

Automated way to obtain motor units' signatures and estimate their firing patterns during voluntary contractions using HD-sEMG

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Abstract—A new, automated way to obtain signatures of active motor units (MUs) from high density surface EMG recordings during voluntary contractions is presented. It relies on clustering of repetitive shapes corresponding to different MU action potentials (MUAPs) present. The number of clusters and the mean shapes of the MUAPs as observed on the electrode grid, are estimated in a fast way without user interaction. The algorithm is tested on simulated signals mimicking a small muscle. Our results show that at least 8 MUAPs can be reliably reconstructed and their MU mean firing frequencies can be estimated.

I. INTRODUCTION

Electrophysiological measurements of the peripheral nervous system such as electromyography (EMG) are often used to investigate neuromuscular disorders. Analysis of single motor unit action potentials (MUAPs) can be of great assistance in assessing the impact of these disorders. Both the number of motor units (MUs) and the MUAPs are affected by denervation and collateral reinnervation [1]. EMG is therefore a helpful tool in the diagnostic process and in monitoring disease progression.

Until recently, single MU analysis has been the sole privilege of intramuscular electromyography (iEMG) measurements, where a needle or wire electrode is being inserted into a muscle [2]. However, the obvious down side

is the invasiveness of this approach.

In the past decade, high-density surface electromyography (HD-sEMG) recordings, which employ a grid of multiple densely spaced electrodes over a muscle, have been used to investigate muscle activity in an alternative, non-invasive way, yet providing comparable results [3]. HD-sEMG utilizes the fact that the EMG signal measured at the surface comes from sources that have different spatial distributions and are active in different time instances. This spatio-temporal signature is usually unique for each motor unit [4]. For many applications the mean spatio-temporal motor unit potential amplitude is of interest as the amplitude size and the distribution might change for instance in motoneuron diseases. In order to address these needs, we propose a method to reliably extract mean MUAP shapes of active MUs.

Several methods have been proposed to obtain MU signatures by various decomposition techniques (e.g. [5, 6, 7, and 8]). As MUAPs coming from the same MU remain unchanged, they will form groups of similar shapes. This enables us to use clustering techniques to obtain multiple observations of the same shapes and then extract the mean, reducing the noise. However, in the case when more MUs are present, frequent overlapping of these MUAPs form mixtures that may appear as outliers. This can often lead to a failure of clustering approaches partly because the number of “natural” clusters cannot be assessed.

In this work, we propose an automated method to estimate MU signatures and their firing patterns in case of low contraction force applied. The method is a multichannel extension of the Wave_clus algorithm [9] that employs superparamagnetic clustering [10]. This is a hierarchical clustering technique, which assesses the number of clusters without user interaction, also leaving a number of shapes (outliers) unclustered. We assess its performance and accuracy on simulated signals made to mimic activity of a small muscle. Abilities to reconstruct the MU signatures are assessed in cases when between 3 and 8 MUs are simultaneously active.

Initial results suggest this approach is feasible and could be used for future health care applications. We argue that obtaining mean MUAP shapes is a necessary first step towards the so-called full decomposition, where every “firing” of each MU is accounted for.

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II. METHODS

This section first describes the dataset that was used for testing our approach. The algorithm itself is composed of the detection and clustering part, where the first is used to identify moments of muscle activity and the latter to identify which MU was active at detected time instances. The goal of clustering is to obtain reliable mean shapes of MUAPs, as observed on the recording grid, taking advantage of the repetitive nature of active MU firings.

A. Data

A surface EMG dataset was created simulating a small hand muscle. The spatio-temporal motor unit potentials were obtained using a finite volume conductor model (ANVOLCON) [11].

Units' shapes generated using the model were realistic, yet highly spatially correlated and with comparable, low amplitude. We used up to 8 different MU templates for our further analysis.

The spatio-temporal simulated signal had 143 data channels, the dimensions of the surface recording grid was 13x11 point electrodes with the inter-electrode spacing of 3mm perpendicular to the muscle fiber and 6mm in fiber direction.

The firing patterns for individual MUs were created taking into account general activation schemes and repetitive activity of muscles [12]. Therefore, MUs had Poisson distributed interspike-intervals with a mean firing frequency ranging from 8 to 24 Hz with increments of 2Hz. Twenty second long simulation signals were created, sampled at 5120 Hz, with added random Gaussian noise of 10 μ V root-mean-square (RMS) value. As a result, every units' shape appeared between 160 and 303 times and the mean SNR for used template shapes was calculated to be 5.6 dB with the standard deviation of 3.3 dB. The SNR was calculated as the ratio of signal and the noise power on the channel with the highest signal peak.

We generated 6 different simulated signals. Marked as signals 1 to 6, they differ in the number of active MUs present: the first signal has 3, and the last one has 8. The principle applied for creating signals was to add one more MU for each "new" signal. All signals were bandpass filtered between 10 and 1000Hz before processing.

B. Detection

Some MUs may exhibit large shapes on some of the recording electrodes (channels), whereas on the others they can be fully covered by noise. The relative position of MUs to the recording electrode grid is not a priori known and hence, the optimal electrodes for the detection of its activity cannot be determined in advance. Therefore, we use a set of scattered electrodes (corresponding to signal channels) for detection and clustering, distributed around the muscle junction so they could describe the propagation of its signals.

Figure 1 shows the 10 electrodes that were used for treating these signals. They are encircled with black boxes. We collect all time instances with muscle activity, the so-called timestamps. On each of these channels, a noise level is estimated as in [13], and the detection threshold is set to be 3 times this value. If this threshold is crossed, a timestamp of a local peak is stored. All timestamps (that indicate presence of MU activity) are gathered and used in the clustering process.

C. Clustering

Clustering is used to obtain mean MUAP shapes. The approach is a multichannel adaptation of the Wave_clus algorithm described in [9].

In the single channel approach, the clustering algorithm has the following steps: all the observations (spikes) are aligned; then, a predefined number of samples prior to and after each detected peak are stored. Discrete wavelet transform is then used to decompose each of the spikes. The 10 most discriminating wavelet coefficients according to Kolmogorov-Smirnov criteria are chosen to represent each spike. We thus have a new feature space of 10 wavelet coefficients, and the "projection" of each spike on that feature space constitutes the inputs for clustering.

In the case of HD-sEMG recordings, single channel observations do not provide sufficient information to reliably discriminate between MUs: sometimes, 2 signatures are very similar, and only certain electrodes enable us to see the difference. Hence, we need to observe several electrodes simultaneously. We assume that the electrodes previously used for the detection are sufficiently scattered over the grid to provide sufficient information to distinguish between different MUAPs.

The Wave_clus algorithm is extended for the case of multichannel observations. This is done by concatenating 22 samples of spikes from specified electrodes: 10 samples are taken before the detected timestamp, and 11 after. This provides input vectors that are 220 samples long. Each timestamp provides one of these input vectors. Similarly to the single-channel approach, the discrete wavelet transform is performed, and 55 (one quarter) of the most discriminating coefficients (for the whole dataset) are then kept and used as inputs for clustering.

This clustering algorithm automatically assesses the number of clusters. Moreover, the clustering process also allows having a group of unclustered elements. In the case of weaker contractions (smaller number of active MUs), we can expect that MUAPs mostly appear alone (non-overlapped), resulting in more clustered elements. If, on the other hand, more MUs are active, the probability of observing overlapped action potentials grows, and the number of unclustered shapes grows.

Among identified clusters, those larger than 50 shapes are being kept. For all clustered timestamps belonging to "large clusters", a median shape is calculated in the length of 151

samples. Similar to clustering, but this time for every electrode in the grid, 75 samples before and after the indicated timestamp are stored. Median is then used to better assess mean signatures and reduce the noise. After that, the singular value decomposition (SVD) is used to further diminish the noise for each median shape. Three elements with largest variance are kept in the reconstruction.

D. Evaluation

Two aspects are of interest when evaluating results: the temporal and spatial accuracy. Quality of the clustering itself is addressed by temporal parameters whereas the spatial determines if the obtained and template shapes belonging to MUs match.

To assess the time correlation of detected and existing trains, sensitivity and precision are used. Sensitivity is defined as the number of properly classified timestamps compared to the number of existing ones (for that particular MU). Precision is the number of properly classified timestamps divided by the number of detected timestamps for particular cluster. Its role is to describe whether the clustering was done properly, i.e. to assess if the assigned elements really belong to the same MU.

Each of the signatures obtained by clustering is aligned and compared with the original shape using 2 spatial validation measures: correlation and the normalized root mean square error (NRMSE). NRMSE is calculated using formula (1), where \hat{x} corresponds to estimated and x to template shapes, while the summing is done on all channels, over all the samples:

$$NRMSE = \sqrt{\frac{\sum (\hat{x} - x)^2}{\sum x^2}} \quad (1)$$

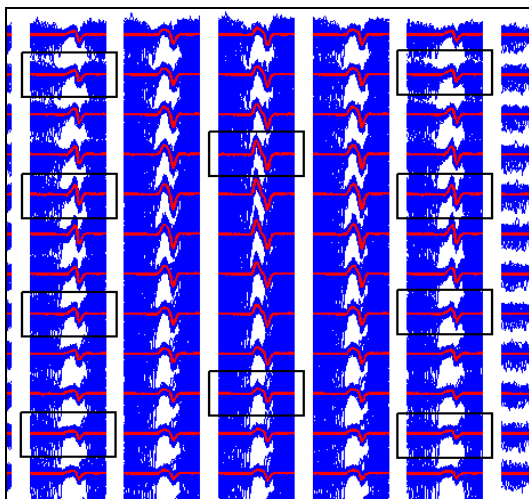


Fig. 1: Aligned MUAPs of a single MU on a central part of the grid (blue), and their extracted mean shapes (red); electrodes used for detection/clustering are encircled with black boxes

III. RESULTS

In all of the 6 used signals, all of the template shapes could be successfully reconstructed. The tendency to overcluster the data was noticed – more clusters than actual units were usually derived. It was always the case that a “large” cluster (one with greater number of elements) is

TABLE I
TEMPORAL MATCHING

	Sig 1	Sig 2	Sig 3	Sig 4	Sig 5	Sig 6
<i>Sensitivity</i>	0.68±0.16	0.55±0.15	0.46±0.16	0.41±0.13	0.35±0.09	0.32±0.11
<i>Precision</i>	1.00±0.00	1.00±0.00	0.88±0.20	0.84±0.19	0.95±0.04	0.91±0.06

Portrayed temporal correlations are between observed and exact clusters; values are shown in a format mean±std

present, whereas sometimes a smaller, similar one was also observed. This is due to the effect of noise which induced enough difference on the MUAPs to be identified as a separate cluster. Thus, as mentioned, only the larger clusters (more than 50 elements) were kept for the analysis.

Table 1 shows temporal quality parameters, sensitivity and precision, where for each signal a mean value and the standard deviation over the identified MUAPs is shown. Lower values for sensitivity indicate that a number of appearances of each MU firing were not accounted for in large clusters that were analyzed. However, this does not represent a problem since the goal is to recover mean shapes and only try to estimate the mean firing rates. High values of precision testify to the fact that most of the shapes were correctly classified.

Figure 1 depicts overlapped observations of the unit where the precision had the lowest value (0.6). Its estimated mean shape (red) has the spatial correlation 0.97 with the template and is thus successfully recovered.

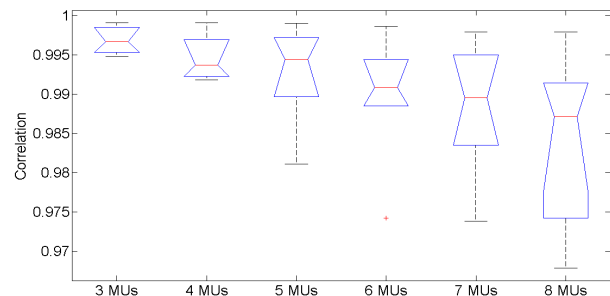


Fig 2: Spatial correlation matching

Figures 2 and 3 show boxplot representations of spatial parameters: the first shows the correlation, whereas the latter reveals the NRMSE. Results are grouped by the number of active MUs used (signals 1 to 6). Red line is a median value, while edges of the “boxes” are quartiles. Whiskers show the extreme values, and the red stars correspond to outliers. Spatial correlation is always high, while NRMSE is low. This indicates that the reconstruction of all the existing MUAP shapes was performed successfully. As a comparison, mean inter-shape correlation (when input shapes are

mutually compared) and the standard deviation are 0.77 ± 0.16 , and for the NRMSE values are 1.04 ± 0.70 .

Largest peak of inter-spike interval (ISI) histograms derived from large clusters, always corresponded to values within variance around the mean firing frequency of MU in question. This made it possible to estimate this frequency.

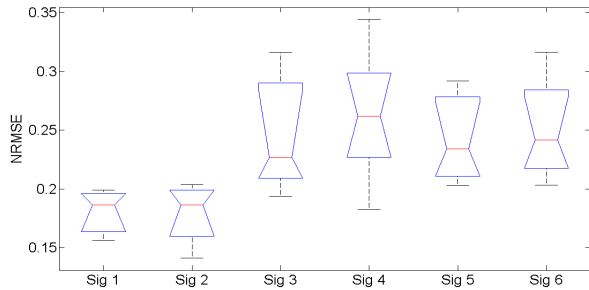


Fig 3: NRMSE

IV. DISCUSSION

We demonstrated a novel way to estimate mean shapes of active MUs from recordings of simulated signals, mimicking low force voluntary contractions of a small hand muscle. This approach uses a multichannel extension of the Wave_clus algorithm.

Signals with variable number of active MUs ranging from 3 to 8, were tested. The used model provided MU signatures of very high spatial correlation and low SNR, realistic for this muscle.

We assess in different ways the quality and effectiveness of our approach. As expected, lower sensitivity (shown in Table I) emphasizes the need for a full decomposition approach, which would be able to account for every observed shape by decomposing it into constituent MUAPs. Steps towards this goal have been taken [8] but the optimal solution to the problem in general is still an open question.

The spatial parameters portrayed in Figures 2 and 3 testify to the successful reconstruction of all of the template shapes: spatial correlation is almost always above 0.98, whereas the NRMSE is always very low.

When increasing the number of present units, the likelihood of finding a lone observation of a single unit (sensitivity) drops. Below a certain point, the number of elements in clusters will be insufficient to estimate the mean shapes reliably which reveals a certain limitation. Increasing the number of present MUAP shapes could thus possibly lead to one or more MUs evading detection. However, the ability to reconstruct at least 8 different MUAPs is demonstrated which is at least as good as in [5,6,7] or better.

Our goal to estimate the mean shapes and the mean firing frequencies from active MUs was successfully met. While the mean shapes could be completely reconstructed, firing patterns could only be characterized through their mean frequencies, due to the relatively small sensitivity.

Future research will be focused on the reconstruction of the exact firing patterns starting with the current approach

results in order to obtain the so-called full decomposition. For this purpose, the development of strategy for “demixing” overlapped observations is needed. Taking the assumption of possessing exact shapes for all constituent units, and the physiological properties of MU firings, this task is achievable (e.g. by using some adaptation of [14]), but the computational complexity can limit its applicability.

V. CONCLUSION

A promising method to identify shapes of constituent MUs in voluntary low force contractions of muscles using non-invasive surface recordings is presented. The exact limitation of the method with respect to maximal number of MUs that could be extracted remains an open question. However, usefulness of the method has been demonstrated. Researches can easily use this approach for quick and reliable extraction of shapes of MU signatures on the high density recording grid and estimation of their mean firing frequencies.

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