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High-Accuracy Recognition of Muscle Activation Patterns Using a Hierarchical Classifier

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***Abstract*—Systems based on Surface Electromyography (sEMG) signals require some form of machine learning algorithm for recognition and classification of specific patterns of muscle activity. These algorithms vary in terms of the number of signals, feature selection, and the classification algorithm used. In our previous work, a technique for recognizing muscle patterns using a single sEMG signal, called Guided Underdetermined Source Signal Separation (GUSSS), was introduced. This technique relied on a very small number of features to achieve good classification accuracies for a small number of gestures. In this paper, an enhanced version called Hierarchical GUSSS (HiGUSSS) was developed to allow for the classification of a large number of hand gestures while preserving a high classification accuracy.**

I. Introduction

The ability to recognize Motor Unit Action Potential Trains (MUAPT) using electromyographic signals collected at the surface of the skin (sEMG) has been used in many applications, including sign language [1], human-computer interface [2], prosthetics [3], etc. [4], [5]. In most applications, an array of differential sEMG sensors is required to achieve acceptable accuracies [5]. However, there are many advantages to using a single sEMG sensor such as: freeing up muscles for use in other applications and interfaces; reducing hardware cost; aesthetics; patient comfort; etc. The major challenge of a single sensor approach is to achieve a high classification accuracy for a large number of muscle patterns and a small number of features. In the seminal work of [6], the authors achieved high accuracy, but for four gestures and using thirty features.

There are a variety of feature types that can be exploited for sEMG gesture classification. Some of these include: number of Zero Crossings, Mean Absolute Value, Slope Sign Changes [6], coefficients of Auto-regressive models [7], [8], Absolute Maximum/Minimum, Maximum minus Minimum, Median Value, Variance, Waveform Length, coefficients of the Short Time Fourier Transform, Wavelets Transform [9], [10], etc. These features can be extracted from either *time* or *time-frequency* domains [7], [8], [9] and be employed by classifiers based on Neural Networks, Support Vector Machines (SVMs), Hidden Markov Models (HMMs), and fuzzy logic controllers [1], [3], [6], [11]. More recently, instead of exploring additional features within the sEMG signals, systems are resorting to alternative sensors such as gyros, magnetometers, and accelerometers [4].

The method presented in this paper, HiGUSSS, is a hierarchical version of our previous Guided Under-determined Source Signal Separation, GUSSS. It also uses a single sEMG signal and a small number of features, but it achieves a higher classification accuracy for a higher number of gestures. The system was tested and compared to traditional classifiers – SVM and distance classifier – using up to nine different hand gestures.

II. Background and Related Work

The work in [13] introduced the idea of GUSSS and the GUSSS ratio. In [13], the focus was on discriminating different Muscle Unit Activation Potential Trains, or MUAPT patterns, that emerge when different gestures are performed. As many systems do, it was assumed that an sEMG sensor captures a combination of statistically independent MUAPTs due to cross talk [15], [14]. But unlike most methods in the literature, the system in [13] relied on a single sensor. This was possible because the main characteristic of the GUSSS ratio is that it can indicate the presence or absence of a particular signature or MUAPT pattern within a sensed sEMG signal. The term "Guided" in GUSSS refers to the fact that the sought-out signature is "injected" into the observed signal in order to obtain a corresponding ratio. A low ratio indicates that the signature is most likely present within the sensed signal. A high ratio, on the other hand, indicates that the signature is not being detected in the signal.

Later, a framework for controlling a power wheelchair using the GUSSS method was developed and tested in [16]. It proposed a control system based on the recognition of hand gestures. The use of hand gestures was simply to illustrate the fact that any muscle activation pattern or signature derived from a natural and repetitive muscle movement can be employed by the system. In the case of a person with severe impairment, any other muscle movement could be used instead (e.g. eyebrow movement). Compared to other systems found in the literature, which use multiple sEMG sources for classification, the method in [16] compared quite reasonably, reaching up to 92% accuracy for three gestures.

Nonetheless, the goal in sEMG-based systems is to achieve higher accuracies and to recognize many muscle patterns. As

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mentioned before, most systems reported so far rely on many sensors or additional peripherals to increase classification rates. The main purpose of this research is to improve the classification accuracy that has been obtained in the past, as well as to increase the number of muscle patterns that can be recognized, while still relying on a single sEMG signal.

Instead of increasing the number of sensors or using additional hardware, improvement of the sEMG systems can be achieved by using a larger number of features and more sophisticated classification algorithms. For instance, SVMs have been used by many researchers for classification of sEMG signals [11], [17], [18]. SVM is a general classification method that finds a high dimensional hyperplane that passes between two classes as far away as possible from all points or samples [19]. An extension to the traditional SVM can be used for multi-class data.

The method proposed here is hierarchical and GUSSS-based. Unlike the hierarchy in [12], which is used to recognize combined motions, here the hierarchy is employed to increase the discriminant power of the classifier.

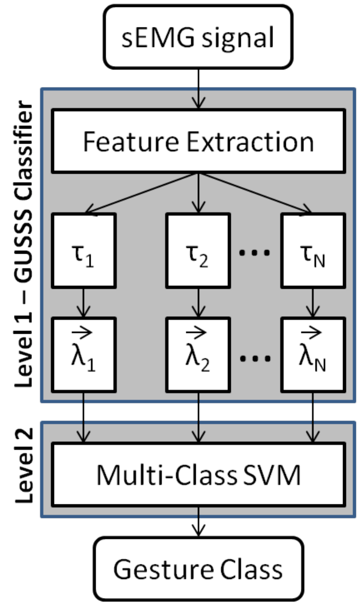

Figure 1. Proposed framework. There are two levels in the hierarchy. The first is a GUSSS-based classifier and confidence generator. The second level is a multi-class SVM classifier.

III. Proposed Method

This work enhances the original classification approach from [13] and [16]. A hierarchical classifier is implemented and additional features are extracted from the sEMG signals. The proposed framework for the method is illustrated in Figure 1 and consists of a two-level hierarchical classifier: 1) a GUSSS-based classifier; and 2) a Multi-Class SVM.

As it can be seen in Figure 1, the first level in the hierarchy involves a number of GUSSS-based classifiers. Basically, these classifiers function as confidence generators, inputing feature vectors extracted from the raw sEMG signal and outputting N confidence vectors $\vec{\lambda}$, where the elements of the vector indicate the confidence that a sEMG signal contains one of the signatures in the tuples – a tuple is a group with an arbitrary number of signatures: e.g. doubles, triples, etc. All of the obtained confidence vectors are concatenated into a second feature vector, which is then input to the classifier at the second level of the hierarchy. The output of the second level classifier is the final class assigned to the observed sEMG signal. The following sub-sections describe in further detail the classifiers at each level, as well as their training process.

A. Class Signatures and Optimal Choice of Tuples

Let us assume that there is a labeled training set with $C \times T$ signals – i.e. T signals from each of the C possible classes (muscle patterns or gestures). First, a signature for each class is obtained. The current approach is to do an averaging of the training signals grouped per class. That is, all T training signals belonging to the same class c are averaged creating a single signature: $s_c = \frac{1}{T}\left(\sum_{class\, c} x_l\right)$, where x_l is the l^{th} training signal of class c.

Each GUSSS-based classifier is associated to a tuple of classes, where the sizes and members can be chosen arbitrarily depending on the gestures, user, muscle activity patterns, etc. The rationale behind the tuples is the following: when a large number of C classes are considered at the same time, there might be much confusion between some of the classes. However, it is possible to find subsets of classes for which the confusion between such classes is minimized. So, the goal of the tuples is to allow similar classes to be separated. However, it is also desirable to group as many classes as possible per tuple in order to reduce the complexity of the algorithm. For this paper, the selection of the optimal number and the membership in the tuples was done empirically after trial-and-error. In the future, an automated method for choosing tuples will be explored.

B. sEMG Features and Level 1 Feature Vectors

As mentioned before, the input to each of the GUSSS-based classifiers is a feature vector extracted from the incoming sEMG signal. The features used and the way to obtain the feature vector for a particular tuple i, denoted τ_i, is described next. A similar procedure is followed for all N tuples being considered. Figure 2 depicts a typical sEMG signal and the features considered.

1) GUSSS ratio: As explained in Section II, the main idea of the GUSSS method is to identify particular signatures within a measured sEMG signal. For any given sEMG signal x, the GUSSS method seeks to identify the presence or not of each possible signature. This is done by iteratively injecting signatures and obtaining ratios for each one of them. For all $n_i = |\tau_i|$ classes in tuple τ_i, the algorithm obtains the ratios $r_1, \ldots, r_{n_i}$. If signal x contains a pattern in class c, ratio r_c is expected to be smaller than all other ratios r_j, for $j \neq c$.

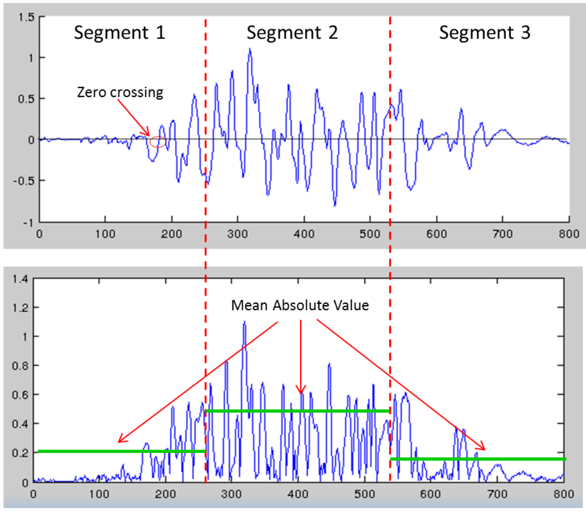

Figure 2. A typical sEMG signal segmented into 3 parts. The zero-crossings are indicated in the top figure. The rectified signal and the MAVs of the segments are shown in the bottom figure.

2) Segmentation of the sEMG Signals: Typically, an sEMG signal from a gesture lasts for around 250 ms to 500 ms. To capture the structural information of the sEMG signals, we divide them into D segments of equal length. The features described next are calculated for each segment of any given signal.

3) Mean Absolute Value: One features commonly used for sEMG signals is the Mean Absolute Value (MAV). The MAV of a signal $x(t)$ is obtained by calculating the average of the absolute values of x at all instants t. If the signal is discrete, then

$$MAV = \frac{1}{K}\sum_{k=1}^{K} |x(k)| \qquad (1)$$

where K is the number of samples that constitute a segment of x.

4) Zero Crossing: Another feature extracted from the sEMG signals is the number of Zero Crossings (ZC), which represents how many transitions from positive to negative (or vice-versa) there are in a segment of a signal.

5) Complete Feature Vector Level 1: After all of the features described above have been extracted, signal x is represented by the following feature vector:

$$\vec{v}_i = [r_1, \cdots, r_{n_i}, m_1, \cdots, m_D, z_1, \cdots, z_D] \qquad (2)$$

where $r_1, \ldots, r_{n_i}$ are the GUSSS ratios for each class in tuple τ_i. The MAVs and ZCs for each segment of the signal are m_k and z_k, respectively, for $k = 1, \ldots, D$.

6) Statistics of the Gesture Classes: As it will be shown shortly, the system uses the mean vector and covariance matrix of each class within the tuples. So, the above feature vectors are extracted for all T training signals in each class and are used to form $\aleph\left(\vec{\mu}_j^i, \sum_j^i\right)$, representing the distribution of class j in the tuple τ_i, where $j = 1, \ldots, n_i$, and $i = 1, \ldots, N$.

C. Distance and Confidence Values

As it was mentioned before, the output of the first level in the hierarchy is a set of confidences that are concatenated to form a second feature vector. The confidences, which are based on Mahalanobis distances, are obtained from each one of the GUSSS-based classifiers.

An input signal y is fed into each one of the optimal tuples described above. For each tuple τ_i, a feature vector $\vec{v}_i$ (eq. 2) is calculated. Then, the GUSSS-based classifiers calculate Mahalanobis distances to the mean vectors $\vec{\mu}_j^i$ of the classes in the tuple τ_i:

$$d_j^i = \sqrt{(\vec{v}_i - \vec{\mu}_j^i)\ \left(\sum_j^i\right)^{-1}\ (\vec{v}_i - \vec{\mu}_j^i)^T}\ ,\ j = 1, \ldots, n_i \qquad (3)$$

If, for example, distance d_j^i is small (close to zero), the confidence that signal y belongs to class j would be high.

To obtain the confidence values, the complementary error function is used: $erfc(x) = 1 - erf(x)$. For normal distributions, $erfc\left(\frac{d}{\sqrt{2}}\right)$, can be seen as the probability of a randomly selected sample to fall at a distance of d standard deviations or more from the mean. For instance, $erfc\left(\frac{0}{\sqrt{2}}\right) = 1$, $erfc\left(\frac{1}{\sqrt{2}}\right) = 0.3173$ and $erfc\left(\frac{2}{\sqrt{2}}\right) = 0.0455$. Numerically, these values are appropriate as confidence values for Mahalanobis distances of 0, 1 and 2, respectively. The confidence value function is defined as:

$$\lambda(d) = erfc\left(\frac{d}{\sqrt{2}}\right),\ d \geq 0 \qquad (4)$$

For the GUSSS-based classifier corresponding to tuple τ_i, the confidence that signal y belongs to class j is given by $\lambda_j^i = \lambda(d_j^i)$. In the end, the classifier produces n_i confidence values: $\vec{\lambda}^i = \left(\lambda_1^i, \ldots, \lambda_{n_i}^i\right)$.

Level 2 Feature Vector: After confidence values are obtained for all N tuples, the second feature vector is created as follows:

$$\vec{u} = \left[\vec{\lambda}^1, \vec{\lambda}^2, , \cdots, \vec{\lambda}^N\right] \qquad (5)$$

D. Level 2 Classifier: Multi-Class SVM

The final classification method consists of a multi-class SVM. To train the SVM, the $\vec{u}$ feature vectors are computed for all training signals, for all classes. When it comes to classification, an incoming signal y is fed through level 1 in the hierarchy to obtain the confidences and to create the $\vec{u}_y$ feature vector. The latter is fed to the multi-class SVM in order to generate the final class assignment.

IV. Experiments and Results

The goals of the experiments performed in this work were the following: 1) contrast with [16] for the same number of gestures (4) and with more gestures (5) – Section IV-B; 2) compare HiGUSSS with non-hierarchical methods – Section IV-C; and 3) investigate how the accuracy varies as the number of gestures increases – Section IV-D.

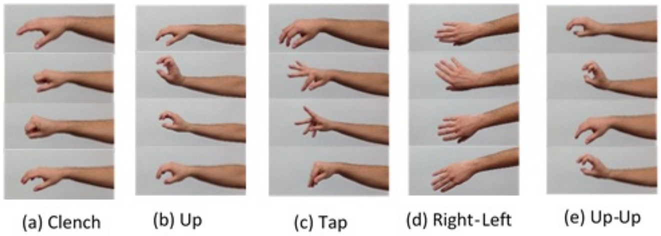

Figure 3. *Hand gestures considered: a) "clench", b) "up", c) "tap" (finger tapping), d) "right-left", and e) "up-up" (done quickly). The figure shows the transition from the resting position to the gesture and back to the resting position.*

A. Data Collection

Seven test subjects were asked to perform at least 100 repetitions of each of the five gestures shown in Figure 3. The sEMG signals of interest, i.e., the ones to be associated with each gesture, are those generated during the transition from a resting position to the actual hand gesture and back to the resting position. Each subject performed all gestures at the same level of effort and rested between gestures.

A single pair of sEMG electrodes was placed near the Extensor Carpi Radialis Longus muscle along the forearms of the human subjects to collect the performed gestures. A reference (ground) electrode was also placed on the wrist of the opposite arm of the subjects. The raw sEMG signals were amplified ($\times 2000$) and low-pass filtered (1 kHz) using a GRASS amplifier (model $15A54$) and sampled using a National Instruments (NI) digitizer at 4 kHz.

The signals were divided into 3 segments (i.e. $D = 3$), and the size of the tuples was set to 2 for all tuples (i.e. $n_i = 2$).

B. Results Using the Proposed Hierarchical Method

To contrast with the work in [13], [16], we first tested the HiGUSSS method with 4 gestures and later with 5 gestures. For each experiment, a 10-fold cross validation was performed. Each time 90% of the signals of all the gestures were used for training. The remaining 10% of the signals were then classified as described in Section III. Tables I a) – c) show the results using 4 gestures and Tables II a) – c) show the results using all 5 gestures. Due to space limitations, the results shown reflect the test subjects with the highest accuracy, with the lowest accuracy, and the average for all test subjects. The confusion matrices show the average percentages over the 10-fold tests. The average correct classification percentages are also presented on the bottom of each table.

Table I
HiGUSSS: Confusion matrices for 4 gestures. The values are average percentages over a 10-fold cross validation.

		Assigned gesture			
		clench	up	tap	up-up
True hand gest.	clench	94.0	0.0	0.0	6.0
	up	0.0	96.0	0.0	4.0
	tap	0.0	0.0	99.0	1.0
	up-up	2.0	5.0	0.0	93.0
Correct classification: 95.5%					

a) Best case

		Assigned gesture			
		clench	up	tap	up-up
True hand gest.	clench	91.0	9.0	0.0	0.0
	up	6.0	93.0	0.0	1.0
	tap	3.0	6.0	88.0	3.0
	up-up	0.0	5.0	1.0	94.0
Correct classification: 91.5%					

b) Worst case

		Assigned gesture			
		clench	up	tap	up-up
True hand gest.	clench	88.8	6.1	2.5	2.7
	up	4.4	94.1	0.4	1.1
	tap	2.5	1.5	94.5	1.5
	up-up	3.7	2.6	0.8	92.9
Correct classification: 92.6%					

c) Average over 7 subjects

Table II
HiGUSSS: Confusion matrices for 5 gestures. The values are average percentages over a 10-fold cross validation.

	Assigned gesture				
	clench	up	tap	up-up	rgt-lft
clench	94.5	0.9	0.0	0.0	4.5
up	2.7	96.4	0.9	0.0	0.0
tap	0.0	0.0	97.3	0.9	1.8
up-up	0.0	2.7	0.9	96.4	0.0
rgt-lft	3.6	0.9	1.8	0.9	92.7
Correct classification: 95.5%					

a) Best case

	Assigned gesture				
	clench	up	tap	up-up	rgt-lft
clench	88.0	12.0	0.0	0.0	0.0
up	5.0	89.0	0.0	1.0	5.0
tap	3.0	3.0	86.0	0.0	8.0
up-up	0.0	2.0	1.0	88.0	9.0
rgt-lft	1.0	8.0	6.0	3.0	82.0
Correct classification: 86.6%					

b) Worst case

	Assigned gesture				
	clench	up	tap	up-up	rgt-lft
clench	86.3	5.9	2.1	2.6	3.2
up	5.1	92.4	0.1	0.9	1.4
tap	3.6	0.6	93.4	0.6	1.8
up-up	3.4	1.7	0.8	91.2	2.9
rgt-lft	5.0	2.3	1.6	2.6	88.5
Correct classification: 90.4%					

c) Average over 7 subjects

C. Hierarchical Method vs. Non-Hierarchical Classifiers

The HiGUSSS was also compared to two approaches for the same features except for the confidences, since the two approaches used are non-hierarchical. So, instead of using a pairwise approach, features were extracted from the training signals for all classes simultaneously. In other words, the feature vectors are similar to the level 1 vectors described in Section III-B5, with GUSSS ratio values for all C classes – i.e. C gestures.

For the distance classifier, the classification was obtained by selecting the smallest Mahalanobis distance from the input signal's feature vector with respect to the means of the class distributions.

Table III
CLASSIFICATION ACCURACIES FOR 7 TEST SUBJECTS. THE VALUES ARE AVERAGE PERCENTAGES OVER A 10-FOLD CROSS VALIDATION (105 SIGNALS PER GESTURE).

	Distance Classifier	SVM	Hierarchical
Subject 1	93.5	94.0	95.5
Subject 2	96.8	95.5	95.2
Subject 3	86.8	86.3	91.5
Subject 4	97.9	97.5	96.4
Subject 5	89.7	88.4	90.0
Subject 6	92.0	88.9	89.1
Subject 7	89.5	90.0	90.5
Overall	92.3	91.5	92.6

a) Four gestures

	Distance Classifier	SVM	Hierarchical
Subject 1	91.2	91.4	93.2
Subject 2	91.3	93.1	95.3
Subject 3	81.8	83.0	86.6
Subject 4	94.2	93.1	95.5
Subject 5	85.8	84.9	86.5
Subject 6	87.8	88.7	87.6
Subject 7	87.4	90.7	87.8
Overall	88.5	89.3	90.4

b) Five gestures

Tables III a) and b) show the correct classification percentages for all 7 test subjects using the three classification methods. Despite the small differences, overall, both the distance classifier and the SVM are outperformed by the proposed hierarchical approach. As pointed out in [13], [16], we attribute the good performance of all classifiers to the GUSSS ratio as a feature in all methods.

D. Accuracy vs. Increasing Number of Gestures

One last experiment was performed using up to 9 gestures to evaluate the effect on the classification accuracy when increasing the number of gestures. Data for 9 gestures were collected from one test subject by the same process described in Section IV-A. The gestures included the 5 shown in Figure 3 as well as four new gestures: "Down", "clench-clench", "open", and "rotate". To complete the "down" gesture the subject bends the wrist towards the ground. To complete the "clench-clench" gesture the subject quickly does the clench gesture shown in Figure 3 two times. To complete the "open" gesture the subject opens the hand extending all of the fingers. To complete the "rotate" gesture, the subject rotates the hand clockwise.

Table IV shows the classification percentages for a test subject using the three classification methods. It's important to notice that as the number of gestures used increases, the gap in classification accuracy between the proposed method and the other two classifiers grows. This trend is illustrated in Figure 4 which shows the classification accuracy plotted against the number of gestures used. A T-test for statistical significance of this result was performed and the hierarchical classifier outperforms the SVM with $t = 4.11$ and $df = 6$ for $p < 0.05$, and the distance classifier with $t = 4.07$ and $df = 6$ for $p < 0.05$.

Table IV
CLASSIFICATION ACCURACY FOR A SINGLE TEST SUBJECT. THE VALUES ARE PERCENTAGES OVER A 10-FOLD CROSS VALIDATION OF 105 SIGNALS PER GESTURE.

	Distance Classifier	SVM	Hierarchical
3 Gestures	97.3	99.0	98.3
4 Gestures	97.7	94.7	98.5
5 Gestures	96.0	93.4	96.8
6 Gestures	92.1	90.0	94.4
7 Gestures	88.2	87.5	91.3
8 Gestures	84.5	82.3	89.1
9 Gestures	83.6	79.0	86.5

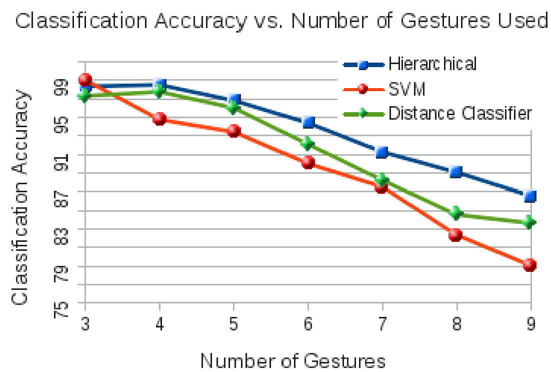

Figure 4. *Classification accuracy vs. number of gestures for the proposed hierarchical approach, the SVM, and the distance classifier, tested with data from one subject.*

V. DISCUSSION AND CONCLUSIONS

The classification results reported in our previous work ([13], [16]) corresponded to some of the gestures used here, and the average performance was around 80% correct classification. Following that work, we aimed at improving the performance of our method both in accuracy and in the number of gestures to be recognized, while still using a single sEMG signal. We first added an additional feature – the ZC – and we segmented the signals, keeping the distance classifier that we had used before. As it can be seen in the results, the distance classifier achieved higher classification accuracies than previously reported – overall averages of 92.3% for 4 gestures and 88.5% for 5 gestures.

We decided to compare the performance of the distance classifier to another commonly used method such as a multi-class SVM. The results obtained with both methods were very similar – 91.5% and 89.3% for 4 and 5 gestures, respectively. During our tests, we noticed that certain gestures were very distinguishable from each other, and certain other gestures were very confused with each other. This observation motivated the tuples and the hierarchical method presented in this work, which aimed at minimizing the confusion between those gestures. The results obtained with the hierarchical approach were, in fact, better than with the non-hierarchical classifiers – 92.6% for 4 and 90.4% for 5 gestures.

Even though the improvement gained by HiGUSSS was relatively small, it was interesting to notice that such improvement was comparatively higher with 5 gestures than with 4 gestures. This observation motivated the experiment discussed in Section IV-D, where we examined the effect on the classification accuracy when increasing the number of gestures. As can be seen from Table IV and Figure 4, HiGUSSS outperformed the other two methods, and the differences in accuracy were statistically significant, as confirmed by the T-tests results. As expected, as the number of gestures increased, the accuracies for all of the classifiers dropped. However, the classification accuracy for HiGUSSS decreased at a lower rate than for the other two classifiers. In the case of 3 gestures, the accuracy of HiGUSSS was about 1% higher than the accuracy of the distance classifier and less than 1% lower than that of the SVM – yet almost perfect. In the case of 8 gestures, HiGUSSS was almost 5% above the distance classifier and almost 7% above the SVM. And with all 9 gestures, HiGUSSS was 7.5% above the SVM, though it was only about 3% above the distance classifier in this case.

The results presented here demonstrate the discriminant power of HiGUSSS. Its better performance compared to the other classifiers is because the hierarchical method employs tuples of gestures instead of comparing each gesture against every other gesture. This is more noticeable as the number of gestures increases.

VI. Future Work

The method proposed here showed a good performance and has potential for many applications such as power wheelchairs, prosthesis, etc. To further validate the method, data should be collected from different muscle groups as well as from people with disabilities. This can give insight on how the algorithm can be improved for diverse users and muscle inputs.

A limitation of the current approach is the manual selection of the optimal tuples. These tuples are important to separate similar gestures. The Hierarchical GUSSS can be further enhanced and exploited by an automatic selection of the tuples.

The GUSSS method relies on the signatures that represent the different gestures. The current approach of calculating the signatures is a simple averaging. Other approaches should be explored to obtain those signatures, for instance, using Independent Component Analysis (ICA) to separate the MUAPT components related to the gestures. Improving the representation of the gestures would have a positive effect on the GUSSS method, and thus, on the proposed hierarchical framework.

Finally, the implementation of the framework in a practical application could take advantage of parallelization for the first level in the hierarchy. The GUSSS-based classifiers related to the tuples could run in parallel to generate the confidences that go to the second level in the hierarchy.

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