Rigorous performance assessment of the algorithms for resolving motor unit action potential superpositions

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Abstract

Background:

It is necessary to decompose the intra-muscular EMG signal to extract motor unit action potential (MUAP) waveforms and their firing times. Some algorithms were proposed in the literature to resolve superimposed MUAPs, including Peel-Off (PO), branch and bound (BB), genetic algorithm (GA), and particle swarm optimization (PSO). This study aimed to compare these algorithms in terms of accuracy and efficiency.

Methods:

Two sets of two-to-five MUAP templates (set1: a wide range of energies, and set2: a high degree of similarity) were used. Such templates were time-shifted, and white Gaussian noise was added. A total of 1000 superpositions were simulated for each template and were resolved using PO (also, POI: interpolated PO), BB, GA, and PSO algorithms. The overall accuracy and running time of each resolution were measured. The Generalized Estimating Equation and the overall rank product were then used.

Results:

The PSO outperformed the other algorithms following by BB, GA, PO, and POI in the first dataset, while the ranking of the algorithm was BB, PSO, GA, PO, POI in the second set. The overall ranking was BB, PSO, GA, PO, and POI in the entire datasets.

Conclusion:

Although the BB algorithm is generally fast, there are some cases in which the BB algorithm spends too much time. The BB, PSO, and GA algorithms have a high enough accuracy in full offline decomposition, but too slow for real-time applications.

***Keywords*—** Resolving Superposition; EMG decomposition; Motor unit action potentials;

Introduction

The electrical signal produced in a muscle is known as the electromyogram or the EMG signal. It is the result of the algebraic summation of motor unit action potentials (MUAP's). EMG signals can be recorded either by surface or intramuscular electrodes. The former is known as surface EMG (sEMG), while the latter is known as intramuscular EMG (iEMG). Both sEMG and iEMG consist of different motor unit action potential trains (MUAPTs) with the firing of motor units repetitively during muscle contraction (LeFever and De Luca, 1982). EMG signals have a variety of applications in rehabilitation, sports science, geriatrics, ergonomics, neuromuscular disorders, and medicine (Gazzoni et al. , 2004). EMG signals can also be used as Human-Machine interfaces to control external prosthetic devices (Farina and Holobar, 2015, Karimimehr et al., 2017). In some applications, it is necessary to decompose the EMG signal to extract MUAP waveforms and their firing times (Lateva and McGill, 2001a). There are many algorithms for iEMG decomposition in the literature (De Luca et al., 1982a, De Luca et al., 1982b, LeFever and De Luca, 1982, Marateb et al., 2011, McGill et al., 2005).

Most of the iEMG decomposition algorithms involve similar signal processing steps (Marateb et al., 2016). The iEMG signal is first high-pass filtered to remove baseline fluctuations and to select potentials arising from muscle fibers near the recording electrode. The segments of the signal that contain potentials that rise significantly above the baseline noise (active segments, AcS's) are then identified. Then, the AcS's are clustered to identify the similarly shaped MUAPs that correspond to the discharges of distinct active MUs, and then every AcS is classified as being a discharge of one or more MU. It is possible that during muscle contraction, two or more MUs fire at the same time or in close temporal succession, and their action potentials overlap with each other to form a superposition (Fang et al., 1999). Some algorithms attempt to resolve superpositions into their constituent MUAPs (full decomposition). A full decomposition is an essential tool for the study of muscle architecture (Lateva and McGill, 2001b), MU coordination (De Luca and Erim, 1994), MU synchronization (Datta and Stephens, 1990) and discharge irregularities (Lateva et al. , 2002).

There are some algorithms proposed in the literature to resolve superimposed MUAPs. They either identify continuous or discrete-time shifts of the involved MUs. One of these algorithms, the exhaustive search algorithm, considers all of the possible discrete-time shifts. It is very time-consuming, especially when a large number of MUs are involved in a superposition. Accordingly, this algorithm is not usually used in practice (Marateb, McGill, 2016). Other sub-optimal algorithms were therefore proposed: Peel-Off (PO) (Christodoulou and Pattichis, 1999, Etawil and Stashuk, 1996, Fang, Agarwal, 1999, LeFever and De Luca, 1982), branch and bound (BB) (Lateva, McGill, 2002), genetic algorithm (GA) (Florestal et al., 2007a), and particle swarm optimization (PSO) (Marateb and McGill, 2009a).

The PO algorithm is a primary and suboptimal algorithm that uses the correlation between the MUAP templates and the superimposed signal to find the best match **(supplementary material; Fig. s1)**. Partial superpositions, in which the MUAPs overlap without peaks being obscured, can be efficiently resolved using this algorithm.

The other algorithms are based on the minimization of a cost function, e.g., the squared error of the residual between the given superposition and the reconstructed waveform based on the estimated time shifts of the involved MUAPs. The BB algorithm is a constructive exact optimization algorithm that smartly considers all possible discrete time-shift cases

(supplementary material; Fig. s2). After finding the best discrete-time shifts, it then uses interpolation, and Newton's algorithm to find the best continuous-time shifts. On the other hand, GA and PSO are population-based probabilistic meta-heuristic optimization solution algorithms. These two algorithms are inspired by nature. GA is inspired by the process of natural selection in Genetics (Florestal et al., 2007b) **(supplementary material; Fig. s3),** while PSO simulates the social behavior of a flock of birds (Marateb and McGill, 2009b) **(supplementary material; Fig. s4)**. These algorithms were used in the literature to minimize the superposition cost function.

In this manuscript, we aimed to compare these algorithms in terms of accuracy and efficiency. We focused on the known-constituent case, in which the MUAPs involved in the superposition are assumed to be known a-priori. We simulated a large number of partial, constructive, and destructive superpositions and resolved them using the PO, POI (Peel-Off with Interpolation factor of 10), BB, GA, and PSO algorithms. We then used proper statistical tests to analyze and compare their performances rigorously.

Materials and Methods

The performance of the algorithms was evaluated using simulated superpositions. Two sets of MUAP templates were used. The templates were taken from iEMG signals from the public domain database at www.emglab.net. The templates were sampled at 10 kHz and high-pass filtered at 10 kHz. Set 1 consisted of ten templates with a wide range of energies (338-1624), while set 2 consisted of six templates with a high degree of similarity (correlation coefficients 0.59±0.28).

Each superposition was involved from N=2 to N=5 templates. The appropriate number of templates were chosen at random from one of the two sets. Each template was time-shifted by a continuous random amount within ± 1.0 ms using a high-resolution alignment algorithm (McGill and Dorfman, 1984). Then the time-shifted templates were added together along with white Gaussian noise with the standard deviation equal to 0.05 times the mean peak-to-peak template amplitude (Marateb and McGill, 2009b). A total of 1000 superpositions were formed for each value of N for each template set, for a total of 8000 superpositions in all. The simulated datasets and also the MATLAB code of the BB algorithm is available **(supplementary material; data_code s1)**. Figs. 1 and 2 show the templates of the sets 1 and 2 with some examples of superpositions.

[Figs 1 and 2 are included here].

Each superposition was resolved using the PO, BB, GA, and PSO algorithms. Also, in order to test whether the PO algorithm would be improved by interpolation, it was also resolved using the PO algorithm after up-sampling the waveforms by a factor of 10, which we will refer to as the POI algorithm. In each case, it was assumed that the identities of the templates involved in the superposition were known. For each resolution, the time shifts estimated by the algorithm were compared with the actual time shifts, and the offset errors were stratified into three classes: < ± 0.1 ms (essentially correct), ≤ ± 0.5 ms (close), > ± 0.5 ms (incorrect). The accuracy of each resolution was measured by the overall accuracy ($I_d = \frac{n_c}{n_i+N}$, where n_c is the number of essentially correct time shifts, n_i is the number of incorrect time shifts, and N is the total number of templates involved in the superposition).

Also, the average and maximum running time of the superposition resolving algorithms was recorded. The simulations were performed on an Intel dual-core 1.83 GHz CPU with 2 GB of

RAM. To identify the rank of the analyzed algorithms on the entire datasets, and number of templates based on the performance indices I_d and running time, the rank of each protocol was identified and then combined using the Rank Product (RP) (Breitling et al. , 2004). Each criterion was considered as a ranker ($k = 2$). The overall RP for each superimposed MUAP resolution method (g) was estimated as below:

$$RP(g) = \left(\prod_{i=1}^{k} r_{g,i} \right)^{1/k} \qquad \text{(Eq.1)}$$

where $r_{g,i}$ is the rank of the method g of the $i - th$ ranker. RP values were then ordered in the ascending order.

Statistical Methods

Continuous variables were reported as MEAN±SD. Generalized Estimating Equation (GEE) method was used for modeling factors associated with repeated responses (i.e., 1000 random realizations of superpositions) (Hardin and Hilbe, 2007). GEE was used to find significant factors (MUAP set and the number of constituent templates) affecting the performance/efficiency of the superposition resolution algorithms. Also, Friedman Post hoc statistical test was used to identify which algorithm significantly outperformed the others. The level of statistical significance of p =0.05 was used in our study. The statistical analysis was performed using SPSS Statistics for Windows version 22 (IBM Corp. Released 2013. Armonk, NY: IBM Corp.).

Results

The performance of the algorithms (BB, GA, PSO, PO, and POI) was assessed on sets 1 and 2 with superpositions involving $N = 2$ to $N = 5$ constituent templates) (Table 1).

[Table 1 is included here].

I_d analysis:

Data set, algorithm, and the number of templates were statistically significant ($p < 0.05$). PSO algorithm was statistically better than the other algorithms ($p < 0.05$) followed by BB, GA, POI, and finally, PO.

Running Time Analysis:

Data set and algorithm were statistically significant ($p < 0.05$). The PO algorithm was significantly better than the other algorithms($p < 0.05$) followed by POI, GA, BB, and finally PSO.

To better analyze the algorithms, the cases in which the PO was not successful (I_d<30%), i.e., cases involving constructive or destructive superposition, were re-analyzed separately (which we will refer to as the hard set). The results for BB, GA, PSO are shown in Table 2.

[Table 2 is included here].

I_d analysis on the hard set:

Data set, algorithms, and the number of templates were statistically significant. BB algorithm was statistically better than others ($p < 0.05$), followed by PSO, GA.

Running Time analysis on the hard set:

Data set, algorithm, and the number of templates were statistically significant. The POI algorithm was significantly better than the other algorithms ($p < 0.05$) followed by GA, BB, and finally PSO.

The overall results using Rank Product:

When combining the I_a and running time based on the Rank Product formula (Eq. 1), the PSO outperformed the other algorithms following by BB, GA, PO, and POI in the first dataset. For the second dataset, the ranking of the algorithm was BB, PSO, GA, PO, POI. In the first hard dataset, the ranking was PSO, BB, and GA, while in the second hard dataset, the ranking was BB, PSO, GA.

Combining the results of the first and second datasets, the overall ranking was BB, PSO, GA, PO, and POI. In the hard datasets, the ranking was BB, PSO, and GA. Thus, we conclude that the BB algorithm outperformed the other algorithms, considering different normal/hard datasets.

It was shown in the literature that the alignment error is affected by the SNR of the superposition. Thus, the overall identification of the BB algorithm for superpositions involving 2 constituent templates of the first set at different noise levels is shown in Fig. 3. The performance of the algorithm was identical from the no-noise condition to the noise level of 0.05, which was used in the current study. The identification rate was higher than 90% when the noise level was 0.1 or less.

[Fig. 3 is included here].

Discussion

In this article, we analyze the most important and popular algorithms that are used for resolving superposition in iEMG decomposition. This study aimed to compare all of these algorithms in hard conditions in terms of both accuracy and computation time.

For creating a hard condition, we used two datasets, one of which included MUAPs with a variety of energies and one of which included MUAPs with similar shapes. We simulated 8000 superpositions that covered all of the possible types of superpositions (constructive, destructive, and partial).

The PO algorithm is the fastest and easiest algorithm for resolving superpositions, but because it is based on finding the highest similarity between the templates and the superposition, it does not do well when it encounters constructive and destructive superpositions. The performance did not improve when signals were upsampled by a factor of 10 (POI), showing that the difficulty is not merely a result of time quantization, but reflects the difficulty of resolving superpositions in which none of the constituent templates are immediately recognizable. PSO and GA algorithms are population-based algorithms, and there is no guarantee that they can reach the global minimum. Also, their speed is not fast enough for real-time applications. The BB algorithm intelligently searches for the global minimum and, in many cases, finds it quickly. However, because resolving a superposition is a non-convex problem and because the search space may be quite large, it sometimes takes many iterations to find the global minimum and prove that it is indeed the global minimum.

Because the PO algorithm was not able to resolve many of the constructive and destructive superpositions, we decided to look at those cases more closely (hard set). The analysis showed that all the other algorithms had a higher I_d on the hard set than on the full set. It seems that BB, PSO, and GA also have some problems in resolving the partial superpositions, and when these cases were removed, the accuracy of these algorithms increased.

Although the BB algorithm is fast in some cases, there are other cases in which the BB algorithm spends too much time. For example, for 5 constituent templates from set number 2, the BB algorithm had a maximum computation time of 21.88 s, which is a massive time for resolving superpositions of MUAPs.

The BB, PSO, and GA algorithms have a high enough accuracy to be suitable for applications that require accurate full decomposition. However, at present, their use is limited to offline applications, since they are too slow for real-time use.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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References

Breitling R, Armengaud P, Amtmann A, Herzyk P. Rank products: a simple, yet powerful, new method to detect differentially regulated genes in replicated microarray experiments. FEBS letters. 2004;573:83-92.

Christodoulou CI, Pattichis CS. Unsupervised pattern recognition for the classification of EMG signals. IEEE Transactions on Biomedical Engineering. 1999;46:169-78.

Datta A, Stephens J. Synchronization of motor unit activity during voluntary contraction in man. The Journal of physiology. 1990;422:397-419.

De Luca C, LeFever R, McCue M, Xenakis A. Control scheme governing concurrently active human motor units during voluntary contractions. The Journal of physiology. 1982a;329:129-42.

De Luca CJ, Erim Z. Common drive of motor units in regulation of muscle force. Trends in neurosciences. 1994;17:299-305.

De Luca CJ, LeFever RS, McCue MP, Xenakis AP. Behaviour of human motor units in different muscles during linearly varying contractions. The Journal of physiology. 1982b;329:113-28.

Etawil H, Stashuk D. Resolving superimposed motor unit action potentials. Medical and Biological Engineering and Computing. 1996;34:33-40.

Fang J, Agarwal GC, Shahani BT. Decomposition of multiunit electromyographic signals. IEEE Transactions on Biomedical Engineering. 1999;46:685-97.

Farina D, Holobar A. Human? Machine Interfacing by Decoding the Surface Electromyogram [Life Sciences]. IEEE Signal Processing Magazine. 2015;32:115-20.

Florestal JR, Mathieu PA, Plamondon R. A genetic algorithm for the resolution of superimposed motor unit action potentials. IEEE Transactions on Biomedical Engineering. 2007a;54:2163-71.

Florestal JR, Mathieu PA, Plamondon R. A genetic algorithm for the resolution of superimposed motor unit action potentials. IEEE transactions on bio-medical engineering. 2007b;54:2163-71.

Gazzoni M, Farina D, Merletti R. A new method for the extraction and classification of single motor unit action potentials from surface EMG signals. Journal of neuroscience methods. 2004;136:165-77.

Hardin JW, Hilbe JM. Generalized Estimating Equations. Wiley Encyclopedia of Clinical Trials: John Wiley & Sons, Inc.; 2007.

Karimimehr S, Marateb HR, Muceli S, Mansourian M, Mañanas MA, Farina D. A Real-Time Method for Decoding the Neural Drive to Muscles Using Single-Channel Intra-Muscular EMG Recordings. International Journal of Neural Systems. 2017:1750025.

Lateva ZC, McGill KC. Estimating motor-unit architectural properties by analyzing motor-unit action potential morphology. Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology. 2001a;112:127-35.

Lateva ZC, McGill KC. Estimating motor-unit architectural properties by analyzing motor-unit action potential morphology. Clinical neurophysiology. 2001b;112:127-35.

Lateva ZC, McGill KC, Johanson ME. Electrophysiological evidence of adult human skeletal muscle fibres with multiple endplates and polyneuronal innervation. The Journal of physiology. 2002;544:549-65.

LeFever RS, De Luca CJ. A procedure for decomposing the myoelectric signal into its constituent action potentials-part I: technique, theory, and implementation. IEEE transactions on biomedical engineering. 1982:149-57.

Marateb HR, McGill KC. Resolving superimposed MUAPs using particle swarm optimization. IEEE Transactions on Biomedical Engineering. 2009a;56:916-9.

Marateb HR, McGill KC. Resolving superimposed MUAPs using particle swarm optimization. IEEE transactions on bio-medical engineering. 2009b;56:916-9.

Marateb HR, McGill KC, Webster JG. Electromyographic (EMG) Decomposition. Wiley Encyclopedia of Electrical and Electronics Engineering: John Wiley & Sons, Inc.; 2016.

Marateb HR, Muceli S, McGill KC, Merletti R, Farina D. Robust decomposition of single-channel intramuscular EMG signals at low force levels. Journal of neural engineering. 2011;8:066015.

McGill KC, Dorfman LJ. High-Resolution Alignment of Sampled Waveforms. IEEE Transactions on Biomedical Engineering. 1984;BME-31:462-8.

McGill KC, Lateva ZC, Marateb HR. EMGLAB: an interactive EMG decomposition program. Journal of neuroscience methods. 2005;149:121-33.

Table I: The performance of the analyzed MUAP superimposed resolution algorithms on sets 1 and 2 in MEAN±SD [minimum,maximum].

		Set 1		Set 2	
Number of Templates (N)	algorithm	I_d% + std [max]	Time(ms) + std [max]	I_d%+ std [max]	Time(ms) + std [max]
2	BB	0.99±0.02 [1.00]	17 ± 3 [35]	1.00±0.00 [1.00]	19±4 [35]
	GA	0.99±0.08 [1.00]	43.11 ± 40.31 [930.51]	1.00±0.03 [1.00]	41±48 [672]
	PSO	1.00±0.00 [1.00]	1564 ± 236 [5565]	1.00±0.00 [1.00]	1561±196 [4018]
	PO	0.49±0.32 [1.00]	0.23±0.09 [1.99]	0.47±0.37 [1.00]	0.15±0.05 [0.51]
	POI	0.52±0.34 [1.00]	1.80±0.15 [4.07]	0.49±0.38 [,1.00]	1.80±0.15 [3.03]
3	BB	0.99±0.07 [1.00]	43 ± 18 [166]	1.00±0.00 [1.00]	67 ± 25 [189]
	GA	0.97±0.12 [1.00]	157 ± 142 [1294]	0.99±0.11 [1.00]	108 ±131 [1476]
	PSO	0.99±0.05 [1.00]	3070 ± 488 [6598]	1.00±0.00 [1.00]	3078 ± 496 6523]
	PO	0.32±0.21 [1.00]	0.23±0.09 [1.11]	0.30±0.23 [1.00]	0.19±0.06 [0.56]
	POI	0.33±0.22 [1.00]	2.57±0.48 [6.42]	0.32±0.25 [1.00]	2.32±0.14 [,3.38]
4	BB	0.98±0.10 [1.00]	144 ± 107 [1317]	1.00±0.02 [1.00]	384 ±230 [1724]
	GA	0.93±0.17 [1.00]	272 ± 268 [3346]	0.97±0.14 1.00]	198 ±182 [2119]
	PSO	0.98±0.10 [1.00]	7113 ± 557 [10076]	0.99±0.07 [1.00]	7210 ± 591 [12663]
	PO	0.26±0.17 [1.00]	0.21±0.06 [0.48]	0.25±0.18 [1.00]	0.23±0.06 [0.45]
	POI	0.27±0.17 [1.00]	3.02±0.42 [6.94]	0.26±0.19 [1.00]	2.86±0.16 [3.92]
5	BB	0.94±0.16 [1.00]	748 ± 1092 [18307]	0.99±0.06 [1.00]	3633 ± 3001 [21888]
	GA	0.84±0.25 [1.00]	326 ± 169 [2375]	0.87±0.28 [1.00]	328 ± 179 [1785]
	PSO	0.95±0.15 [1.00]	10940 ± 1132 [16762]	0.94±0.20 [1.00]	11012 ± 1002 [16405]
	PO	0.21±0.14 [1.00]	0.24±0.06 [0.56]	0.21±0.14 [0.80]	0.24±0.07 [,0.50]
	POI	0.21±0.15 [1.00]	3.47±0.29 [6.49]	0.21±0.15 [0.80]	3.41±0.27 [8.38]

BB: Branch and Bound; GA: Genetic Algorithm; PSO: Particle Swarm Optimization; PO: Peel-Off; POI: The interpolation of the signals by the factor of 10 and then running Peel-off.

Table II: The performance of the analyzed MUAP superimposed resolution algorithms on selected hard sets 1 and 2 where the Peel-off algorithm was not successful in MEAN±SD [minimum,maximum].

		Hard Set 1		Hard Set 2	
Number of Templates (N)	algorithm	I_d% + std [max]	Time(ms) + std [max]	I_d%+ std [max]	Time(ms) + std [max]
2	BB	1.00±0.00 [1.00]	17 ± 4 [35]	1.00±0.00 [1.00]	19 ± 4 [33]
	GA	1.00±0.00 [1.00]	26 ± 10 [82]	0.99±0.06 [1.00]	31 ± 34 [495]
	PSO	1.00±0.00 [1.00]	1553 ± 150 [2485]	1.00±0.00 [1.00]	1568 ± 221 [3825]
3	BB	0.99±0.05 [1.00]	41 ± 17 [166]	1.00±0.00 [1.00]	65 ± 25 [189]
	GA	0.98±0.11 [1.00]	146 ± 138 [1294]	0.99±0.11 [1.00]	93 ± 93 [1237]
	PSO	1.00±0.03 [1.00]	3079 ± 504 [5620]	1.00±0.00 [1.00]	3089 ± 496 [6482]
4	BB	0.98±0.09 [1.00]	141 ± 109 [1317]	1.00±0.00 [1.00]	390 ± 237 [1724]
	GA	0.94±0.16 [1.00]	274 ± 260 [2717]	0.97±0.14 [1.00]	188 ± 164 [2119]
	PSO	0.99±0.08 [1.00]	7120 ± 577 [9882]	0.99±0.08 [1.00]	7200 ± 579 [9805]
5	BB	0.94±0.16 [1.00]	723 ± 1144 [18307]	0.99±0.06 [1.00]	3626 ± 2970 [21888]
	GA	0.85±0.25 [1.00]	320 ± 164 [2375]	0.88±0.27 [1.00]	314 ± 139 [1600]
	PSO	0.95±0.16 [1.00]	10938 ± 1148 [16762]	0.95±0.20 [1.00]	11011 ± 1019 [16405]

BB: Branch and Bound; GA: Genetic Algorithm; PSO: Particle Swarm Optimization.

Captions to illustrations

Fig. 1: Ten MUAP templates in set 1 (top) and some examples of superpositions with 2-5 constituent MUAPs (bottom).

Fig. 2: Six MUAP templates in set 2 (top) and some examples of superpositions with 2-5 constituent MUAPs (bottom).

Fig. 3: The overall identification of the BB algorithm for 2-constituent superpositions from the first set at different noise levels. The standard deviation of the added noise was the noise level multiplied by the peak-to-peak of the superimposed signal.

Fig.1

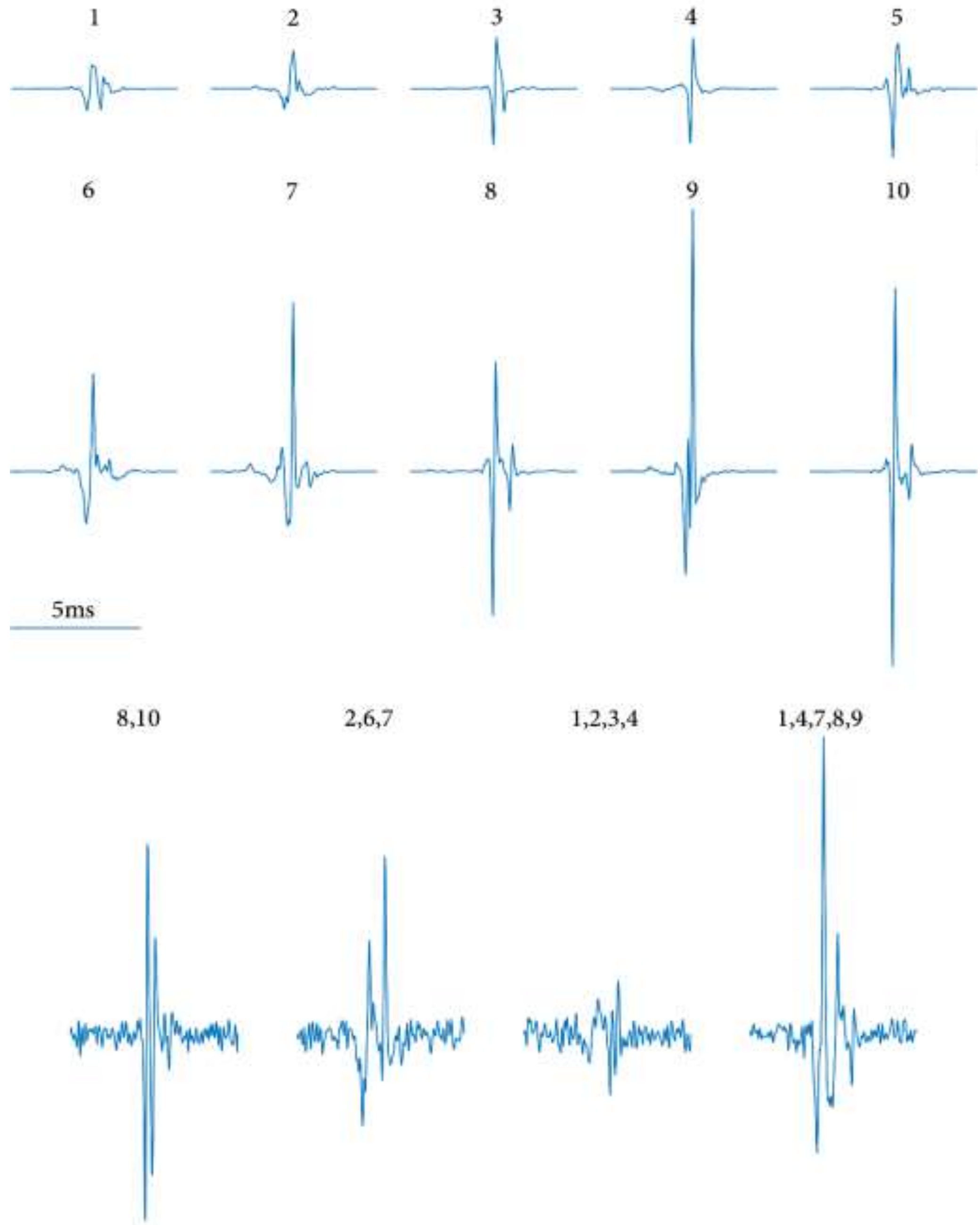


Fig.2

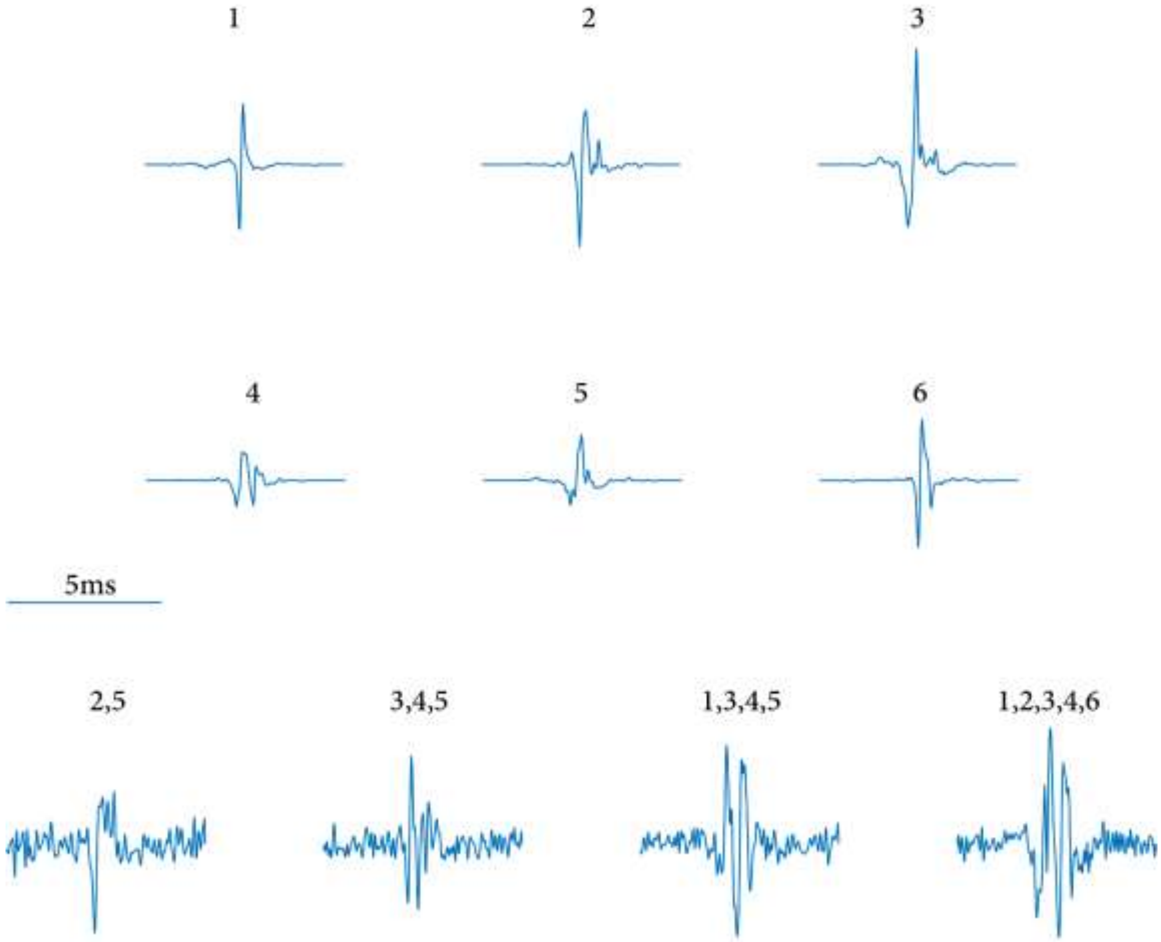
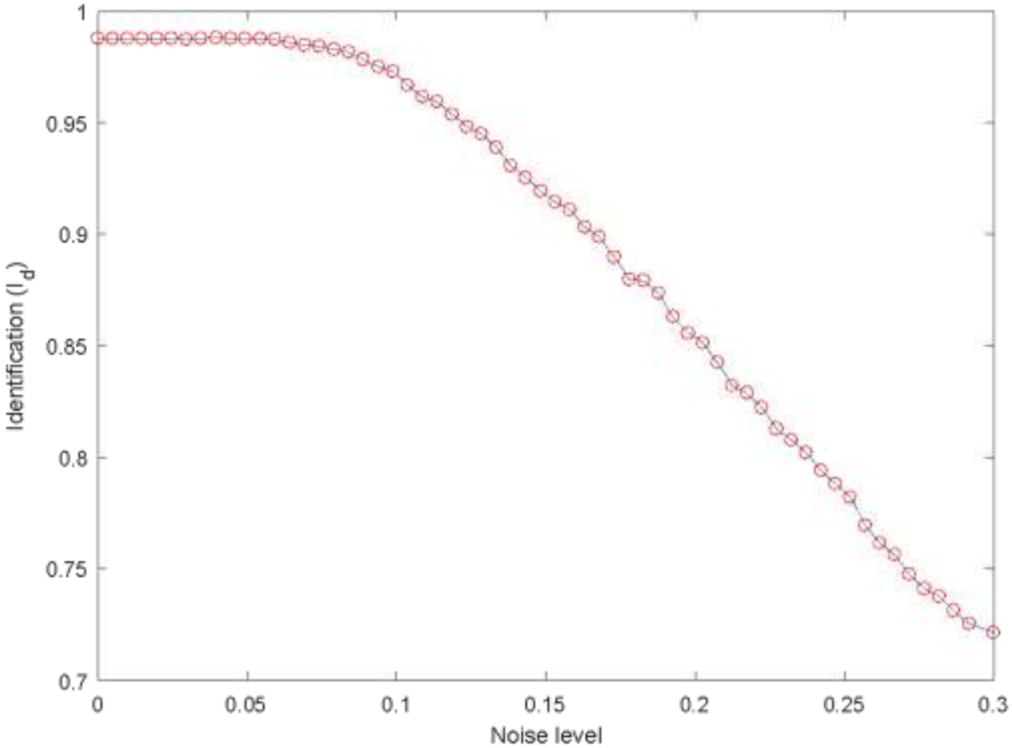


Fig. 3


Identification (I_d)
Noise level
1
0.95
0.9
0.85
0.8
0.75
0.7
0
0.05
0.1
0.15
0.2
0.25
0.3