Real-time ECG and EMG Analysis for Biking using Android-based Mobile Devices

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***Abstract*—We developed an application for *Android*™-based mobile devices that enables a real-time calculation of heart rate and cadence for biking. Therefore, both ECG and EMG data are acquired in real time by *Shimmer*™ sensors and transmitted via *Bluetooth*™, as well as processed and evaluated on the mobile device. The ECG algorithm is based on the Pan-Tompkins algorithm for QRS-Detection and offers a heart beat detection rate of more than 94%. The EMG algorithm offers a treadle detection rate of more than 91%. The application's range of features is complemented by GPS data for the calculation of speed and location information. It is available for download and can for example be used for controlling the user's training status, for live training supervision and for the subsequent analysis of the various training runs.**

***Keywords*-biomedical signal analysis; electrocardiography; electromyography; wearable body sensor networks; android application; training support**

I. Introduction

A stationary bicycle (also known as exercise bicycle) finds its application in competitive sports and medicine, but is mostly used for performance analysis, endurance training and cardiac stress test. It is also a common training method for strengthening the cardiovascular system, increasing endurance and fat burning. During the exercise on the stationary bike, the current heart rate as well as the cadence is measured and displayed which enables a real-time training supervision. Heart rate and cadence are the main features for the evaluation of the athlete's training status. One disadvantage of using a stationary bike as a training device is the monotony during training.

There have been various approaches for increasing the exercise motivation, for example by Yim and Graham [1] in 2007, who integrated the physical activity on a stationary bike into games. A study by Haddock et al. [2] in 2009 achieved the result that the addition of video games to stationary cycling has a greater energy expenditure than cycling without game support.

The integration of gaming into sports is important and helps improving the training motivation. But another approach would be not to make training on stationary bicycles more interesting and diversified, but to find a solution that transfers the given training conditions onto the open road.

There is definitely a need for mobile training support systems that are easy to use and provide a reliable real-time feedback during training as well as a subsequent analysis of the runs. However, there are currently no applications that fulfill these needs. For this reason, our aim was to develop an application for *Android*™-based mobile devices that fits the desired purpose of use and that pays special attention to the everyday suitability.

Mobile devices (especially smart phones) have already become a fundamental part of daily life and with its continuously increasing processing power, they are more and more used for biomedical signal processing [3] [4], especially for ECG analysis [5] [6] [7].

Our contribution in this paper consists of multiple parts. Firstly and secondly, we provide an algorithm for real-time calculation of the heart rate of an ECG signal and an algorithm for real-time calculation of the cadence in an EMG signal, respectively. Thirdly, we present the implementation of our algorithms as an *Android*™ application, as well as the features we added to enhance the range of functions, like the saving of the runs for a subsequent training analysis or the calculation of speed and location information from GPS data. Fourthly, we conduct an evaluation of our application and the implemented algorithms with a special focus on its suitability in everyday use.

II. Methods

A. Data Acquisition

The live data that is streamed to the mobile device is acquired by *Shimmer*™ (Realtime Technologies Ltd., Dublin, Ireland) sensor nodes with a sampling rate of 256.4 Hz for both sensors. Shimmer is a compact, lightweight wireless inertial sensor platform with expansion modules for providing sampled ECG and EMG signal data in real-time.

For ECG data, we used the lead II according to Einthoven's triangle. The ECG electrodes are placed below the right clavicle and on the lower edge of the rib cage. The EMG electrodes are placed on the anterior thigh parallel to the muscle fiber orientation, about 10 cm above the knee joint. The Vastus lateralis as well as the Vastus medialis muscle both deliver satisfactory results. The reason why we

978-1-4799-4959-5/14 $31.00 © 2014 IEEE
DOI 10.1109/BSN.2014.20

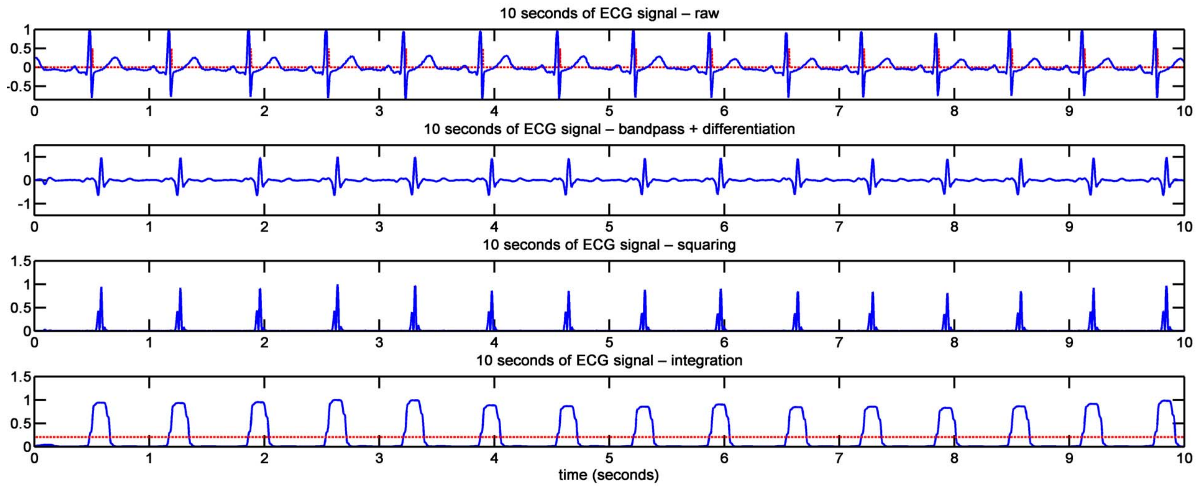

Figure 1. **Processing pipeline for the ECG signal**. In this figure, 10 seconds of the signal were extracted for the processing. *From top to bottom*: (1) raw ECG signal (*blue, solid*), detected heart beats by the algorithm (*red, dashed*); (2) signal after bandpass filter and differentiation, (3) signal after squaring operation; (4) signal after moving-window integration (*blue, solid*), threshold (*red, dashed*).

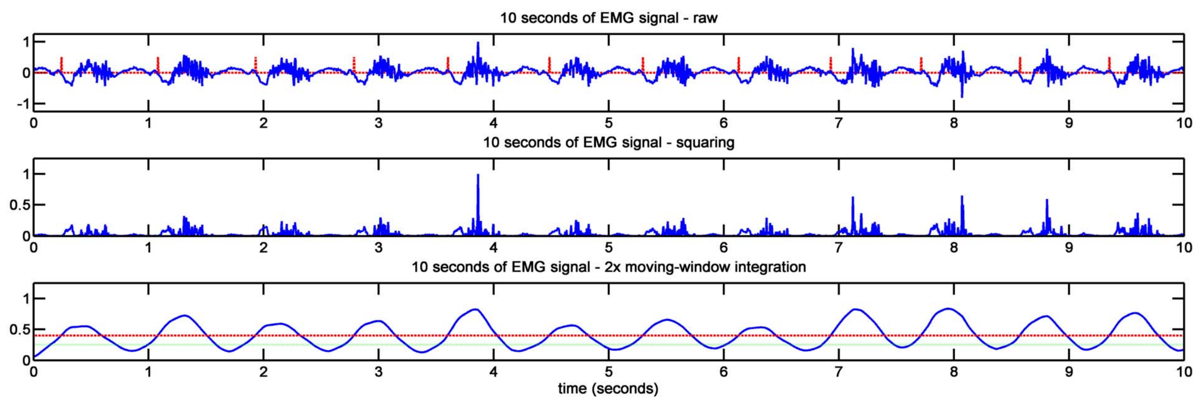

Figure 2. **Processing pipeline for the EMG signal**. In this figure, 10 seconds of the signal were extracted for the processing. *From top to bottom*: (1) raw EMG signal (*blue, solid*), detected treadles by the algorithm (*red, dashed*); (2) signal after squaring operation, (3) signal after double moving-window integration (*blue, solid*), threshold (*red, dashed*), minimum threshold for avoiding misdetection (*green, dotted*).

used the EMG signal instead of the signal of an accelerometer is to keep the option of additional analysis open for future work, like for example the detection of muscle fatigue.

B. Heart Beat Detection

This algorithm is based on an algorithm that was proposed by Pan & Tompkins [8] in 1985 for a real-time QRS detection. We slightly simplified it in order to fit the requirements of a resource-efficient calculation on a mobile phone. For a heart beat detection, the raw ECG signals are processed with different digital filters which processing steps in order of application are seen in Figure 1: (1) a band-pass filter composed of cascaded low-pass and high-pass filters, (2) a five-point-differentiation followed by (3) a pointwise squaring operation and (4) a moving-window integration. Finally, the heart beats are detected using the mean value of the signal as a threshold.

The heart beat detection algorithm is used for the real-time calculation of the current heart rate (as an average of the last five heart rate values), the average heart rate since start and the number of total heart beats since start.

C. Treadle Detection

The algorithm for the detection of treadles in the raw EMG signals has been developed according to EMG signal processing techniques in [9] and [10]. First, the energy of the signals is computed, which is followed by a dual moving-window integration. For the treadle detection, the threshold value is determined by computing the signals' mean value. The processing pipeline of the treadle detection algorithm is showed in Figure 2.

The treadle detection algorithm is used for the real-time calculation of the current cadence (an average of the last five cadence values), the average cadence since start and the number of total treadles since start.

D. Implementation

The application was implemented in *Java*™ using the *Android SDK 4.4.2 (API 19)* (Google Inc., Mountain View, USA). Android was chosen because of its open nature and its market share of more than 80 % (Q3, 2013) [11]. Additionally, it offers an easy solution for integrating *Shimmer* sensor nodes via *Bluetooth*.

The algorithms for heart beat and treadle detection had to be implemented focusing on real-time processing. Therefore, the number of convolution operations that are required for our algorithms is reduced to a minimum, for example by computing a impulse response for the heart beat detection algorithm, combining the low-pass filter as well as the high-pass filter and the five-point-differentiation.

Since the application has to process the acquired date in real-time, our implemented algorithms are performed on windowed signal sections. Therefore we had to find a trade-off in the determination of the proper window size. 300 samples (at a sampling rate of 256.4 Hz) has proven to be the optimal window size for the task of our application. In addition, circular buffers were used for the buffering operations during signal processing in order to avoid overhead. This window size ensures that the signal windows contain at least one heart beat per window (assuming a minimum heart rate of about 60 beats per minute (bpm) during training). Decreasing the window size would improve the application's performance by a lower processing time, but as a side-effect, some windows would be processed without containing a heart beat or a treadle event. Increasing the window size has a negative impact for the real-time processing and results in a higher computational load.

The window sizes of the moving-average filters for both ECG and EMG signals are 75 samples which is equal to a fourth of the window size of the signal. If there are no treadles to be detected in the window (e.g. at a downhill period with no cycling or at a traffic light stoppage), a minimum threshold (in our implementation, 0.25 of the maximum value in the signal window) has to be set for avoiding misdetections.

E. Derived Features

The GUI displays the relevant data during training. The raw ECG signal is plotted live using the *Androidplot* plotting component. Furthermore the current heart rate, the average heart rate and the number of total beats since start were calculated from the ECG signal and displayed in the GUI. The displayed information from the EMG signal signal are the current cadence as well as the average cadence and the total number of treadles since start. In order to enhance the range of features of our application for provide a better live feedback, we added GPS location data. This allows the calculation of the current speed in km/h as well as the average speed since start and the total distance traveled. Furthermore the GPS data is used for route tracking likewise as for the display of the current position in a *Google Maps*™ fragment. The application setup (including a screenshot of the user interface during training) is shown in Figure 3.

Figure 3. **Schematic application setup**. The mobile phone receives live data from the two *Shimmer* sensors via *Bluetooth* and GPS data for location and speed features. The application (a screenshot of the main interface is visible in the figure) processes the data and displays the information.

For the subsequent analysis of the training as well as for the comparison between different training sessions, the logging of data that is recorded during the run was enabled. The logged data is saved on the external storage after the end of the run. We also implemented a "Share Button" for our application that enables sharing the user's training results via *Facebook*™. Reaching a large user community via social networks easily creates "team spirit" and increases training motivation by the competition with other users.

III. Evaluation

For the evaluation, tests of each 60 seconds were performed by two probands on a stationary bike. Data logging was enabled during the tests so that the ECG and EMG signals could be evaluated in real-time on the mobile phone as well as transferred to the PC for a subsequent evaluation. The signals were plotted in *MATLAB*™ in order to manually count the heart beats in the ECG signal as a gold standard. The total number of treadles was counted during the test. The mobile phones used for the evaluation were a *Google™ Nexus 5 (LG D821)* and a *HTC™ One S*.

For the presentation of the results, the number of heart beats and treadles detected by the application were set in relation to the number of total heart beats and treadles.

Table I
EVALUATION RESULTS FOR THE HEART BEAT DETECTION ALGORITHM

	Total Beats	Detected Beats	Detected Beats (%)
Sample 1	62	61	98.39 %
Sample 2	90	87	96.67 %
Sample 3	96	90	93.75 %
Sample 4	134	123	93.18 %
Sample 5	103	99	96.17 %
Sample 6	88	83	94.32 %
Total	**573**	**543**	**94.76 %**

Table II
EVALUATION RESULTS FOR THE TREADLE DETECTION ALGORITHM

	Total Treadles	Detected Treadles	Detected Treadles (%)
Sample 1	60	54	90.00 %
Sample 2	70	62	88.57 %
Sample 3	86	82	95.35 %
Sample 4	93	84	90.32 %
Sample 5	118	108	91.53 %
Sample 6	99	90	90.91 %
Total	**526**	**480**	**91.25 %**

IV. RESULTS

The results for the real-time heart beat detection in the ECG signals are shown in Tab. I. Of 573 total beats, 543 beats were detected by the application. Overall detection rate of the algorithm was 94.76 %. Tab. II presents the results for the real-time treadle detection in the EMG signals. The application detected 480 out of 526 total treadles correctly, which is equal to a detection rate of 91.25 %. The results were equal for both used mobile phones.

V. DISCUSSION

With detection rates of 95 % for heart beats and 91 % for treadles, the results show that the algorithms implemented for our application provide solid results for the given task.

The reason why not all events could be detected in the implementation of our algorithms lies mostly in the windowing of the signals for enabling a real-time processing, through which important signal parts were lost. This is particularly noticeable in the treadle detection algorithm for the EMG signal due to the fact, that the width of the relevant signal parts in the EMG signal is wider than the QRS complex in the ECG signal. For this reason, the treadle detection rate in our application is inevitably lower than the heart beat detection rate. As already mentioned, a variation of the window size did not show any notable improvement. This is a deficit that definitively needs to be improved in further work. Because of the continuous motion of the user's body during biking, the accuracy of the algorithms (especially the heart beat detection algorithm) is diminished by motion artifacts and by artifacts resulting from the friction between electrodes and clothes. The usage of more suitable electrodes or other sensor platforms could probably reduce this problem.

Due to the fact that both algorithms are running simultaneously and in real-time, the application creates high computational load (especially the convolution operations). Anyway, it does not restrain the operability of the mobile device due to the fact that it is only used for a live feedback of the user's training parameters and is not used for any further functions. During the training, a lot of data is accumulated after the end for enabling a subsequent review and analysis. Currently, the data is saved on the external storage after the end of the training which takes a long time. By parallel saving the data during the recording, the waiting time for the data to be saved is improved and the performance of the application is increased.

VI. CONCLUSION

We developed an application that implements algorithms for the real-time detection of heart beats in an ECG signal and treadles in an EMG signal. Despite the fact that the detection accuracy was not perfect, our solution provides a solid training support and supervision and is a new possibility for a live training feedback combined with the feature of a subsequent training analysis.

We must mention that the purpose of this application is not to be diagnostically reliable (e.g. for the monitoring of cardiac arrhythmia) so that the results are satisfactory. So far, some improvements are still required for enhancing the everyday suitability, especially for long-distance training runs. Furthermore, the number of probands has to be increased in future work to assure the correct functionality of the application.

As a next step a heart rate monitoring could be implemented in order to suggest the optimal speed depending on the training purpose – for instance fat burning or cardio training. Another enhancement would be an automated evaluation of the training data after the run and a feedback whether a training improvement was be achieved or not.

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