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Relationship between Muscle Synergies and Skills of Basketball Players

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ABSTRACT

Introduction: "Muscular synergy" is one of the methods for determining the relationship between the central nervous system and muscles which are involved in performing a specific movement. To perform each movement, certain patterns are followed through the central nervous system that control the number of synergies, and these patterns are modified and optimized during the skill. The present study aimed to classify basketball athletes based on muscular synergy analysis.

Material and Methods: For the purpose of the study, the electromyography (EMG) signals of six dominant hand muscles were recorded during performing three basketball skills. Subsequently, synergy was identified using the non-negative matrix factorization method. In the next stage, the cosine similarity feature was calculated separately; furthermore, the time and frequency of the main signal were analyzed, and the neural network was evaluated using MATLAB software.

Results: The result of the classification was obtained by applying the dimensioned reduced matrix of all the existing features with a reliability of 73.68%. In addition, the results demonstrated that the cosine similarities between the muscles of each person could lead to the training of the neural network and classification of individuals at different levels of skill.

Conclusion: The present study suggested a new idea regarding synergistic features for classifying athletes based on EMG signal. However, the use of time and frequency features only facilitated differentiation between a maximum of two groups.

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Introduction

Quick training and optimal performance of a skill have received permanent attention in the training of that skill. However, each skill has its own different contexts since each sport has its specific techniques. Several studies have been focused on different skills so far [1-3]. Previous studies have targeted such sports as pole vault [4, 5] and rugby [6] using an electromyogram signal. Based on the evidence, patterns in the spinal cord are coordinated with simple movement commands in the brain called brain coefficients, and the movement is performed for any skill [7-9]. Therefore, one can reconstruct the electromyography (EMG) signal with two signals of the brain and motor patterns of the spinal cord. In addition, the EMG signal analysis using time-invariant synergies extracted from EMG data by non-negative matrix factorization demonstrates the feasibility of a possible synergy-based controller for hand neuroprostheses [10].

Furthermore, previous research used muscle synergy analysis to investigate the effect of cutaneous stimulation in patients with Parkinson's disease in performing movements [11]. Based on the literature, healthy people and people with cerebral palsy can be distinguished using muscle synergy [12]. Studies have previously addressed the analysis of various vital signals in different sports, the results of which are ultimately used for specific and useful purposes. Previous studies also used the electroencephalography signal to analyze basketball sport and EMG signal in other sports. Accordingly, the EMG signal can be applied in basketball in order to obtain new valuable results.

Among the skills and sports, basketball is one of the highly technical sports which requires extensive time and cost to be learned and become skillful in. Therefore, it is required to seek a method for determining the skill level and reaching the complete potential of each person in this sport in the shortest time. In the present study, the costs and time for training the volunteers were considered necessary for achieving a professional level in basketball. In other words, this requires several parameters, including correct training and targeting of training courses with the aim of reducing the costs and the time to reach the athlete's peak performance, as well as increasing the full potential of an athlete's ability.

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A motor skill in sports is associated with muscular synergy in skilled people. An athlete can be most effective in a sport during the shortest time and with the lowest cost if he/she can achieve muscular synergy. To the best of our knowledge, the present study was the first attempt to record and analyze the EMG signal in basketball athletes and their muscular synergy in groups of different basketball skills. To this end, the participants were divided into four skill groups, and the surface EMG signals of six dominant hand muscles were recorded in each individual during the performance of three basketball skills. Then, the recorded signals were analyzed and classified using the neural network.

It should be stated that the signal recording had some problems. For example, the cables of the electrodes inhibited achieving the correct and facile basketball skills. Furthermore, the motion artifacts affected the EMG signal and needed filtering.

Materials and Methods

Participants

The current study was conducted on 32 male participants aged 20-22 years. The study population was assigned into four groups of fully professional, professional, beginner, and non-professional, each of which contained 8 members. None of the research groups had a history of muscular neurological problems. The first group included highly professional basketball players. The second group included professional players who had relatively high experience in basketball professions. Additionally, the third group encompassed the beginners in this profession who were just familiarized with this sport and its motor skills and had a short history of activity in this field. The fourth group consisted of unprofessional and ordinary people who had no familiarity with basketball skills without any activity in the sport.

Synergy Model

Several methods are available for the identification of constant synergy. The non-negative matrix factorization (NMF) method is considered one of these methods. In this algorithm, according to *Equation (1)*, the non-negative matrix of $M \in R^{m \times n}$ is decomposed into two non-negative matrices of $C \in R^{n \times r}$ and $W \in R^{m \times r}$ with a decreasing degree of r while $r < min\ (m, n)$ relies on the problem [13]. Figure 1 displays a schematic representation of this method.

The assumption of the statistical independence of the generators is not considered in the NMF method. Therefore, it is more compatible with the nature of the correlation between synergies and the extraction of variable synergies over time [14]. Therefore, the NMF method has a relative advantage over the other analytical methods based on the literature.

A multivariate forecasting algorithm (vector autoregression) was used to select the appropriate synergy based on *Equation (1)*, which determines the similarity percent of the EMG signal to the regenerated signal for each number of synergies, along with the most optimal number of synergy [15]:

$$vAF = 1 - \frac{\|EMG - W*C\|^2}{\|EMG\|^2} \quad (1)$$

where $W*C$ and EMG represent the value of the regenerated signal and original signal value, respectively [16].

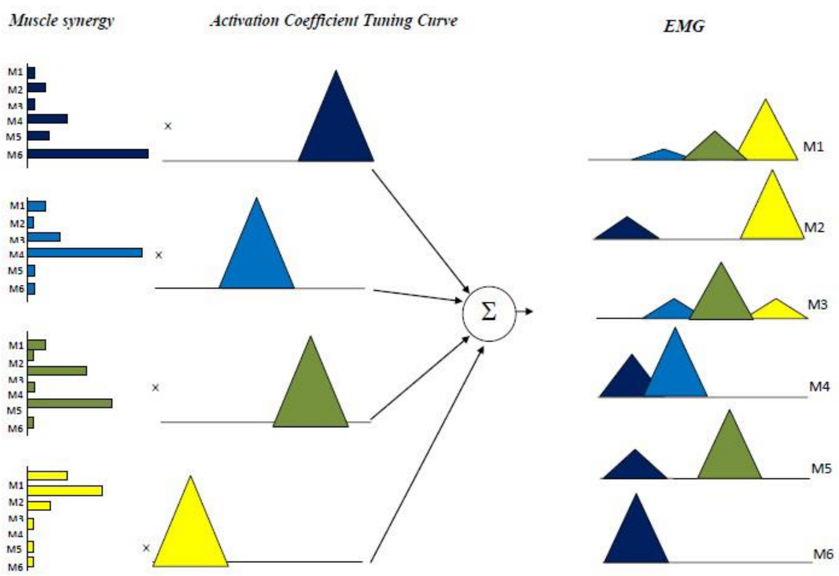

Figure 1. Schematic representation of the linear combination of muscle synergies

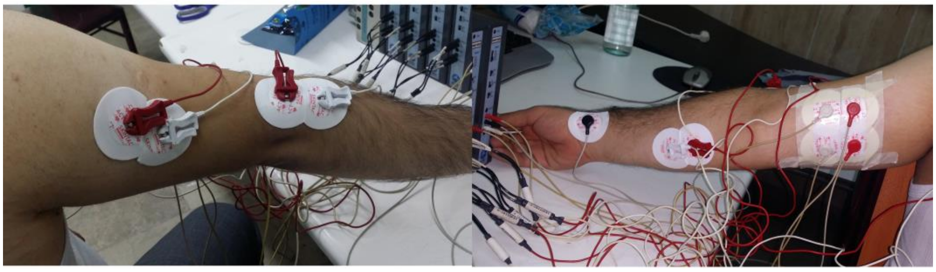

Figure 2. Place of the electrodes on the muscle in a subject in the non-professional group, A) view of the inner muscles of the participant's hand, B) A view of the outer muscles of the participant's hand

Features

Cosine Similarity

Cosine similarity represents the similarity of the two vectors in the space of the interior product of the two vectors. This value equals the cosine of the angle between the two vectors. By assuming vectors *X* and *Y*, their cosine similarity can be calculated using *Equation (2)* [9]:

$$CS = \cos(\theta) = \frac{X.Y}{\|X\|.\|Y\|} \tag{2}$$

This feature basically calculates the cosine of the extracted synergy angles two by two and determines the similarity based on the obtained value. This value ranges between -1 and 1 and demonstrates the dissimilarity to the similarity of the two vectors [17].

Mean Absolute Value

Mean absolute value (MAV) is considered one of the most famous features used in EMG signal analysis [18, 19]. The MAV feature is an average of the absolute values related to the amplitude of the EMG signal in a section, which can be defined according to *Equation (3):*

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{3}$$

where *x* is the value of the EMG signal, and *N* denotes the number of recorded EMG signal points.

Waveform Length

Waveform length (WL) is a measure of EMG signal complexity [19, 20], which can be calculated according to *Equation (4):*

$$WL = \sum_{i=1}^{N-1}|x_{i+1} - x_i| \tag{4}$$

where *x* and *N* represent the amplitude of the EMG signal and number of recorded EMG signal points, respectively.

Willison Amplitude

Willison amplitude (WAMP) indicates the total number of times the difference between the two adjacent segments of EMG signal surpasses the desired threshold. The number of times a signal exceeds this value is called frequency. Therefore, WAMP is regarded as a measure of EMG signal frequency. This feature is related to motor unit action potentials and contraction force in muscles and is estimated based on *Equation (1)* [21]:

$$WAMP = \sum_{i=1}^{N-1}\left[f(|x_n - x_{n+1}|)\right]; \quad f(x) = \begin{cases} 1, & if \ \ x \geq thershold \\ 0, & otherwise \end{cases} \tag{5}$$

where *x* is the amplitude of the EMG signal.

Root Mean Square

Root mean square (RMS) is one of the well-known parameters in EMG signal processing and is modeled as the Gaussian random process of amplitude modulation, which is related to constant force and nonvolatile contraction. Furthermore, this feature is similar to the standard deviation method. The mathematical formula of this feature is expressed in *Equation (6)* in which the signal amplitude is represented by *x* [21].

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2} \tag{6}$$

Mean Frequency

Mean frequency (MNF) is the average frequency feature which is calculated as the sum of the EMG power spectrum [20]. Additionally, this frequency is divided by the total intensity of the spectrum. The central frequency (f_c) and the center of gravity spectrum are the other names of MNF [22]. This feature can be defined as presented in *Equation (7):*

$$MNF = \sum_{i=1}^{M} f_i P_i \ / \ \sum_{i=1}^{M} P_i \tag{7}$$

where f_i, P_i, and *M* demonstrate the frequency of the spectrum at the ith frequency, EMG power spectrum at the ith frequency, and frequency length, respectively.

Signal Recording

The lids were attached to each of the muscles according to the SENIAM standard [23]; subsequently, each participant made three desired movements.

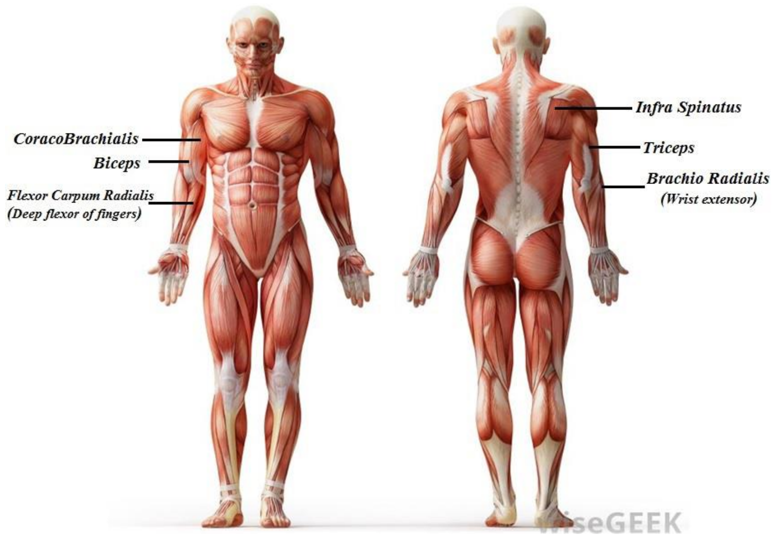

Figure 3. Location of the recorded muscles

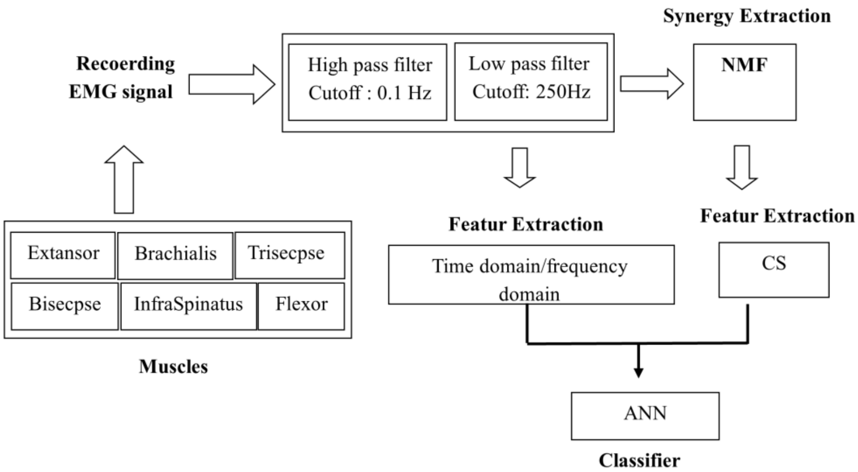

Figure 4. Diagram block of steps for performing the study

In addition, signals were recorded from six muscles of the dominant hand (i.e., biceps muscles, triceps, coracobrachialis, infraspinatus, wrist extensor, and the deep flexor of fingers) for each participant (Figure 2) during executing three selected skills, including back passing, ball getting, and finger roll [23-25].

These muscles were selected based on the selected skill movements (Figure 3).

The device was set at 5,000 with a sampling rate of 1 kHz, followed by setting high- and low-pass hardware filters with discrete frequencies of 10 and 500 Hz, respectively [26, 27]. Each participant repeated each of the movements five times, and the EMG signal of the muscle was recorded during each repetition so that the best record was finally selected considering the EMG signal features, noise, and motor artifacts among the five records.

The best-recorded signal was selected using the time and frequency features of the EMG signal. In the first step, the signal with a lower noise is more acceptable. Furthermore, the amplitude of surface EMG signal starts from low frequencies in the frequency domain and reaches its peak around the frequency of 50-80 Hz and then it gently starts to reduce until reaching its minimum value at the frequencies of 200-250 Hz [28, 29]. Regarding this, the best signal was selected from the five recorded signals of each individual for each skill by determining the signal frequency spectrum based on fast Fourier transform and the compliance with the characteristics of the obtained signal frequency spectrum.

Signal Processing

Based on the information range of the EMG signal strength, the signal was filtered with low- and high-pass filters with the cutoff frequencies of 250 and 0.1 Hz, respectively [28].

Synergy Extraction

In the present study, the NMF method was utilized to extract muscle synergy. Additionally, the VAF criterion was used to perform this analysis. More precisely, this criterion examined the similarity between the original EMG signal and the NMF-reconstructed matrices in order to improve the result if the similarity of the matrices was less than 96%. In this regard, the number of synergies should be increased for enhancing the similarity [30].

Feature Extraction

Using the cosine similarity feature, the similarity between the synergy of both muscles was extracted from each person as the features of the same person, which were obtained for each person regarding a total of 15 features and was considered as the feature vector for applying the classifier. An increase in the number of classifier inputs is considered as one of the effective methods for increasing the classification accuracy of the groups. Regarding this, some of these features on existing signals, including MAV, WL, WAMP, RMS, and MNF, were evaluated by considering that the number of time and frequency features extracted from the EMG signal was high based on the previous evidence [21]. Eventually, all of these 20 features from the first column to the twentieth were placed in MNF, MAV, RMS, WAMP, and WL, respectively, and the cosine similarities between each individual muscle were placed in the space of the features.

Classification

To evaluate the results of classification by applying the matrix containing only 15 features, the cosine similarity and feature matrix, including all 20 cosine similarities, as well as the mentioned time and frequency features were separately applied to the neural network. To apply each of the feature matrices, a certain structure was considered for the neural network. Briefly, the training function for this network function of back-propagation was used with the scale conjugate guardian method. The stop conditions were adjusted according to the standard of neural network toolbox on the number of replicates for 100 repetitions, error rates, and evaluation of validation data with six adjustments. To compare the classification power of the cosine similarities against time and frequency features, each of these two classes of features was applied to the neural network with a similar structure after being applied with decreased dimensions to equal dimensions in order to compare the obtained results with previous structures.

Given that the number of features is high, compared to the number of data, the creation of a decreased dimension in the feature space is necessary for obtaining features in a space with fewer dimensions in order to classify the existing data in four classes with appropriate accuracy by employing the neural network classifier. The result of decreasing this dimension could demonstrate which combination of the extracted features from the EMG signal could have a major impact on data classification. Accordingly, the linear discriminant analysis method was used for decreasing dimension, and the result was finally applied to the neural network as the input.

As mentioned earlier, the number of the extracted features is high, compared to the existing data. Therefore, the efficiency of the neural network in learning the data is low and the desired result in the data classification is unachievable. On the other hand, increasing the number of data is a long process. Accordingly, the use of the K-fold cross-validation method is considered the best alternative for further and better training of the neural network. Therefore, a K of 0.1 was used to apply the feature matrix due to the least bias and the desired result. Figure 4 illustrates the diagram block.

After filtering the recorded signal from the six muscles of the hand, as well as the analysis of time and frequency features, the cosine similarity feature of the obtained syntheses was extracted by the NMF method and then applied to the neural network for classification.

Results

After preprocessing and noise reduction, synergy patterns were extracted using the NMF method. This method decomposed the EMG signal into non-negative coefficients and the two matrices of W and C were obtained, indicating the weights and coefficients of the matrix, respectively. In matrix W, the number of rows and columns corresponds to the number of recorded muscles and synergies, respectively. However, in matrix C, the number of rows equals the number of synergies; furthermore, the number of columns relies on the recording time for each sample. Figure 5 displays an example of the synergy extraction of the signal related to one of the participants showing the extraction of four synergies.

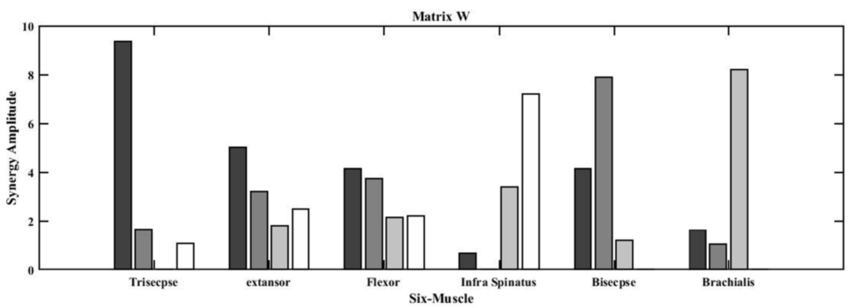

Figure 5. W matrix with six muscles and four synergies for each of the six muscles (Four synergies were extracted, which were proportional to the skill level of each person, and the level of effectiveness of each synergy in each muscle was different.)

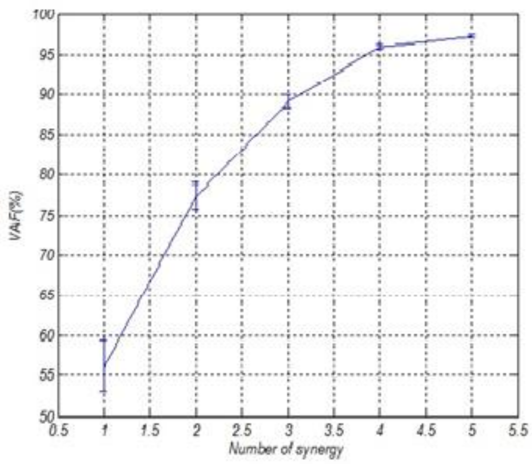

Figure 6. Percentage of initial signal similarity with the reconstructed signal for each number of extracted synergy
Note. The most optimal number of synergies was determined based on this criterion.

Based on the skill level of each participant, the evaluation of the effect of each of the four synergies in each of the muscles is different. In other words, the role of each synergy is more obvious in one muscle while less in the other. On the other hand, the same role of synergy in a joint muscle is different for a person with a different skill level. In the present study, the first level of the similarity of the two signals was higher than 96% of the 96.35 value for four synergies. In Figure 6, the VAF value is expressed in percentage for different synergy values ranging from one to five. In addition, the horizontal and vertical axes represent the number of synergies and VAF values in percentage, respectively.

The number of suitable synergies was determined to be four for every group and all movements. Furthermore, an increase in the number of synergies increased the similarity of the two signals, and the reconstructed signal was more similar to the original signal. Furthermore, the main purpose of synergy extraction, namely dimension reduction, was observed since the excessive increase in the number of synergies failed to detect the dimension reduction.

Therefore, four synergies were extracted from each EMG signal using the VAF criteria. The comparison of these synergies among the moments of each group indicates the results. For example, the obtained results from synergy extraction related to the subjects in the non-professional group during the ball grip skill demonstrated that the fourth synergy failed to involve the first muscle, while the first synergy had the highest involvement in the third, fifth, and sixth muscles. Contrarily, the second synergy failed to involve the third, fifth, and sixth muscles, while it played a stronger role in the first and second muscles.

Among the beginners, the first synergy involved the first, second, fourth, and sixth muscles while playing a less significant role in the third and fifth muscles. Based on the results, the second synergy had a further contributing role in the fifth and sixth muscles in this group. For the fourth synergy, no involvement was observed in the third, fifth, and sixth muscles. The obtained results from synergy extraction related to the professional subjects revealed that the first synergy played a prominent role in all muscles. Additionally, involvement was found in nearly all muscles for the second and third synergies; however, it was lower than the first synergy. Considering the last synergy, involvement was not observed in the second and sixth muscles.

Among the completely professional group, the role of the first synergy was clearly observed among the first, second, third, and fifth muscles; nonetheless, this synergy was less evident in the other muscles. In addition, the second synergy was observed in the second and fourth muscles, and the third synergy played a role in the third and fourth muscles. Eventually, the last synergy played a trivial role in the fifth muscle.

The extracted synergies from the recorded signals during the roller finger skill in the non-professional group indicated that the first synergy played a significant role in the first, second, third, and sixth muscles. The second synergy was only observed in the fifth muscle and involved in no other muscles. Based on the results, the third synergy played a significant role in the fourth muscle, while it was less involved in the other muscles, and the last synergy was involved in the fourth and sixth muscles. Among the beginner group, the first synergy was involved in the fourth and fifth muscles, while a proper involvement was found in approximately all muscles regarding the second synergy. Furthermore, the third synergy had fairly good involvement in the last two muscles, and the last synergy was involved in the first and sixth muscles.

The role of the first synergy could be observed in all muscles in the professional group. Furthermore, the role of the second synergy was more evident in the last two muscles. Additionally, the third synergy was more involved in the fourth muscle, while it was less involved in the other muscles, which is similar to the role of the last synergy which was more involved in the second muscle. The strong involvement of the first synergy could be observed in the last muscle in the completely professional group, and the second synergy had relatively good involvement in almost all muscles. Concerning the third synergy, the first and third muscles were more involved, compared to the other muscles, and the fourth synergy was involved in the first three muscles.

The extracted synergies of the signal regarding the back pass skill among the professionals demonstrated involvement in all muscles considering the first synergy. Regarding the second synergy, involvement was observed in the second, fifth, and sixth muscles. In addition, the involvement of the third synergy was detected in the last muscle, while the last synergy was more involved in the first muscle. Based on the extracted synergies among the beginners, the first synergy was involved in almost all muscle activities, while the second synergy was more observed in the first and fifth muscles. The third synergy contributed to all muscles, and the last synergy was involved in the second and third muscles. In the professional group, the first synergy was observed in the second, fourth, fifth, and sixth muscles.

Regarding the second synergy, involvement was found in the first muscle. Furthermore, the role of the third muscle was more prominent with regard to the third and fourth synergies. The results related to the extracted synergies in the completely professional group represented that the first synergy was involved in all muscles although a better involvement was observed in the last three muscles. Regarding the second synergy, more involvement occurred in the last four muscles. Considering the third and fourth synergies, no significant involvement was detected in this group.

By the extraction of the introduced features, the matrix of the features was applied to neural networks with several different arrangements leading to the classification of the neural network with 15 inputs (cosine similarity features between each two muscle pairs of each person extracted from human muscle synergy) and four outputs (i.e., fully professional, professional, beginner, and non-professional classes). On a database of 96 signals, 32 individuals were trained. The features of the neural network to apply the matrix of cosine similarity features included five neurons in the hidden fold. In addition, the percentages of data distribution in the three classes of training, evaluation, and testing data were 85%, 5%, and 10%, respectively. The network had seven neurons in its hidden fold by applying the cross-validation method. The results were demonstrated in 10 repetitions of the neural network training, along with five neurons of the hidden fold with a random distribution of data (Table 1).

Table 1. Results of the neural network for 10 times of training with the input of the matrix of the cosine similarity features
Note. Results of applying this matrix have a roughly good percentage of accuracy due to the high number of features.

Trains	Accuracy (%)
Train 1	70%
Train 2	100%
Train 3	90%
Train 4	50%
Train 5	90%
Train 6	100%
Train 7	80%
Train 8	80%
Train 9	80%
Train 10	60%
Mean±SD=80%±16.3299	

Due to the high number of features, the K-fold cross-validation method with a K of 10 was used to train the neural network with the seven hidden neuron layers.

Table 2. presents the results of training the neural network using the K-fold cross-validation method

Folds	Accuracy (%)
Fold 1	73.04%
Fold 2	93.16%
Fold 3	85.76%
Fold 4	88.68%
Fold 5	93.79%
Fold 6	91.39%
Fold 7	79.59%
Fold 8	85.52%
Fold 9	60.16%
Fold 10	78.49%
Mean±SD=82.96±10.48	

Additionally, the participants were trained again with 20 inputs (i.e., 15 cosine similarity features used in the previous training, four time features, and one frequency feature of the EMG signal) and similar outputs with previous training. The neural network for applying a matrix with 20 features contained seven neurons in the hidden layer. Furthermore, the percentages of data distribution in three categories of training, evaluation, and testing data were 65%, 15%, and 20%, respectively.

The neural network could not respond well since the number of feature space dimensions was high, compared to the number of the samples. Therefore, the feature space reduced using the linear discriminant analysis (LDA) dimension reduction technique, and then the reduced dimension matrix was applied as the input to the neural network with seven hidden neurons (Table 3).

Table 3. The results of the neural network training with the reduced-matrix nerve using the linear discriminant analysis method for 10 different training protocols
Note. The application of this matrix to the neural network demonstrated relatively good results.

Trains	Accuracy (%)
Train 1	68.4%
Train 2	73.7%
Train 3	89.5%
Train 4	52.6%
Train 5	89.5%
Train 6	94.7%
Train 7	78.9%
Train 8	68.4%
Train 9	63.2%
Train 10	57.9%
Mean±SD=73.68%±14.2540%	

Table 4. Presentation of the neural network results with different features
Note. The cosine similarities represented better results.

Feature matrix	Accuracy
Cosine similarity features matrix	68.06%±12.24%
Time and frequency domain features matrix	59.89%±8.82%

Table 5. Comparison of previous research with the current study
Note. The main difference between this project and previous research is the higher number of studied groups, as well as the use of features extracted from muscle synergy, along with time and frequency features and the classifiers.

	Research Topic	Sport	Groups	Result
Maud Bassement et al.	Kinesiology in lower limbs	Pole vault	Beginner/professional	RMS was significantly different between the two groups.
Julien Frère et al.	Examination of the activity of the hand muscles for detecting the effective phases	Pole vault	Professional	Muscle activity showed different patterns of mean overall intensity at each phase.
Jeremy K. Cutsforth-Gregory et al.	Diagnosis of muscle dystrophy with EMG	Running	Runner/non-runner	EMG can be effective, but it is generally responsive
Current project	Determination of skill levels with hand activity by muscle synergy	Basketball	Fully professional/ professional/ beginner /non-professional	Classification of individuals among four groups was accomplished with 73.68% accuracy.

RMS: root mean square, EMG: electromyography

The results of the diminished dimension in the feature space, performed by the LDA method, represented a combination of three features, which played a significant role in categorization.

To compare the matrix classification power of the cosine similarity features with time and frequency features, both matrices were reduced to three dimensions by means of the LDA method in order to create equal dimensions. Subsequently, they were separately applied to the neural network with the same structure. The structure of this network was arranged with five hidden layer neurons and data distribution percentages were 65%, 15%, and 20% for training, evaluating, and testing data, respectively. Table 4 presents the results of both training protocols as the mean and standard deviation of 10 different replications from the neural network training.

The results of the present research were compared with those of the previous studies. The most similar studies and different viewpoints were investigated, the details of which are briefly presented in Table 5.

The results indicated that people can be classified at different skill levels in a sport by using the features extracted from the recorded EMG signals of the involved muscles during an exercise. In addition, the features of muscle synergies in humans are considered as the main factors in differentiating the groups in terms of a skill. In other words, synergy varies among individuals in different groups and can be considered a factor in classifying individuals.

Discussion

Based on the results, the vector was derived from the LDA dimension method after applying to the neural network classifier, and classification was conducted with a lower percentage of accuracy, compared to the first feature matrix. The results are considered logical since the neural network was trained with the space feature with lower and more compact dimensions. In addition, the extracted features of synergies had more power to distinguish the data and could determine the neural network more accurately for differentiating people with different levels of skill in basketball by performing the three above-mentioned movements. Therefore, the features of muscle synergy can be effective factors in data classification.

The evaluation of the extracted synergies demonstrated that the synergies of individuals were different among the groups while they were similar in the same group. Therefore, these synergies can be considered as a measure for separating people with different skill levels in a particular field. Therefore, the classification was trained based on the features of the extracted synergies. As the findings indicated, training and classification based on these features had stronger results, compared to the other time and frequency features.

Conclusion

To the best of our knowledge, the present study evaluated the EMG signal of people in basketball and the results suggested that the extracted features of this signal, as well as the obtained synergies from the EMG signal, were helpful in the classification of individuals in the field of basketball in terms of skill levels. Accordingly, the patterns for a particular movement are different in each individual’s spinal cord based on the skill level of that individual. Furthermore, the coefficients sent from the brain toward these patterns in people with more skills are more favorable, compared to those in individuals with fewer skills. Accordingly, the EMG signals of people differ in a similar movement. In other words, the synergies of people with different skills vary in a particular movement or discipline and can be a criterion for differentiating people in terms of skill levels.

Other similar studies compared two groups in this regard by using frequency and time features. However, the present study evaluated the features of extracted synergies from the EMG signal, and the comparison was conducted among more than two groups (i.e., four groups). Finally, the neural network classifier and percentage accuracy of class differentiation were reported by means of each class of features.

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References

1. Lindberg M, Frisk-Kempe K, Linderhed H, Eklund J. Musculoskeletal disorders, posture and EMG temporal pattern in fabric-seaming tasks. International Journal of Industrial Ergonomics. 1993;11(3):267-76.
2. Roman-Liu D, Bartuzi P. The influence of wrist posture on the time and frequency EMG signal measures of forearm muscles. Gait & posture. 2013;37(3):340-4.
3. Finneran A, O'Sullivan L. Effects of grip type and wrist posture on forearm EMG activity, endurance time and movement accuracy. International Journal of Industrial Ergonomics. 2013 ;43(1):91-9.
4. Bassement M, Garnier C, Goss-Sampson M, Watelain E, Lepoutre FX. Using EMGs and kinematics data to study the take-off technique of experts and novices for a pole vaulting short run-up educational exercise. Journal of science and medicine in sport. 2010;13(5):554-8.
5. Frère J, Göpfert B, Slawinski J, Tourny-Chollet C. Effect of the upper limbs muscles activity on the mechanical energy gain in pole vaulting. Journal of electromyography and kinesiology. 2012;22(2):207-14.
6. Charlton PC, Mentiplay BF, Grimaldi A, Pua YH, Clark RA. The reliability of a maximal isometric hip strength and simultaneous surface EMG screening protocol in elite, junior rugby league athletes. Journal of science and medicine in sport. 2017;20(2):139-45.
7. Bahalgerdy F. The Combination of Reinforcement Learning and Synergy Patterns to Controlling of Human Arm Movements on the Horizontal Plane. MSc thesis of Biomedical Engineering. Islamic Azad University Science and Research Brach. 2017.
8. Kaboodvand V. Extraction and analysis of muscle synergies in arm reaching movement. Bioengineering Department MSc Thesis. Amirkabir University of Technology (Tehran Polytechnic). 2014.
9. Sabzevari V. Extraction of hand muscle synergies in reaching movement using fuzzy cognitive map and nonlinear quantifiers. Faculty of Biomedical Engineering-Department of Bioelectric Ph.D Thesis. Islamic Azad University Science and Research Brach, Tehran, Iran. 2015.
10. Cole NM, Ajiboye AB. Muscle synergies for predicting non-isometric complex hand function for commanding FES neuroprosthetic hand systems. Journal of neural engineering. 2019;16(5):056018.
11. Hu ZX, Xu SQ, Hao MZ, Xiao Q, Lan N. Muscle synergy changes with cutaneous stimulation during resting tremor and reaching task in Parkinson's disease. In2019 9th International IEEE/EMBS Conference on Neural Engineering (NER). 2019; 9: 73-76.
12. Li T, Chen X, Cao S, Zhang X, Chen X. Human hands-and-knees crawling movement analysis based on time-varying synergy and synchronous synergy theories. Math. Biosci. Eng. 2019; 16:2492-513.
13. Lee D, Seung S. Algorithms for non-negative matrix factorization. Adv Neural Inf Process Syst. 2001; 13:556‑62.
14. D'Avella A, Tresch MM. Modularity in the motor system: decomposition of muscle patterns as combinations of time-varying synergies. Advances in neural information processing systems. 2001; 14:141-8.
15. Wojtara T, Alnajjar F, Shimoda S, Kimura H. Muscle synergy stability and human balance maintenance. Journal of neuroengineering and rehabilitation. 2014;11(1):129.
16. Steele KM, Rozumalski A, Schwartz MH. Muscle synergies and complexity of neuromuscular control during gait in cerebral palsy. Developmental Medicine & Child Neurology. 2015 ;57(12):1176-82.
17. Sabzevari VR, Jafari AH, Boostani R. Muscle synergy extraction during arm reaching movements at different speeds. Technology and Health Care. 2017;25(1):123-36.
18. Zardoshti-Kermani M, Wheeler BC, Badie K, Hashemi RM. EMG feature evaluation for movement control of upper extremity prostheses. IEEE Transactions on Rehabilitation Engineering. 1995;3(4):324-33.
19. Hudgins B, Parker P, Scott RN. A new strategy for multifunction myoelectric control. IEEE transactions on biomedical engineering. 1993 Jan;40(1):82-94.
20. Oskoei MA, Hu H. Support vector machine-based classification scheme for myoelectric control applied to upper limb. IEEE transactions on biomedical engineering. 2008 Mar 5;55(8):1956-65.
21. Phinyomark A, Phukpattaranont P, Limsakul C. Feature reduction and selection for EMG signal classification. Expert systems with applications. 2012 Jun 15;39(8):7420-31.
22. Du S, Vuskovic M. Temporal vs. spectral approach to feature extraction from prehensile EMG signals. InProceedings of the 2004 IEEE International Conference on Information Reuse and Integration. 2004; 344-50.
23. Rahatabad FN, Jafari AH, Fallah A, Razjouyan J. A fuzzy-genetic model for estimating forces from electromyographical activity of antagonistic muscles due to planar lower arm movements: the effect of nonlinear muscle properties. Biosystems. 2012;107(1):56-63.
24. Rahatabad FN, Fallah A, Jafari AH. A study of chaotic phenomena in human-like reaching movements. International Journal of Bifurcation and Chaos. 2011;21(11):3293-303.
25. Kim HK, Carmena JM, Biggs SJ, Hanson TL, Nicolelis MA, Srinivasan MA. The muscle activation method: an approach to impedance control of brain-machine interfaces through a musculoskeletal model of the arm. IEEE transactions on biomedical engineering. 2007 ;54(8):1520-9.
26. Azab AM, Onsy A, El-Mahlawy MH. Design and development of a low cost prosthetic arm control system based on sEMG signal. InASME International Mechanical Engineering Congress and Exposition 2015; 57380: V003T03A080.
27. https://www.biopac.com/wp-content/uploads/EMG-Guide.pdf available at: 12/November 2019
28. Konrad P. The ABC of EMG: A practical introduction to kinesiological electromyography. 2005.
29. Maleki A. Modeling and Reanimation Control of Paralysed Arm for C5/C6 SCI Patients Using. Faculty of Biomedical Engineering-Department of

Bioelectric Ph.D Thesis. Amirkabir University of Technology, Tehran, Iran. 2009.
30. Tang L, Li F, Cao S, Zhang X, Wu D, Chen X. Muscle synergy analysis in children with cerebral palsy. Journal of neural engineering. 2015;12(4):046017.