LOCOMOTION ANALYSIS USING A SIMPLE FEATURE DERIVED FROM FORCE SENSITIVE RESISTORS

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ABSTRACT
The paper describes a novel method for the classification of modes of locomotion that can be implemented using particularly low power wearable sensors, and low complexity feature extraction and classification algorithms. It is based on the analysis of the time lag between initial heel and ball contact of the foot. The lag is computed from two force sensitive resistors, appropriately mounted under the sole. The paper discusses the biomechanical considerations behind our method and presents an experimental evaluation using the example of level walking and stair climbing/descending. The results suggest that the described method is efficient in classifying different modes of locomotion on a step basis.

KEY WORDS
Activity Recognition, Wearable Computing, Locomotion Analysis

1 Introduction
Activity recognition with wearable devices is a rapidly growing field with a variety of applications [1, 2, 3]. In this context, mode of locomotion analysis plays a particularly important role. It can provide information of the user’s activity which is e.g. useful for health monitoring, facilitate indoor tracking and provide a basis for complex activity analysis that can also be very useful to analyze various medical problems.

One of the key challenges, faced in particular by continuous, long time monitoring applications, is the size and power consumption of both, the sensors and the computing device needed to perform the classification. To achieve wide acceptance, monitoring systems must be small and unobtrusively integrated in the user’s outfit. Furthermore, they should operate for extended periods of time on small batteries.

1.1 Paper Contribution
To address the above concerns, the work presented in the paper focuses on the introduction and evaluation of a new, particularly simple feature to distinguish different modes of locomotion. The feature is derived from the signals of two FSRs placed under the foot. The sensors consume little power, are unobtrusive and can be easily integrated into the shoes. In addition, unlike many common mode of locomotion analysis schemes, our method requires little computing power which means that it can be implemented on a miniaturized system with long battery life.

1.2 Related Work
Recent work on activity recognition with body-worn sensors has mainly focused on using inertial sensors, especially accelerometers [4, 5]. To distinguish between different modes of locomotion, such as level walking, ascending and descending stairs, various features (wavelet coefficients [6], average signal power Rms [4]) and classification algorithms like neural networks [4] and bayes classifiers [7] have been investigated to tackle the recognition task. Body-worn force sensitive resistors (FSRs) have been used to detect the different gait phases (stance, heel-off, swing, and heel-strike) by applying a rule based detection algorithm to the sensor signals [8]. In the SmartSole project [9], FSRs are used together with other sensors for monitoring gait parameters such as speed, cadence, number of steps, stride length, and distance walked.

2 Theoretical Considerations
Normally, during level walking, the heel is the first part of the foot to touch the ground. After this initial contact, body weight is transferred to the corresponding leg (loading response), the foot is flat, heel and ball of the foot are both contacting the ground. When walking downstairs, body weight is transferred to the ball of the foot as the foot falls onto the step below. Thus, the ball normally strikes the step below first, followed by the heel. This also applies for ascending stairs. Rieners et. al. [10] carried out experiments to investigate the biomechanics and motor-co-ordination in humans during stair climbing at different inclinations. They showed a clear difference in foot placement for the different modes of locomotion. The foot is normally pointing downwards (front first) during descent (-16.6°±4.7°) as well as during ascent (-4.7°±6.4°) whereas during level walking it is always pointing upwards (19.0°±4.4°).
Our approach to locomotion analysis is based on these findings. Instead of measuring the foot orientation angle at initial ground contact directly, the approach uses the time difference between initial heel and ball ground contact. This measure can be easily obtained using force sensitive resistors which change their electrical resistance depending on the applied physical pressure, and a simple signal processing scheme. The simple construction of the FSR, basically two sheets of printed substrates, and the easy interfacing make the sensors suitable for wearable applications. When walking, FSRs placed under the heel and the ball measure the force load applied on the foot. This can be used to detect initial ground contacts of the heel and the ball of the foot, respectively.

3 Experiments

3.1 Setups

For the experiments two FSRs are used. They were placed under the outer sole of the right shoe, one FSR under the heel, the other under the ball of the foot. The analog signals of the FSRs were sampled at 100 Hz, digitally converted (12 bit resolution), and sent to a remote PC. Several test subjects were instructed to walk repeatedly a predefined path including stairway and level walking, without any further instructions, e.g. concerning speed of walking. Throughout the experiment, the data was manually labelled. The labels consisted of walking, descending and ascending.

3.2 Sensor Signals

Figure 1 shows the FSR signals for the three modes of locomotion. In the lower (descending) and upper graph (level walking), initial ground contacts of the heel and the ball can be clearly identified by the sharp positive signal transitions from no load to maximum load\(^1\) which are followed by a constant signal level\(^2\). For ascending (middle graph), only the signal from the FSR mounted under the ball shows these characteristic transitions followed by constant signal levels. The signal transitions from the heel FSR are sometimes less pronounced (see e.g. 3rd transition of heel signal at approx. t=1 sec ), indicating only few load on the heel. Sometimes, during stair ascend no transitions at all are found in the heel signal. This happens when only the front part of the foot is placed on the stairs during ascending. As can be seen, the relative positions between corresponding transitions of the heel and ball signal vary with the different modes of locomotion.

\(^1\)Max. load corresponds to maximum detectable pressure range of FSRs.

\(^2\)Applied load exceeds maximum detectable load.

3.3 Feature Extraction

The feature extraction requires the identification of initial ground contacts from the heel and the ball. This is achieved by searching the FSR signals for large load changes. A threshold detector is triggered as soon as enough load is applied to the sensors. Starting from the point in time when the ball signal exceeds the chosen threshold level, the algorithm looks whether a corresponding heel contact has already been detected prior to the ball contact. If so, the lag can be calculated from the time difference between the occurrences of corresponding ball and heel contacts. Negative lags indicate that ground contact was established with the ball first. If no corresponding heel contact was recognized prior to a ball contact, the algorithm waits for a corresponding heel strike to occur within a given time window\(^3\). If a heel strike is detected, the lag is calculated and becomes positive. If no heel strike was found before the next ball contact is recognized -indicating another step-, no lag value is calculated. In the lower graph of figure 2, typical time lags are illustrated. Time lags around 0 seconds indicate that ball and heel contact were detected at the same time. Points in time, where no corresponding heel strikes but ball strikes are found are marked with circles. This mostly happens during ascending where only the front part of the foot is placed on the steps. In such cases, the lag is set to 0. This will be justified in the next section. The upper graph of figure 2 shows the corresponding activities in time. Note that walking on landings in between two floors is defined as level walking. Moving one floor up requires ascending stairs, level walking on a short landing and ascending stairs again.

\(^3\)Throughout the experiments, the time window was set to 0.5 seconds. For more flexibility, the time window should be adapted to the maximum size of the window which is defined by the occurrence of the next ball strike.
Figure 2. Upper graph: Activities, Lower graph: Lag (circles indicate missing heel strikes)

3.4 Feature Distribution

Figure 3 depicts the lag distribution for the three modes of locomotion for six different runs (1 to 6). The lag distributions vary only little between runs 1 to 6 and indicate a good separation of the different modes of locomotion. As can be seen in the graphs, a lag of 0 occurs very often, but only during ascending. This is mostly due to the fact that subject #1 only puts the front part of his feet onto the stairs when he is ascending, so that no heel strike occurs. According to Rienner et. al [10], the feet are placed more or less horizontally (-4.7°±6.4°) onto the ground during ascending. As a consequence, calculated lags would be theoretically close to 0. Setting the lag to 0, in cases, when only ball strikes are found which happens mainly during ascending, is therefore a good justification. Apart from the intra-variability, the inter-variability of the time lag was also evaluated. Figure 4 illustrates the lag distributions extracted from the measurements of four test subjects. The results show a small inter-person variability for the three activities. Subjects #1, #3 and #4 show a similar behavior concerning foot placement on the stairs during ascent, whereas subject #2 shows a different behavior (small positive median lag value for ascending, middle box).

Figure 3. Boxplots of calculated lags from six runs of same subject: left boxes (level walking), middle boxes (ascending), right boxes (descending)

Figure 4. Boxplots of calculated lags from measurements of four test subjects

4 Locomotion Analysis

The lag feature is used as input data for a bayesian classifier (see eq. 1). The required probability distributions (likelihoods) are estimated from the data using histograms of fixed binwidth. The three required class priors are set equally to 1/3. The recognized activity is the one with the maximum a posteriori probability (MAP detector [11]).

\[
P(\text{class}|\text{feature}) = \frac{P(\text{class})P(\text{feature}|\text{class})}{P(\text{feature})} \quad (1)
\]

A six-fold cross validation using the data sets from the six runs (1 to 6) of subject #1 was carried out. Table 1 shows the resulting confusion matrix. From the three modes of locomotion, level walking is best recognized. This is due to the fact that the foot orientation at initial ground contact is very distinctive. The overall recognition rate was 98.2%. Compared to other work, the recognition rates that are achieved with the introduced lag feature are competitive. In [5], the overall recognition rate was 98.8%. 83 to 90% were achieved by [12] and around 90% by [4].
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<th>Descend</th>
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Table 1. Confusion Matrix

5 Conclusions and Outlook

The initial results show that the introduced lag feature is suited for distinguishing level walking from ascending and descending stairs. The recognition proved to be robust with the use of two FSRs only. The intra-variability of the lag distributions of one subject and the inter-variability between 4 different subjects have been presented. The lag distributions were very similar for the different runs and subjects. They suggest a rather general, person-independent recognition method. Further investigations are required to evaluate the robustness of the described feature for different types of stairs and individual walking behaviors including e.g. walking speed. The experiments were constrained to three modes of locomotion. Hill climbing and other activities that may interfere with the recognition (e.g. standing and transferring weight from one foot to another) have to be considered as well.

References


