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Can smartphones help with running technique?

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Abstract

Running is one of the most popular sports for the masses. However, not every runner might run properly. Incorrect running technique decreases movement efficiency and increases the risk of injury. In this work, we present the development of a smartphone application to provide feedback on running technique on the example of arm carriage. Recognition algorithms were developed in a preliminary study with 10 participants. Investigating sensor positions and modalities, we found that a single IMU on the upper arm yielded an accuracy of 80.73% for the assessment of arm movement. We implemented our approach as a smartphone application and found that runners improved their arm movement using our application within a user study including 23 participants. Results from questionnaires revealed high user acceptance (average rating of 8 from 10 possible points).

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Keywords: Sports, running, wearable system, smartphone, user study.

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 [1]. One of the main reasons for this popularity might be that most people are able to run. However, not everyone might run properly. Improper running technique yields not only a decreased efficiency but also increases the risk of sustaining an injury [2]. 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, which 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 [4].
The majority of runners are ambitioned fitness runners[1] that might not have access to a trainer. Miniaturization and increase in sensing accuracy has emerged the use of wearable computers in sports including smartphones. To support runners, several smartphone applications are available for track provision [5], motivation [6], social interaction [7], or workout logging. There also exist commercially available systems for workout logging such as the *nike+iPod kit*[2], the *Garmin Forerunner*[3], or the *adidas micoach*[4]. These systems allow the user to monitor her regular workout, track improvements, and define fitness goals.

[1] http://www.runningusa.com/
[2] http://www.apple.com/ipod/nike/
[3] http://www.garmin.com/
[4] http://www.adidas.com/micoach/

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However, most systems focus on monitoring the final performance in terms of time, distance, speed, etc. rather than performance determining factors. Oliver et al. presented a phone-based system that used music to influence the running exercise [8, 9], providing feedback targeting running endurance. We aim at using the smartphone to provide feedback on upper body running technique, which might have potential especially to support ambitioned fitness runners who train on their own and do not have access to a trainer. Improving running technique might help decrease the injury risk, improve movement efficiency, and help the runner run faster. In this work, 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?

2. Preliminary Study

In a preliminary study, we investigated the required sensor modalities, sensor positioning, and developed algorithms robust to speed and across runners (e.g. gender, age, skill level).
A good upper body form is essential for injury-free and efficient running [3]. This includes a strong torso and no 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 to pay attention for the arms to not cross the symmetry line of the body [2].

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.

2.1. 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 [10]. ETHOS consists of a 16-bit 3D accelerometer with a measurement range of 6 g, 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.

2.2. Experimental Procedure

The preliminary study was performed on a treadmill allowing for constant supervision by an assistant and video recordings 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

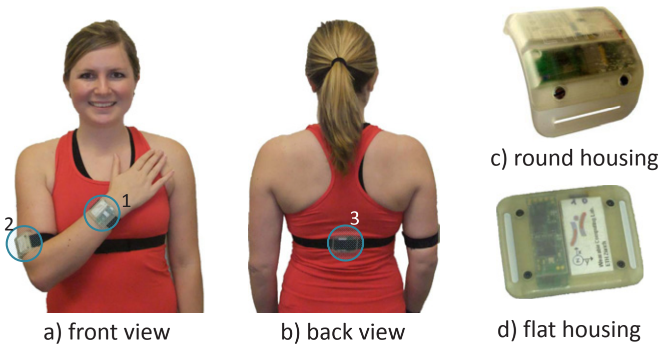

Fig. 2. Front (a) and back (b) view of the sensor positioning and close-up of the round (c) and flat (d) housing type.

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. Data was 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.

2.3. Data Analysis

For the data analysis, we followed the established pattern recognition chain of subsequent feature calculation 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 5 s sliding window with a 2 s overlap. Each window was thus averaging over approximately 5 arm swings. This yielded a 18-dimensional feature vector. The classification accuracies of the three arm carriage classes for different classifiers and sensor positions using all features are given in Table 2.3.

Sensor position	**Naive Bayes**	**kNN**	**SVM**	**Logistic Regression**
Upper Back	46.46 %	45.28 %	45.31 %	50.28 %
Upper Arm	65.68 %	73.99 %	78.17 %	80.73 %
Lower Arm	67.04 %	66.53 %	77.83 %	72.54 %

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

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 could be explained from analysis of the video footage: 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.

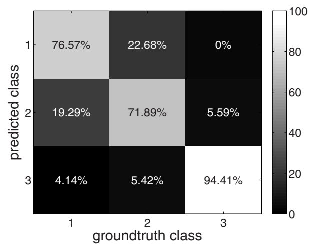

Fig. 3. Confusion matrix of the three arm carriage classes. Mainly classes 1 and 2 were confused. From inspecting the video footage we found that some subjects performed more or less the same arm movement for these classes.

With a wrapper feature selection 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). Figure 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.

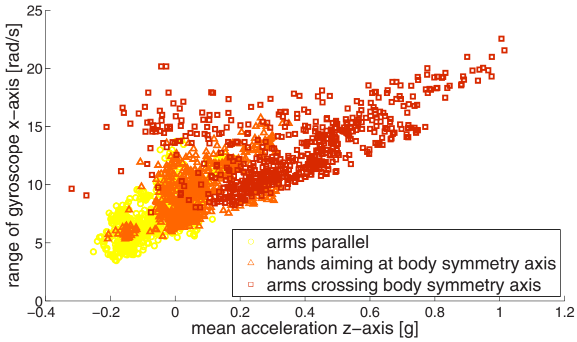

Fig. 4. Scatter plot of two features of the upper arm sensor of the different arm movements. The plot reveals that classes are not strictly separated.

3. 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 5 s 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 5 s.
- 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.

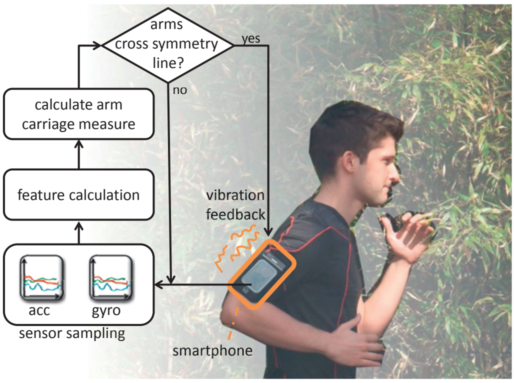

Fig. 5. Runner with the smartphone and schematic representation of the application.

4. 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 (*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.

4.1. Influence of Feedback on Arm Carriage

Data of 5 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

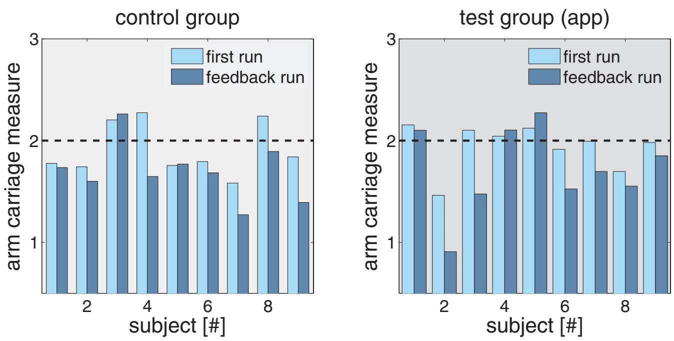

Fig. 6. Mean arm carriage measure of both runs. The first run was carried out without instructions. For the second run, subjects were divided in two feedback groups: haptic feedback from the smartphone or a single verbal instruction from the experiment leader to pay attention to arm carriage. The dashed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

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 ($p = 0.044$) and the trainer ($p = 0.002$) group improved their arm movement significantly. 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. 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.

4.2. 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 if 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 would have 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.

5. Conclusion and Outlook

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. In a user study we found that runners improved their arm carriage using our application. This amount of improvement was similar to that elicited by a single oral feedback from the experiment leader. The results suggested that a smartphone might be useful for runners, especially if they 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.

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.

References

[1] T. F. Novacheck, The biomechanics of running, Gait & Posture 7 (1998) 77 – 95.
[2] T. Miller, Programmed to Run, Human Kinetics Publishers, 2002.
[3] J. Puleo, P. Milroy, Running Anatomy, Human Kinetics Publishers, 2010.
[4] S. Subotnick, Sports & exercise injuries: conventional, homeopathic & alternative treatments, North Atlantic Books, 1991.
[5] K. Takata, M. Tanaka, J. Ma, R. Huang, B. Apduhan, N. Shiratori, A wearable system for outdoor running workout state recognition and course provision, in: Autonomic and Trusted Computing, Springer, 2007.
[6] F. Gil-Castiñeira, A. Fernández-López, C. L. Bravo, N. Cid-Vieytes, D. Conde-Lagoa, E. Costa-Montenegro, F. J. González-Castaño, Runwithus: a social sports application in the ubiquitous oulu environment, in: Proc. of the 10th International Conference on Mobile and Ubiquitous Multimedia, 2011.
[7] F. F. Mueller, S. O'Brien, A. Thorogood, Jogging over a distance: supporting a "jogging together" experience although being apart, in: CHI '07 extended abstracts on Human factors in computing systems, 2007. doi:http://doi.acm.org/10.1145/1240866.1241045.
[8] N. Oliver, F. Flores-Mangas, Mptrain: a mobile, music and physiology-based personal trainer, in: Proceedings of the 8th conference on Human-computer interaction with mobile devices and services, ACM, 2006, pp. 21–28.
[9] R. de Oliveira, N. Oliver, Triplebeat: enhancing exercise performance with persuasion, in: Proc. of the 10th international conference on Human computer interaction with mobile devices and services, 2008.
[10] H. Harms, O. Amft, R. Winkler, J. Schumm, M. Kusserow, G. Tröster, ETHOS: Miniature Orientation Sensor for Wearable Human Motion Analysis, in: IEEE Sensors, 2010.