Identifying Noisy Electrodes in High Density Surface Electromyography Recordings Through Analysis of Spatial Similarities

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Abstract— **In this study we developed a technique for identifying noisy electrodes in high density surface electromyography (HD-sEMG). The technique finds the spatial similarity of each electrode in the electrode array by counting the number of interactions the electrode has. Using this information the technique identifies noisy electrodes by finding electrodes that are significantly dissimilar to the other electrodes. The HD-sEMG recordings used in this study were taken from three participants who performed two isometric contractions of their biceps at 40% and 80% of their maximum voluntary contraction (MVC) force. White Gaussian noisy was added to a varying number of recorded signals before being digital filtering to generate a variety of recordings to test the technique with. In the recordings, groups of 2, 4, 8, and 16 electrodes had noise added such that the signal to noise ratios (SNR) were 0, 5, 10, 15, and 20dB. The results show that the technique can reliably identify groups of 2, 4, and 8 noisy electrodes with SNRs of 0, 5, and 10 dB.**

I. Introduction

The presence of noise in surface electromyography (sEMG) signals is a common problem when studying neuromuscular activity. There are many factors that contribute to noise in sEMG signals, some of these factors include poor contact between the electrode and skin, small electrode displacements, variations in the electrode and skin impedances, and power line interference [1], [2], [3], [4]. To ensure high quality sEMG signals, and thus allow accurate analysis of the muscle activity, it is important to identify noisy electrodes before any experimental recording. In doing so, appropriate steps can be taken prior to analysis to minimise or eliminate the noise either through signal processing techniques or changes to the experimental procedure.

For sEMG recording systems the quality of signal is usually determined by measuring the skin impedance before recording [5] or by visually inspecting the recorded signal for abnormalities [6]. However, the skin impedance can change in intervals as small as one second [4] making it an unreliable measure to base a signal's quality on. Also, with the introduction of high density surface electromyography (HD-sEMG), which uses one or two dimensional arrays of electrodes, visual inspection of each recorded signal is very time consuming and more prone to errors [7]. Therefore, techniques which automatically identify noisy electrodes are required when using HD-sEMG.

Previously, there have been a limited number of studies that have investigated outlier detection techniques to automatically identify noisy electrodes in HD-sEMG [6], [8]. However, the gold standard for these studies was visual inspection of the HD-sEMG data by an expert. Not only is this not an objective measure of the data but it also limits the data which can be used to validate their techniques to signals with noise that can be easily identified through visual inspection. Therefore it is likely these techniques will have difficulty identifying less obvious noise.

In this study a novel technique for identifying noisy electrodes in HD-sEMG was developed. This technique is based on our previous work investigating the normalised mutual information (NMI) as a means of identifying similarities between electrodes in an array [9], [10], [11]. The technique identifies noisy electrodes in HD-sEMG by finding electrodes that are significantly dissimilar with the other electrodes. This technique was then tested using HD-sEMG recorded from the biceps. Noise was artificially added to a varying number of electrodes in the HD-sEMG recordings at different signal to noise ratios (SNR) to demonstrate the performance of the proposed technique in a variety of different scenarios.

II. Methodology

A. HD-sEMG Recording Device

The W-EMG 64 channel EMG Detection Device (Bitron, Italy) was used in these experiments. This device records HD-sEMG using two arrays of 32 electrodes (a 4 by 8 grid of electrodes) with an inter electrode distance of 5mm. The arrays were arranged into a 4 by 16 grid (4 columns, 16 rows) of electrodes. The HD-sEMG device uses a 24bit ADC to sample the sEMG at 2441Hz and is band pass filtered (10-500Hz).

B. Experimental Data

For this study HD-sEMG recordings from our data base were used to test the proposed technique. In these recordings the participants performed isometric contractions of the biceps brachii at 40% and 80% of their maximum voluntary contraction (MVC) force. In this study only the initial 5 seconds of each HD-sEMG recording was used.

The electrode array was placed above the estimated location of innervation zone for the short head of the biceps brachii (see [12] for details). The array was placed such that the columns of the array were close to parallel with the muscle fibre direction. Two reference electrodes were also placed on the elbow.

Three healthy male participants (Age range: 27 to29 years) with no current or prior muscular injuries and disorders volunteered to participated in the experiment after signing an informed consent form. The experiment was approved by

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University Human Research Ethics Committee and conducted in accordance with Helsinki Declaration (revised 2004).

C. Adding Artificial Noise

A Gaussian driven process was used to emulate data from noisy electrodes which has been passed through an acquisition system. White Gaussian noise was added to the clean data before digital filtering (band pass filter between 20 and 300Hz and a notch filter at 50Hz). The different SNRs used in this study to test the effectiveness of the method were 0, 5, 10, 15, and 20dB.

The electrodes and the number of electrodes with noise added to their sEMG signals also varied. This was to ensure each electrode was tested with and without noise and it allowed investigation of how this method behaves with different noisy electrodes. The different sizes of the noisy electrode groups used in this study were 2, 4, 8, and 16. For each group size there were 32, 16, 8, and 4 entirely unique and random combinations of electrodes respectively.

Considering all combinations of the different SNRs and noisy electrode groups there are a total of 300 different HD-sEMG recordings generated from each HD-sEMG recording. Therefore, with three participants and two HD-sEMG recordings from each, a total of 1800 different recordings were generated and tested in this study.

D. Data Analysis

The data for each HD-sEMG recording was split into w non-overlapping windows of N samples. The data was then organised into a three dimensional matrix $\mathbf{S}$ of dimensions $R \times C \times W$. Each element of $\mathbf{S}$, $S_{r,c,w}$, is populated with N samples recorded during window w by the electrode located in row r column c where $r = 1, 2, \ldots, R$, $c = 1, 2, \ldots, C$, and $w = 1, 2, \ldots, W$. In this study $R = 16$, $C = 4$, $N = 500$, and $W = 24$ (approximately 4.92 seconds).

The number of interactions each electrode had during each window was then calculated as described in [10]. An electrode has an interaction with another electrode when the NMI of their recorded signals is greater than a predefined threshold represented by the variable v where $0 \leq v \leq 1$. In [10] the number of interactions for each electrode was arranged into a matrix labelled $\mathbf{D}$ which has the same dimensions as $\mathbf{S}$. Each element of $\mathbf{D}$, $d_{r,c,w}$, represents the number of interactions the electrode located at row r column c had during window w which is given by:

$$d_{r,c,w} = \left(\sum_{q_1=1}^{R} \sum_{q_2=1}^{C} \begin{cases} 1, & \text{if } NMI(S_{r,c,w}; S_{q_1,q_2,w}) \geq v \\ 0, & \text{if } NMI(S_{r,c,w}; S_{q_1,q_2,w}) < v \end{cases} \right) - 1 \quad (1)$$

Where $NMI(S_{r,c,w}; S_{q_1,q_2,w})$ is the NMI between the signals recorded by the electrodes located in row r column c and row q_1 column q_2 during window w.

When analysing the number of interactions for each electrode it was found that the electrodes with noise had zero interactions more often than the other electrodes. To represent the number of zero interactions an electrode has over W windows the following function is used:

$$Z(r,c) = \sum_{w=1}^{W} \begin{cases} 1, & \text{if } d_{r,c,w} = 0 \\ 0, & \text{else} \end{cases} \quad (2)$$

Where r and c is the row and column location of the electrode. To automatically identify the noisy electrodes the value of $Z(r,c)$ was made constant and the NMI threshold, v, varied. Electrodes that had a significantly lower v for a given value of $Z(r,c)$ were considered noisy. To do this a matrix $\mathbf{V}$ with R rows and C columns was generated with elements $V_{r,c}$ given by:

$$V_{r,c} = min\{v | Z(r,c) \geq W/2\} \quad (3)$$

Where $V_{r,c}$ is the smallest value of v that meets the condition $Z(r,c) \geq W/2$ and $v = \{0.01, 0.02, \ldots, 1\}$. The median and standard deviation (SD) of $\mathbf{V}$ were then calculated and any elements lower than or equal to 2 SDs below the median were considered noisy. Electrodes located at the same location as noisy $\mathbf{V}$ elements were then identified as noisy electrodes.

E. Statistical Analysis

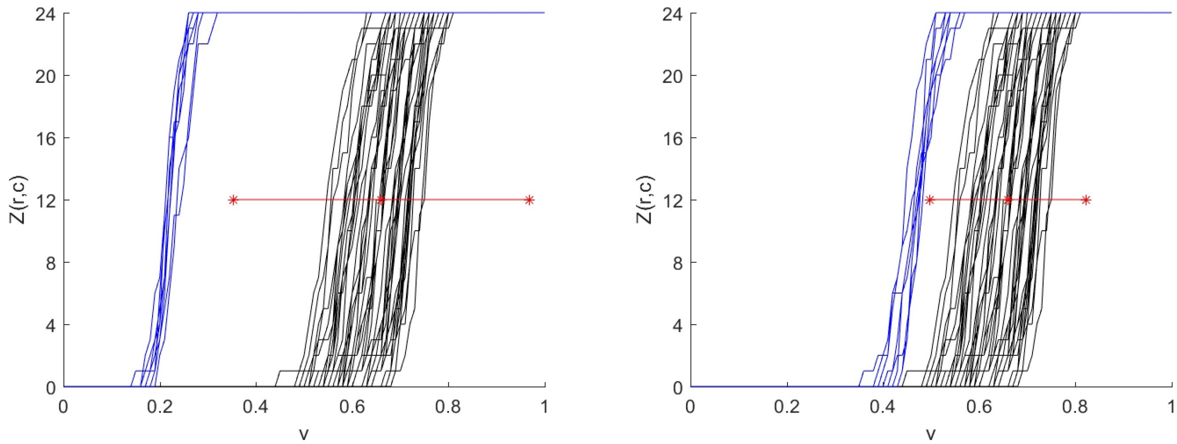
For each of the 1800 HD-sEMG recordings a confusion matrix was generated based on the output of the proposed technique. To summarise all these results the average confusion matrix for each SNR and noisy electrode group size combination (20 combinations) was generated. From these average confusion matrices the sensitivity, specificity, and accuracy for each SNR and noisy electrode group size combination was calculated.

III. Results

A. $Z(r,c)$ Vs v Plot

The plots of $Z(r,c)$ Vs v, as shown in Fig. 1, illustrates the process used in the proposed technique and the effect different SNRs have on the same data. For Fig. 1a and Fig. 1b the horizontal axis represents the NMI threshold, v, and the vertical axis is the number of times an electrode has zero interactions across 24 windows, $Z(r,c)$. Each plot line represents a different electrode from the HD-sEMG recording, the blue lines are electrodes with noise added to them and the black lines are electrodes that had no noise added to them. The horizontal red line represents the median value of $v\pm$ 2 SD for when $Z(r,c) = 12$, the centre star is the median and the other two stars are 2 SD away from the median. Both Fig. 1a and Fig. 1b have 8 noisy electrodes and were generated from the same HD-sEMG recording except the SNR in Fig. 1a is 0dB and in Fig. 1b it is 10dB. These values of v are the elements of $\mathbf{V}$ found using (3).

From the examples in Fig. 1 it was observed that the noisy electrodes commonly had more zero interactions then any non-noisy electrodes. This creates a large gap between the noisy and non-noisy electrodes and as the SNR increased the gap between the noisy and non-noisy electrodes decreased. This can be seen when comparing Fig. 1a and Fig. 1b and was commonly observed amongst the other HD-sEMG



(a) 0dB SNR (b) 10dB SNR

Fig. 1: Zero interactions for different NMI thresholds. The horizontal axis represents the NMI threshold, v, and the vertical axis are the number of times an electrode has zero interactions across 24 windows, $Z(r, c)$. Each plot line represents a different electrode from the HD-sEMG recording, the blue lines are electrodes with noise and the black lines are electrodes with no noise. The horizontal red line represents the median value of $v\pm$ 2 SD for when $Z(r, c) = 12$, the centre star is the median and the other two stars are 2 SD away from the median. Both (a) and (b) have 8 noisy electrodes and were generated from the same HD-sEMG recording except the SNR in (a) is 0dB and in (b) it is 10dB

recordings. These observations were used as the basis for developing the proposed technique.

B. Statistical Analysis

Table I, II, III, and IV are the statistical results for identifying the noisy electrodes in each HD-sEMG recording using the proposed method. Each table shows the average sensitivity, specificity, and accuracy achieved for each SNR tested for each of the noisy electrode group sizes. The SNR is given in dB and the sensitivity, specificity, and accuracy are given as percentages with the SD.

The noisy electrode group sizes of 2 and 4 had very high sensitivity for SNRs of 0, 5, and 10 dB. However they rapidly deteriorated for 15 and 20dB. The sensitivity for the group size of 8 electrodes was also very high for SNRs of 0 and 5 dB but it dropped at 10dB and then rapidly decreased at 15 and 20dB. For the group size of 16 electrodes the sensitivity was poor and continued to drop as the SNR increased. Across all the results the specificity was very high, the smallest value being 97.64% from the 4 noisy electrode groups. The accuracy was also high for most of the results with it only dipping below 90% for the group sizes of 8 and 16 electrodes, the lowest accuracy being 75.13%. The SDs for the results were below 2% for specificity and 10% for accuracy, however, the SDs of the sensitivity results reached 39.87%.

TABLE I: Results for Groups of 2 Noisy Electrodes

SNR (dB)	Sensitivity (%)	Specificity (%)	Accuracy (%)
0	100	99.97 $\pm$ 0.20	99.98 $\pm$ 0.19
5	100	99.90 $\pm$ 0.39	99.90 $\pm$ 0.38
10	99.74 $\pm$ 3.61	99.33 $\pm$ 1.05	99.34 $\pm$ 1.02
15	36.72 $\pm$ 39.87	98.14 $\pm$ 1.61	96.22 $\pm$ 2.18
20	8.07 $\pm$ 19.14	97.64 $\pm$ 1.91	94.84 $\pm$ 2.04

TABLE II: Results for Groups of 4 Noisy Electrodes

SNR (dB)	Sensitivity (%)	Specificity (%)	Accuracy (%)
0	100	99.98 $\pm$ 0.17	99.98 $\pm$ 0.16
5	100	99.95 $\pm$ 0.29	99.95 $\pm$ 0.27
10	95.31 $\pm$ 12.73	99.69 $\pm$ 0.65	99.41 $\pm$ 0.97
15	32.29 $\pm$ 33.03	98.58 $\pm$ 1.43	94.43 $\pm$ 2.59
20	8.07 $\pm$ 13.33	97.74 $\pm$ 1.95	92.14 $\pm$ 2.14

TABLE III: Results for Groups of 8 Noisy Electrodes

SNR (dB)	Sensitivity (%)	Specificity (%)	Accuracy (%)
0	100	100	100
5	100	100	100
10	71.61 $\pm$ 30.37	99.78 $\pm$ 0.60	96.26 $\pm$ 3.84
15	22.14 $\pm$ 23.67	99.67 $\pm$ 0.79	89.97 $\pm$ 3.09
20	6.51 $\pm$ 9.64	98.47 $\pm$ 1.69	86.98 $\pm$ 2.15

TABLE IV: Results for Groups of 16 Noisy Electrodes

SNR (dB)	Sensitivity (%)	Specificity (%)	Accuracy (%)
0	77.60 $\pm$ 30.45	100	94.40 $\pm$ 7.61
5	44.79 $\pm$ 33.92	100	86.20 $\pm$ 8.48
10	20.31 $\pm$ 23.11	100	80.08 $\pm$ 5.78
15	6.77 $\pm$ 9.91	100	76.69 $\pm$ 2.48
20	4.17 $\pm$ 4.76	98.78 $\pm$ 1.49	75.13 $\pm$ 1.52

IV. Discussion

By identifying the number of interactions each electrode has in every window we have summarized how many electrodes are similar to each electrode. This is the intent of (1) and is used to spatially map similarities in [10], spatial similarities in general are also discussed in greater detail in

[11]. However, in the case of identifying noisy electrodes it is the dissimilarities that are of interest. In this study the noisy electrodes in the electrode array were found to have fewer interactions and would often have no interactions depending on the value of the NMI threshold, v, as shown in Fig. 1. These characteristics come about due to the similarity of an electrode being decided through the number of electrodes it is similar to rather than simply identifying it's similarity with a single electrode. Therefore, the dissimilarity of the noisy electrodes was emphasized due to the noise being uncommon across the electrode array creating the gap shown in Fig. 1.

There are inherent theoretical limitations when using the interactions of each electrode to identify noisy electrodes which should be accounted for before using this technique. Two distinct groups of electrodes are required for this technique as shown in Fig. 1. If the noisy electrodes group is large enough the standard deviation of $\mathbf{V}$ will increase so much so that parts of the noisy electrode group will be considered non-noisy, increasing the number of false negatives. If the number of noisy electrodes is more than half the total number of electrodes than it is expected that a significant increase in false positives will occur since the median will be shifting closer to the noisy electrode group. Another limitation is dissimilar sEMG caused by placing the electrode array across multiple superficial muscles. In such a scenario it is likely the technique will identify the electrodes over the smaller muscle as noisy if the recorded sEMG from the different muscles are dissimilar.

The proposed technique performed well under the tests used in this study for SNRs of 0, 5, and 10dB. For groups of 2, 4 and 8 noisy electrodes a steep decrease in the sensitivity occurred when the SNR reached 15dB. When plotting $Z(r, c)$ Vs v plots of the results it was observed that as the SNR increased the gap between the noisy and non-noisy electrodes decreased as shown in Fig. 1. For 15 and 20dB the gap was so small that it violated the underlying assumption of the proposed technique that there are two distinct groups of electrodes. In this case the technique had difficulty identifying noisy electrodes as shown in the results in Table I, II, III, and IV. For groups of 16 noisy electrodes the group size was large enough that the SD was too large, causing false negatives and the high specificity seen in Table IV. However, it should be noted that 16 noisy electrodes accounts for one quarter of the total number of electrodes and as such automated identification may not be appropriate in this case. With such a large percentage of noisy electrodes the user may need to consider whether to proceed with the recording or instead reposition the electrode array.

While the proposed method performed well in terms of the accuracy and specificity it would be advantageous to also improve the sensitivity of the technique. One way of achieving this would be to change the method used to identify the two groups of electrodes, as shown in Fig. 1. Also further investigation is required into the impact of noisy electrodes on the analysis of HD-sEMG data. Particularly, at what point a recording becomes too noisy to be used in the analysis.

V. Conclusion

This study has developed a novel technique demonstrating that spatial similarities of the electrodes in an electrode array can be used to identify noisy electrodes in the HD-sEMG recordings. Noisy electrodes with SNRs of 0, 5, and 10dB were reliably identified for groups of 2, 4, and 8 noisy electrodes. While results for larger groups of electrodes, accounting for a greater proportion of the electrodes, and those with lower levels of noise were less consistent.

References

[1] A. Searle and L. Kirkup, "A direct comparison of wet, dry and insulating bioelectric recording electrodes," *Physiological Measurement*, vol. 21, pp. 271–283, 2000.

[2] E. Huigen, A. Peper, and C. A. Grimbergen, "Investigation into the origin of the noise of surface electrodes," *Medical and Biological Engineering and Computing*, vol. 40, no. 3, pp. 332–338, 2002.

[3] E. A. Clancy, E. L. Morin, and R. Merletti, "Sampling, noise-reduction and amplitude estimation issues in surface electromyography," *Journal of Electromyography and Kinesiology*, vol. 12, no. 1, pp. 1–16, 2002.

[4] L. A. Geddes and M. E. Valentinuzzi, "Temporal changes in electrode impedance while recording the electrocardiogram with dry electrodes," *Annals of Biomedical Engineering*, vol. 1, no. 3, pp. 356–367, 1973.

[5] D. J. Hewson, J. Y. Hogrel, Y. Langeron, and J. Duchłne, "Evolution in impedance at the electrode-skin interface of two types of surface emg electrodes during long-term recordings," *Journal of Electromyography and Kinesiology*, vol. 13, no. 3, pp. 273–279, 2003.

[6] C. Grönlund, K. Roeleveld, A. Holtermann, and J. S. Karlsson, "Online signal quality estimation of multichannel surface electromyograms," *Medical and Biological Engineering and Computing*, vol. 43, no. 3, pp. 357–364, 2005.

[7] G. D. Fraser, A. D. C. Chan, J. R. Green, and D. T. MacIsaac, "Automated biosignal quality analysis for electromyography using a one-class support vector machine," *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 12, pp. 2919–2930, 2014.

[8] H. R. Marateb, M. Rojas-Martnez, M. Mansourian, R. Merletti, and M. A. Maanas Villanueva, "Outlier detection in high-density surface electromyographic signals," *Medical & Biological Engineering & Computing*, vol. 50, no. 1, pp. 79–89, 2012.

[9] A. Bingham, S. P. Arjunan, and D. K. Kumar, "Estimating the progression of muscle fatigue based on dependence between motor units using high density surface electromyogram," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Conference Proceedings, pp. 3654–3657.

[10] A. Bingham, S. P. Arjunan, and D. K. Kumar, "Measuring the interactions between different locations in a muscle to monitor localized muscle fatigue," in *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2017, Conference Proceedings, pp. 3461–3464.

[11] A. Bingham, B. Jelfs, S. P. Arjunan, and D. K. Kumar, "Normalised mutual information of high-density surface electromyography during muscle fatigue," *Entropy*, vol. 19, no. 12, 2017.

[12] M. Barbero, R. Merletti, and A. Rainoldi, *Atlas of Muscle Innervation Zones*. Springer-Verlag Mailand, 2012, vol. 1.