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Feedback Provision on Running Technique with a Smartphone

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Abstract

Most runners run by themselves and do not have access to a trainer for feedback on their running form. We thus investigated the use of a standard smartphone for feedback provision while running, which is available to almost everyone. We investigated the use of body-worn sensors for assessing running technique on the example of arm carriage. In a pre-study with 10 runners we found that arm carriage can be monitored by a single sensor on the upper arm. We developed an Android application to monitor arm carriage in real time. The application was validated in a user study with 23 participants. Results from questionnaires revealed high user acceptance.

Keywords: *Wearable Technology, Running, Feedback, Signal Processing.*

1. Introduction

Running is one of the most popular sports for the masses. Approximately 30 million Americans run in total, including recreational and competitive runners [9]. One of the main reasons for this popularity might be the simplicity of running: just put your shoes on and go. However, not everyone might run properly. Improper running technique yields not only a decreased efficiency but also increases the risk of sustaining an injury [8].

The majority of runners are ambitioned fitness runners that might not have regular access to a trainer. To improve their technique they thus often have to rely on self perception. Sensor miniaturization and increase in sensing accuracy has emerged the use of wearable sensors in sports. GPS trackers and heart rate monitors are already well established [2]. However, these focus on monitoring the final performance rather than performance determining factors such as running technique. In previous work, we demonstrated that wearable sensors can be worn unobtrusively during a running workout and can be used to monitor running technique [17], skill level [16], and fatigue [14]. In this work, we aim at investigating real time feedback provision on running technique based on our analyses. Therefore, we chose to focus exemplarily on arm carriage while running.

A stable core is essential for good running technique [3]. The arms function to stabilize and balance the core by counterbalancing the opposite leg. It is, thus, essential to drive the arms forward and not sideways. A sideways movement not only increases the energy consumption but also destabilizes the whole movement [3]. Additionally, a poor performance of arm swing with too much sideways movement creates stress on the pelvic [11]. Running books therefore advise to focus on the arms not crossing the symmetry line of the body [11, 3]. We aim at detecting this crossing of the symmetry line of the body and to provide a feedback subsequently.

State of the art smartphones provide integrated sensors and already are a constant companion of many recreational runners. In this work, we aim at investigating the use of a smartphone as feedback provider as it is available to a wide range of ambitioned fitness runners who don't have access to a trainer but still want to focus on their running technique. We performed a preliminary study to identify the most valuable sensor positions using dedicated on-body sensors which were developed in previous work [7]. Based on our findings we developed a smartphone application to detect faulty arm carriage and to provide real time feedback [18]. Finally, we perform a user study to evaluate our developed application. Questionnaires are used to assess the users' acceptance of such a system. We address the following research questions:

- Which sensor position and which modalities can be used to monitor arm carriage while running?,
- Are a smartphone's internal sensors suitable for this task?,
- What is the users' perception of such a system?

This paper is an extended version of our previous work [18] and is structured as follows: In Section 2 we present related work on smartphone applications for runners. Section 3 presents a preliminary study to assess the feasibility of monitoring wrongly performed arm movement while running. From the findings of this study, we developed a smartphone application, as described in Section 4. The application was evaluated within a user study (Section 5). The conclusion is presented in Section 6.

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2. Related Work

Several smartphone applications are available for track provision, motivation of users, social interaction, or workout logging. The latter is the most popular with commercially available systems including the nike+iPod kit or the adidas micoach. Both systems monitor the regular workout with a mobile phone or an iPod and additional sensors, e.g. a step counter. In [12], the authors presented myHealthAssistant, a system which tracked activity levels throughout the day and logged running intensity and heart rate. Running was detected in real time on an Android smartphone using a state-of-the-art activity recognition approach. Authors in [13] presented a mobile health and fitness companion, a smartphone application that tracked running workouts in terms of distance, duration, pace, and heart rate. Interaction with the user is mainly based on speech. Authors in [5] developed a digital fitness connector that allows for connecting several off the shelf fitness devices such as pedometers to a smartphone. This device then allows logging workout data from the fitness devices using the smartphone. RunWithUs [4] is a smartphone application designed to motivate users to participate in sports. It can be used for tracking workouts and for keeping personal records of exercise. MPTrain is a phone-based system that uses music to influence the running exercise [10]. The user can set goals for the workout, e.g. alternating 3min at 75% and 2min at 90% of the maximal heart rate, similar to a treadmill computer. The phone receives heart rate data via bluetooth from a chest strap and adapts the played music to match the target heart rate. The follow-up of the system with main advances in the user interface was presented in [1] and was named TripleBeat. The system presented by Takata et al. [19] used wearable sensors such as heart rate, temperature, and a step counter to recognize a runner's workout state (warm-up, main workout, cool-down) and to provide a track according to the goal of the workout and the current state.

While there are various approaches in using a smartphone as feedback provider in running, they focused on providing feedback on the workout rather than running technique. In related work, we investigated the use of an IMU for real-time streaming of motion data to a smartphone [15]. We then used the smartphone to provide feedback to the runner. The user acceptance of visual over audio feedback was compared.

3. Preliminary Study

We performed a preliminary study to investigate feasibility of assessing arm carriage while running using body-worn sensors. The detection should acquire arm carriage independent of a running speed and work across all runners (e.g. gender, age, skill level). Additionally, we investigated different sensor positions to identify the optimal sensor placement.

A good upper body form is essential for injury-free and efficient running [3]. This includes a strong torso and not too much sideways rotation. Too much upper body rotation increases the stress on the pelvis, increasing the risk of an injury. Additionally, a sideways movement wastes energy. Therefore, training books on running in general suggest paying attention for the arms to not cross the symmetry line of the body [8].

We thus defined three classes of arm carriage (depicted in Fig. 1) to investigate the feasibility of detecting faulty arm carriage using wearable sensors. The runner on the left performs proper arm movement, driving the arms in forward direction (class 1), supporting the propulsion and providing balance. The runner in the middle aims with her hands at the symmetry line of the body, slightly increasing upper body rotation (class 2). Rotation is further increased with the arms crossing the symmetry line in the third, rightmost class (class 3), expressing a faulty movement.

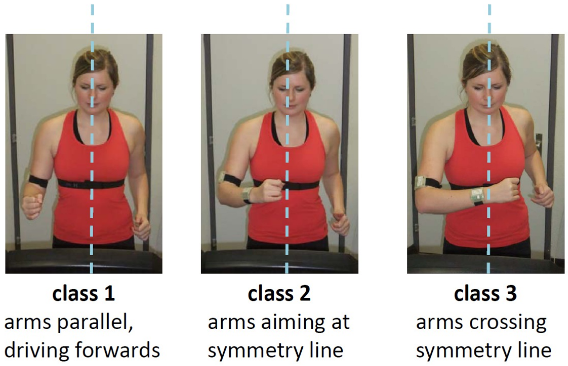

Fig. 1. Classes of arm carriage performed in the preliminary study. Training books advise to not cross the symmetry line of the body.

3.1. Measurement Setup

Throughout the preliminary study, each runner wore 3 ETHOS units to monitor the upper body and arm movement. The measurement setup is depicted in Figure 2. ETHOS is a small and unobtrusive inertial measurement unit (IMU) that was developed for the measurement of human movement in unconstrained environments [7]. ETHOS consists of a 16-bit 3D accelerometer with a measurement range of ±6g, a 16-bit 3D gyroscope with a range of ±2000°/s, and a 3D 12-bit digital compass. Data was sampled at 100 Hz and stored to a local microSD card for later offline analysis. Multiple ETHOS units were synchronized with a hub that uses the sensors' real time clocks (RTCs) for synchronization. ETHOS can be used to stream data to a smartphone using the ANT+ protocol.

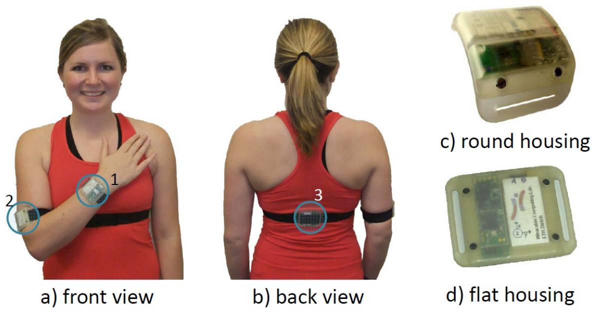

Fig. 2. Front (a) and back (b) view of the sensor positioning and close-up of the round (c) and flat (d) housing type.

3.2. Experimental Procedure

The preliminary study was performed on a treadmill allowing for constant supervision by an assistant and video recording for labeling purposes. Participating runners were advised to complete two runs at 8 km/h and 10 km/h, respectively. Each of these two runs consisted of three 2 min-runs performing the following tasks: 1) arms parallel, 2) arms aiming at the symmetry line of the body, 3) arms crossing the symmetry line of the body. The three tasks are depicted in Figure 1. We chose

these tasks to continually monitor arm carriage from proper technique (arms driving parallel) to improper technique (arms crossing the symmetry line). With this, we wanted to identify features that were significant across different runners and running speeds rather than monitoring different runners and then using annotations to train our system, which would have been prone to introducing bias.
Data were collected at different speeds to identify speed-independent features. Runners were allowed to pause for as long as desired in between runs. 10 runners of different skill levels participated in the preliminary study.

3.3. Data Analysis

For the data analysis, we followed the established pattern recognition chain of subsequent feature extraction and classification. As features, we calculated the mean value, standard deviation, and range (max - min) of the signal of each axis and modality (acceleration and rate of turn) of the sensor data over a 5s sliding window with a 2s overlap. Each window was thus averaging over approximately 5 arm swings. This yielded an 18-dimensional feature vector. We then used a leave-one-subject-out cross validation scheme. The accuracies of classifying the arm carriage classes correctly with respect to different sensor positions and classifiers using all of the above features are provided in Table 1.

Table 1. Classification accuracies depending on sensor position and classification method.

Sensor position	Naïve Bayes	kNN	SVM	Logistic Regression
Upper arm	65.68%	73.99%	45.31%	80.73%
Lower arm	67.04%	66.53%	77.83%	72.54%
Upper back	46.46%	45.28%	78.17%	50.28%

The results show that the sensors on the arm (sensors 1 and 2, Fig. 2) outperformed the one on the back (sensor 3, Fig. 2) with the sensor on the upper arm having performed slightly better than the one on the wrist. The confusion matrix (depicted in Fig. 3) revealed that mainly classes 1 and 2 were confused. This was a promising result, since the faulty arm carriage (class 3) seems to be reliably detectable by the algorithms.
Analysis of the video footage provided further explanation for the confusion of classes 1 and 2: some subjects performed more or less the same arm movement for the first and second task, aiming towards the center of the body during both runs. However, an accuracy of 94.41% was achieved for the detection of the arms crossing the symmetry line.
To identify most valuable features, we chose a wrapper feature selection approach. This approach allows investigating different features and combinations of features in terms of their performance for the recognition using the algorithm itself [6].

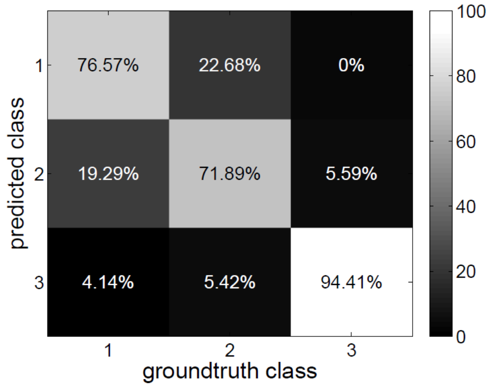

Fig. 3. Confusion matrix of the three arm carriage classes. Mainly classes 1 and 2 were confused. From inspecting the video footage we found that some subjects performed more or less the same arm movement for the these classes.

We found that two features represented the differences of the classes best while being robust across speed and subjects; namely the mean of the z-axis acceleration and the range of the x-axis gyroscope. This finding was consistent with our observations: During the faulty arm carriage subjects not only rotated their arms more (yielding the higher range of x-axis rate of turn) but also lifted their elbows higher (yielding the change in mean of z-axis acceleration). Fig. 4 depicts a scatter plot of these two features calculated from the upper arm sensor for all subjects. From the scatter plot we observed a linear relationship between the two features and the arm carriage output. Since one might not be able to draw sharp lines between the different arm movements and to be able to capture small changes of arm movement, we decided to use a linear regression for the assessment. The regression was trained with all data from the preliminary study and the two described features, namely the mean of z-axis acceleration and the range of rate of turn measured on the x-axis.

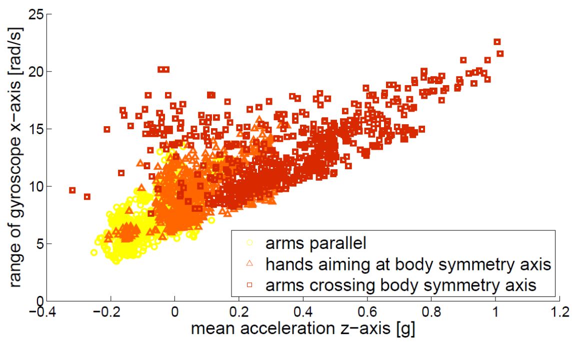

Fig. 4. Scatter plot of two features of the upper arm sensor of the different arm movements. The plot reveals that classes are not strictly separated.

4. Smartphone Application

From the preliminary study we found that a single sensor on the upper arm can be used to assess arm carriage during running. Since most runners wear their smartphone on the upper arm during a workout, we decided to use the internal sensors of a smartphone instead of an ETHOS unit that would stream data to the smartphone. This aimed at our goal of an unobtrusive system. Since the best results were achieved when using acceleration and rate of turn data, we used a Samsung Galaxy SII phone that provided integrated acceleration and gyroscope sensors. The smartphone ran Android 2.3.3.

To evaluate the suitability of the phone's integrated sensors, we performed the same run as described in the preliminary study with a runner wearing both an ETHOS unit and a smartphone. The sampling rate of the phone's acceleration and rate of turn sensors was set to the highest available sampling rate ("SENSOR DELAY FASTEST"). From the measurements we found that this corresponded to a sampling frequency of 98 Hz to 99 Hz, similar to that of ETHOS. The phone's integrated accelerometer measured in a range of ±2g, we thus experienced clipping during running. However, the mean values of the 5s sliding window were still comparable to those measured with the ETHOS system. The integrated gyroscope provided a sufficient measurement range of 1145°/s. We found that the output of the regression (arm carriage measure) of the data collected with ETHOS was within a decimal place of the arm carriage measure calculated from the integrated sensors' data. We thus rounded the output to the next 0.2.

The real-time application for arm carriage measure was implemented as follows:

- The application stored sensor values to a buffer for 5s.
- Every 5 s, features were calculated from the buffer and the arm carriage measure was calculated.
- When the measure exceeded a value of 2 (2 equals "arms aiming at symmetry line"), the smartphone provided a vibrotactile feedback.

Feedback was thus provided every 5 s. The duration of the vibration was set to 800 ms. It increased by 500 ms with every 0:5 increase of arm carriage measure, i.e. arms overcrossing symmetry line more. The vibration's intensity could be set in the phone's settings and was set to the maximum. The vibration pattern was the smartphone's standard vibration pattern. The intensity and the duration of the vibration were evaluated during short runs wearing the phone with the arm strap on bare skin and over a thin long-sleeved shirt. A more profound evaluation of the feedback's intensity, duration, and frequency across several subjects was performed during the user study, presented in the next section. The smartphone was secured to the right upper arm of the runner with a regular workout strap. A schematic representation of the application and a runner wearing the smartphone are depicted in Fig. 5.

5. User Study

We performed a user study with 23 beginning runners (4 female and 19 male, aged between 21 and 30) to evaluate the proposed system. Subjects were recruited from university staff and students using notices posted on campus. The notice said we were looking for beginner runners who were capable of running 20 min nonstop. It mentioned that the goal of the study was to test a smartphone application for runners but did not mention the detailed focus, i.e. monitoring of arm carriage, to ensure an unbiased baseline measurement. The user study was performed outdoors on a circular-shaped track frequently used by runners. Each runner had to complete two 20 min runs with a break in between runs. For the first run, subjects were not given any instructions and were told that the smartphone would calibrate itself to the individual runner. Data were stored on the smartphone's SD-card during this run for later offline analysis. The vibrotactile feedback was turned off. For the second run, subjects were assigned to test and control group. The test group

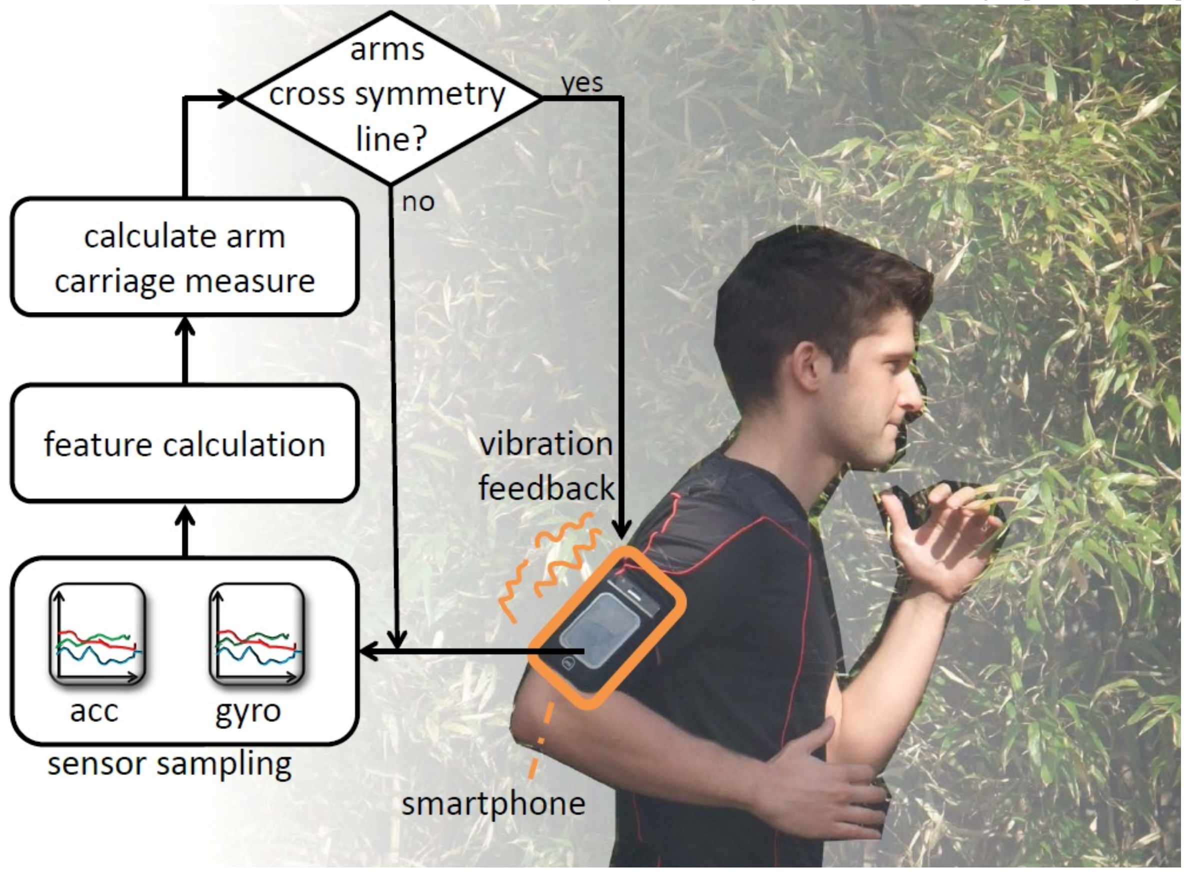

Fig. 5 Runner equipped with the smartphone and a schematic representation of the application.

(app) got feedback from the developed application, i.e. vibrotactile feedback when arm carriage was performed poorly. The control group (human) was instructed by the experiment leader to pay attention to their arm movement once before the feedback run. No further feedback was provided during the run. Subjects completed a visual analogue scale-style questionnaire for further evaluation of the developed app subsequent to the runs.

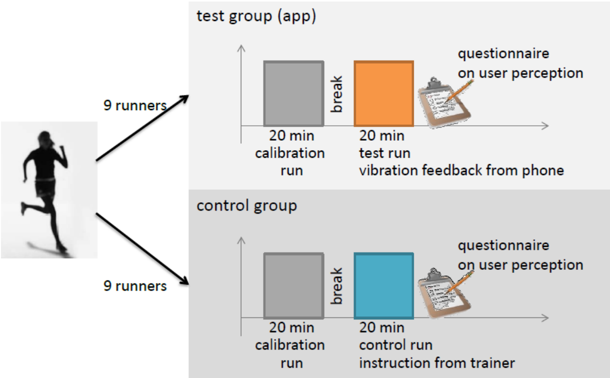

Fig. 5. Overview of the experimental procedure during the user study.

5.1. Influence of Feedback on Arm Carriage

Data of five runners were discarded since runners could not run for the 20 min and instead kept switching between running and walking, which led to high signal noise. Figure 6 depicts the mean arm carriage measure over the 20 min of both runs for both groups of the remaining 18 subjects. Subject 5 of the app group reported that when the app did not vibrate he changed his arm movement to check whether it still worked, which might explain his increase. With a one-way repeated measures ANOVA test we found that runners of both the app ($p = 0.04$) and the trainer ($p < 0.01$) group improved their arm movement. We thus concluded that arm carriage could be modified using the feedback from our application. However, in our study providing feedback with a smartphone was not more successful than a single verbal instruction.

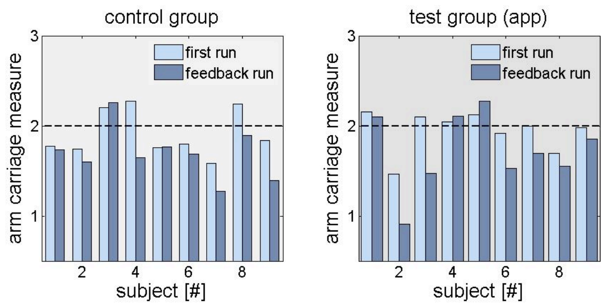

Fig. 6. Mean arm carriage measure of both runs. The first run was carried out without instructions. For the second run, subjects were randomly divided in two feedback groups: vibration feedback from the application or a single verbal instruction from the experiment leader to pay attention to arm carriage. The dashed horizontal line indicates the threshold above which arms cross the symmetry line. For the app feedback, vibration set in when this threshold was exceeded and increased in duration with further increase.

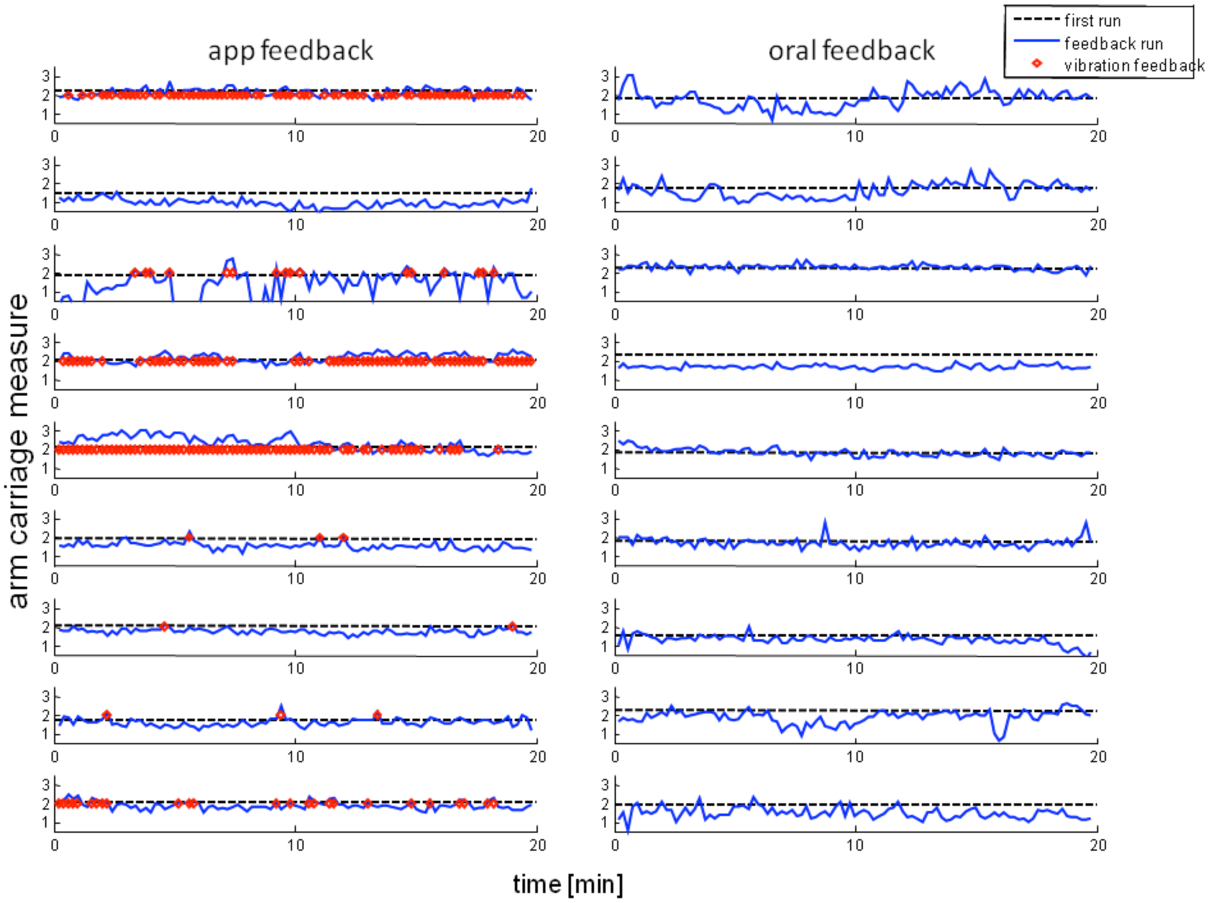

Fig. 7 Arm carriage measure of the second (feedback) 20 minute run is depicted in blue. For comparison, the mean value of the first run is depicted in black (dashed). The left columns depict the runners from the app feedback group. The runners on the right received an oral feedback prior to the second run.

We included the course of the arm carriage measure of all runners in Figure 7. The runners shown on the left received vibration feedback from the app when the arm carriage measure exceeded a value of 2 (arms crossing symmetry line). Runners on the right were instructed verbally by the experiment leader how proper arm carriage is performed and were instructed to focus on performing proper arm carriage. From the signals of the feedback run (in blue) we observed that some runners did not change their arm carriage compared to the first run (mean arm carriage measure of the first run is depicted in black, dashed). While some runners of the non-app group (right) changed their arm carriage in the beginning (runners 1,2, and 7), they returned to their regular arm carriage later on.

For further investigation, it would be useful to increase the number of participants to have more runners with a faulty arm carriage and to investigate developments over a longer time span, e.g. several weeks.

5.2. User Perception

The questionnaires revealed that subjects did not feel restricted in their movements wearing the smartphone. They rated on average 1.3 of 10 on the visual-analogue scale on the question whether wearing the smartphone affected their run. They rated the duration and intensity of the vibration as comfortable (8.4 and 8.3 of 10, respectively). The frequency of feedback was rated not to be too often (0.8 of 10). Most did not prefer another type of feedback but if they had to choose one human voice and music interrupts were mentioned. When asking subjects whether or not the application changed their arm carriage all except subjects 4 and 7 ticked yes. Subjects of the group app rated it easy to be aware of their arm carriage with 8.3 on average (of 10), whereas the other group rated on average 4.03. Overall, subjects thought the app will improve their running technique, as they rated with 8 of 10 on that question.

Table 2. Evaluation of user perception with a questionnaire.

Question	Rating (0=no, 10=yes)
The mobile phone affected me during run	1.3
Did you notice the vibration easily?	8.3
Was the duration of the vibration comfortable?	8.4
Was the intensity of the vibration comfortable?	8.3
Did the vibration occur too often?	0.8
Would you prefer a different type of feedback?	1.3
Did the app help you in becoming aware of your arm movement?	8.3
Do you think the app will help you improve your running technique?	7.9
Would you use the app regularly during training?	8

6. Discussion and Conclusion

We presented the development of a smartphone application targeting on improving arm carriage while running using vibrotactile feedback. Within a preliminary study we investigated sensing positions, modalities and features to assess different arm carriage classes using ETHOS units. We found that a single sensor on the upper arm sufficed this task, yielding a classification accuracy of 80.73%. Based on the findings from the preliminary study a smartphone application was developed, which provided vibration feedback when faulty arm carriage was detected. The application was designed to run on an Android smartphone using the phone's internal accelerometer and gyroscope. 23 runners participated in our user study for the application validation. Each runner was randomly assigned to the app group or to a control group and performed two runs: a baseline run and a feedback run. The app group received a vibration feedback from the smartphone during the second run.In contrast runners in the control group were instructed by the experiment leader how proper arm carriage is performed and were asked to pay attention to proper arm carriage. We found that runners improved their arm carriage in both scenarios similarly. While feedback from a smartphone did not outperform the verbal instruction by a person, the advantage of using a phone is its availability: almost everyone has access to a smartphone while most runners (especially regular fitness runners) train on their own and do not have access to a trainer.
This is supported by the high user acceptance of the system that we achieved, which was evaluated with questionnaires.
We thus conclude that feedback provided by a smartphone might help runners improve their technique.

7. Outlook

The application could be further improved by investigating the detection of other common mistakes in running and could be extended to provide features for workout monitoring and track provision. Additionally, it would be interesting to perform a longitudinal study to investigate if runners forget the verbal instruction after several runs and if and how the smartphone-based approach would help to guard against falling back in the wrong arm carriage pattern.
It would also be beneficial to include different areas of faulty technique detection to benefit runners further.

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