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SPATIAL FEATURES EXTRACTION FROM HD- EMG SIGNALS FOR ROBUST CLASSIFICATION OF GESTURES FOR REAL-TIME APPLICATIONS

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Abstract—Signals from electromyography (EMG) are used to infer the user's motor goals. It has been haphazardly used in HMI to manage neuro-rehabilitation tools like prosthetics and therapy machines. High-Definition Surface Electromyography (HD-sEMG) could be the recording of muscle activity at a defined skin area using a second array conductor. This method enables the spatial and temporal analysis of EMG data. New studies have indicated that the requirement for these kinds of analyses grows as the geographic range of HD-EMG maps expands. In this study, HD-EMG recording is examined for its potential application in controlling prosthetic devices for the upper limb. For this study, we categorized eight different fitness-related hand gestures. Throughout this process, we consulted three different feature sets.Options for histogram-oriented gradients (HOG), choices for working in the time domain (TD), and, by extension, the clustering of HOGs and Average Intensity Hysteresis (AIH).The classifier's performance was most likely elevated when many options were combined.
IndexTerms—Myoelectric, Spatial features, histogram.

INTRODUCTION

Muscle tissue generates EMG signals, which are sensed by surface electrodes in the myoelectric prosthesis. The captured signal is employed to regulate the motion of the robotic appendage using additional actuators. Amputees and others who have lost the use of a limb or other bodily or cognitive function due to disease, old age, or an accident can benefit from these prostheses [1].

Myoelectric control can be either direct or pattern-recognition-basedcontrol. With direct control, one prosthetic movement is controlled by a pair of opposing muscle sites. Steam-powered robotic arms with a wide range of joint movements and grasping options would be limited if they had more degrees of freedom than control input available from humans.Change management is one strategy for overcoming this obstacle, and the patient should try out different joints and grips to see what works best for them. A considerable period is needed to actualize a fancy task [2], yet change management was unworkable and not obvious. Finally, electromyogram crosstalk may be caused by the participation of more than one muscle in the area of muscle activity recorded and quantified close to the skin's surface. Myoelectric management using a pattern recognition approach has been pushed forward by the need to increase the count of DOF which is intuitively controlled [3-5] due to the limitations of the direct, change system, and Crosstalk electromyogram.

Martin uses HD-EMG signals to control upper limb prosthesis according to pattern identification.The classifier's effectiveness is robust to electrode shift thanks to spatial characteristics extracted from the HD-EMG map, with accuracy = 93% over 9 motions.Geng [6] uses a 4-electrode array for the lower body to determine 8 gesture categories that correspond to 2 motion patterns and 7 efforts. Spatial features have been created using the graduate shift channel approach in conjunction with intensity features collected from the 5-segmented map that matches muscles [7]. This classification performed better, with a precision of 94.5% and a sensitivity of 95.6%.Meenakshi et al. [8] employ 3D electrodes in an array with 256 channels structured in a 4*8 matrix grid.Meenakshi handles the instantaneous image capturing of HD-EMG. A neural network was used to recognize gestures and categorize instantaneous sEMG images.By using a basic majority voting method across 60 frames, the recognition rate increased to 98.7%.

In our research, the abstraction options have been planned for gesture recognition supported by 2 techniques; the primary one is the HOG algorithmic program whereas the opposite method is the average intensity options. By employing the JKL classification, researchers were able to compute those options inside the framework of categorizing eight different hand motions for upper limb prosthetics.The recognition process has been simplified because of the alternative extraction procedures that have been planned. The research and findings confirmed the efficacy of the HD-EMG data distribution of abstraction of myoelectric strength across muscles for the classification of activities.

Pattern Recognition Approach

EM Gelectrodes

EMG is the non-invasive recording of muscular electrical activity using electrodes placed in the skin, on the muscle, or implanted directly into the muscle.Both invasive and noninvasive methods of connecting the patient to the robotic prosthesis are possible; in the case of the former, surgical implantation of an interface device is required. Hence, surface myogram is the preferred non-invasive recording method. Due to the skin/conductor interaction, the surface conductor can be either dry or gelled, depending on the patient's preference. Different surface electrodes, such as multi-channel electrodes, were shown in a recent study. Using a linear array of surface electrodes, multi-channel electrodes can employhigher than 2 channels for data collection and processing [9, 11]. As can be seen in Figure 1, HD-sEMG channels are positioned on the skin overlying the muscle area in an array of deliberately separated electrodes.As can be seen in Figure 1, HD-sEMG channels are located on the skin overlying the muscle area in an array of deliberately separated electrodes.

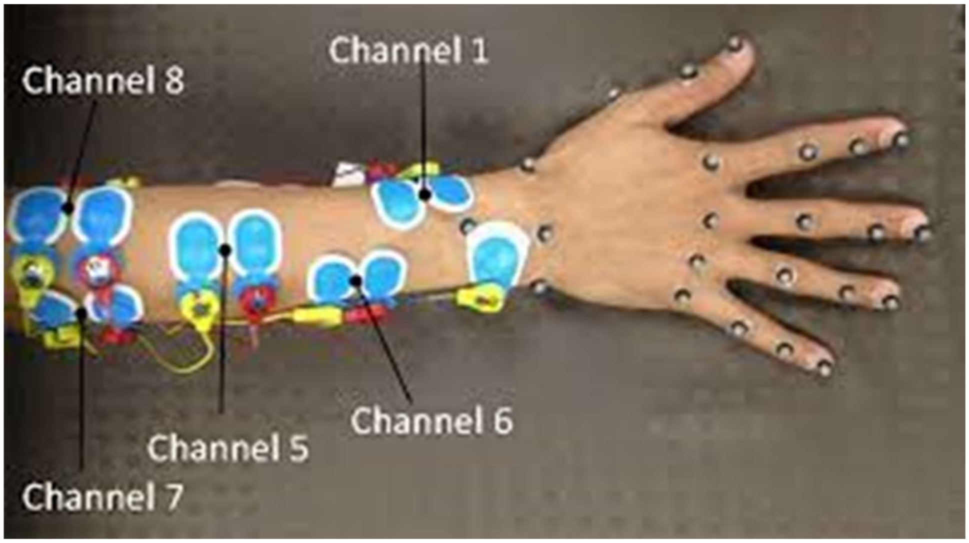

FIG.1.(A) The HD-sEMGelectrode array on the right forearm with 8 channels [12]

Participant

There is data available from a variety of sources, including the CSL-HDEMG data collection, which contains 27 motions done by 5 patients. By wrapping the conductor array around the top forearm muscles during data collection, a grid of 7x24 channels was formed using 192 electrodes. Because of its ten forearm electrodes, the NinaPro data set is regarded as the scientific gold standard for hand prosthetics. The NinaPro dataset is divided into two databases: DB1 contains 52 gestures recorded throughout 10 trials by 27 people, and DB2 has 50 gestures monitored throughout 6 trials by 40 people [8].

The HD-sEMG data employed in this study may be found at http://zju-capg.org/myo/data. It has 128 channels generated in an 8 by 16 matrix as a second set of densely spaced electrodes. The DB-a study has eighteen participants. All subjects did 8 isometric hand motions in total. Each action was performed ten times [9].

After the participant has performed gestures, CapgMyo data does not require a consistent amount of contraction force. The degree of contraction force was considered a potential parameter for gesture detection [6]. Gesture recognition is made easier by using the contraction force. Additionally, it is impossible to impose a specific contraction force on users during a practical application. Figure 2 depicts the required gestures for our experiment.

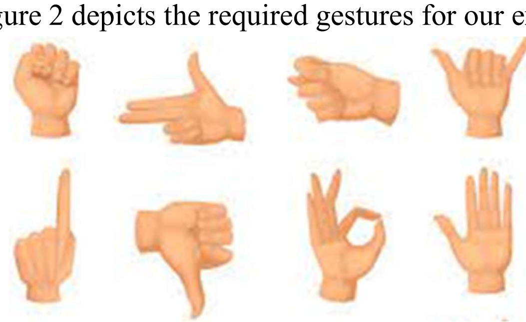

FIG.2.Configuration of Hand gestures

C. sEMG-Topography

The HD-EMG heatmap displays the muscle's power distribution in space. It was hoped that sEMG-maps and sEMG-topographies might have medical applications. It has recently found application in the field of gesture recognition. To create a single-channel EMG map, we did the following:

$$AM_{i,j} = RMS\left(sEMG_{i,j}\right) \tag{1}$$

Where,

AM→ Amplitude Modulation @(i, j)

$sEMG_{i,j}$→EMGsignal @ (i, j).

RMS→RootMeanSquarerateofEMG.

At the coordinates(i,j)of the 2D electrodes, each pixel on the map represents the RMS value of channels.The segmented map was designed for numerous non-overlapping 200ms timeframes, which has been the recommended window size for many investigations of pattern recognition-based prosthetic regulation [12].

HD-EMG mapping is the dispersion of strengths over the muscle in three dimensions. The surface electromyography (sEMG) map has been created for medicinal use.In recent times, it has found application in the field of gesture recognition. Most investigations of pattern recognition, especially those based on prosthesis control, advocate a window length of 200ms, hence the metameric map was computed for some non-overlapping 200ms temporal periods [7]. The metameric map was then averaged as ASM.

$$ASM_{i,j} = \frac{1}{M}\sum_{n=1}^{N} S_{i,j}^{2}(n) \tag{2}$$

$$ASM_{i,j} = \frac{1}{M}\sum_{m=1}^{M} SM_{i,j}$$

(3)

Where,

$ASM_{i,j}$→ Averagesegmentedmap@ (i, j),

$SM_{i,j}$→ Segmented map @ (i, j),

$S_{i,j}$→EMGsignal@ (i, j),

M→Total non-overlapping windows.

N→ Total samples,

D. Feature extraction

Certain proposition strategies, like using the RMS value to calculate myogram amplitude or the TD option, are easy, while others, like the Fourier and riffle-based analyses, are more difficult.According to recent research, tasks are becoming more and more common as HD-EMG maps are distributed spatially. The spatial alternatives pertinent to HD-EMG maps were retrieved and used in recognition, whether singly or in combination, to boost their accuracy [4].

Much research suggests a non-linear relationship between myogram amplitude and produced force. As a result, the intensity alternatives were assessed as a benchmark for the normal intensity of HD-EMG maps [8].

$$I = log_{10}\frac{1}{N}\sum_{i,j} AM_{i,j} \tag{4}$$

Where$I$→Intensityfeatures,$AM_{i,j}$ →Intensitypixelvalue @(i, j).

The typical segmental map could be shown as a series of images, with each part of the image representing a different channel. Hence, the problem with hand gestures is recast as an issue with the composition of the image. For this purpose, we implement the bar graph destined Gradient (HOG) based algorithm to derive the abstraction options from the typical HD-EMG chart. The HOG algorithm is related to the low-cost feature extraction technique used in computer vision for object recognition. HOG) measures the frequency of gradient orientation in small image regions. Our findings suggest that the HD-EMD default map's H options signify HOG possibilities.
Using concatenation, we used a combination of Intensity abstraction choices and H abstraction options to create a single feature vector. The Intensity (I) attribute was analyzed in a unique manner than Roja [10] did for this work. Each (i,j) window does not overlap with the next, HD-EMG maps were computed, along with the corresponding intensity maps. After that is established, we can calculate the overall median volume across all channels. Hence, 128 channels can be mixed in sequence with possibilities arising from the HOG algorithmic program, yielding 128 intensity options. AIH was the abbreviation used to designate these possibilities [13,14].

Time, frequency, and time-frequency evaluations are all possible for classical alternatives. In this study, we used TD alternatives to compare the two feature sets throughout categorization.The evaluation metrics for options are computed as:

$$S = \frac{T_P}{T_P + F_N}$$

$$P = \frac{T_P}{T_P+F_P} \tag{5}$$

$$A_{cc} = \frac{T_P + T_N}{T_P + F_P + T_N + F_N}$$

The use of the JKL classifier was made possible because of how easily it could be implemented and trained. It classifies eight isometric hand gestures by identifying the optimal hyperplane that divides information points into their respective categories. As compared to other kernel performances, linear kernel performance provided greater accuracy[1].
Three distinct JKL classifiers were implemented following diverse feature sets retrieved from HD-sEMG data.
- Classifier using H options.

- Classifier usingAIHoptions.
- Classifier usingTD options.

The classifier's effectiveness was assessed using Precision (P),Sensitivity(S), and Accuracy (A_cc) whereasTP (True Positive) refers to the percentage of samples that have been correctly assigned to a single category. The collection of samples that don't fit neatly into any predetermined category and weren't assigned to it is known as the Voluntary State (True Negative); False Negatives (FN) are samples that should have been categorized as belonging to one class but were instead assigned to another. False positive (FP) occurs when a set of samples that do not influence a particular class is wrongly classified as belonging to that class.Figure 3 depicts a systematic depiction of the JKL classification technique based on AIH options.

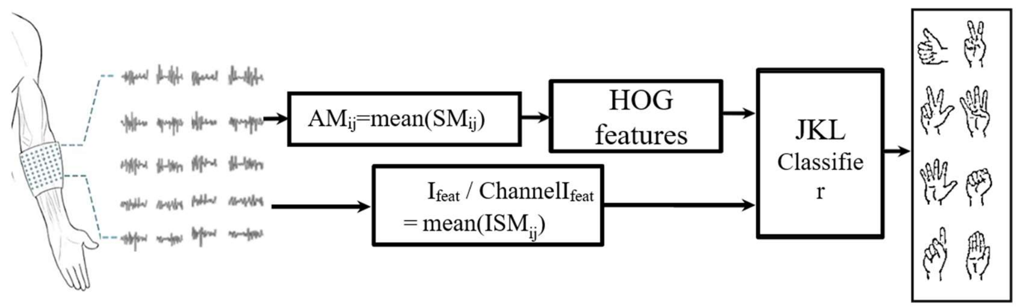

FIG.3.A schematic depiction of a JKL technique for gesture identification.

III. Results and Discussion

Signals for EMG were picked up from a small region surrounding the HD-sEMG electrodes, suggesting that the muscle degradation was localized. The electrodes in this second array are laid out in a grid with 16 rows and 8 columns. Band-pass filtering was done between 30 and 360 cps on the nonheritable HD sEMG data, and the results were analyzed using a sampling rate of 1,000 cps. Every move was captured ten times for each subject. The channel was collected for a sample of 1000 seconds for each test. The categorization of 8 hand gestures was evaluated on five capable subjects. The classification learned from the first 7 trials and was put to the test in the last 3(70% coaching set, half-hour take a look at set).

In our research, we compared two different feature sets (H and AIH). The outcomes show how far each feature set can go in identifying the eight most common gestures.Comparison of the JKL technique effectiveness depends on H, AIH options, and the effectiveness of a traditional classifier (TD features). The mean and variance-adjusted mean scores for each gesture were calculated using data from five subjects.The outcomes of the gesture recognition aided AIH options are shown in Table 1. Table 1 shows that the JKL classification technique based on AIH options typically achieves lower VAR and improved performance.

Table1.A_{cc},S and$P$ of8GestureRecognition

Performance of JKL classification technique based on feature extraction.

Gestures	Accuracy%	Sensitivity %	Precision%
G1	98.14±1.22%	93.3 ±14.9%	100±0%
G2	100±0%	100±0%	98.67±2.06%
G3	98±1.04%	99.38±2.67%	95±11.18%
G4	100±0%	100±0 %	100±0%
G5	98.36±1.2%	99.46±1.02%	98.98±0.8%
G6	98.99±1.04%	86.6 ±29.8%	100±0%
G7	100	100±0%	100±0%
G8	99.3±0.7%	98.76±1.14%	91±12.6%
Average	99.0±0.52	97.2±7.89	97.95±5.8

Fig. 4 depicts the results obtained using three distinct JKL classification techniques, all of which made use of a different collection of features. Notably, AIH outperformed the other options after mishandling the other selected features. They are shown as average accuracy scores (99.3%, 98.3%, and 98.7% for the AIH, H, and TD options, accordingly).Moreover, TD surpasses H in terms of accuracy and sensitivity (95%±100%, 93.3%±10.15%, 96.5% ±7.8%, 94.9%±7.86%). The sensitivity and accuracy forAIH, meanwhile, were (97.5%±5.587%, and 98.37%±3.6%). When comparing the performance of several classifiers against AIH, there is often a striking difference. AIH options had a quality deviation of 3.6%, down from 100% for H and 7.8% for TD options.

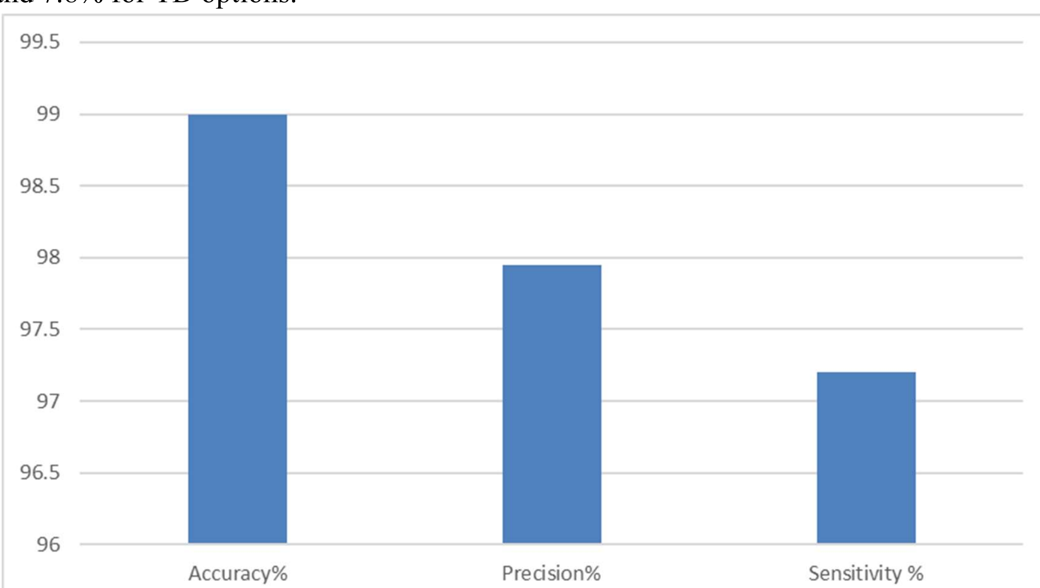

FIG.4Action of JKLclassifierin termsofA_cc,S andP

When compared to Geng's [9] results, which employed the same data (with a 500-person training set and a 50-person testing set) and the capability of deep learning to categorize 8 gestures, the accuracy was 9.5%. In the typical configuration, which includes a linear kernel operation, the efficiency when compared to the JKL classification is poor, with approximately 18 average accuracies. The average accuracy for the JKL classification relying on AIH options in our investigation was 99.37%. Our findings support the idea that choosing options is just as important as choosing a classification.

Our findings were also compared to those of Rojas [7]. Rojas integrated the intensity feature estimated in an entirely distinct manner from our research with abstraction alternatives extracted using the mean shift algorithm. Rojas divided the forearm HD-sEMG map into three smaller maps to better focus on the muscle. Each map's intensity characteristic is computed as a solitary feature. This results in the integration of 3 intensity and 2 mean shift options.Raja [7] used 30 minutes for testing. While the JKL classification technique in our research satisfied P=98.37% and S=97.5%, its LDA classification technique reached precision =97.5% try to sensitivity =97.4%.

Fig. 5 depicts the performance of the classifier of each hand motion across 5 subjects. G1, G2, G3, G4, G5, and G8 have greater accuracy for AIH than other alternatives. While G6 and G7 achieved good accuracy for TD. The typical interpretation of the 1.39-percentage-point difference in VAR between AIH and TD options. [14]

The classifier's accuracy was marginally degraded when the number of training trials was decreased. Hence, as shown in Fig. 6, training the JKL classification technique based on AIH options on a range of trial sizes ranging from 1 to 7. It is frequently discovered that the accuracy of the training classification on each trial for 5 participants was 92.7%, 98.9%, 89.5%, 90.6%, and 91.6%, with a mean accuracy of 92.7%, which is quite good for a single-sample training process. Yet after training through 3 trials, the best possible score of 97.9% was achieved.

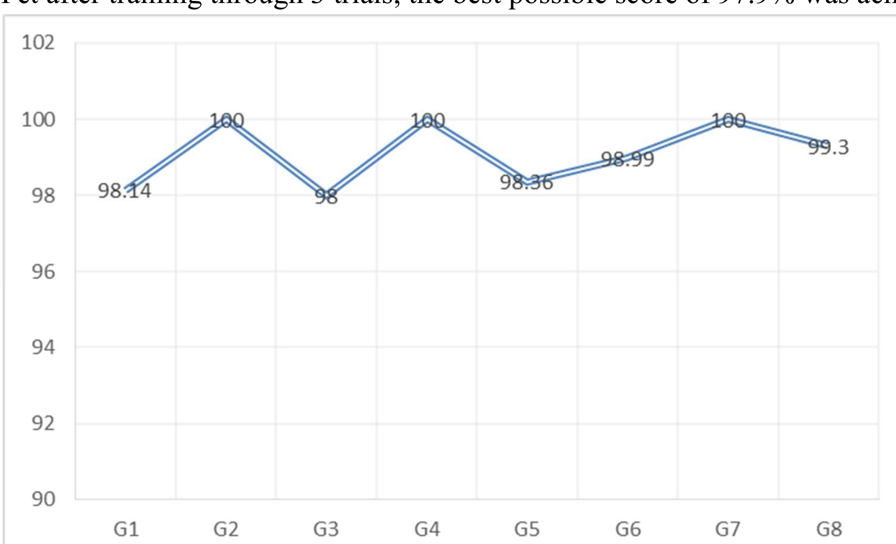

FIG5.A_ccof gesture recognition.

IV. Discussion and Conclusion

Data of HD-sEMG was gathered from the CapgMyo quality data DB-a. It has 128 channels, each of which is 8*16, and has been recorded for 1,000 sample instants. Each channel was separated into 5 non-overlapping 200ms frames. HD-EMG maps were generated for each metameric window using RMS values, and the average activation map was generated by averaging the intensities of all metameric maps for each channel. Various feature configurations were taken out. The HOG rule is used to obtain spatial choices from the mean activation map. Combining HOG and intensity options are linked to AIH options. The components of a vector whose average intensity for each channel is calculated by averaging the intensities of each metameric window are sufficient for the total channels. TD possibilities, with 5 alternatives calculated for each channel's VAR, RMS, WL, ZC, and MAV. The action acknowledged the use of sets of alternatives determined by a support vector machine classifier. The study demonstrates the likelihood of each feature set detecting the gesture. When compared to competing feature sets, the AIH's results were superior (ACC_AIH=99%, P_AIH=97.95%, S AIH=97.2%). There was a notable improvement in classifying motion.; The classifier's effectiveness must be reliable; therefore it must be robust to fatigue and electric conductivity from electrode-skin interaction. So, it will be interesting to see how well the JKL classifier based on AIH options for shift electrodes and tiredness performs in future research. In the same vein, the recognition performance can be enhanced further by making use of complementary tools, such as frequency content.

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