in our studies the runners performed exceptionally well even without any concurrent feedback or notifications that might have alerted them to stay focused on forefoot running. We were not able to confirm a poor performance for runners that merely received classical coaching.

We interpret our data as follows. The conditions for group zero and one were almost identical and no considerable differences for the second running block could be observed between both groups. In each of the two groups with no concurrent visual feedback there were three participants who performed considerably worse than the others with an average HSR larger than 50% (P0, P6, P33, P39, P40, P42). All others were able to achieve a HSR below 20% which means that 70% of our participants without concurrent visual feedback were able to successfully implement forefoot running with the classical coaching approach. The remaining 30% had problems to correctly and consistently implement the upfront coaching instructions for the whole duration of the second running block. The study conducted by Hassan et al. [41] had a slightly smaller sample size of six recruited participants per condition. The six runners assigned to their classical coaching group could have belonged to the latter category of runners or our coaching could have been more effective but in dialog with the authors of this previous study best efforts were taken to match their inclusion criteria and to reproduce their described method of classical forefoot coaching. Despite indications that their classical coaching subjects might not be representative for the whole population of recreational and amateur runners they did show that forefoot running can be learned without instructions at all by the use of EMS feedback which is more invasive than our proposed self-serviced visual feedback on smartwatches. We also identified a slight variation in the task for the runners to chose a competitive running speed which might be another explanation for the different observations. Future studies should track the rated perceived exertion (RPE) for better comparability.

Two of the three runners of group zero (P40, P42) who had a poor HSR larger than 50% in the second running block were able to significantly improve their HSR in the third running block by the use of the visual feedback methods on the smartwatch. A single participant (P39) was not able to perform forefoot striking during the whole experiment. One of these two participants (P42) who did significantly improve the HSR in the third running block enhanced his HSR to about 32%. The detailed HSR data for the complete third running block of this participant revealed that he did not improve his HSR in the first third of the third running block but he did improve his HSR significantly in the two remaining thirds in the same manner as the other participant (P40) did for the complete third block. The former participant started with the visualization with long time interval first. Interestingly, the latter participant coincidentally ran with textual feedback first and was not able to improve his HSR at all by using the textual feedback method. As soon as this runner (P42) was asked to switch to the next randomly assigned type of visual feedback, which was the visualization with a short time interval in his case, he was able to avoid heel strikes and successfully implemented the forefoot running technique. We suspect that the textual feedback method failed to assist the participant in performing forefoot striking because of its shortcoming to clearly communicate the FST of the current stride. In the interviews, most participants described this feature as a very important aspect of concurrent feedback.

6 CONCLUSIONS

On the basis of two experiments, this work evaluated the application of smartwatch-based visualizations as an assistive feedback method for learning a new running technique. The conducted studies with in total 40 included participants assessed the ability of recreational and amateur runners to implement a forefoot running technique for a three-km workout. The experiments showed that most runners are in general able to apply the new running technique without concurrent feedback but the runners prefer to use concurrent feedback for self-controlled learning, motivation, and adjustment of their running technique. Furthermore, the proposed visualization methods for self-serviced concurrent visual feedback on the smartwatch were preferred over textual data representations. The results indicate that runners who have issues with implementing the new running technique without concurrent feedback benefit more from the proposed data visualization that directly maps every stride to interactive graphical elements than from the commonly used abstract numerical display of FST data.

7 LIMITATIONS AND SCOPE

Transitioning from a rearfoot to a forefoot striking style (and vice versa) may impose risks and the ideal strike pattern is a controversial topic [3, 86]. We explicitly instructed all participants verbally and in the informed consent that they should immediately stop the experiment if they felt uncomfortable and that the experiment might cause sore calf muscles.

As motivated in Section 1, we decided to visualize a runner's FST in order to explore the user acceptance and utility of real-time visualizations on smartwatches during sports activities. The proposed visualization is applicable to any real-time metric of interest that is suited to be mapped to binary data, e.g., to encode if the vertical oscillation of a runner exceeds a specific threshold. Other glyph designs would also allow to encode more complex data. If applied to sports other than running, it's crucial that the athlete is able to glance at the visualization, e.g., when lifting weights it's often hard to glance at a smartwatch.

8 FUTURE WORK

We investigated how smartwatch-based concurrent visual feedback affects the implementation of a new running style in a short three-kilometer workout in a laboratory environment. A future long-term study in a natural running environment, which is the outdoors for most runners, could show a stronger separation of the experiment's conditions since runners with concurrent feedback are expected to be more engaged in reaching daily and long-term training goals. Moreover, as proposed by Mueller et al. [63] for interactive jogging systems in general, a promising enhancement in particular for smartwatch-based assistive visualizations would be to dynamically adjust the visualization parameters during a workout based on contextual factors, e.g., the athlete's level of exertion or the current success rate.

Future studies could evaluate assistive visualization designs that encode more than just a single metric over time in order to support the training of more complex skills. This goal would increase the impact of graphical data visualizations over textual data representations and over no concurrent feedback.

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A MEASURED DATA

Table 1 details the running data and Table 2 the glance data captured in the experiments.

Subject Group 0	Block 1 (1 km)	Block 2 (3 km)	Block 3 (1 km)	Pace
P37	98.86	16.29	2.65	9.50
P38	92.56	1.57	2.03	7.50
P39	94.89	89.32	87.40	9.50
P40	95.14	52.06	5.87	11.90
P41	93.44	3.68	4.03	10.00
P42	97.20	84.14	31.61	11.00
P44	95.68	4.93	4.18	7.90
P45	97.45	6.86	7.51	8.50
P46	96.61	1.84	2.14	8.00
P47	92.47	0.27	0.85	10.00
Median	95.41	5.90	4.11	9.50
Mean	95.43	26.10	14.83	9.38
SD	2.15	35.45	27.04	1.42

(a) Group 0 (Exp. II): Classical coaching only without notifications.

Subject Group 1	Block 1 (1 km)	Block 2 (3 km)	Block 3 (1 km)	Pace
P0	99.52	98.66	96.53	10.00
P1	97.83	0.64	0.77	12.90
P2	96.57	0.08	0.09	9.50
P3	98.67	0.40	0.59	9.50
P5	92.37	13.27	0.62	12.00
P6	99.64	99.91	100.00	13.00
P32	98.22	4.46	1.19	12.00
P33	95.58	71.68	58.57	9.70
P34	91.78	0.08	0.12	12.00
P36	98.37	9.52	27.25	11.60
Median	98.02	6.99	0.98	11.80
Mean	96.86	29.87	28.57	11.22
SD	2.80	42.45	41.27	1.40

(b) Group 1 (Exp. I): Classical coaching only.

Subject Group 2	Block 1 (1 km)	Block 2 (3 km)	Block 3 (1 km)	Pace
P7	97.87	5.20	12.71	10.00
P9	95.73	2.87	6.59	8.10
P10	94.84	1.00	0.34	11.00
P11	95.53	28.21	26.65	9.10
P12	98.99	0.44	1.31	10.20
P13	92.86	0.04	0.00	10.50
P14	97.94	0.93	1.57	12.00
P15	99.89	2.65	7.95	10.30
P16	93.66	6.04	3.25	10.00
P31	91.23	8.65	3.84	11.50
Median	95.63	2.76	3.55	10.25
Mean	95.85	5.60	6.42	10.27
SD	2.81	8.42	8.14	1.12

(c) Group 2 (Exp. I): Visualization with short time interval (5 s).

Subject Group 3	Block 1 (1 km)	Block 2 (3 km)	Block 3 (1 km)	Pace
P17	99.33	0.35	0.53	11.10
P20	92.29	0.00	0.00	10.50
P22	95.60	0.00	0.00	9.00
P23	95.40	4.84	14.09	10.80
P24	98.28	0.03	0.08	7.50
P25	97.43	0.03	0.10	10.60
P26	96.61	0.71	1.58	13.50
P27	96.19	1.84	0.12	11.90
P28	95.90	1.08	2.47	14.00
P30	95.10	0.32	0.98	11.00
Median	96.04	0.34	0.32	10.90
Mean	96.21	0.92	2.00	10.99
SD	1.93	1.50	4.33	1.91

(d) Group 3 (Exp. I): Visualization with long time interval (90 s).

Table 1: Heel strike rates (in %) and pace (in km/h) for participants (P) of group one (b), two (c), three (d), and zero (a).

Subject Group 2	Number of glances	Removed glances	
P7	28	1	3.45%
P9	24	4	14.29%
P10	39	5	11.36%
P11	37	0	0.00%
P12	34	0	0.00%
P13	23	0	0.00%
P14	13	0	0.00%
P15	27	22	44.90%
P16	30	1	3.23%
P31	6	31	83.78%
Median	27.50	1.00	3.34%
Mean	26.10	6.40	16.10%
SD	10.31	10.95	27.48%

(a) Group 2 (Exp. I): Visualization with short time interval (5 s).

Subject Group 3	Number of glances	Removed glances	
P17	23	0	0.00%
P20	55	1	1.79%
P22	64	0	0.00%
P23	18	2	10.00%
P24	55	0	0.00%
P25	37	0	0.00%
P26	10	6	37.50%
P27	17	0	0.00%
P28	41	1	2.38%
P30	5	1	16.67%
Median	30.00	0.50	0.89%
Mean	32.50	1.10	6.83%
SD	20.82	1.85	12.14%

(b) Group 3 (Exp. I): Visualization with long time interval (90 s).

Table 2: Glance data for participants (P) of group two (a) and three (b): corrected total number of glances (in #) and number of removed glances (in # and %) after video verification.