Embedded Classification of the Perceived Fatigue State of Runners

Towards a Body Sensor Network for Assessing the Fatigue State during Running

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***Abstract*—This paper presents methods for collecting and analyzing biomechanical and physiological data from several body sensors during recreational runs in order to classify an athlete's perceived fatigue state. Heart rate, heart rate variability, running speed, stride frequency and biomechanical data were recorded continuously from 431 runners during a free one-hour outdoor run. During the activity the sportsmen answered questions about their perceived fatigue state in 5 min intervals. The data were analyzed using specifically designed features computed for each of the 5 min intervals. The features were used to train different classifiers, which were able to distinguish two levels of the runner's fatigue state with an accuracy of 88.3 % across multiple study participants.**

Feature selection evidenced that a heart rate variability feature and two biomechanical features were best suited for classification of the perceived fatigue level. Therefore, the classification system needs the information from various sensors on the human body. The resulting classifier was implemented on an embedded microcontroller to show that it would be feasible to integrate it directly into a body sensor network. Such a wearable classification system for fatigue can be used to support sportsmen, for example by changing their training plan or by adapting their equipment to the specific needs of a fatigued athlete.

Keywords-body sensors; sensor network; fatigue classification; embedded classification; biomechanics;

I. Introduction

Smart sensors embedded in clothes and equipment for sports enable novel opportunities to support and guide athletes. A prominent example is the adidas_1 running shoe, which is the first shoe that features a wearable embedded system (Fig. 1). This shoe is built to adapt to various running conditions like the prevailing surface situation or the runner's speed and fatigue state by changing the cushioning of the sole using a motor driven cable system. However, a precise classification of the mentioned conditions is mandatory for this adaptation. To facilitate the classification, the heel compression signal of the runner is continually measured and processed by the embedded microcontroller of the adidas_1. A description of the adidas_1, its functionality and embedded system hardware can be found below and in more detail in [1].

In this paper, we consider the task of classifying the fatigue state of a runner. A fatigue classification system would enable automatic changes to the training plan or even allow an adaptation of the training gear to the current fatigue level of the runner. Athletes could directly benefit from such a system, as it could lead to a lower level of fatigue after the training session, reduce the risk of overtraining and prevent injuries during the training [2]. In the particular case of running with the adidas_1, the shoe can be adapted according to the prevailing fatigue state, for example by stabilizing exhausted muscles by providing more stiffness. However, this is just one example. Similar actions could be taken in other endurance sports, where it is equally important to actively support an athlete by adapting the equipment to the amount of fatigue.

To realize an automated fatigue classifier, physiological as well as biomechanical information from the athlete must be considered. Hence the final implementation will most probably consist of multiple body worn sensors, which form a body sensor network to collect the required data. This data would then be transferred wirelessly to a central processing node (e.g. a wristwatch or a mobile phone), which runs a fatigue classification algorithm.

In order to build such an embedded classification system, multiple steps are required. The first step is to determine the necessary physiological and biomechanical parameters to describe the current fatigue state of the runner. The next step is to acquire a large enough data set, which contains the selected parameters together with ground truth information about the current fatigue state of the runner. From this data set features are extracted, which are possible indicators for the fatigue of the subject. These features are then used to train a fatigue classifier. Finally feature selection must be performed to extract the most relevant features for fatigue classification and to reduce the number of needed sensors and to reduce the computational effort for the final body sensor network.

Many features of physiological and other signals have been proposed as indicators of fatigue by sports researchers and psycho-physiologists, but these are normally individually evaluated and their use for classification purposes is rarely tested [3]. Furthermore, no application that is known to the authors has been proposed to conduct online, embedded classification.

In this paper, we show how we apply pattern recognition techniques to identify a feature set to appraise the perceived fatigue level of sportsmen during a free one-hour-outdoor run. During data collection different wearable sensor systems were used to obtain physiological as well as biomechanical data from the subjects. This included the heart rate (HR) and heart rate variability (HRV), as well as the compression of the heel of the adidas_1. The HR signal was chosen because previous studies have shown that the heart rate and especially heart rate variability is important for assessing psychological stress [3] and physiological fatigue [4]. The heel compression was chosen because also in this case, previous studies have shown that the measured signal can provide information about the fatigue state [5]. Additionally ground truth information about the perceived fatigue state of the runners was collected. This was done by inquiring the subjects periodically about their perceived fatigue level during the physical activity, which was accomplished using a specially programmed mobile phone. Self-rating the fatigue state is a widely used method to get information about fatigue [6]. The collected data was then used to compute several features from the signals and to train a fatigue classifier. Feature selection was performed to extract the most relevant features and build an embedded version of the classifier, which could be used in a future implementation of a body sensor network based fatigue classifier.

In summary, the purpose of this paper was to show that using information from various body sensors, it is possible to classify the perceived fatigue state of an athlete on an embedded system. This can be used to build a body sensor network based fatigue classifier, which can in turn support sportsmen, for example by changing their training plan or by adapting their equipment to the specific needs of a fatigued athlete.

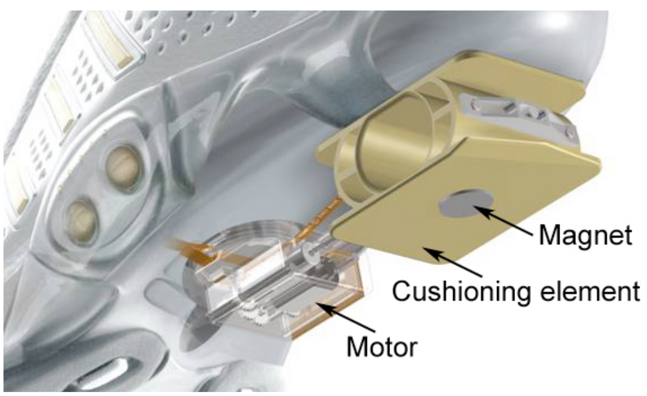

Figure 1. The adidas_1 shoe (w. cushioning element, magnet, motor unit).

II. METHODS

A. Data Collection

A total of 431 runners participated in the one-hour outdoor running study. The subjects were not specifically chosen according to running experience, age or gender; instead, the group contained both low and high activity runners and represented an average runner population.

The measurement system consisted of 3 separate sensors. Firstly, we used a Polar RS800 Running Computer [7], which included an S3 stride sensor and a chest strap. This system is capable of measuring running speed, stride frequency, barometric height, heart rate (HR) and the time between two consecutive heart beats (RR-interval). RR-intervals were measured with a resolution of 1 ms, the sampling interval for the remaining four signals was set to 5 seconds.

Secondly, we continuously measured the heel compression signal of the runners using the adidas_1 running shoe [1]. Fig. 1 shows the measurement principle. A hall sensor mounted at the top of the cushioning element detects the magnetic field strength induced by a small magnet. The sensor was sampled with a rate f_s of 342 Hz. The sensor-magnet distance d_m was computed from the field strength with an accuracy of 0.1 mm.

Lastly, we used a Nokia 6110 Navigator cell phone with a custom-built Java software. It played sound files with predefined fatigue questions and recorded the related answers. Additionally it recorded the GPS position of the athlete from an inbuilt GPS receiver. The phone was placed in a belt that was attached to the upper arm of the participants. The runners also wore a Bluetooth headset that was wirelessly connected to the phone to capture their answers.

At the beginning of the experiments, the participants were standing and a short pre-recorded instruction message was played to them. Once this was completed, they were asked about their fatigue state for the first time and then they were asked to start running. After that, the perceived fatigue state was asked every 5 minutes. The athletes were instructed to answer each question about their subjective fatigue level with a self-rated grade as given in Tab. I. An example run is visualized in Fig. 2 using the Google Earth (Google Inc., Mountain View, CA, USA) software. This representation allowed us to assess specific events in the free outdoor runs by means of an intuitive visualization.

From the ratings in Tab. I, we derived two fatigue classes ω_k, ($k = 1, 2$), which were used to label each five minute interval near the beginning and near the end of the runs. Class ω_1 corresponded to low perceived fatigue (self-ratings 0-4, 51.6% of the labels), ω_2 corresponded to high perceived fatigue (self-ratings 5, 6, 48.4% of the labels). Each interval was labeled according to the recorded fatigue state given at the end of the interval.

TABLE I. ATHLETE SELF RATING TRANSCRIPTION

Spoken Answer	Meaning
0	Not at all
1	Very little
2	Little
3	Somewhat
4	Rather
5	Very
6	Extremely

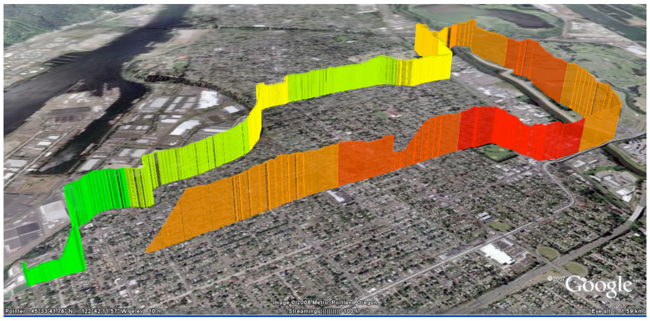

Figure 2. Visualization of an example run in Portland, OR, USA. Running speed is displayed as the height of the band along the running track. The fatigue levels from Tab. I are color coded: Green and yellow (light gray in b/w) means little or no perceived fatigue; orange (medium gray) represents the medium and red (dark gray) the extreme perceived fatigue classes.

B. Feature Extraction

For each step, we extracted 19 biomechanical features denoted by $F1 \dots F19$ from the heel compression signal. Fig. 3 shows $F1 \dots F10$. Features $F11 \dots F19$ all represent the standard deviation (SD) of different attributes (see e.g. [5]). In order to get the interval features, we computed mean (M) and standard deviation (SD) over all steps contained in the respective interval, resulting in 2*19 = 38 biomechanical features denoted by $F1_{M} \dots F19_{M}$ and $F1_{SD} \dots F19_{SD}$.

Three additional features were calculated directly from the heart rate signal. The first feature was the gradient of the HR signal. It was calculated from fitting a polynomial of degree one to the HR signal, with the gradient being the coefficient of this polynomial. The second feature was the standard deviation of the first feature. The third feature was the offset of the HR signal. It was defined as the difference between the mean HR while standing and listening to the initial instructions and the mean HR in the analysis window.

Additionally, the RR-intervals were used to compute nine heart rate variability (HRV) features using two different methods: the Poincaré plot [8] (PP, four features) and the Lomb-Scargle periodogram [9] (LSP, five features). The four PP features are described in [5]. The five LSP features were computed from the mean energy in the five frequency bands 0 Hz - 0.1 Hz, 0.2 Hz - 0.3 Hz, 0.6 Hz - 0.7 Hz, 0.7 Hz - 0.8 Hz and 0.8 Hz - 0.9 Hz. These bands were selected according to a preliminary analysis [10].

C. Classification

Two different classifiers were compared for their classification rates. These were Support Vector Machine [11] (SVM, linear kernel) and Linear Discriminant Analysis [12] (LDA). They were selected as both of them have been shown to be successfully applicable in other studies [13, 14].

For both classifiers a leave-one-runner-out cross-validation (LORO CV [15]) was performed. For LORO CV, all except the feature vectors from one runner were used for classifier training. The remaining feature vectors from the left out runner were then used for testing. This was done for every runner. The classification accuracy was calculated as the mean of the single classification rates.

D. Feature Selection

For a possible embedded implementation of the body sensor data classification system, only limited processing power is available. Therefore a feature selection was performed to find the best performing feature vector in order to reduce the number of features. A forward feature selection strategy was used for this purpose, with the LORO CV classification accuracy as optimization criterion. Both classifiers were tested for performance and the best performing one was selected.

Without restriction of generality, the system was optimized for three features. However, different target numbers of features could be selected depending on the employed microcontroller.

E. Microcontroller Implementation

According to feature selection, the best three-feature vector and classifier was implemented on microcontroller hardware (ATmega 32, 8-bit RISC-based, 32KB flash memory, 2KB SRAM, 16 MHz clock speed: Atmel Corp., San Jose, CA, USA). The ability of this implementation to compute online classification results, which could be used for a body sensor network data classification, was tested.

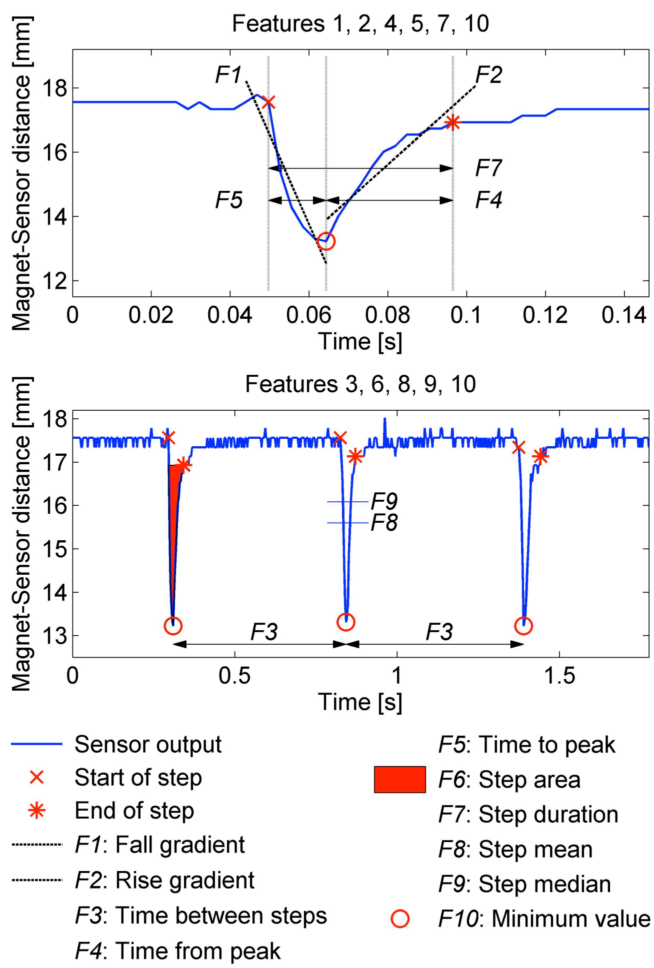

Figure 3. The biomechanical features $F1 \dots F10$ that originate from the heel compression signal during running.

III. RESULTS

Regarding data collection, 177 of the 431 study participants had to be excluded from further processing for various reasons. More specifically, two runners had incomplete audio data due to malfunctioning of the Bluetooth headset, and 17 other participants had incomplete data from the Polar RS800 system. The remaining runners had to be excluded because of unusable data from the adidas_1 shoe. In 69 cases, data collection was erroneous due to short interruptions in the battery connection and therefore data loss. In another 89 cases, the runners were mid- or forefoot strikers. The measurement system of the adidas_1 is located at the heel of the shoe and can therefore only record data for rearfoot strikers which account for more than 80% of the population [16].

Classification without feature selection for the different feature groups resulted in the classification rates given in Tab. II.

TABLE II. CLASSIFICATION RATES WITHOUT FEATURE SELECTION

Feature Type	SVM	LDA
$F1_{M,SD} \ldots F19_{M,SD}$	88.2%	87.3%
HR + PP	68.5%	68.0%
LSP	61.7%	62.4%
All features	89.8%	88.3%

Classification with feature selection resulted in the selection of the features $F2_M$, $F4_M$ and the LSP feature describing the energy contained in the band from 0.8 Hz - 0.9 Hz. The LDA classifier was selected as the best performing one. The classification rate for this combination of features and classifier was 88.3%.

We compared the classification results of the microcontroller implementation with those of our desktop PC implementation. The results were identical.

IV. DISCUSSION

The evaluation of the collected data revealed that despite our efforts during collection, a high number of datasets was unusable. We made sure that batteries were always fully loaded and applied a salt-water solution to the HR measuring chest strap to ensure collecting usable data. However, most unusable datasets originated from the forefoot runners in our participant population. We did not want to ask runners specifically whether they are fore- or midfoot strikers before the run to prevent a change in running style. Following this procedure, we had to cope with data loss for these runners. However, no additional bias was introduced thereby. Nevertheless, the negligence of forefoot runners is a disadvantage of our current measurement system and additional sensors in the forefoot have to be incorporated in future studies.

The LDA and SVM classification experiments with all features showed that both classifiers yielded similar results, with the SVM being slightly better. The shoe features alone resulted in the best performance, followed by the HR + PP features and the LSP features with lowest classification rates.

Using all features, classification rates of up to almost 90% were reached. This showed that the classification of the fatigue level of a runner is possible with adequate accuracy.

In the feature selection experiments the three feature vectors usually contained at least two shoe features combined with either one LSP feature or one PP feature. Overall, the LSP features outperformed the PP features during feature selection. Good classification results without either LSP or PP features were not achievable. This indicated that for a final implementation, a body sensor network that delivers physiological as well as biomechanical data is needed.

It is also notable that the best three-feature combination resulted in classification rates comparable to those using all features. This was beneficial for the implementation of the online classification system on a microcontroller, which could not compute a high number of features.

The microcontroller implementation was successful, showing that such a system can be implemented in future body sensor networks using embedded systems for the classification of fatigue in endurance sports. Such systems will allow to guide and assist a multitude of athletes.

V. CONCLUSION

This research demonstrated the application of pattern classification methods to detecting perceived running fatigue using data from several body sensors. The finally implemented system used biomechanical as well as physiological features for classification. We showed that this system is capable of recognizing the fatigue state of a runner with high accuracy on an embedded system. This suggests that an automatic system can precisely support an athlete, for example by providing more shoe stiffness by the adidas_1 running shoe when a sportsman gets fatigued.

Further work will be conducted to incorporate additionally collected speed, stride frequency and altitude information. Moreover, we will also collect new information from different body sensors. Possibilities are biosignals such as body temperature or movement signals from inertial measurement sensors like accelerometers or gyroscopes. We also have to incorporate sensors to allow for the measurement of biomechanical parameters from forefoot runners. Additional features can be derived from these sensors and used to further enhance the fatigue classification ability of a body sensor network specifically designed for this purpose.

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