Low-cost Assistive Device for Hand Gesture Recognition using sEMG

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ABSTRACT

In this paper a low-cost solution for surface EMG (sEMG) signal retrieval is presented. The principal goal is to enable reading the temporal parameters of muscles activity by a computer device, with its further processing. Paper integrates design and deployment of surface electrodes and amplifier following the prior researches. Bearing in mind the goal of creating low-cost solution, the Arduino micro-controller was utilized for analog-to-digital conversion and communication. The software part of the system employs support vector machine (SVM) to classify the EMG signal, as acquired from sensors. Accuracy of the proposed solution achieves over 90 percent for six hand movements. Proposed solution is to be tested as an assistive device for several cases, involving people with motor disabilities and amputees.

Keywords: Arduino; EMG; feature extraction; movement classification; Support Vector Machine

1. INTRODUCTION

Electromyography (EMG) is method used to measure electrical activity of muscles. Generally, two types of electrodes may be used. The first are the needle electrodes, these are used only by qualified professionals, usually solely for medical purposes. Second type, surface electrodes can be used by much wider range of users for they do not disrupt the surface of the skin. Measurement using second type is referred to as surface electromyography (sEMG).

sEMG method is now generally employed as a solution for controlling the prostheses of amputees. Furthermore it can be utilized by common users, e.g. as an alternative for controlling computer machine. Movement recognition using sEMG is a complex process, which can be broken down into several tasks. The device first needs to acquire signal - this involves proper placement of electrodes directly on the surface of the skin. The extracted signal is then processed by the amplifier. Once it has been amplified the filter is deployed to cut the noise frequencies. The next step is digitalization process, which converts analogue signal to a stream of samples, data in this form are suitable for further processing, i.e. signal processing. This phase includes segmentation, feature extraction and classification. The output of this process is a recognized movement. For the developer, the principal requirement for such device is the capability to recognize several movements with suitable accuracy.

2. EMG SIGNAL ACQUISITION

EMG is rather weak biosignal. According to [1] the range of the input signal voltage is from 10 μV to 1 mV and the frequency varies from 5 Hz to 1000 Hz, while the main frequency range is 10 Hz to 200 Hz. Extraction of sEMG signal is achieved using hardware device consisting of electrodes and amplifier with filter. Project SENIAM [2] published list of recommendations for successful EMG signal acquisition, the following list contains those with the largest significance:

- width of electrode in the direction of muscle fiber should not be greater than 10 mm,
- inter-electrode distance should be 20 mm and should remain constant during measurement,
- skin should be cleansed with alcohol,
- electrodes should be oriented in parallel to muscle fibers.

Bearing in mind just presented recommendations, the electrode concept is following the design introduced in [3], where set of stainless steel electrodes are attached to a plastic plate, resulting in the fixed inter-electrode distance. The reference

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electrode is located between by the active ones, more specifically in the midpoint. Illustration of the electrode with the exact dimensions is shown in Fig. 1.

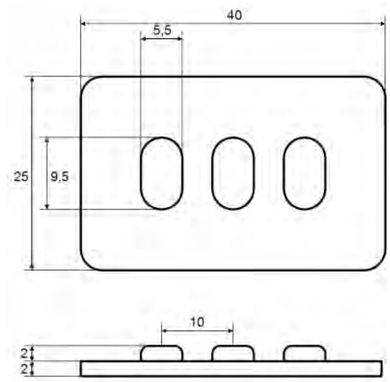

Figure 1. sEMG electrode dimensions.

Another crucial hardware component is the amplifier with filter. According to Day [4], well suited for our task is instrumentation amplifier. Important properties of this type of amplifier include high common mode rejection ratio and high input impedance. The output of amplifier is connected to band-pass filter. The primary function of this filter is to reject very low and very high frequency components of the signal, while the center frequencies should pass. Circuit used in this project is resulting from the design originally proposed by [5] and [6]. This hardware component consist of instrumentation amplifier connected to multiple feedback band-pass filter and uses MC33204P integrated circuit, which is composed of four operational amplifiers. Advantage of this circuit lies in the possibility of its operability, together with Arduino microcontroller. The distance between electrodes and the amplifier should be as short as possible, to achieve this the sensor is built as one integrated component. Electrodes are directly attached to the amplifier. Sensors include electrodes that are attached by pins to the amplifier board, consequently more types of electrodes may be used, while distance between source of signal and amplifier will remain short. Photograph of the proposed sensor is shown in Fig. 2. The electrode is detachable, allowing utilization of multiple sensor types, providing the pin layout is the same.

Digitalization of measured data is accomplished by Arduino, where all sensors are connected to its analogue pins. Once signal is extracted, measured values are stored in buffer. When it becomes full, the values from all the channels are sent out to computer device via serial line. Note that Arduino uses USB connection to emulate serial port. Buffering was introduced to improve the performance of the system. According to Nyquist criterion, EMG signal has to be sampled at minimal frequency 1000 Hz [7]. Arduino A/D has only one A/D converter, which is multiplexted for all analog pins. Each conversion is time demanding, hence for higher sampling rate the resolution has to be lowered. However, 1000 Hz sampling rate for 3 channels can be also achieved while not requiring change of the resolution.

Figure 2. Assembled sEMG sensor for hand attachment.

3. SIGNAL PROCESSING METHOD

Prior to further processing, the acquired signal must be segmented. According to Evaluation of EMG processing techniques using Information Theory [8], segment should not be too long (above 300 ms) nor too short, since they could cause poor classifier performance. Optimal length for temporal features is from 100 ms to 300 ms.

Having a raw signal as an input for the classifier would be inefficient. Thus, the next phase of signal processing is the feature extraction, which maps the signal samples to some value or vector. The feature should contain enough information about the signal and yet it should be simple for the fast classification. According to [9], three types of features are used: time, time-frequency and frequency. Frequency domain features are based on methods such as Fourier or wavelet transform. They extract very useful information about the signal, however require extended period for computation when compared to time domain features. Hence time features are more acceptable for the real-time applications due to significantly lower computational overhead.

Four features were selected, which represents different types - some are influenced more by amplitude, some by frequency or both, all of them are the time features. The first, mean absolute value (MAV) is an average of absolute values of samples over some time [10]. Next, the root mean square (RMS) is the effective value of periodic signal or energy of signal. In continuous signal it is integral of function. In sampled discrete signal, it is computed as sum of square roots of samples [10]. In the paper [9] focused on utilization of sEMG for facial expressions recognition were the best results achieved using with this feature. Another feature, the waveform length (WL) contains the information about amplitude and frequency properties in a single value [10]. It may be expressed as signal waveform stretched to straight line, where the length of that line would be a feature value. The last, zero crossings (ZC) value is influenced by frequency properties of the signal. It counts the number of times signal crosses a zero [10].

The next phase is a signal classification. This comprises of introducing a boundary between data sets belonging to the other classes. In this project the Support Vector Machine (SVM) classifier is utilized. This classifier was invented by V. Vapnik [11], and became one of the most used classifiers in bioinformatics. SVM estimates this hyperplane to maximize the margin between different classes. The earliest variant of Support Vector Machine used linear classifier, for that reason it could divide only linearly separable classes. To overcome this disadvantage a kernel trick, which maps a features to another space, where they can be separated, was introduced.

In order to enhance the performance of SVM, certain pre-processing of features is required. According to [12], scaling the features can dramatically affect the success of classifier - SVM is based on computing the distance between various points in space, if the range of one feature is much larger than the others, other features can be suppressed. In order to prevent this, it is good practice to scale all the features to range 0 - 1.

Utilization of grid-search algorithm and cross-validation for finding the best parameters to train the classifier is another valuable recommendation as suggested by [12]. Different values of C and γ are tested and success rate is computed by 10-fold cross-validation. This implies that the training set is divided to ten parts. Nine parts are used during the training itself and tenth is used to test the model. This procedure is repeated for all this parts. Parameter values that achieve the best results are used to train the classifier on the whole training set. Trained SVM should have a good generalization ability.

4. APPLICATION FOR SEMG PROCESSING

The most important portion of sEMG processing is carried out by software application. The following requirements were considered when designing the software for sEMG classification: receiving the digitalized signal from Arduino microcontroller, real-time signal plotting, feature extraction, classifier training and hand movement classification.

Software part of the solution is implemented using Qt framework, which allows communication between threads using signal and slots mechanism. This is considered to be easy and thread-safe choice. For classification, the libsvm [13] is used. Library implements whole SVM life-cycle, including training, predicting and cross-validation of the model.

4.1 Signal processor types

Two types of signal processor are used, i.e. trainer and classifier. Trainer handles SVM training, extracts features from the signal and stores them together with specific label for movement number. Movement number is the input from user, thereafter the user may trigger the training. Before training, all stored features are pre-processed.

Grid-search of the best parameters with 10-fold cross-validation is used for finding the best classifier, as kernel is used the Radial Basis Function (RBF). The result of successful training is the classifier, to permit correct operation the same options as were used for training are to be used. These options consist of number of channels, features used and scaling factors for all the features. As soon as the classifier is set up, it receives signal samples, performs feature extraction and scaling, and finally uses SVM to get the specific class of the motion. Results are then displayed to the user.

4.2 Running modes

Final application allows three modes, according to signal processor used, these are:

- Test - this mode is used to check the correct electrode placements and signal acquisition. Note that no signal processing is performed.
- Training - mode uses Trainer as signal processor. It is used to train the classifier.
- Classification - this mode utilizes Classifier as signal processor, performs hand movement classification using SVM and displays the result to the user.

The application is shown in Fig. 3. The major part are signal plotting widgets. In the training and classification mode, these widgets display feature values and are placed in the left part of the window. Movement class is set by spinner in Training mode, the very same spinner is used for displaying classification result in the classification mode.

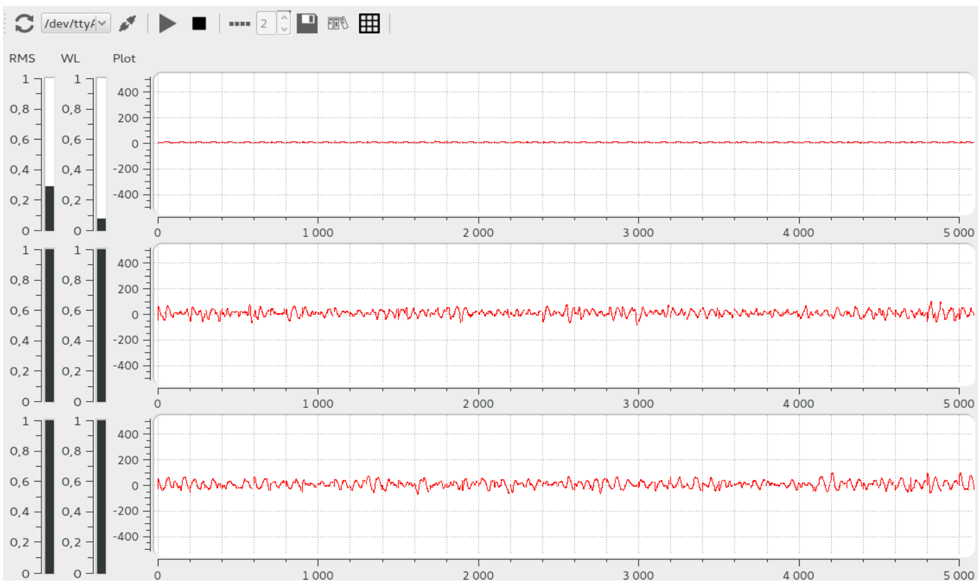

Figure 3. Application main window.

5. RESULTS

Experimental evaluation was carried out on the sample of ten persons. Classifier was trained using one feature per time, as supported by application. Prior to electrode placement the skin was cleansed and treated with electrode gel. Sensors placement is depicted in Fig. 4 on muscles - flexor carpi ulnaris, extensor carpi ulnaris, palmaris longus.

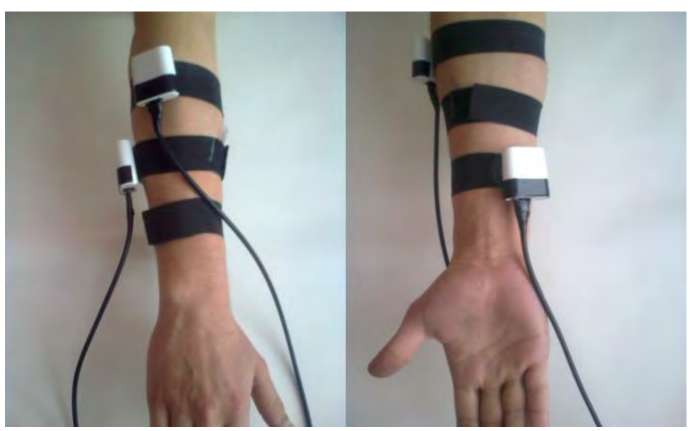

Figure 4. Electrode placement during tests.

Subsequently the training procedure begun, where for each movement were recorded from 5 to 6 seconds of data, these served as an input for the training of the classifier. Grid search with 10-fold cross-validation algorithm was used to find best learning parameters for Support Vector Machine. Validation success rates are shown in Table 1. Training data from three channels is shown in three dimensional space in order to provide better concept of features performance.

Cross-validation is good way to estimate the performance of the classifier. Yet, the real performance may differ and therefore all the classifiers were tested after training procedure. This was done with aim to interpret the real performance. Testing subjects performed all the movements and classification results were recorded and compared with the real movement data. Further the results for all the test subjects were averaged and average classification success rate for all the features was computed. The results are displayed in Table 1. Motions numbers 1 to 6 correspond to numbers depicted in Fig. 5.

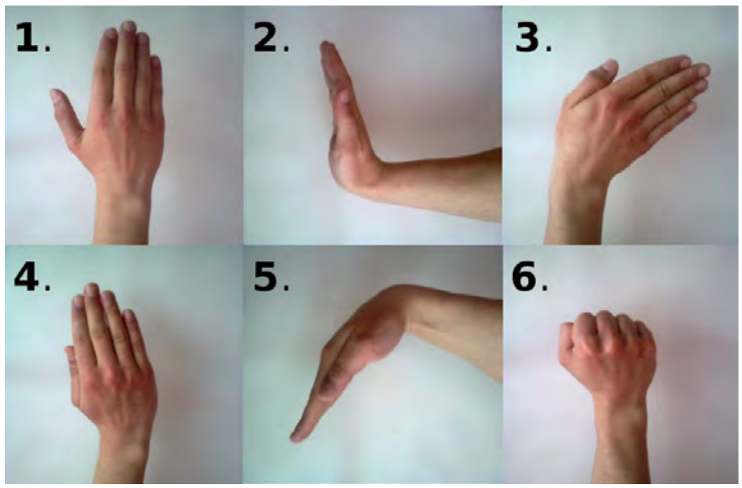

Figure 5. Detected movements [1. neutral position (NePos), 2. wrist extension (WrExt), 3. wrist adduction (WrAbdR), 4. wrist abduction (WrAbdL), 5. wrist flexion (WrFlx), 6. fingers flexion (FiFlx)].

Table 1. Features success rate.

Motion/Feature	**MAV**	**RMS**	**WL**	**ZC**	**ALL**
NePos	95.00 %	95.24 %	100.00 %	92.96 %	98.25 %
WrExt	80.51 %	86.67 %	93.25 %	87.14 %	95.00 %
WrAbdR	75.24 %	57.00 %	91.09 %	63.64 %	76.22 %
WrAbdL	92.95 %	87.30 %	95.24 %	53.79 %	95.83 %
WrFlx	68.85 %	85.22 %	93.46 %	50.46 %	91.67 %
FiFlx	74.40 %	84.39 %	71.97 %	61.01 %	90.03 %
Average	81.16 %	82.64 %	90.83 %	68.17 %	91.17 %
Cross-validation	91.43 %	94.29 %	96.99 %	78.69 %	95.32 %

Considerably favorable results were achieved using MAV feature. Training set is displayed in Fig. 6. Different movements created distinctive point clusters. Classification errors occurred once feature points were too close or were overlapping. RMS feature, displayed on Fig. 7, achieved similar classification performance as MAV feature. RMS has similar nature as MAV, this results in analogous errors in classification. Nevertheless, it may be concluded that this feature provides slightly enhanced performance when compared to MAV. WL feature was the best in the cross-validation success rate. As the Fig. 8 shows, the values for different movements undoubtedly created separated point clusters - classifier is able to separate these. Based on testing it was apparent that feature is sensitive to signal changes. A small change in signal resulted in the big change of a feature value. Feature was sensitive to both, amplitude and frequency changes.

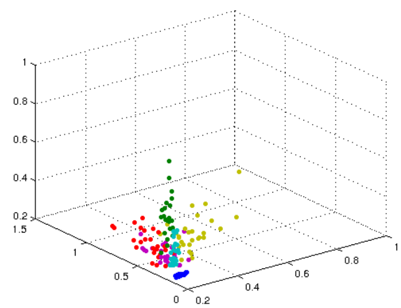

Figure 6. MAV training set.

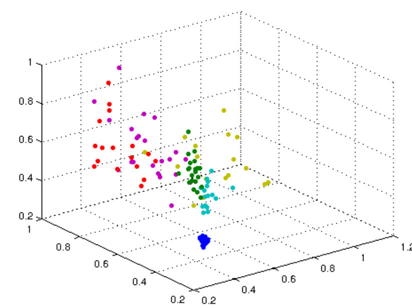

Figure 7. RMS training set.

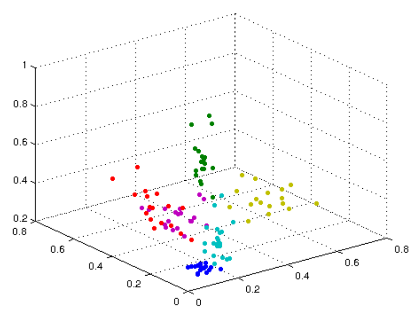

Figure 8. WL training set.

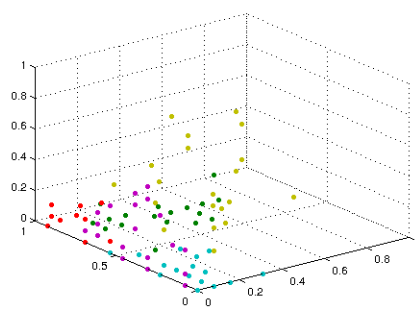

Figure 9. ZC training set.

The worst of success rate was achieved by classifier which used ZC feature, this is apparent also from Fig. 9. Notice that groups of feature points for specific movements are overlapping. Poor performance might have two causes - since the feature value is affected by the frequency properties of the signal, it may be possible, that the different movements do not have sufficient frequency properties for classifier to be able to distinct them. Second possible cause is that frequency properties are distinctive enough and sensor just cannot detect them or it filters them out.

The last features used was a vector consisting of all supported features. This feature achieved very promising success rate during cross-validation, however did not outperformed WL feature. When considering the real performance it was still the best of all alternatives. One of the test subjects achieved classification success rate of 97%. Difference between success rate computed during cross-validation and real performance was the lowest when compared to other features. For this reason this feature is assumed to be the most appropriate for the real usage. We propose a possibility of one feature not being able to distinct two motions, yet still achieving significantly better performance when combined with others. This deficiency in performance eliminated by utilizing another feature from vector, note that such feature by itself does not need to achieve 100% success rate. Features can complement each other during classification, although the very high count of extracted features may cause performance issues. When four features were used, no visible degradation of performance was observed, hence some of the features are redundant and can be removed from the extraction.

6. DISCUSSION

Despite the fact that designed system cannot be used for purely medical purposes, nor it was aimed to, it could be used as alternative interface between human and machine. Manufacturing costs of proposed solution require minimal financial input. Despite the simple electrode and amplifier design, the system is able to recognize six classes of hand movements. In the future, EMG acquisition system could be improved in terms of ease of use. Sensors should be miniaturized and placed in a sleeve-like device, which will make the proper placement less difficult.

7. ACKNOWLEDGEMENT

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