Real Time Monitoring using sEMG

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Abstract: A Wearable Electromyography device includes the advantage of Electromyography (EMG) sensors and provides a wired or wireless human machine interface (HMI) for interacting with computing systems and attached devices associated with electrical signals generated by specific movement of the patient’s muscles. Following initial automated self-calibration and positional localization processes, measurement and interpretation of muscle generated electrical signals is accomplished by sampling signals from the EMG sensors of the Wearable Electromyography Device. Initially, the Wearable Electromyography Device is donned by the user and placed into a coarsely approximate position on the surface of the patient’s skin.

Keyword: Wearable device, sEMG, Pattern Classification, sensors, patient monitoring system

I. History

In recent years, hand gesture recognition has become a very active research theme because of its potential use in human-computer interaction (HCI). Identification of hand gesture has numerous human computer interface (HCI) applications related to controlling machines and computers. Some of the commonly employed modalities include vision based systems, mechanical sensors, and the use of electromyogram, an indicator of muscle activity. Surface Electromyography has an advantage of being easy to record, and is non-invasive. Surface Electromyogram (SEMG) is a result of the spatial and temporal integration of the motor unit action potential (MUAP) originating from different motor units. It can be recorded noninvasively and used for dynamic measurement of muscular function. It is typically the only in vivo functional examination of muscle activity used in the clinical environment. The analysis of EMG can be broadly categorized into two:

• Gross and global parameters.
• Decomposition of EMG into MUAP.

Hand movement is a result of complex combination of multiple muscles. While previous research have reported success in the use of multiple channels SEMG recording for the purpose, but the system is sensitive to the location of the electrodes and suitable for five discrete movements only. The cross-talk that exists due to multiple overlapping muscles in the forearm makes the system sensitive to the inter-subject variability and this problem is more significant when the muscle activation is relatively weak. To identify the movement and gesture of the hand more precisely, it is important to identify the muscle activity of each of the muscles responsible for the action. Similarity in the spectrum and other properties of the activity from the different muscles makes the separation of these difficult. There is a need to separate the muscle activity originating from different muscles. With little or no prior information of the muscle activity from the different muscles, this is a blind source separation (BSS) task.

II. Related Work

Nowadays many different types of biosignals, such as skin conductance or electrocardiogram, can be measured with many differing procedures. Depending on the respective signal, these biosignals are utilized in industrial applications, such as medicine or entertainment. Some biosignals have also been shown to be suited for the creation of a new communication interface between humans and computers. In this area the use of biosignals offers brand new possibilities when compared to the conventional, mostly audio-visualy based human-computer interfaces. Thus, with the help of biosignals, it is today possible to detect emotions, make music or develop smart clothes. The famous polygraph is also based on biosignals.

Many biosignals based interfaces are used for controlling and communication. For disabled people especially, they offer the possibility of making their lives easier. There have been some promising attempts for the development of a new generation of biosignal controlled prostheses [8], which are much more user-friendly and more easily accepted than customary prostheses. Even people with severe disabilities and whose normal communication channels do not work anymore may receive help by the creation of a new communication interface based on biosignals. This is one major aim of brain computer interface (BCI) research, where communication can take place simply by measuring thoughts. Besides BCIs, which mainly use electroencephalographic signal (EEG), the most important biosignal for controlling interfaces have become the signals received from the EMG. This is due in great part to the fact that most bioelectric signals, such as the EMG or EEG, can be recorded in a comparatively simple and inexpensive manner thanks to the use of electrodes.
As it is usually possible to receive the bioelectric signals free of pain by placing the electrodes on the surface of the skin, user acceptance compared to other biosignal measurement methods is also proportionally high.

The EMG signal represents the natural electrical activity of the human body, which is used to control the skeletal muscles. Nowadays it is possible to control, in addition to the aforementioned prostheses, robots, mobile phones and MP3 players with the help of EMG signals. These systems are usually based on the performance of several gestures which are recognized through their EMG signal and in this vein trigger specific actions. The type of gesture depends on the number and the positioning of the measuring sensors and varies from nearly motionless arm gestures, to hand gestures and movements of single fingers, for example for virtual typing.

In 1999, NASA also successfully developed an EMG based controlling interface: It simulates the landing of an aircraft which is solely controlled by gestures resulting from the navigation of a virtual joystick. In this work an EMG based real-time controlling interface was developed to navigate an RC car with the help of four different hand gestures only. Contrary to other existing gesture based controlling interfaces which often require many different EMG channels placed on multiple muscles to be able to distinguish the different gestures, there is only one single EMG channel used in the present case.

III. Methodology

The real-time scheme of SEMG pattern recognition system used in this work is shown in figure1. The four major components are sensing, pre-processing, feature extraction and classification. The EMG signal of the performing arm muscles is detected by electrodes connected to a sensor.

In order to qualify the incoming raw signal for further processing the signal is pre-processed first. The goal of pre-processing step is to prepare and amplify the signal for the subsequent steps and reduce noise artifacts. The features were extracted from the SEMG signal and the incoming patterns, which represent gesture movements, are matched by using the minimum distance classifier technique.

IV. Extraction of MUAPs

We used AtlasSense platform technologies sensor which enables to record EMG signals of up to 1600μV in an active range of 20 to 500Hz. For the recording the EMG signal, four pair of pregelled Ag/Agcl electrodes was fixed on the skin of the subject. One pair of electrodes are connected to observe muscles, mainly the flexor Carpi radialis and the Palmaris longus, both of which are responsible for wrist movements, as well as the flexor digitorm superficialis, which is used for finger movements.

All the electrodes are situated in a line in the middle of the forearm parallel to the length of the forearm muscle fibers. By placing the first electrode near the wrist, it is possible to examine the muscles of the forearm between their tendon insertions and their motor points, which seems to be the best location for constant measurements. MUAPS using wavelets EMG signal is time series data. Therefore, it is not easy to infer operator’s intention of motions from raw EMG signal; electrodes placed on a muscle, measure a superposition of single Motor Unit Action potentials (MUAPs), artifacts and background noise. Basic shapes of surface MUAPs can be represented by only a few wavelet functions. The clinically interesting features of the EMG signal are the number of active motor units and the MUAP waveform. Quantitative analysis in clinical electromyography (EMG) is very desirable; with
the development of computer aided EMG equipment different methodologies in the time domain and frequency domain have been followed for quantitative analysis. Wavelet transform provides two dimensional time-frequency representation. Wavelet transform has the ability to localize in the statistics of nonstationary signals and it provides an alternative to short-time Fourier Transform (STFT) which uses a single analysis window. The wavelet transform uses short window at high frequency and long window at low frequencies. In the case of db4, WT coefficients at the highest-frequency scales provide high time-resolution of only four signal samples. This allows the db4 wavelet to effectively track the MUAP main spike transient signal at a time resolution that the STFT simply can’t match [4]. In our work we have used db4 for four levels to decompose the signals.

V. Feature extraction

To be able to classify a performed gesture some distinctive features have to be found and taken from each matched pattern. Therefore several features were extracted, including common statistical feature like RMS, Entropy and Standard Deviation.

VI. Experimental setting

We conducted a more comprehensive experiment with a total of 16 subjects. First of all, we collected personal information about the subjects, including age (average 21 year’s) gender (08 females and 08 males), weight (Average: 50.44Kg) and performing hand (16 right hands, nil left hander). The experiment consisted of two phases. ten subjects participated in the first phase and for each subject, we recorded six Finger gestures of hand position and total 60 gesture are taken from each gesture we have taken three feature values which was averaged and finally the average of 10 subject’s feature were taken as a standard samples. The remaining 06 subjects with 6 gestures of finger of right hand were taken as test samples.

VII. Results

Using this wearable device delivers smart biomedical monitoring instrumentation technology solutions that integrate several benefits. Using this multiple outputs can be show in a single platform. Using the above setup, we can measure Activity, Biological impedance, Blood pressure pulse wave,
VIII. Conclusions

We have described a system, able to measure various parameters. This enabling technologies were surface sensors used to measure the EMG signals, signal processing used to transform the signals in to feature sets, and pattern classifier to provide sufficient robustness for the non linear and non stationary nature of the underlying signal data. The significant challenges were to apply this classification for HCI for the beneficial of human beings, improve the classification by applying multilevel neural networks.

References


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