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# A STUDY ON THE EFFECTS OF ELECTRODE PLACEMENT ON THE PERFORMANCE OF EMG CLASSIFICATION OF HAND AND WRIST MOVEMENTS

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**Abstract:** Surface Electromyographic signals have been used to control robotic prosthesis by means of carefully designed patter recognition algorithms. There are several challenges yet to be solved considering this field, such as the classifiers' dependency on the correct positioning of the electrodes, since even small displacements of those could cause great differences on the sampled signal. This is highly pertinent considering the difficulty of repeating the same position of an electrode at every fitting of prosthesis socket. In this paper, we investigate those effects in the performance of a well-established classifier and possible strategies to train it to account for drastic changes in the position of the EMG electrodes. For that, three Support Vector Machine (SVM) classifiers were trained with data collected from the upper-forearm, while volunteers performed four hand and wrist movements with a set of four active EMG electrodes positioned around the arm evenly spaced. Each SMV was trained with data collected with the set of four electrodes placed at three different positions around the arm. Among the tested electrode positions, the performance of the SMVs were statistically similar among all three positions for three of the tested movements and among two of the positions for the remaining one.
**Keywords:** Electromyography, EMG Classification, Support Vector Machine, Electrode Placement.

## Introduction

A largely studied solution to help amputees perform their day-to-day activities is the use of robotic prosthesis driven by myoelectric signals, which are electric potentials generated by muscular activity. Electromyographic (EMG) signals are relatively easy to acquire, since they can be obtained through non-invasive methods with the use of surface electrodes, making them a good choice for a prosthesis control. The EMG signal is acquired from specific muscles, processed and classified to generate proper commands to the prosthetic device. However, the signal is highly dependent on the electrode position and its distance to the target muscle region. Since the electrodes are fixed to the socket of the prosthesis, their position relative to muscles of the stump, for instance, could shift over different fittings. Since the performance of traditional EMG pattern recognition systems is associated with the quality and reasonable stability of the data, it is likely that changes in the electrodes position will lead to poor performance.

Many studies have tried to address this issue using, for example, a larger number of electrodes or even a net of electrodes over the stump, with relative success [1, 2 and 3]. However, increasing the number of electrodes also increases the processing involved, and it has already been shown that the increase in the performance of an EMG classifier isn't significant after four electrodes [4]. Other way to tackle the problem would be using more robust classifiers that can withstand changes in the signal [1 and 5], or even training the classifier with the electrodes slightly shifted [2]. But none of these approaches were consolidated as satisfactory.

In this study, we intend to investigate the robustness of a Support Vector Machine (SVM) to withstand variations in the position of four pairs of electrodes over the stump and correctly classify EMG patterns.

## Materials and methods

For EMG signal acquisition, the electromyograph MyosystemBr1-P84 (DataHominis Tec Ltda) was used. Four active single differential EMG electrodes were used (gain 20x) and evenly spaced (90 degrees) around the upper-forearm. The reference electrode was positioned at the contralateral wrist. The signals were sampled at 2kHz and band filtered between 20 and 500Hz [4, 5 and 6]. An auxiliary channel was also used to acquire a synchronization signal (trigger), so that the exact moment that the volunteer was cued to perform each movement could be known.

In order to change the position of the electrodes while maintaining their distance between each other (90 degrees), we designed a bracelet made of an elastic fabric with four placing sites for the electrodes equidistant from each other. Given that the volunteers had different arm diameters, we made two bracelets with different sizes to ensure that the electrodes were well fixed but not too tight, as well as to avoid discomfort to the volunteers and maintain the quality of the signal. With this electrode bracelet, the different placement of the electrodes maintaining the distance between them could be easily done, as shown in Figure 1.

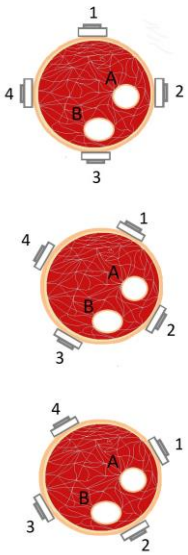



Figure 1: Representation of the transversal section of the right forearm showing the three positions tested in this work for the sets of electrodes 1 through 4 (mounted on a bracelet); where A is the Radius and B is the Ulna. Top: Bracelet position 1; Middle: Bracelet position 2; Bottom: Bracelet position 3.

Five healthy non-amputated volunteers aged 20 to 24 years participated in the study. The volunteers were instructed to perform four different movements: wrist pronation, wrist supination, hand closing and finger clipping, as illustrated in Figure 2. Each movement was performed 40 times in a random order, making a total of 160 movements. The volunteers had 3 seconds to perform the movement and then an interval of 5 seconds between each movement for resting. At each 40 movements, the volunteers also had 1 minute (or more) for resting and avoid fatigue. Each volunteer performed this paradigm three times, one for each position of the bracelet shown in Figure 1.

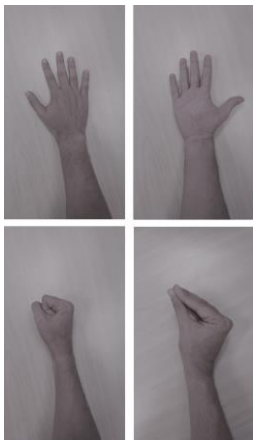


Figure 2: Movements performed by the volunteers: wrist pronation, wrist supination, hand closing and finger clipping.

In order to process the correct window, the data of each volunteer was pre-processed using a Hilbert filter of 4th order with a cut off frequency of 8Hz comparing the signal with a resting interval so the algorithm could differ the envelope signal of a movement and a resting interval. Since this procedure also detects the movement to return to resting position it was coupled with the cue signal to consider only movements detected within the interval of interest, as shown in Figure 3.

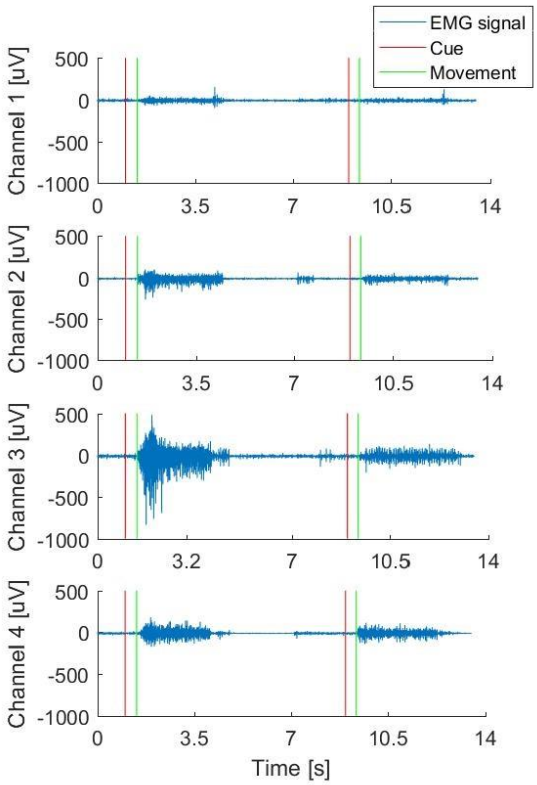



Figure 3: Four channels of EMG signal with cue moments and beginning of movements detected by our algorithm, for hand closing (signal at the left) and finger clipping (signal at the right).

With the contraction intervals correctly separated for each electrode channel, windows of the first 200ms of the movements were considered for signal processing. This window has been chosen to minimize the time response of the algorithm, reducing possible delays in a real life situation, such as the activation of a prosthetic device, as other studies have discussed [7]. From each window of each channel a set of five largely used features [7, 8] were extracted to be used as input for the classifying algorithm: Mean Absolute Value (MAV), Zero Crossing (ZC), Waveform Length (WL), Slope Sign Change (SSC) and Variance (VAR). These features were organized into a matrix nW x nC, nW being the number of windows (a total of 160 per bracelet position) and nC the number of features (5 for each of the four channels, 20 in total). An output vector (160 x 1) was also generated, having the correct movement assigned to each line of features in the input matrix.

Although other strategies such as Artificial Neural Networks or Linear Discriminant Analysis (LDA) could be used for the task of classifying our data, the authors

decided to use a Support Vector Machine (SVM) as the classifying algorithm since it is considered as a highly robust classifier and has shown good results in other studies [9].

Since SVM can only classify between two different classes and this study focused on four movements. an ensemble of SVMs with the one-versus-one code design was used. A 4-fold cross validation was applied to evaluate the robustness of the classifier for new input data.

The data was classified using a different SVM classifier for each electrode bracelet position and for each volunteer.

All calculations and manipulations used in the pre-processing and classifying steps were done using MATLAB. The whole experiment was approved by the *Universidade Federal de Uberlândia*'s Ethics Committee through the protocol number: 1.864.919.

**Results**

Table 1 shows the results of the 4-fold cross validation of the SVM classifiers for each subject and each bracelet position. An average of the performance of the classifiers in all three positions was also calculated to provide sense of general behaviour.

Table 1: Classification performance for each volunteer over the three bracelet positions and the average of three values.

| Volunteers | Pos 1 | Pos 2 | Pos 3 | Average |
|---|---|---|---|---|
| V1 | 0.8974 | 0.9342 | 0.8816 | 0.9044 |
| V2 | 0.9306 | 0.8162 | 0.8056 | 0.8508 |
| V3 | 0.7237 | 0.8397 | 0.7632 | 0.7755 |
| V4 | 0.6776 | 0.8125 | 0.9231 | 0.8044 |
| V5 | 0.7027 | 0.9145 | 0.6218 | 0.7463 |
| All | 0.7864 | 0.8634 | 0.7990 | 0.8163 |

In order to determine whether the classifications in each position are statistically equal, we gathered the performance results from all folds of every volunteer, a total of 20 different results, and applied a Kolmogorov-Smirnov test (given the size of the data groups, and their non-Gaussian distribution). We performed this test separately for each movement performed. Given that the null hypothesis of the Kolmogorov-Smirnov test implies that both data groups are the same, if the p value calculated by the test is less than 0.05 then the null hypothesis can be rejected with 95% of certainty, therefore, the groups are considered statistically different. The results presented in Table 2 are arranged comparing the three electrode bracelet positions (position 1 with 2, 1 with 3 and 2 with 3).

Table 2: Results of the Kolmogorov-Smirnov test (p value) for the paired performances of each fold for each movement and each bracelet position.

| Movements | 1 and 2 | 1 and 3 | 2 and 3 |
|---|---|---|---|
| Closing | 0.7710 | 0.0591 | 0.4973 |
| Clipping | 0.0232 | 0.7710 | 0.1349 |
| Pronation | 0.0591 | 0.1349 | 0.7710 |
| Supination | 0.7710 | 0.7710 | 0.7710 |

It is also worth analysing each volunteer separetely, since the amount of data for each volunteer separately is not enough for a statistical similarity test Tables 3 and 4 present the means and standard deviations for each bracelet position and each movement for volunteers 1 and 5 respectively.

Table 3: Means and standard deviations of the classification performances for each bracelet position and each movement for volunteer 1.

| Moves | Value | Pos 1 | Pos 2 | Pos 3 |
|---|---|---|---|---|
| Closing | Mean | 0.9500 | 1.0000 | 0.8139 |
| | Std | 0.0577 | 0.0000 | 0.1294 |
| Clipping | Mean | 0.8444 | 0.9472 | 0.9444 |
| | Std | 0.0648 | 0.0611 | 0.0642 |
| Pronation | Mean | 0.9222 | 0.8972 | 0.8639 |
| | Std | 0.0521 | 0.0818 | 0.1075 |
| Supination | Mean | 0.8722 | 0.8889 | 0.8972 |
| | Std | 0.1252 | 0.1571 | 0.1415 |

Table 4: Means and standard deviations of the classification performances for each bracelet position and each movement for volunteer 5.

| Moves | Value | Pos 1 | Pos 2 | Pos 3 |
|---|---|---|---|---|
| Closing | Mean | 0.8917 | 0.9722 | 0.6694 |
| | Std | 0.0909 | 0.0556 | 0.0862 |
| Clipping | Mean | 0.5944 | 0.8972 | 0.5889 |
| | Std | 0.0525 | 0.1415 | 0.0846 |
| Pronation | Mean | 0.5694 | 0.8972 | 0.6694 |
| | Std | 0.0699 | 0.0818 | 0.2465 |
| Supination | Mean | 0.7556 | 0.8972 | 0.5694 |
| | Std | 0.1089 | 0.0818 | 0.1982 |

**Discussion**

The last line of Table 1 shows that the average performance of the SVM classifiers across all volunteers for positions 1 and 3 were very similar, while position 2 has a better performance. But it's not safe to say that there is difference between positions once if each volunteer is separately analysed we notice that for volunteer 1 this difference between positions becomes smaller, moreover, this table shows the performance of all movements together instead of showing each separately. Therefore, the need for a statistical test.

Analysing Table 2 we can say with 95% confidence that the only pair of data groups that showed statistical difference were the groups for positions 1 and 2 for

finger Clipping. For all other movements, the data groups were considered statistically similar and shouldn't, therefore, have great classification difference given the electrode positioning. Still, it's possible to see that the confidence of similarity between groups is higher for Supination. This opens ground for a different discussion: whether all movements show this similarity. But there is a need for a greater data set to further this discussion.

We can also discuss from Table 1 that there is a great performance difference between volunteers, therefore it would be interesting to analyse the similarity of results for each volunteer separately. Through Table 3 we can see that indeed there is great similarity among the results for the Supination movement and the greatest differences are found between positions 2 and 3 for hand Closing and positions 1 and 2 for finger Clipping. We could infer that finger movements are more influenced by electrode positioning than wrist movements.

While these results were present in the individual analysis of each volunteer, volunteer 5 showed comparisons that would imply in a different conclusion, as shown in Table 4. A possible reason for these results would be an unnoticed error during the data acquisition. In order to clarify this question a bigger data set with more volunteers would be needed.

## Conclusion

Considering the classifiers's results we can see that the overall performances can still be improved, maybe by using different classifiers or by changing some settings of the used classifiers. Still, the performance from each electrode bracelet position were considered as statistically similar, given that the only considered statistical difference was between positions 1 and 2 for finger Clipping. Gathering the analysis from Tables 2 and 3 we could assume that the classifiers performance for finger movements is not highly dependent of electrode movements, though the performance for wrist movements is even less dependent.

There are still some points to be further analysed, such as the performance similarity for each individual volunteer. Therefore, we propose to continue this given study using a bigger data set with more volunteers, which would strengthen the reliability of the statistical analysis, and refining the classifying algorithm so that we might ensure a better overall performance, assuming that it will maintain the robustness in front of electrode placement. We also intend to apply this paradigm in real time to further verify its robustness.

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