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Analyze The Human Movements To Help CNS To Shape The Synergy Using CNMF And Pattern Recognition

Ghada M. Bani Musa[a*], Adel Al-Jumaily[b], Fady Alnajjar[c],Shingo Shimoda[d]

[a,b] University of Technology Sydney, Sydney 2000, Australia
[c,d] Intelligent Behavior Control Unit, Brain Science, Nagoya, Japan

Abstract

The Biomedical Signals have been studied for developing human control systems to improving the quality of life. The EMG signal is one of the main types of biomedical signals. It is a convoluted signal. This signal (EMG signal) controlled by the Central nervous system (CNS). It has been a long time expected that the human central nervous system (CNS) uses flexible combinations of some muscles synergy (MS) to solve and control redundant movements. Synergy muscles activities are different in a single muscle. In the concept of Synergy muscle, the CNS does not directly control the activation of a large number of muscles. There are two main movements can help CNS to shape the synergy. The automatic body response and the voluntary actions. These activities remain not too bright. Some studies support the hypothesis that the automatic body responses could be used as a reference to familiarize the voluntary efforts. It has been validating by analyzing the human voluntary movement and the automatic mechanical motions from the muscle synergy. Based on the validation, there was a proposition that the automatic synergy motion may express some features which could support the CNS to shape the voluntary synergy motion using the nonnegative matrix factorization (NMF). Thus the target of the presenting work is to analyses the human movements from the muscle synergy to help CNS shapes the synergy movement by suggestion using the concatenated non-negative matrix factorization (CNMF) method and the pattern recognition method. Then compare the two results and see if that help CNS to shape the synergy movements and which method has more accuracy.

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Keywords: Muscle Synergy; Electromyography (EMG); Central nervous system (CNS); automatic body response; voluntary action component; classification; pattern recognition.

* Corresponding author. Tel.: +6-141-054-8264 .
E-mail address: Ghada.m.banimusa@student.uts.edu.au

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1. Introduction

Electromyography (EMG) based techniques are used for assessing, analyzing and recording the data by detecting the EMG signals generated during the relaxation of muscles or powerful muscles. On the other hand, the Synergy EMG (SyEMG) has known that the CNS control muscles in groups, more confident than individually to generate healthy and dynamic movements[1]. Muscle synergies had been used to solve the redundancy problem. SyEMG has viewed Muscle synergies (MS's) as a specific example of structural units, which are task particular ensembles of elements within a neuromotor system. There are two main movements can help CNS to deal with muscles to activate a group of muscles: The automatic body response (reflexives) and the Voluntary movements[2-4]. The automatic body response (automatic synergy) in structuring the voluntary movements (voluntary synergy) still needs to resolve. Some hypothesis based on the experiments results found that the automatic response in human formed as automatic movements[4]. Within this automatic action, the CNS can store the movement to create a voluntary movement which is the reaction movements.

This paper aims to simplify the human movements to shape the muscle synergy using CNMF, and then to use a typical pattern recognition method to classify the muscle synergy.

Nomenclature

m	The muscles number
n	Number of synergies
t	Time
E	Residuals between the recorded M and the calculated WC
$\| \ \|_F$	Frobenius norm of a matrix

2. Synergy EMG Using Pattern Recognition

Pattern recognition is researching object description and classification method. It is a collection of mathematical, statistical and inductive techniques. It includes many methods which help the development of numerous applications in different fields. CNS use many surface electromyography (sEMG) channels that show a vast ability to control the combined muscles (Synergy EMG). However, this control needs to be adapted when applied for upper limb muscles. Combining of EMG data from upper limb muscles can be used to classify hand movements[5].

This paper aims to evaluate real-time pattern recognition control of hand motions in four different environments, (Rx, Vc, Vm, Vn). This work uses two methods: using the experiment data with CNMF matrix and then apply same experiment's EMG data to the pattern recognition process with a significant change in using the features and classification methods.

The present work is to support the hypothesize that the automatic synergy powerfully shapes the formation of voluntary synergies. It also supports that this effect may increase whenever facing unfamiliar movement by mean of creating a reaction movement (voluntary motion)[4], also demonstrate how many synergies used in each movement.

3. Data Acquisition

3.1. Participants

The used data in this paper support the hypothesis to apply the new method. It had been recorded in Intelligent Behavior Control Unit, Brain Science Institute, BSI-TOYOTA Collaboration Centre of RIKEN, Nagoya, Japan. Three neurologically healthy participants, right-handed with no reported muscular impairment on the upper limb had been engaged in this study.

The study protocol was discussed and explained to the participants to be familiar with the objective of the study. They were [(means ± SD), weight 69.25 ± 9.1kg, height: 175 ± 6.2cm, age: 34.5 ± 5.1yr] participated in the study[4]. The RIKEN ethics committee approved the protocols of all participants[4].

3.2. Equipment

Participants were holding a robotic manipulandum sitting on a fixed chair beside, as shown in Fig. 1(a) Delta.3 manipulandum (260mm height and 40mm diameter) has been used to collect the data[4].

Delta.3 was controlled and used to apply different resistances in various tasks. The knob position and force have been sampled at 100Hz[4].

4. Electromyography (EMG) Methods

Surface EMGs recorded from six shoulders prime muscles: deltoid anterior (AD), pectoralis major (PM), biceps brachii (BI), latissimus dorsi (LD), teres major (TM) and infraspinatus (IS). The electrodes have been placed in accordance position to the sEMG's guidelines. EMG data has been synchronized with manipulandum through the experiment. To Support the previous hypothesis, we suggest working on Synergic EMG signal. To work on Synergy EMG, we have to process the EMG signal and extract the Synergy EMG signal as shown in Fig. 1(b) and Fig. 1(c). Fig. 1(b) illustrates the process to analyze synergy EMG. It starts from raw EMG data through several steps to extract the muscle synergy using CNMF; using this technique, each muscle can be activated by various synergies.

Consequently, there are no similar two muscle activation patterns. These findings imply that the nervous system may use a limited set of control signals to activate a large number of muscles[6]. When the EMG signal is used for analysis, the synergy reflected only synchronized muscle activity. If a synergy is active at a given time, all muscles within that synergy are active[7]. Generally, muscle synergies are suggested as a solution to muscle's degree of freedom problem in motor control action potential instead of having to manage many thousands of motor units or dozens of muscles, However, using the CNMF concatenates the original EMG data of individual trials or all trials[8, 9] and while keeping the synergy pattern fixed among those trials. By keeping the synergy adjusted among participants, signal variability between the trails is limited to the coefficients and therefore is a stronger approach[8, 10]. After the CNMF had been applied, The variance accounted for (VAF) threshold was found to identify the minimum number of synergies that adequately reconstructed the characteristics of the recorded EMGs[4].

Fig. 1(c) shows the using of pattern recognition for classification method, to classify the movement by using new features and classification to get the synergy EMG result. It starts with the raw EMG data, filter the data using the butter filter, apply the result to extract features, and apply it to a classification system as a muscle synergy data, that helps to classify the hand movement to get a better result.

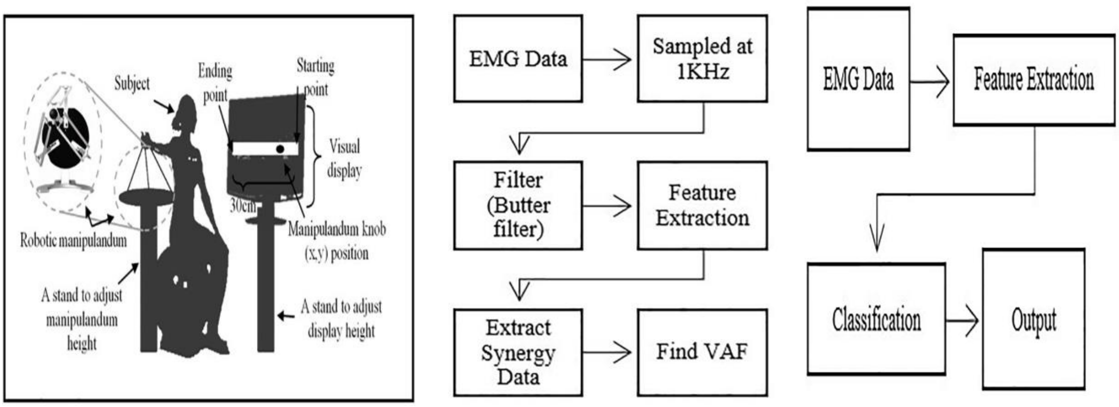

Fig. 1. (a) Delta.3 manipulandum devise (b) CNMF extracting method (c) Pattern recognition method

4.1. Filter

It helps to remove some unwanted components (noise) or features from a signal. In other words, eliminating some unwanted frequencies to reduce background noise. Since EMG is affected by noise, a butter filter is applied.

4.2. Feature Extraction

EMG feature extraction is one of the necessary procedures to extract the useful information from the EMG signal. No additional signal transformation is needed. We used the following features[5, 11-14]:

- Slope sign change (SSC): Counts the number of times that EMG signal slope sign changes. This presents the frequency information of the EMG signal.
- Zero crossings (ZC): A representation of frequency information of the signal at time domain. It counts the number of times that EMG signal amplitude values cross the zero amplitude level.
- Waveform length (WL): A measure of the complexity of the EMG signal. It is defined as increasing length of the EMG waveform over the time.
- Hjorth parameters (Hjorth): Is normalized slope used in EMG. Moreover, Hjorth parameters are used for signal processing as surface detection and feature extraction.
- Sample skewness (skw): Is a measure of the asymmetry of a signal or measure of X order.
- Absolute values (MAV): A standard and easily implemented feature of the time domain. It finds the mean of EMG amplitude values over sample length of the signal.
- Multiscale wavelet packet (mwpf): An alternative means of extracting time-frequency information from vibration signals. It is a combination of wavelets. A recursive algorithm computes the coefficients, making each newly computed wavelet packet coefficient sequence the root of its analysis tree.

4.3. Classification System

After extracting the EMG signals features, they are ready for classification. There are many available classification algorithms. The most common classification algorithms are the K-Nearest Neighbour Algorithm (KNN), Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN) and Support Vector Machines (SVM). In this work, Linear Discriminant Analysis (LDA) algorithm is used. The use of LDA for data classification is applied to classification problem in pattern recognition.

We decided to proceed with LDA in hopes for providing better classification compared to other classification algorithms[15].

5. Experiments Protocol

Voluntary and automatic actions synergies relationship have been verified through the experimental work[4], the following are the four main movements that was considered in the experiments to support the hypothesis:

5.1. Reflex response (Rx)

This measures the automatic responses from the manipulandum with zero resistance of the participants. Seated participants have been grasping the knob of the manipulandum, and the arm was positioned 90 degrees straight.

5.2. Voluntary action

At this point, there was no produced resistance from Delta.3. The movement was just from the participant with zero resistance from the manipulandum robot. By the end of this task, the movement will be familiar to the participants.

5.3. Voluntary action in a modified environment (Vm)

The experiment position is the same as above (shown in Fig. 1(a)) with 70% resistance applied randomly by the manipulandum. On this part of the experiment, there is resistance from the participant. It is random depends on the manipulandum action.

5.4. Adaption to the modified environment (Vn)

Participants can adjust the movement to the modified environment through training. In two identical sets for fifteen trials, Participant has modified the environment continuously using the previous position.

6. Data Analysis

Voluntary and automatic actions experiments stretch reflex magnitude was measured using the EMG data. The baseline was eliminated through processing the EMGs. Concatenated non-negative matrix factorization (CNMF) was used to extract the Muscle synergy from the recorded EMG data. Raw EMG data was applied on classification method.

6.1. CNMF Methodology

Concatenated non-negative matrix factorization (CNMF) is used to extract the characteristic frequency components and obtain the corresponding connectivity matrices across conditions and subjects[10, 16, 17]. In equation 1, a matrix with a dimension of m=6 (the number of muscles) was extracted from the processed EMG data of each experimental trial. It is multiplied by the recorded time t (variables based on the task). In each trial, synergy activation coefficients were identified using the synergy muscle space (W) which weights the muscles based on their activations and the neural command (C)[4, 18].

$$M_{m\times t} = W_{m\times n} C_{n\times t} + E_{m\times t} \tag{1}$$

VAF is measured with a threshold of >90% was adopted to detect the minimum number of muscle synergy. In this study, the threshold used to ensure that the estimated number of synergies would well preserve the characteristics of the recorded EMG data[4].

$$VAF = 1 - \|E\|_F^2 / \|M\|_F^2 \tag{2}$$

6.2. Pattern recognition Methodology

EMG pattern recognition with a large number of EMG channels provides an approach to assessing the signal information available from the recorded muscles. The feature data collected from the original EMG data are consistently used in the training and testing parts. The raw EMG data is used with window size of 200 ms, and processed them to a butter filter between 20 and 450 Hz. Then, the features have been extracted using: Slope sign change (SSC), Zero crossings (ZC), Waveform length (WL), Hjorth parameters(hjorth), Sample skewness (skw), Absolute values (MAV), Multiscale wavelet packet (mwpf). After extracting the features from the EMG signals, they are ready for classification. The LDA classiffication method was used.

7. Results

All participants completed the tasks based on equation 2.Fig. 2 (a), Fig. 2(b), Fig. 3(a) shows the number of muscle synergies required to achieve >90% overall VAF and >75% VAF which are two muscles synergy in this case which mean two synergies required to reconstruct to a feature of the recorded EMG data, these synergies were utilized in the automatic and the voluntary actions in the regular environment and help to shape the movement.Fig. 3(b) shows that one synergy is enough to reconstruct the EMG data and shape the movement[4] and it is achieved > 95% VAF.

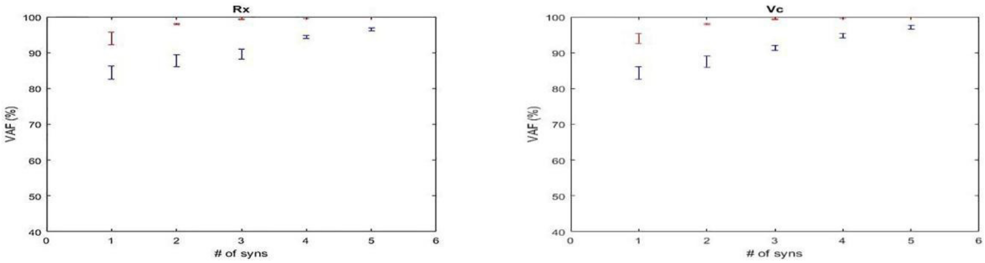

Fig. 2. (a)VAF of all possible synergies from Rx (b) VAF of all possible synergies from Vc

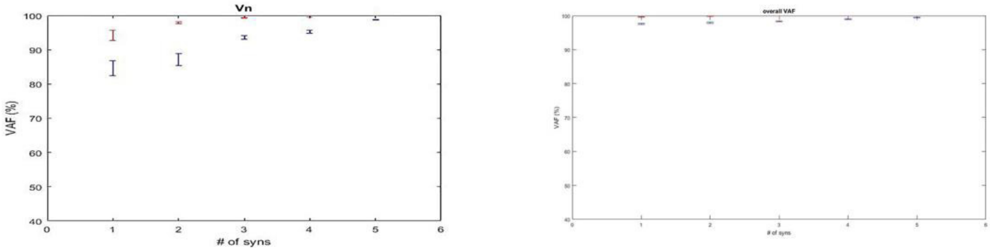

Fig. 3. (a) VAF of all possible synergies from Vn (b) VAF of all possible synergies from Vm

Using the pattern recognition method, Fig. 4 (a) and Fig. 4 (b) have been achieved with 0 % error and 100% accuracy. Comparing both methods, the pattern recognition method helps the CNS to shape the movement with 100% accuracy and the CNMF method with > 95% overall VAF. This supports our hypothesis for analyzing the automatic movements and the voluntary actions movements for helping the CNS system to shape the synergy movement.

Fig. 4. (a) Classification results (Error) for four movements. (b) Classification results (Majority vote) for four

8. Conclusion

Many techniques were used to analyze and control the synergy EMG signal with limited achievement results. The automatic body response movements and the voluntary actions movements can help CNS to shape the synergy. Using the CNMF method and pattern recognition method with >95% overall VAF and 0% error, respectively, helped the CNS to shape the synergy movements with good results. On our future work, we want to improve the repeatability and reliability for automatic body movement and voluntary action movement for shaping the muscle synergy analysis using a new approach.

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