# *Mobile EMG Analysis with Applications in Sport and Medicine*

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*Abstract*—**Surface Electromyography (EMG) is an important tool for medical diagnosis, rehabilitation and sports biomechanics. While it is usually used to perform recording of data under laboratory conditions, wearable sensors have enabled also mobile recording of dynamic movements. This has led to feedback applications which require real-time processing of the EMG data on mobile devices. This paper presents our mobile EMG analysis framework, which consists of a wearable recording device, a wireless mobile sensor framework and a real-time biosignal analysis library. Additionally we present two example applications from sport and medicine. This includes real-time classification of fatigue during running and an application for classification between patients with Parkinson's disease and healthy controls.**

***Keywords: surface electromyography, biomechanics, sports, wearable body sensor network, realtime feedback, wavelet analysis, pattern recognition, classification.***

## I. INTRODUCTION

Surface electromyography (EMG) is an important tool for medical diagnosis, rehabilitation, sport applications and biomechanics [1]. It has been used for the quantification of tremor [2, 3], the diagnosis of neuromuscular disorders [4, 5, 6] and the assessment of neuromuscular coordination [7], training state [8] or fatigue [9] during sports movements.

Measurement techniques for EMG vary from invasive needle based systems to easy to use systems using pre-gelled surface electrodes [1]. Recently, there is even a trend towards gel-free electrodes or even no-contact capacitive measurement systems, which allow easier application and reduce artifacts during longer wear. In general, with the introduction of wearable body sensor networks [10], measurement systems have become smaller and smaller and new applications have been introduced [25]. This includes feedback applications during sports and various applications in home care, rehabilitation and other areas of medicine [11, 12].

While a high quality mobile measurement of the EMG signal is an important step towards feedback applications, sophisticated analysis methods must also be available to extract the required information from the EMG signal. Standard methods in this context include simple root-mean-square analysis to detect muscular events or the integration of the signal to estimate total muscle activation during a certain interval [1]. Usually also the frequency content of the EMG signal is analyzed using short time Fourier analysis, as this can provide hints towards muscular diseases or muscle fatigue. While these techniques can provide basic information on the current activation state of a muscle, they do not provide advanced information on neuromuscular coordination and they cannot reflect small changes in the muscle activation pattern due to central fatigue or neurological disorders. More advanced analysis methods like the Wavelet transformation [13] or pattern recognition and classification [14, 15] have been proposed to overcome this limitation. However, most implementations of these methods so far are limited to post-hoc analysis, as they are not able to run in real-time on mobile devices. To use these methods for feedback and wearable applications, a mobile recording and analysis framework for EMG signals would be required.

The purpose of this paper is to present a mobile analysis framework and Android demonstrator for real-time EMG processing. Additionally we present two example applications for this framework, which includes a real-time classification of fatigue during running and a study using EMG for the detection of Parkinson's disease during walking.

## II. METHODS

A working system for mobile analysis of EMG signals (or any other biosignal) consists of three major components: the wearable sensor nodes which acquire the raw data, a mobile device receiving and processing the data and the actual analysis algorithms running on the device [16]. In the following we give a few examples for wearable EMG recording devices and introduce our mobile sensor framework to connect wireless sensors with an Android mobile phone.

Finally we present a mobile analysis library for biosignals, which can be used to analyse a variety of signals either on a PC or an Android mobile device.

### A. *Wearable EMG Devices*

Recently many different devices have been appeared on the market which support mobile recording of the surface EMG. In general, there is a trend towards wireless and cable-free systems, which allow greater freedom and range of motion. Combined with gel-free electrodes, these systems allow recording of the EMG during ambulatory procedures and with short setup-time. Examples for available small systems are the Delsys Trigno wireless EMG system or the SHIMMER wireless sensor platform [17]. Both systems are very small, non-hindering and can transmit the data wirelessly to a mobile device. There is also a new trend for these devices to be compatible with smartphones and tablet computers using Bluetooth technology. Recently even completely new input devices like the MYO [25] have been introduced, which record and directly process the EMG signal on the device before using it to control flying drone or the cursor on the screen.

### B. *Mobile Sensor Framework*

After data is collected using a sensor node, it must be transmitted to a device for processing. To support rapid developing of example applications, we recently proposed a mobile sensor framework [16] shown in Figure 1. The main focus of the framework is the Android platform, which is a widely supported open platform running on many phones. The framework allows easy access to data from various mobile sensors, e.g. ECG, EMG or kinematics. Additionally it allows playback of pre-recorded data stored on the device, which is especially helpful for development and evaluation of algorithms.

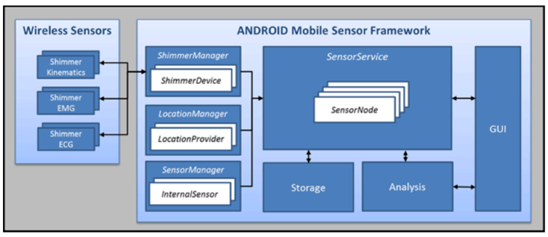


Figure 1. The Mobile Sensor Framework as implemented for the Android platform. Data from various wireless sensors can be received and processed in real-time.

### C. *Real-time Analysis Library for Biosignals*

While the mobile sensor framework collects and provides the sensor data, the main focus of the mobile analysis are the processing algorithms. To simplify the development of real-time applications we have created various real-time implementation of standard algorithms [18, 19], which have been combined in a Java library. It includes algorithms for pre-processing (high and low-pass filter), event detection (Pan-Tompkins), feature extraction (FFT, Wavelets, statistics) and classification (Linear Discriminant Analysis, Support Vector Machine). Special consideration was given the non-linearly scaled Wavelet transformation [13], as this algorithm has been used in various EMG analysis studies. A full real-time implementation of this algorithm was created and tested [18]. Since all algorithms were implemented in Java, the library allows both post-hoc analysis of collected data and real-time processing. As the Java library is platform independent it can be used on a standard PC running any operating system as well as on various mobile devices like Android phones.

### D. *Android Demonstrator*

To demonstrate the possibilities of the real-time analysis library and the mobile sensor framework an Android demonstrator has been created which contains various example applications [16, 18, 19]. Figure 2 shows the interface of the Android demonstrator performing a real-time Wavelet transformation of the incoming EMG signal.

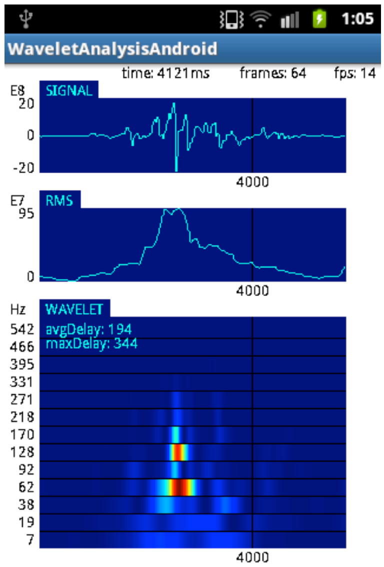


Figure 2. The Android demonstrator performing a real-time Wavelet transformation of an EMG signal. The app displays the incoming raw signal (top), the result of the RMS analysis (middle) and the resulting Wavelet intensity pattern (bottom).

## III. APPLICATION EXAMPLES

### A. *Detection of Fatigue During Running*

#### 1) *Motivation*

Recreational running is one of the most popular sports in the world. However, many recreational runners are inexperienced and overestimate their abilities. Especially muscle fatigue during prolonged running can cause changes in muscle properties and control strategies, which increases injury risk. While indicators of muscle fatigue may not yet be apparent to the runner himself, they are already present in the muscular activation patterns and can be detected using surface EMG [9]. Using data and methods from a previous study [9], we created an Android demonstrator which enables real-time detection of muscle fatigue during running.

*2) Methods*

During a previous study [9], twelve female recreational runners performed an endurance run of one hour at approximately 95% of their maximum aerobic speed. EMG signals of the tibialis anterior (TA), gastrocnemius medialis (GM), vastus lateralis (VL) and semitendinosus (ST) were recorded using a wearable EMG recording device. Data was collected at 2 minute intervals during the whole run and labeled as non-fatigued (15-25 minutes into the run) or fatigued (45-55 minutes into the run). For each interval a period of ±300 ms around heel strike was segmented. Using a standard PC, the EMG data were transformed into intensity patterns using the non-linearly scaled wavelet transform [13]. The transformed patterns were used to train a Support Vector Machine classifier to distinguish between non-fatigued and fatigued state. A real-time version of the classifier was then implemented in JAVA using the real-time biosignal analysis library and integrated into an Android demonstrator [18]. The mobile sensor framework enabled the demonstrator to use either live data from a Shimmer sensor node or pre-recorded EMG signals for evaluation. The final application performed a Wavelet transformation of the incoming signal, displayed the result on the screen and classified the pattern into fatigued or non-fatigued state using the previously trained classifier.

*3) Results*

Both the transformation and the fatigue classification were able to run faster than real-time on all tested devices. The classifier on the mobile device achieved the same classification rate of up to 94.4 % when using the same data as in the previous analysis performed on a PC in in [9]. Table I shows detailed results of the runtime evaluation of the Wavelet transformation. The additional runtime of the classifier was negligible. Table II shows a detailed analysis of the classification rates.

TABLE I. RUNTIME OF THE MOBILE WAVELET ANALYSIS

| **Device (CPU cores)** | **1000 Hz** | **500 Hz** |
|---|---|---|
| Samsung Galaxy Ace (1) | 157 ms/s | 57 ms/s |
| Samsung Galaxy Tab 10.1 (2) | 6.9 ms/s | 0.6 ms/s |
| Asus Transformer Prime (4) | 7.5 ms/s | 0.6 ms/s |

**(Results are shown in ms runtime per second of raw signal)**

TABLE II. CLASSIFICATION OF NON-FATIGUED VS FATIGUED

| **Value / Muscle** | **TA** | **GM** | **VL** | **ST** |
|---|---|---|---|---|
| Total patterns | 225 | 266 | 248 | 166 |
| Non-Fatigued patterns | 126 | 154 | 148 | 110 |
| Fatigued patterns | 99 | 112 | 100 | 56 |
| **Avg. classification** | 89.2 % | 88.3 % | 84.6 % | 94.0 % |
| **Max. classification** | 93.3 % | 91.4 % | 89.9 % | 94.4 % |

## *B. Classification of Parkinson's Disease*

*1) Motivation*

Diagnosis and severity staging of Parkinson's Disease (PD) is usually performed by subjective clinical examination of major motor symptoms [20]. However, these examinations are rater dependent and focus only on the symptoms and ignore their neuromuscular cause. As previous studies have shown, Parkinson can cause specific changes in myoelectric activation during gait that can be resolved using surface EMG [5]. Using data collected in this study [5] and our analysis library, we created an analysis pipeline to classify the EMG signals.

*2) Methods*

While data collection is ongoing, the data of 10 subjects have been used for this analysis. This included 5 subjects with Parkinson's Disease and 5 healthy controls. All subjects performed a 10 meter walk exercise, while EMG data of the tibialis anterior (TA), gastrocnemius medialis (GM) and gastrocnemius lateralis (GL) was collected. Data was automatically split in single steps using data from an additional three-axis accelerometer mounted on each heel. For each step a period of ±300 ms around heel strike was segmented. The analysis library was used to compute various statistical features (variance, skewness, kurtosis, RMS energy) and frequency features (dominant frequency, mean frequency, median frequency, total power). Additionally each step was transformed using the Wavelet transformation and an average step pattern was computed for each subject. All features and the Wavelet pattern were then used to train a Support Vector Machine classifier to distinguish between PD and healthy controls. Finally a real-time version of the trained classifier was implemented in the Android demonstrator.

*3) Results*

Table III shows the result from the classification experiments. Results of the real-time Android version were identical to the PC version when tested on the same data. As has been shown before in [5], Kurtosis of the TA was the best feature with a significant difference (p=0.013), see Figure 3.

TABLE III. CLASSIFICATION RESULTS FOR PD VS. CONTROL

| **Muscle** | **Sensitivity** | **Specificity** | **Best Feature** |
|---|---|---|---|
| TA | 1.0 | 0.8 | Kurtosis |
| GM | 0.8 | 0.8 | Mean Freq. |
| GL | 1.0 | 0.8 | Mean Freq. |

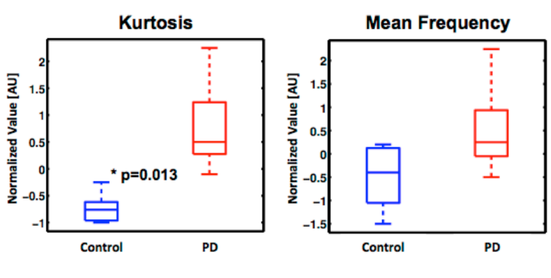


Figure 3. The best features when classifying PD vs control. The difference in Kurtosis was significant (p=0.013).

## IV. CONCLUSION AND OUTLOOK

In this paper we presented a mobile analysis framework for real-time EMG analysis. We presented an analysis library for biosignals and showed how it can be combined with our mobile sensor framework to create an Android demonstrator. Additionally we presented two example applications. The first, a real-time classification of fatigue during running, showed how the library can be used to create real-time feedback. Combined with previous approaches for fatigue classification [23, 24] and special mobile devices [25] this could lead to powerful fatigue detectors. The second example showed that the framework can also be used in the classical analysis of EMG data from Parkinson patients. Combined with results using motion sensors [21, 22] this could improve diagnosis and disease staging.

In the future powerful devices and analysis algorithms will allow mobile recording and analysis of the surface EMG signal in a variety of everyday situations. This will lead to the use of the EMG signal as an input device as in [25], allow feedback training applications or enable systems that can provide early detection of neuromuscular diseases in a home environment.

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