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Classification of Surfaces and Inclinations During Outdoor Running using Shoe-Mounted Inertial Sensors

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Abstract

Embedded mobile systems for analysis and classification become more and more important in the field of sports and sports science. Small and lightweight sensors in sportswear offer the possibility to monitor the athletes in a realistic environment, e.g. during an outdoor run. During the activity, the sportswear can automatically adapt to the current environment and hence optimizes the performance of the athlete. A major need is a running shoe, which can automatically be adapted to the current ground.
In this paper, a classification system was developed, which distinguished between different surfaces and inclinations based on inertial sensors. They were placed on the heel of a running shoe and acquired kinematic data of 21 subjects. For each subject, several rounds of an one hour outdoor run were available and were used for the evaluation of the system. The classification system reached a mean classification rate of more than 80 %.

1. Introduction

Embedded mobile systems for analysis and classification become more and more important in the field of sports and sports science. Small and lightweight sensors in sportswear offer the possibility to monitor the athletes in a realistic environment, e.g. during outdoor running. During the activity, the sportswear can automatically adapt to the current environment.
For example, the authors in [3] showed that the data of a heel compression sensor can be used to adapt the cushioning setting of a running shoe to the current surface. A hall sensor was mounted at the top of the cushioning element and measured the magnetic field strength induced by a small magnet. The surface classification system reached a classification rate of more than 80 %. The same sensor setup and running shoe were used for the classification of inclinations during running in [4]. In this case, the system achieved a classification rate of only 67.2 %.
In contrast to [3] and [4], an inertial sensor was used in [1] to estimate the inclination of walking. Acceleration signals of the trunk and the heel were acquired for five subjects. Neural networks were trained and tested with kinematic data during treadmill and outdoor running, respectively. The outdoor test circuit involved roads of various inclines. The correlation between predicted and actual inclines was 0.98, and the maximum speed-predicted error was 16 %.
[3] and [4] showed that data of a heel compression sensor on the shoe could be used for the classification of different surfaces, but were less suitable for the classification of inclinations. However, the authors in [1] achieved a high correlation of predicted and actual inclination based on kinematic data of an inertial sensor.
For the adaptation of sportswear to the current environment of the athlete, the possibility to classify both surfaces and inclinations with the same sensor type is important, in order to reduce the cost and the complexity of the sportswear.
Thus, the purpose of this paper was to develop an automatic classification system that distinguished between different surfaces and inclinations based on data of inertial sensors mounted on a running shoe.

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With the knowledge of the surface and inclination, a running shoe can automatically adapt to the current ground. This optimizes the performance of the athlete, prevents injuries of the athlete [7] and makes running more attractive.

2. Materials and Methods

2.1 Hardware Equipment

An ITG-3200 digital triple-axis gyroscope (InvenSense, Sunnyvale, California) and a BMA150 digital triple-axis accelerometer (Bosch Sensortec, Reutlingen, Germany) were rigidly mounted on the heel of a running shoe (adidas Duramo 2, adidas AG, Herzogenaurach, Germany), see Figure 1. The sensors were aligned with the body axis. A custom data logger stored the kinematic data on a SD-card. The gyroscope and accelerometer had a range of $\pm$ 2000°/s and $\pm$ 8g, respectively. The data sampling rate was 1000 Hz.
In order to acquire the current location of the runner during the data acquisition, the Global Positioning System (GPS) position was captured by a HTC Legend Android-based smartphone (HTC Corporation, Taoyuan, Taiwan). The data sampling rate was 1 Hz.

Figure 1. Inertial sensors mounted on the heel of an adidas Duramo 2 (box) and data logger (circle).

2.2 Data Collection

A running study was performed, in which 21 male subjects participated (age: 38.3 $\pm$ 10.8 years, height: 175.6 $\pm$ 4.6 cm, weight: 71.7 $\pm$ 7.9 kg). The participants were asked to run several rounds on a predefined route (distance: 2.1 km), until a duration of about one hour was reached. The average number of rounds was 5.7 with a standard deviation of 0.6. The route included parts with different surfaces (grass, street trail) and inclinations (uphill, flat, downhill). Table 1 shows the distance and inclination of the conditions that were used for the analysis. Furthermore, the number of instances are given for each condition. An instance was defined as the kinematic data of a subject for a certain condition. Since the subjects performed several rounds, one instance of a certain condition was available for each round. The instances of GF, TF and SF were used for the classification of surfaces. The instances of SF, SU and SD were used for the classification of inclinations.

Table 1. Information of conditions grass flat (GF), trail flat (TF), street flat (SF), street uphill (SU) and street downhill (SD). Columns show condition (Cond), distance (Dist), inclination (Inc) and number of instances (# Inst).

Cond	Dist [m]	Inc [%]	# Inst
GF	175	-2.3	117
TF	75	-4.4	119
SF	110	-0.9 to 1.2	120
SU	65	10.5	119
SD	65	-10.5	120

2.3 Labeling and Preprocessing

For the labeling of the kinematic data to the conditions, shown in table 1, a GPS-based procedure was applied. The GPS positions of the start and end borders of the five conditions in table 1 were defined in Google Earth (Google Inc., Mountain View, California) before the running study took place. They were projected onto the runner's GPS position acquired by the smartphone. After the synchronization of the inertial sensors and the smartphone, the labeled instances were available.
These instances might contain kinematic data of different conditions in the proximity of the borders. Thus, 20 % of the kinematic data at the beginning and at the end were not used.
Since the different lengths of the instances should not influence the classification results, the length was chosen to be the length of the shortest instance, which was eight seconds. Longer instances were symmetrically cut in the direction to the center of the condition.

2.4 Feature Extraction

Each of the eight second instances consisted of recordings from three accelerometer and three gyroscope axes. For each axis, 11 features in the time and frequency domain were computed. In total, 66 features were computed for each instance.
In the frequency domain, the spectral centroid and the

bandwidth were computed. Furthermore, the mean, standard deviation, skewness and kurtosis of the amplitude of the fast Fourier transformation were used as features.
In the time domain, five Linear Predictive Coding (LPC) [8] coefficients were computed. The autocorrelation method of autoregressive modeling was used to determine the filter coefficients [5]. The Yule-Walker equations were solved by the Levinson-Durbin algorithm [6].

2.5 Feature Selection and Classification

Since there is no single classifier that is suitable for all classification tasks [2], different classifiers were compared. In detail, Linear Discriminant Analysis (LDA), k-Nearest Neighbor classifier (kNN) and Support Vector Machine (SVM) were used [2, 9]. The linear kernel (SVM linear), polynomial kernel (SVM poly) and radial basis function kernel (SVM RBF) were used in the case of SVM.
For performance assessment, the mean class dependent classification rate and the overall mean classification rate were computed with a leave-one-subject-out procedure. In order to reduce the number of features, the sequential forward selection algorithm [9] was used. The feature selection was cross-validated in every leave-one-subject-out trial with an inner leave-one-subject-out loop.
The parametric classifiers were optimized by using a grid search approach. The k-parameter of kNN was evaluated for $k = [1, 2, ..., 15]$. The cost parameter C of the SVM was evaluated for $C = 10^N, N \in [-1, 0, 1, 10, 100]$. The γ parameter of the RBF kernel was evaluated for $\gamma = 10^N, N \in [-7, -6, ..., 1]$. The degree parameter d of the polynomial kernel was evaluated for $d = [2, 3, 4, 5]$.

3. Results

For one participant, the GPS system started the recording after the grass condition at round one. Thus, the grass condition of this participant could not be used. Two participants left the predefined route in one round, so that several conditions were also not usable in those cases. The number of instances that were available for the classification experiments can be seen in table 1.

3.1 Classification of Surfaces

The mean class dependent and overall mean classification rates can be seen in table 2. The best classifier was SVM RBF with a mean classification rate of 85.3 %.
The best classification rates for the parametric classifiers could be achieved using the following parameters: $k = 9$ (kNN), $C = 1$ (SVM linear), $C = 10$ and $\gamma = 1$ (SVM RBF), $C = 1000$ and $d = 4$ (SVM poly).
Sixty percent of the selected features were in the time domain. Eighty-one percent of the features were selected from an accelerometer signal. These numbers were based on the result of the feature selection of all optimized classifiers.

Table 2. Classification of surfaces: classification rates in percent.

Classifier	Grass	Trail	Street	Mean
LDA	90.1	70.0	77.2	79.1
SVM linear	90.0	85.7	78.8	84.8
SVM RBF	87.8	84.4	83.7	**85.3**
SVM poly	90.1	84.2	74.5	83
kNN	87.8	85.4	76.4	83.2

3.2 Classification of Inclinations

The mean class dependent and overall mean classification rates can be seen in table 3. The best classifier was SVM RBF with a mean classification rate of 81.2 %.
The best classification rates for the parametric classifiers could be achieved using the following parameters: $k = 7$ (kNN), $C = 1000$ (SVM linear), $C = 1000$ and $\gamma = 1$ (SVM RBF), $C = 100$ and $d = 3$ (SVM poly).
Seventy percent of the selected features were in the frequency domain. Seventy-seven percent of the features were selected from a gyroscope signal.

Table 3. Classification of inclinations: classification rates in percent.

Classifier	Uphill	Downhill	Flat	Mean
LDA	87.6	87.1	64.4	79.7
SVM linear	73.7	88.9	67.1	76.5
SVM RBF	83.5	81.1	79.0	**81.2**
SVM poly	84.9	84.1	70.2	79.8
kNN	82.1	86.5	72.5	80.3

4. Discussion

For the adaptation of sportswear to the current environment of the athlete, the possibility to classify both surfaces and inclinations with the same sensor type is important, in order to reduce the cost and the complexity of the sportswear.
The acquisition system, used in this paper, consisted of

inertial sensors on the heel of a running shoe. The classification system distinguished between different surfaces and inclinations with a mean classification rate of 85.3 % and 81.2 %, respectively. Since the algorithms for the surface classification in [3] were optimized for the restricted embedded system hardware environment, it is difficult to compare the classification rates of both approaches. But the rather high classification rates achieved by using inertial sensors are a good starting point for further research and show that the system is applicable for discriminating both surfaces and inclinations.
In a real-time application on a mobile system, the misclassification rates of the current system might increase in the proximity of the transition of two conditions and if a single condition last less than eight seconds. The reason is that the instance includes kinematic data of two different conditions. Thus, in order to improve the performance of the system, it is proposed to decrease the length of the instance. Furthermore, a majority voting of the classification results of subsequent instances reduces the misclassification rate.
As it can be seen in the tables 2 and 3, the mean class dependent classification rates vary between the conditions. The classification rate of grass is rather high compared to street and trail. The classification rate of flat is rather low compared to uphill and downhill. In order to improve the performance of the system, it is proposed to use additional features, e.g. wavelets.
After the feature selection routine, 60 % of the features were in the time domain and 81 % were based on an accelerometer axis in the case of classifying surfaces. In the case of classifying inclinations, 70 % of the selected features were computed in the frequency domain and 77 % were based on a gyroscope axis. This implied that depending on the classification of surfaces or inclinations different feature groups were important. Furthermore, depending on the classification of surfaces or inclinations either features of the accelerometer or gyroscope signal had a major impact on the classification.
For a real-time application in mobile use, a classifier would be preferred which can discriminate combinations of surface and inclination, e.g. street up, trail down, grass flat. In this case, the current system can be modified to a hierarchical classification system. In the first step, the surface is classified and in the second step the inclination or vice versa.
All in all, the classification system showed that surfaces and inclinations can separately be discriminated by using only inertial sensors placed on a running shoe. No further sensor types have to be used for these classification tasks, which reduces the cost and the complexity of the sportswear.

5. Conclusion

Embedded mobile systems for analysis and classification become more and more important in the field of sports and sports science. For the adaptation of sportswear to the current environment of the athlete, the possibility to classify both surfaces and inclinations with the same sensor type is important, in order to reduce the cost and the complexity of the sportswear.
In this paper, a classification system was developed, which could discriminate between different surfaces (grass, street and trail) and inclinations (uphill, flat and downhill) with a classification rate of more than 80 %. For data acquisition, only inertial sensors were used.
The system can now be implemented on an embedded mobile system for real-time application. It is proposed that the classification of the surface and inclination with only one sensor type is one part of an intelligent shoe in the future, which helps the athlete to improve the own performance day by day and reduces the risk of injuries. This makes running more attractive.

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