Motor-Evoked Potential Decomposition Using Independent Component Analysis

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Define the Problem:

The spinal cord contains the circuitry to control posture and locomotion after complete paralysis, and the circuitry can be enabled by electrical and/or pharmacological stimulation. During the stimulation, evoked potential is recorded from the muscle to predict posture and locomotion performance. The evoked potential is composed of the superposition of the activity of various motor units corresponding to different spinal sensorimotor networks. Currently, few details are known as to which components of the spinal sensorimotor networks are dynamically facilitated or depressed during the stimulation. Therefore, decomposition of the superimposed evoked potential into individual motor units may help us to develop a deeper insight of the sensorimotor networks, thus help us design optimal stimulation parameters.

What is EMG Decomposition?

EMG decomposition is the process of discovering the significant motor units that contribute to a detected EMG signal. Fig 1 illustrates of the EMG decomposition process, and depicts the relationship between a decomposed EMG signal and the activity of individual motor units. In order to understand the EMG decomposition process, it is important to be familiar with the composition of an EMG signal first.

A *muscle fibre action potential (MFAP)* is a fundamental component contributing to a detected EMG signal, which results from the propagation of an action potential (AP) along the excitable membrane of a muscle fibre. The characteristics of MFAP depend upon the diameter of the fibre, the speed with which it conducts APs (its conduction velocity), its location relative to the detection electrode and the configuration of the detection electrode. Larger diameter fibres create larger MFAPs. APs conducted more slowly create MFAPs that have longer durations. The magnitude and high frequency content of a MFAP decrease as the distance between the electrode and fibre or the surface area of the electrode increase. [1]

The fibres of a muscle are not excited individually. They are controlled together in groups, called motor units. Formally, a *motor unit (MU)* is an alpha-motoneuron, its axon and all of the muscle fibres it innervates. As such, individual MFAPs are, under normal circumstances, not detected. Instead a summation of all of a motor unit's MFAPs or a *motor unit action potential (MUAP)* is detected. The goal of EMG decomposition is to separate the significant motor unit action potential (MUAP) in the EMG signal [1]

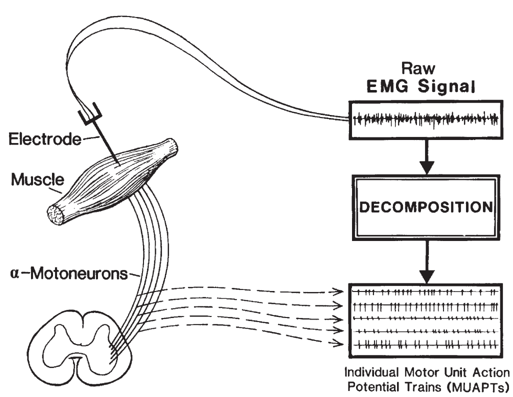

Figure 1. Illustration of the process of EMG decomposition [1]

Why EMG decomposition is important?

With neuropathic diseases, the number of MUs is reduced and the sizes of the remaining MUs are increased, resulting in the change of the MU number and morphology. Thus, the number and morphology of the MUs can provide clinically important information. [1] Hence, decomposing EMG signal into individual MU can help us to:
1) Understand the spinal sensorimotor network of the patients, the response of this network under different stimulation conditions, and the change of the network with different treatment strategies;
2) Design optimal stimulation parameter & drug dosage to improve treatment.

Current Techniques for EMG Decomposition

At present, most researchers use machine learning techniques to decompose EMG signal, which assume that each motor unit has a characteristic shape. Therefore, the shape of the motor units is used as the feature for EMG decomposition. Fig 2 shows the four stages of using machine learning for EMG decomposition.

1) MU detection. In this step, the motor units are detected from the EMG signal by defining some detection thresholds based on some statistics computed from the signal.

2) MU clustering. After the MU detection, a short signal is used (usually the first 5s) for clustering different motor units into different groups. The clustering algorithm mainly has two goals: i) determine the correct number of motor unit groups; ii) assign the motor units contained in this short signal to the correct groups.

3) MU classification. After the MU clustering, the motor units in the first 5s are assigned into different groups thus can play as the "training set" for classifying the remaining motor units. Supervised learning methods are used to classify the motor units in the remaining of the signal to these pre-defined groups.

4) Superposition resolution. When two or more motor units discharge at close time, they will overlap together in the EMG signal and difficult to be decomposed. Thus, in the last step, some strategies need to be applied to resolve the superimposed motor units.

Figure 2. Flow chart of the EMG decomposition algorithm using machine learning technique

Generally, the machine learning technique is complicated. For many algorithms, it needs experts to manually adjust the decomposition results in order to achieve high accuracy. Also, since this technique use motor units shape as the characteristic for EMG decomposition, so it's difficult to resolve motor units with similar shapes.

Proposed Technique: Independent Component Analysis (ICA)

Independent Component Analysis is a powerful technique which is able to separate the underlying independent components linearly mixed in several sensors/channels.

One critical requirement of ICA is "multiple channels". In order to separate N independent components (ICs), ICA requires N channels. In most cases of indwelling EMG recording, however, only one channel is available for each muscle. In this case, can ICA be applied to EMG decomposition is this case?

The answer should be "no", since ICA is not applicable to single channel. Luckily, however, the signal we are dealing with is special: the evoked potential is periodic due to the 40Hz electrical stimulation. If assuming that each motor unit has fixed latency, then we can align each period using stimulation as the marker, and use different periods as the "multiple channels". Fig 3 shows an example of aligning different stimulation periods using the stimulation. 80 periods (2s) are aligned in total, and the lowest trace represents the first stimulation pulse. Now we have 80 channels of signals, which can be decomposed by ICA.

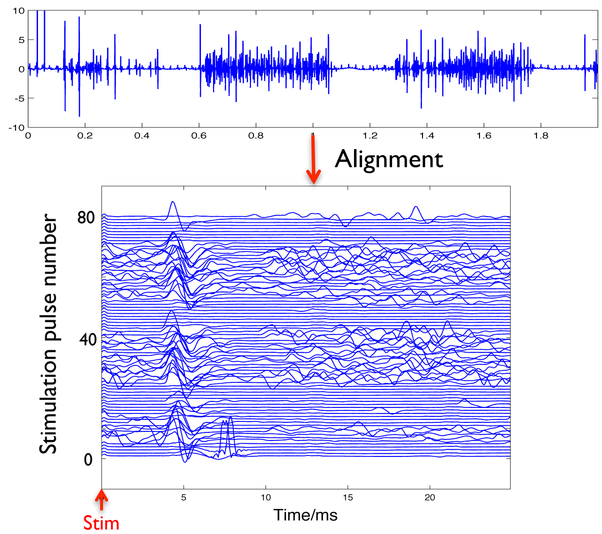

Figure 3. Top: Evoked potential recorded from the right soleus (bandpass filter 10-3333Hz); Bottom: The evoked potential is aligned using stimulation as the marker (totally 80 periods are aligned, and the lowest trace represents the first pulse)

The critical assumption here is "each motor unit has fixed latency over different stimulation periods". Generally, this assumption is reasonable, the reasons are as follows: i) the distance of different networks to the electrodes is fixed, also the conduction velocity is fixed, therefore the latency is fixed for each motor units. In addition, different networks have different distances to the electrodes, so each motor unit has its characteristics/unique latency; ii) from Fig 3 we can see that motor units of the MR (4-6ms) occur with almost the same latency, this plays as a proof of our assumption; iii) the firing rate for a normal subject is less than 20Hz. In our case the stimulation period is 40Hz, so we would expect that there is only one instance of each motor unit per stimulation period, and these motor units are triggered/modulated by the stimulation.

Apply ICA to Decompose the Evoked-Potential into Individual Independent Components

After aligning the different stimulation periods, we can apply ICA to separate the underlying independent components. Fig 4 shows the aligned signal (left) and the separated independent components (right). The beauty of the results here is that each independent component (IC) only contains one "motor unit", which means that our decomposition algorithm works! To see this clearly, we plot out the first 40 motor units (Fig 5), and we can see that they are indeed in the morphology of motor units.

So far, we have successfully decomposed the EMG signal into individual motor units. Then, we are wondering: which channels contain motor units, and how the motor units evolve with time?

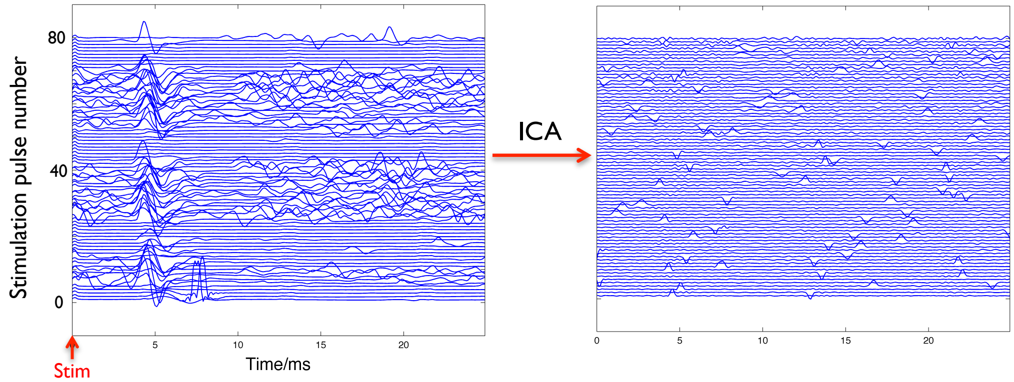

Figure 4. Left: Aligned evoked potential. Right: Decomposed Independent Components (ICs) after ICA. Clearly we can see that in most ICs there is only one “motor units”, which means the decomposition is successful.

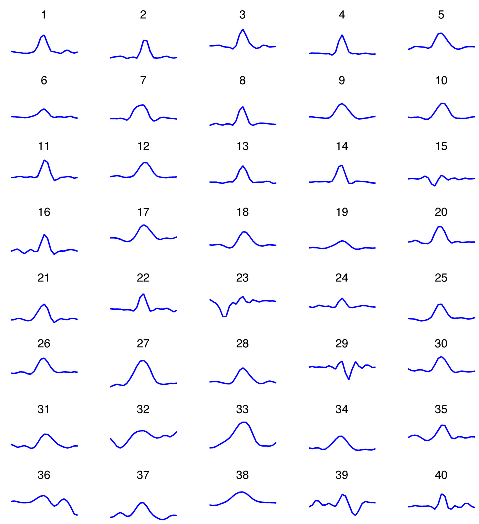

Figure 5. The first 40 Motor Units (the MUs with small power and at the two ends of the signal were ignored)

Back Project the Independent Components

To see which channels contain the motor units, we can project each IC back into the original coordinate. Fig 6 illustrates the results of some of the back-projected ICs. In this example, the rat is stepping, and we can see ~3 bursts in the aligned signal (middle). IC15 represents a motor unit of the middle response (MR, 4-6ms). We can see the IC only occurs during the bursting, which indicates our method is accurate. IC32 and IC34 represent motor units of the late response (LR, >7ms). From this “back-projection” figure, we can see how each motor units evolve with time (i.e. when it starts, when it ends, and how its amplitude changes with time, etc.)

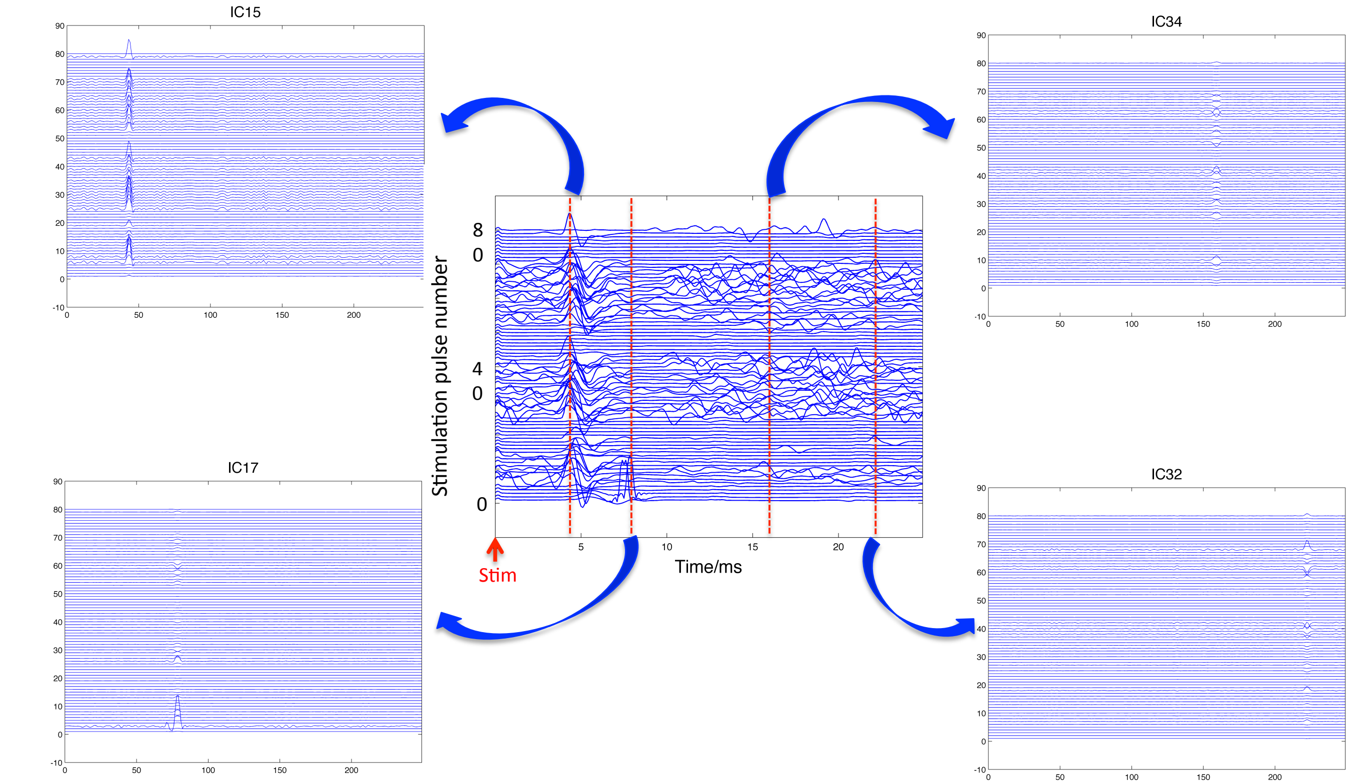

Fig 6. Back projection of the ICs. We can see which periods/channels contain the IC, and the time evolvement of each IC. The activation time of the motor units agree with that of the aligned signal.

Compare ICA with Machine Learning Techniques in EMG decomposition

Compared with machine learning technique, ICA is simple but accurate. Also, it is able to resolve different motor units with similar shapes, since it uses the latency information for decomposition rather than the shape information. In addition, ICA is fast, and doesn't need the manual intervention from experts to achieve high accuracy. Table 1 summarized the comparison of these two techniques.

Table 1. Comparison of machine learning and ICA in EMG decomposition

Machine Learning	ICA
- Complicated - Difficult to resolve similar shape MUs - Require relatively long signal - Need manual intervention to achieve high accuracy	- Simple - Can resolve similar shape MUs - Can deal with very short signal - No need of manual intervention
- Can deal with MU of varying latency - Can determine the amplitude of MUs - Applicable to all EMG signals (including single channel recording)	- Must deal with MU of fixed latency - Can't determine the MU amplitude - Only applicable to evoked-potential and multichannel EMGs

Compare the Motor Units Under Different Conditions

Now we have successfully decomposed the EMG signal into individual motor units and see how the motor units evolve with time. Let's take a step further. Can we compare the motor units between different conditions, so that we can have the insight that how the different stimulation parameters influence the spinal network?

Recall that we assume each motor unit has its unique latency. Therefore, using "latency" as the feature of the motor units, we can find how many "common" motor units there are for two different conditions, by counting the number of motor units with the same latency.

Take the condition of "different drug combination" as an example. We have four conditions: eEmc, eEmc+quip, eEmc+strych, eEmc+both. Here "eEmc" represents spinal cord epidural stimulation; "quip" respresents quipazine, which is a serotonergic agonist; "strych" represents strychnine, which is a glycine receptor blocker; "eEmc+both" represents electrical stimulation combined with both drugs.

The data I used was recorded from the left soleus muscle (extensor) when the rat is standing. The aligned signal of 80 periods (2s) under these four conditions is shown in Fig 7, and the results of the number of "common motor units" between different stimulation conditions is summarized in Table 2.

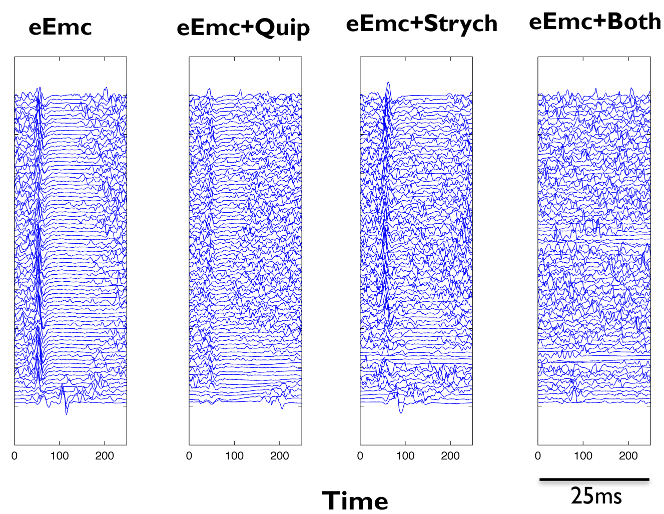

Figure 7. Aligned signal under different drug combinations (80 periods are aligned).

In Table 2, the number of common motor units are expressed in the form of "N_{Total} (N_{MR}, N_{LR})", "N_{Total}" represents the common motor units in total; "N_{MR}" represents the common motor units during MR (4-6ms), and N_{LR} represents the common motor units during LR (>7ms),

Table 2. Number of common motor units between two conditions. The signal was recorded from the left soleus muscle when the rat is standing. The results is expressed in the form of "N_{Total} (N_{MR}, N_{LR})".

	eEmc	eEmc+quip	eEmc+strych	eEmc+both
eEmc	80 (10,49)	39 (5,24)	27 (6,17)	27 (2,20)
eEmc+quip	39 (5,24)	80 (8,56)	38 (5,25)	25 (3,17)
eEmc+strych	27 (6,17)	38 (5,25)	80 (8,55)	28 (2,20)
eEmc+both	27 (2,20)	25 (3,17)	28 (2,20)	80 (7,58)

From the table we can see:
1) eEmc+both has the least common MR with others;
2) eEmc and eEmc+strych have the most common MR; etc.
These observations are consistent with Fig 7, which shows that eEmc+both suppressed the MR therefore it has the least common MR with others; also, MR is the most obvious under the conditions of eEmc and eEmc+strych, therefore they share the most common MRs. These consistencies indicate that our decomposition method is accurate.

In addition, the number of common motor units is generally large (>25), this also verify that the motor units we obtained are meaningful. Since if these motor units are just some random results, then the probability for two different conditions to have more than 25 common motor units is generally <10%.

Further Study

"Common motor units" is one way to study the influence of different conditions on motor units. The accuracy of this method can be further improved by ruling out the motor units that are less important (i.e. the motor units with less energy). Some other interesting ways include studying how the morphology and number of motor units change under different stimulation parameters, and change with time after the treatment.

As for the EMG decomposition technique, another possible improvement is the combination of ICA and machine learning (combine both the latency and shape information) to achieve higher accuracy of EMG decomposition.

Conclusion

In summary, we proposed an innovative technique – independent component analysis (ICA) for EMG signal decomposition. The results show that this technique successfully decomposed the EMG signal into individual motor units with high accuracy. We also project each motor unit back to see which periods contain the motor unit, and how the motor unit evolves with time. In addition, we compared the common motor units between different conditions, and suggests some other possible ways to study how the different conditions influence on the motor units and the underlying neural network.

References:

[1] Stashuk D. EMG signal decomposition: how can it be accomplished and used?[J]. Journal of Electromyography and Kinesiology, 2001, 11(3): 151-173.