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ORIGINAL ARTICLE

Human Muscle Synergy Analysis to Approach the Understanding of Brain Control Algorithm

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Abstract

Purpose: Muscle synergy is a functional unit that coordinates the activity of a number of muscles. In this study, the extraction of muscle synergies in three types of hand movements in the horizontal plane is investigated.

Materials and Methods: So, after constructing the tracking pattern of three signals, by LabVIEW, the Electromyography (EMG) signal from six muscles of hand was recorded. Then time-constant muscle synergies and their activity curves from the recorded EMG signals were extracted using Non-negative Matrix Factorization (NMF) method.

Results: Comparison of these patterns showed that the non-random motions' synergies were more similar than the random motions among different individuals. It was observed that in all movements, the similarity of the synergies in one cluster was greater than the similarity of their corresponding activation curves.

Conclusion: The results showed that the complexity of the recurrence plot in random movement is greater than that of the other movements.

Keywords: Muscle Synergy; Electromyography Signal; Non-Negative Matrix Factorization; Phase Space; Recurrence Quantification Analysis.

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1. Introduction

The term muscle synergy has been extensively studied in the literature [1-3]. The qualitative definition of synergy is built on three bases: sharing, flexibility/sustainability, and task dependency [4, 5]. Electromyography (EMG) Signal analysis using linear and nonlinear tools is, therefore, a basic need. EMG patterns are trackers of muscle synergies and their activation coefficients. One way to learn about the mechanism of motor deficits and spinal cord injuries is to study muscle synergies [5]. Understanding the mechanism of central nervous system control of hand movement and the creation of efficient human-machine interfaces depends on the extraction of synergistic patterns [5]. Two time-invariant and time-varying models have been identified for muscle synergy [3]. In the time-invariant model there is no lag time between different muscles of a synergy, that is, if a synergy is activated at a certain time, all the muscles related to that synergy will be activated at the same time [6]. In the time-varying model, different muscle synergies have their own temporal activity profiles, and there may be different time delays between activating different synergies [6]. Different matrix decomposition methods are used to derive time-invariant synergies [7]. Considering matrix decomposition topics is one of the recent trends in blind source separation. The blind source separation method is to obtain a set of independent sources that are combined with an unknown system [8]. Many real data are non-negative, and their hidden components have physical meaning only when they are non-negative. In practice, when under control components have physical interpretation, non-negative and data fragmentation is often desirable and necessary [9,10]. The Non-negative Matrix Factorization (NMF) method has been studied by many researchers but has been further refined by the work of Lee and Seong published in Nature and NIPS Journals [9,10]. The trajectory of a dynamic system in phase space can describe the development of system behavior over time and in phase space [11]. The primary purpose of Recurrence Plot (RP) is to visualize the dynamic systems' trajectory in phase space, which is particularly useful in high-dimensional systems. The RP provides important information about the temporal evolution of these trajectories [12,13]. In addition to the visual information obtained from RP, several complexity measures that quantify the small-scale structures of recurrence plot are known as Recurrence Quantification Analysis (RQA). These criteria are based on the density of the recurrence points and the structures of the horizontal and vertical lines of the recurrence plot. Calculating these criteria in small windows (sub-matrices) in RP results in a time-dependent behavior of these variables [11]. Much research has been done on muscle synergy [14-21]. Di Eola and *et al.* stated that the CNS's production of muscle activity patterns to achieve a variety of behavioral goals is a key issue in controlling movement. As a result, the EMG signals of thirteen muscles of four frogs were recorded during jumping, walking, and swimming movements. Their results showed that there were similarities between the synergies extracted from different movements [22]. Ting *et al.* examined muscle synergies to control force during a balance task. They used nonlinear matrix factorization to determine the muscle synergies of equilibrium reactions in cats to investigate the practical importance of such synergies for natural behaviors [23]. Sabzevari *et al.* extracted muscle synergy during arm reaching movements at different speeds. They showed that a lower reconstruction error can be obtained by the center of the muscle synergy clusters in comparison with the average of the activation coefficient [5]. Kabbodvand *et al*. extracted synchronous muscle synergies during fast arm reaching movements. They used a modified nonnegative matrix factorization to resolve the tonic component problem of EMG [24]. The purpose of this research was to study and compare muscle synergies in sinusoidal, quadratic, and random motions (which one cannot anticipate).

2. Materials and Methods

2.1. EMG Recording and Experiments

The subject should sit behind a desk in a height-adjustable chair so that his hand is parallel to the ground (during the test the subject's hand moves freely on the horizontal surface) and follow the marker on the monitor on the horizontal screen while holding a 1.5 kg weight with his hand on the desk. The tracking duration of each pattern is 24 seconds. From each subject, during each of these movements, a surface electromyogram signal of six muscles is recorded for moving elbow and shoulder motors (including two short and long head biceps brachii, two medial and lateral head triceps brachii, deltoid muscle, and Pectoralis major muscle) that plays the most role in these movements. At the beginning of each session, the subject practiced the movements in question. The purpose of the exercises was to get the person used to the movements, the recording protocol, the environment, and the test space. To prevent muscle fatigue after each movement and before the next movement begins, the subject rests for 13 seconds.

In this study, Biopack MP100 was used to record EMG signal. Six healthy male volunteers (with no history of musculoskeletal disorders) ranged in age from 18 to 23 years with a height of 121 to 183 cm and a weight of 62 to 75 kg participated in the experiments. The hand tested in all protocols is the right hand. To eliminate the power line interference, the Notch filter key of the electromyogram recorder was turned on. Also, the highpass filter cutoff frequency was set to 20 Hz and the low pass filter cutoff frequency was set to 500 Hz. The gain of Biopack system is 5000. Six channels of this device were used to record the signal. To reduce the impedance of the skin, it is necessary to prepare the skin. To cleanse the skin of fat and perfume, the electrode position on the muscle should be cleaned with alcohol-soaked cotton. Dead skin cells also have high electrical resistance, so they should be wiped off the surface of the skin using a type of abrasive such as very soft sandpaper. During this stage, the skin should be cleaned with alcohol-soaked cotton continuously. This step should be done carefully so as not to damage the skin. The qualitative criterion for skin preparation is that the electrode position is slightly reddened by abrasion. Surface hairs of skin should be removed at the location of the electrodes. In the recordings of this study, the surface hair of the skin was first shaved and the dead skin cells were abraded with soft abrasion number 1500, the skin was then cleaned with white alcohol-soaked cotton. SKINTACT self-adhesive disposable electrodes were used. Finally, the skin's electrical impedance was measured with a multi meter, which must be less than ten kilo ohm. Electrodes were positioned according to a specialist and (http://seniam.org/sensor_location.htm), the electrode was positioned at the center of the muscle mass. Figure 1 shows one of the subjects during the experiment. Much of the EMG signal power is in the frequency range of 10 to 500 Hz. To make the signal from the samples reproducible, according to the Nyquist principle, the sampling frequency was set twice to 500 Hz [26].

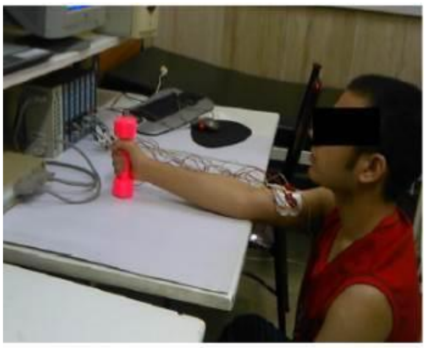


Figure 1. Picture of one of the subjects during the experiment

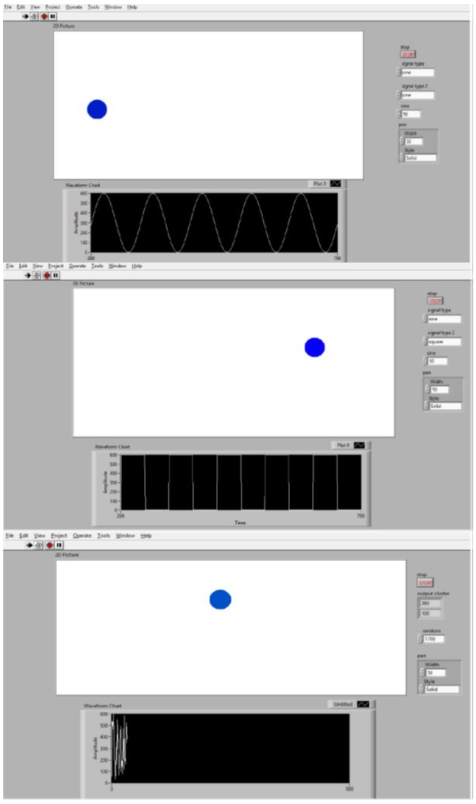
2.2. Creating a Tracking Pattern in LabVIEW Software

In this study, three types of sinusoidal, square, and random motions in the horizontal plane were investigated. To do this, a tracking pattern of three sine, square, and random signals on the computer are made by LabVIEW software. At the beginning of the program to build a follow-up pattern, a synchronous program was placed, for this purpose, by clicking the mouse, the marker and the patient signals are synchronized to extract features such as the average of delay and patient movement speed.

Figure 2a shows the square motion. In this case, by moving the cursor to the right, the patient places her elbow on the table in the extension position, and when the cursor moves to the left, they place her elbow on the table in the flexion position. Figure 2b shows the sinusoidal motion. In this case, the patient puts his elbow on the table in extension mode by moving the cursor to the right in a sinusoidal position, and when the cursor goes to the left, they put their elbow on the table in flexion mode, and do it quickly. Figure 2c shows the random motion of the cursor. In this case, the patient moves his elbow on the table in the same direction by moving the pointer in a random position, and move their elbow by placing the pointer in any random place. First random numbers between 0 and 1 are generated in the block and then multiplied by 500 to increase the range of arbitrary numbers.

2.3. Data Preprocessing

In this study, the rectified signal amplitude peak curve was used to normalize the signal [27]. According to [28], at first, the EMG signal was rectified using absolute magnitude then passes through a low-pass filter with a cutoff frequency of 400 Hz. After deleting offset, signals are normalized to their maximum value. The purpose of applying these steps to the raw signal is to achieve EMG signal envelope.



(a)

(b)

(c)

Figure 2. a) Square motion of the pointer and the generated square signal, b) Sinusoidal motion of the pointer and the generated sinusoidal signal, c) Random motion of pointer and generated random signal

2.4. Non-Negative Matrix Factorization (NMF)

Many real data are non-negative, and their hidden components have physical meaning only when they are negative. In practice, when components under control have a physical interpretation, negative analysis and sparsing of the data are often desirable and necessary [9, 10]. The NMF problem is expressed as follows:

If the negative data matrix $Y \in R_{+}^{I\times T}$I (Y≥0) is given and J is the order of dimension reduction (J≤min(I,T)), accordingly, two non-negative matrices A= [a_1, a_2,…, a_J] ∈ $R_{+}^{I\times J}$, X=B^T = $[b_1, b_2, \dots, b_J]^T$ must be obtained, which are the factors of Y (Equation 1):

$$Y=AX+E=AB^T + E \tag{1}$$

That matrix $E \in R^{I\times T}$ Shows the approximation error. Factors A and X have different physical meanings in different applications [8]. The standard NMF model assumes that matrices A and X are non-negative. Unlike blind resource separation methods based on Independent Component Analysis (ICA), the NMF method does not assume resource independence. The NMF problem can also be expressed $Y^T \approx X^T A^T$, so the concepts of "source" and "combination" in the NMF are often arbitrary. In order to estimate the matrices A and X, a similarity criterion must be considered to quantify the difference between the data matrix Y and the estimated model matrix ($\hat{Y}$ = AX). The simplest and most common similarity criterion used is based on Frobenius norm [8] (Equation 2):

$$D_F(Y||AX) = \frac{1}{2}\,||Y - AX||_F^2 \tag{2}$$

2.5. Recurrence Quantification Analysis (RQA)

The primary purpose of recursive diagrams is to visualize the trajectory of dynamic systems in phase space, which is especially useful in high-dimensional systems. The usual patterns in recursive diagrams are related to specific behavior of dynamic systems, so RPs provide important information about the temporal evolution of these trajectories.

Large-scale patterns in RP, introduced as typology, can be categorized into homogeneous groups, periodic, drift, and disrupted [10]. A closer look at the recursive diagrams reveals smaller-scale structures called textures, which are grouped into different groups. In addition to the visual information obtained from RP, several complexity metrics that quantify small-scale structures of recurrence diagrams are known as RQA. These criteria are based on the density of the recurrence points and the structures of the diagonal and vertical lines of the recurrence diagrams. Calculating these criteria in small windows (sub-matrices) in RP leads to time-dependent behavior of these variables [11]. Figure 3 shows the block diagram of research steps.

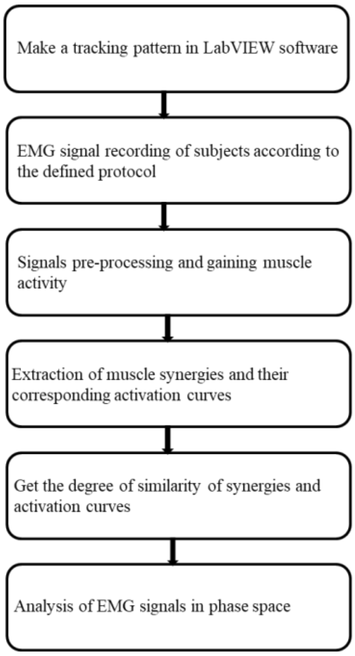


Figure 3. Block diagram of research steps

3. Results

3.1. Choosing the Right Number of Synergies

Variant Allele Frequencies (VAF) was calculated for one to five synergies to determine the appropriate number of synergies in each of the sine, square, and random tracking hand movements. Finally, in all three movements considering the three synergies, the VAF criterion was 90% in the EMG signal envelope.

3.2. Muscle Synergies Extraction

After obtaining the signal envelope, muscle synergies were extracted using NMF algorithm. The NMF algorithm was run ten times with random start points to reduce the probability of finding local optimal ones and the response with the least reconstruction error was considered as the final answer. Three synergies were obtained for each subject in each movement. So there are eighteen synergies for each of the six subjects in each movement. At each movement, the eighteen synergy sets were categorized into three groups based on their similarity (using the cosine similarity criterion). The synergies of the members of each cluster were very similar. Clustering the synergies into three groups is illustrated in Figure 4.

The last column of each shape is the center of the cluster ($\bar{W}$). Figure 4a shows the first, second, and third synergies of sinusoidal motion. The cosine similarity criterion between the members of the first synergy cluster is between 0.77 and 0.98, with a mean of 0.9138 and a standard deviation of 0.0611. The cosine similarity criterion between the members of the second synergy cluster is between 0.72 and 0.99, with a mean of 0.8953 and a standard deviation of 0.105. The cosine similarity criterion between the members of the third synergy cluster is between 0.81 and 0.98, with a mean of 0.9214 and a standard deviation of 0.0571. As can be seen in the sinusoidal hand motion tracking, the members of the synergies of each cluster are very similar.

Figure 4b shows the first, second, and third synergies of square motion. The cosine similarity criterion between the members of the first synergy cluster is between 0.86 and 0.99, with a mean of 0.94 and a standard deviation of 0.0399. The cosine similarity criterion between the members of the second synergy cluster is between 0.92 and 0.99, with a mean of 0.97 and a standard deviation of 0.0245. The cosine similarity criterion between the members of the third synergy cluster is between 0.73 and 0.98, with a mean of 0.87 and a standard deviation of 0.0846. As can be seen in the square hand motion tracking, the members of the synergies of each cluster are very similar. Figure 4c shows the first, second, and third synergies of random motion. The cosine similarity criterion between the members of the first synergy cluster is between 0.61 and 0.98, with a mean of 0.87 and a standard deviation of 0.1003. The cosine similarity criterion between the members of the second synergy cluster is between 0.50 and 0.98, with a mean of 0.83 and a standard deviation of 0.1683. The cosine similarity criterion between the members of the third synergy cluster is between 0.59 and 0.98, with a mean of 0.89 and a standard deviation of 0.0984. As can be seen in the random hand motion tracking, the similarity of the synergy members of each cluster is less than the square and sinusoidal tracking movements. Also, as can be seen in all movements, in the first synergy, the activity of the short and long head biceps brachii is more than that of the other muscles. In the second synergy, the activity of the pectoralis major muscle is greater than

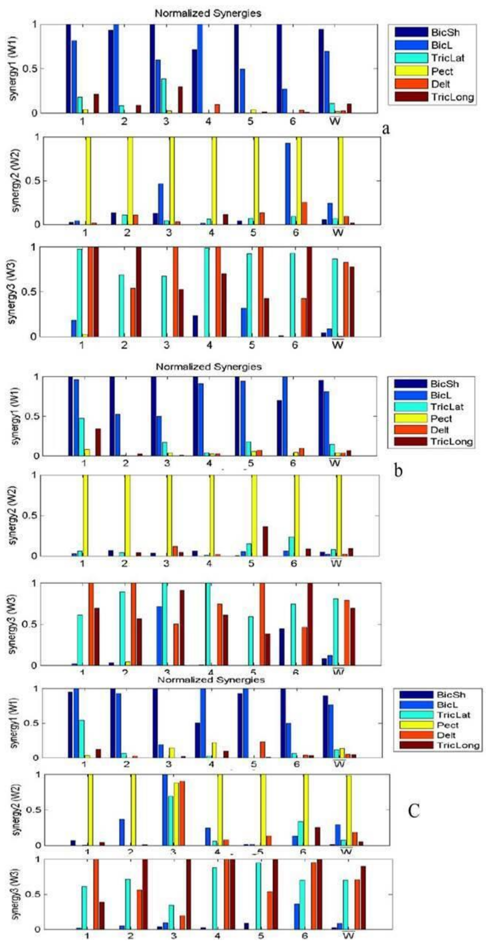


Figure 4. Clustering the synergies into three groups in a) Sine Motions b) Square Motions c) Random Motions. The last column of each shape is the center of the cluster ($\bar{W}$)

that of the other muscles. In the third synergy, the deltoid muscle, the lateral head, and the long head of the triceps brachii have the highest activity.

3.3. Comparison of the Similarity of Synergy Activity Coefficients

After clustering and analyzing the extracted synergies, their corresponding activation coefficients were also compared. In sinusoidal motion the cosine similarity of the members of the first cluster was between 0.24 and 0.6 (mean: 0.42, standard deviation: 0.11), the second cluster between 0.15 and 0.54 (mean: 0.33, standard deviation: 0.13), in the third cluster between 0.13 and 0.52 (mean: 0.32, standard deviation: 0.12. Figure 5 shows mean Clustered Muscle Activity Curves in a) Sine Motions b) Square Motions c) Random Motions.

3.4. RQA Features Extraction

At this point, the only pre-processing of the data was downsampling. Then the phase space trajectory of all the muscles' signal was reconstructed and RP tools were applied to the trajectories and the recurrence matrix was calculated. Then, based on this matrix, indices of the rate of recurrence, certainty, entropy, laminarity, etc. were extracted. In Table 1 the mean features extracted from the RQA in sinusoidal, square, and random tracking motions are shown.

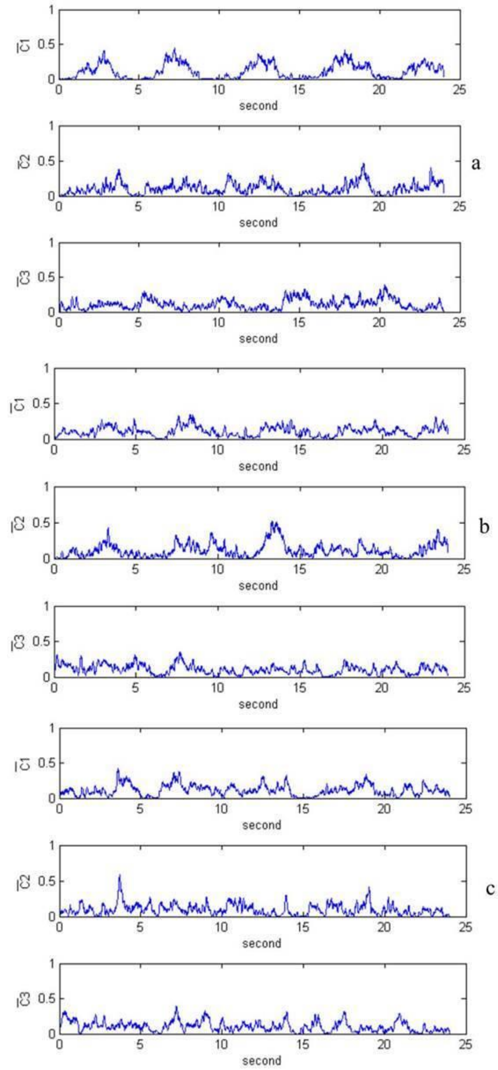


Figure 5. Mean Clustered Muscle Activity Curves in a) Sine Motions b) Square Motions c) Random Motions

Table 1. The mean features extracted from the RQA in sinusoidal, square, and random tracking motions

Muscle	Movement Type	RR	DET	Lmax	ENT	LAM	TT
Biceps (short head)	sinusoid	0.090	0.063	12.300	0.867	0.069	3.296
	square	0.058	0.113	52.600	1.338	0.040	2.803
	random	0.091	0.127	55.500	1.319	0.071	3.378
iceps (Long head)	sinusoid	0.049	0.046	20.300	0.899	0.044	2.270
	square	0.029	0.096	41.500	0.927	0.006	2.089
	random	0.101	0.091	40.000	1.125	0.069	2.864
Triceps (Long head)	sinusoid	0.017	0.002	3.800	0.175	0.004	2.061
	square	0.019	0.040	16.600	0.570	0.003	2.552
	random	0.025	0.019	21.000	0.607	0.003	2.569
Pect	sinusoid	0.098	0.063	24.500	1.322	0.049	3.273
	square	0.088	0.047	24.300	1.242	0.045	3.285
	random	0.094	0.092	45.000	1.618	0.028	2.750
Pectoralis major	sinusoid	0.028	0.094	4.500	0.335	0.020	2.146
	square	0.093	0.169	107.500	1.344	0.087	3.449
	random	0.044	0.044	24.800	1.408	0.052	3.883
Triceps (Long head)	sinusoid	0.068	0.016	6.600	0.518	0.013	3.098
	square	0.053	0.035	21.300	0.778	0.025	2.629
	random	0.110	0.112	65.000	1.199	0.058	3.250

As can be seen in all muscles, the mean entropy value (ENT) of the random motions is higher than the other motions, indicating an increase in the complexity of the recurrence plot (relative to the diagonal lines) in the random motions relative to the other motions. The certainty value (DET) is always slightly lower in sinusoidal motion than in other movements, indicating less predictability of the system, although one can predict the motion to be performed, the body system has more chaotic behavior that could be due to less precision of the subjects in the movement. The laminarity property (LAM) is the same in almost all movements. The small amount of this feature indicates the chaotic behavior of the system. The recurrence plot for the first subject's six muscles in the three sinusoidal, square, and random movements is shown in Figure 6. As can be seen, most diagrams have a pattern similar to the periodic pattern created by the sweep of the hand on the horizontal plane. The diagrams of some muscles are similar to the homogeneous pattern, which results in the behavior of the system approaching the static process.

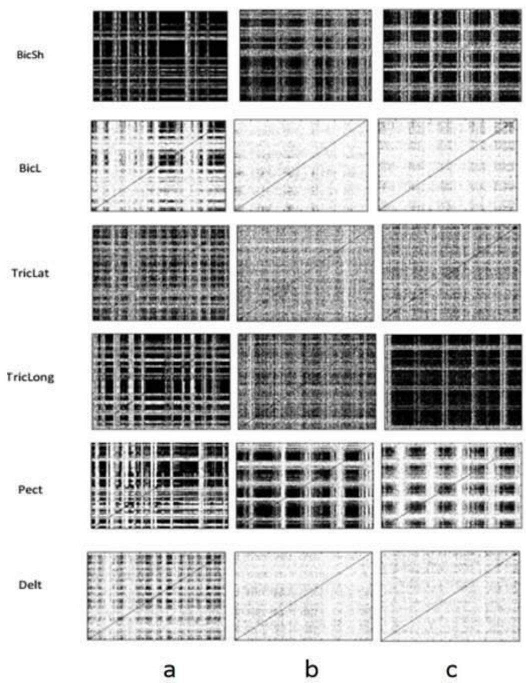


Figure 6. Recurrence plot in three a) random, b) sequential and c) square movements for a subject

For better comparison, the mean values and the standard deviation of the cosine similarity of the first, second, and third synergies in all motions are given in Figure 7.

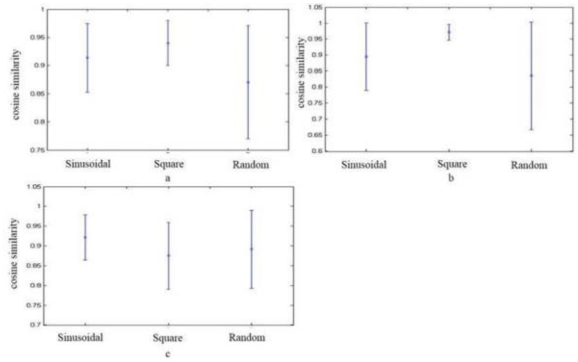


Figure 7. Mean and the standard deviation values of cosine similarity of the a) first, b) second, and c) third synergies in all motions

The cosine similarity of the center of the first, second, and third synergy clusters between all movements is shown in Table 2. As the comparison of the centers of clusters of different movements of synergy shows that the mean of different people's synergies in hand movements on the horizontal plane is very similar. The mean and standard deviation values of the cosine similarity of the activation curves of the subjects in the three sinusoidal, square, and random motions in the first, second, and third clusters are shown in Figure 8. As can be seen, in most cases, the similarity of the activation curves is less than that of the sinusoidal and squared motions.

4. Discussion

In the previous methods such as [29], reinforcement learning has been used to control the movements of the muscles, and old and conventional methods have been obtained to control movements by the brain [29, 30] but in this paper, an attempt has been made to check that the brain has no control over single muscles and controls them synergistically.

Table 2. The cosine similarity of the center of the first, second, and third synergy clusters between all movements

Movement Cluster Number	Square and Sinusoidal movement	Random and Sinusoidal movement	Square and Random movement
First Cluster	0.9967	0.9914	0.9965
Second Cluster	0.9732	0.9931	0.9522
Third Cluster	0.9986	0.9870	0.9820

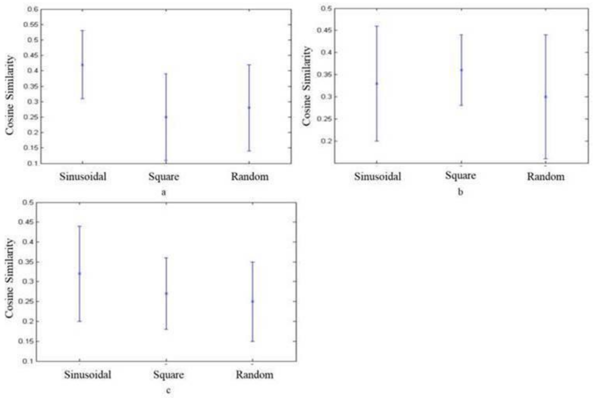


Figure 8. Mean and standard deviation values of the cosine similarity of the activation curves of the subjects in the three sinusoidal, square, and random motions in the a) first, b) second and c) third clusters

In this paper, the aim was to understand the musculoskeletal system in human movements, other studies have been shown, the study of human movement using traditional methods such as reinforcement learning algorithms, fuzzy controllers, and the use of neural network controllers, but the use of synergistic theory and the fact that in the control brain, in such a way that the brain issues general motor commands and its interpretation and translation are done in the spinal cord, is an important discussion that a lot of research can be done about them.

In this paper, the aim was to better identify the musculoskeletal system in human movements and with a synergy perspective, it has tried to interpret and analyze it. Its applications include rehabilitation and better identification of motor diseases (Parkinson's and MS) and their treatment.

The recursive diagrams for the six muscles of subjects in the three sinusoidal, square, and random motions showed that most of the diagrams were similar to the pseudo-periodic pattern created by the repetitive rotational movements of the hand on the horizontal plane. The diagrams of some muscles are similar to the homogeneous pattern, which results in the behavior of the system approaching the static process [5] noted that synergies in hand movements on the horizontal plane were highly similar among different individuals, which was also the result of this study. Their results also showed that although the synergy patterns were similar at different speeds, they were applied differently, which was the case in this study. Muscle synergies in arm reaching movements in the frontal plane have been extracted and studied [24]. Synergies of each movement were extracted using a modified NMF method. A synchronous model has been used. Their results indicated the existence of synchronous synergies in fast arm reaching movements, which is in accordance with the results of this study. The existence of synchronous synergies in reaching movements has also been confirmed in other studies, such as [3, 20].

In this study, muscle synergies were extracted in three types of sinusoidal, square, and random movements to compare non-random and random movements. For this purpose, a pattern of motion tracking was first created on the computer, then the EMG signal of six hand muscles of subjects was recorded while performing the movements. The NMF method, which is by far the most suitable method for synergy extraction, extracted time-constant synergies. There were three synergies per movement per person. Then, the synergies of each movement were divided into three clusters according to the degree of cosine similarity between individuals. Comparison of the synergies of each cluster using the cosine similarity criterion showed that the similarity of the synergies of each cluster in non-random motions (sine and square motions) was greater than random motions. This comparison was also done for the activation curves corresponding to each synergy, which was the same result. It was observed, however, that in all movements, the similarity of the synergies in one cluster was greater than the similarity of their corresponding activation curves, which states that although the muscle synergies are very similar, they are not applied equally to different subjects.

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