A New Method to Assess and Enhance Athletes' Performance Based on Muscle Synergy Patterns: A New Approach to Design a Biofeedback Training Scheme

Armin Hakkak Moghadam Torbati, Mohammadamin Gholibeigi, and Shahab Jami

ABSTRACT

Objectives: There has been a big challenge for athletes at any level to reach their ultimate performance. According to a Motor Control theory, accurate programming of movements during the last stage of preparation to work out can improve athletes' performance. So, this study aims to design a performance analysis method that can be used to classify athletes and give them feedback during exercise. In this way, athletes and coaches can consider exercise schemes to modify and ameliorate athletes' performance.

Methods: The participants were made up of 20 men between 25 to 30 years old. These subjects include ten professional football players and ten amateur football players. The same trials in 6 successive days were done by all athletes, both professional and amateur. Two different types of conditions were designed for all participants. In the first three days, subjects were asked to shoot a penalty kick (football player) 10 times in an actual situation like what they do in a competition. These procedures were done in the simulation condition, in the next three days designed by the computer (Xbox). Surface electromyography (sEMG) was recorded from the gastrocnemius and tibialis anterior muscles during trials.

Results: Results showed the maximum error between basis vectors in all of the professional subjects in each situation, real and game, were 0.48 and 0.37, respectively (Mean square error index), which are very low relative to the range of data (5.1). In contrast, the minimum error among amateurs in each situation was 13.18 and 18.72, which are a high amount compared with the range of data (7).

Discussion: Professional athletes always, in both situations, use their muscles in the same way. In fact, professional athletes' muscles follow specific patterns due to slight errors, while amateurs' muscles do not.

Keywords: muscle synergy, performance assessment, performance enhancement, talents identification, virtual reality.

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I. INTRODUCTION

Achieving the optimal level of performance has been a big challenge and the primary purpose for many athletes at any level (Hribernik *et al*., 2021; Xiang *et al*., 2018). Various technologies and exercises can help athletes reach their personal best (Hribernik *et al*., 2021). Moreover, according to a Motor Control theory, professional performance means accurate programming of movements during the last stage of preparation to work out (Keele, 1968). This theory emphasizes high accuracy in exercise programming. Therefore, to reach an effective exercise program for improving athletes' ability, they should be assessed thoroughly (Fukuda, 2018), then logical and progressive functional upgrading techniques can be applied (Radnor *et al*., 2020).

The assessment presents a general overview of the current status of athletes or teams. Making a decision about athletes without evaluation is an assumption. Evaluation has many applications ranging from choosing athletes to standard methods of training. Although testing will lead to ideal results during practice or competition conditions, creating a balance between collecting useful and specialized information can lead to complex engineering methods, making it difficult for athletes and trainers. Another restricting factor for trainers to assess is a limited budget to implement an advanced engineering approach (Fukuda, 2018). Considering that the assessment of athletes is implemented with different physical features, it should be noticed whether this method or device can be used for all groups of athletes. Besides, validity, discriminant validity, occurs when different groups of people with other characteristics can be discriminated as expected

(Fukuda, 2018). So, one of the main aims of this study is to design an accurate method based on engineering science that is able not only to evaluate performance distinction between different athletes but also has essential features such as a cheap, safe, and user-friendly interface as well as its capability for people with various physical attributes.

The significant gap is in the motor skill competency enhancement related to sports performance. Although using Technology in current years for athletes' improvement has received attention, beneficial Technology for the advancement of athletes' performance is scarce. Technology can help athletes improve in three ways: tracking devices for performance improvement, equipment for quantitative evaluation and giving feedback, and visual feedback devices to analyze the results (Buchheit *et al*., 2014; Thomas *et al*., 2016). Furthermore, a higher level of neural plasticity in teenagers paves the way for motor skill competency to develop(Bult *et al*., 2018), though this development is impossible without exercise and feedback (Hardy *et al*., 2012). So, the demand for biofeedback design in exercises to assess athletes' performance and improve motor skill competency in athletes between teen and adult years with minimum risk of injury is tangible. One goal of this study is to present a method to design this type of biofeedback.

Another application of performance assessment is talent identification (Lloyd *et al*., 2019). In designing assessment, it should also be noticed that a tiring process can negatively affect athlete performance during a repeated cycle.

In conclusion, this study aims to find a performance assessment method that can be used for categorizing different groups of athletes, including professional and amateur. This method should be featured as an easy-to-use, affordable, safe, talent finder, and non-fatiguing which can be used for people with different body attributes. Moreover, this method should be usable in designing biofeedback to improve athlete performance according to motor competency. As in previous studies, it was proven that the movement pattern of athletes is different from skill levels, and motor skill is highly associated with muscle synergy (d'Avella *et al*., 2005; d'Avella *et al*., 2003; Nowshiravan Rahatabad *et al*., 2021); the authors' hypothesis in this paper is that using muscle synergy can present an engineering method with mentioned features.

II. Material and Methods

A. Participants

In this work, the participants were made up of 20 men between 25 to 30 years old. These subjects include ten professional football players and ten amateur football players. Table 1 demonstrates the participants' characteristics.

Before conducting the experimental studies, all participants were asked to fill in a consent form.

TABLE I: Football Players' Characteristics

Amateur football player subject	Height (cm)	Weight (kg)	Years of football experience
1	184	79	6
2	179	68	8
3	182	80	5
4	188	85	6
5	190	91	10
6	175	74	8
7	186	83	6
8	178	82	9
9	184	78	6
10	188	82	8

B. Recording Protocols

The same trials in 6 successive days were done by all athletes, both professional and amateur. Two different types of conditions were designed for all participants. In the first three days, subjects were asked to shoot a penalty kick (football player) 10 times in an actual situation like what they do in a competition. Similar procedures were done in the simulation condition, in the next three days designed by the computer (Xbox). In detail, subjects mimicked what they had done in the last three days to shoot a ball, but this time they stood in front of a television while the sensors of Xbox were attached to them. sEMG was recorded from the gastrocnemius and tibialis anterior muscles during trials. The placements of electrodes were determined according to the SENIAM website. Six Ag/Agcl surface electrodes of 10 diameters were used to record each subject's sEMG (skin tact). Before starting the protocol, the skin of respective muscles was cleaned with alcohol for better connections.

C. The Proposed Approach to Compare the Performance of Athletes

A wide range of attempts is being made to assess (Echemendia *et al*., 2019; Fukuda, 2018) and improve the performance of athletes, both physical and psychological (Ives *et al*., 2002; Radnor *et al*., 2020).

Permanent capability in doing skilled actions is considered as the main index. This type of learning is transmitted to muscles by CNS with defined patterns to complete a motor skill (Shumway-Cook *et al.*, 2007). These patterns, which a group of muscles uses, are recognized as muscle synergies (Abd *et al.*, 2021; Esmaeili *et al.*, 2019). Using involved muscle synergies is one of the current methods to investigate the relationship between the nerve system and the performance of athletes (Nowshiravan Rahatabad *et al.*, 2021). The proposed manner in this study is to assess the performance of athletes based on muscle synergy patterns because these patterns are permanent.

D. Synergy

Muscle synergy is a coordinated local and temporal activity from a group of muscles that work together to maintain a particular performance. Synergy is divided into synchronous (constant synergy with variable coefficients) and asynchronous (variable synergy with constant coefficients). Linear vectors are used to split each muscle's performance. The sum of these vectors with particular coefficients reconstructs the electromyogram signal at any given time.

$$M(t) = \sum_{i=0}^{k} c(t)_i w_i \tag{1}$$

M represents the pattern of time-varying muscular activation in the participating muscles. The ith dimensional basis vector is called w_i. The ith basis vector's scalar activation coefficient is c(t)i (Torbati *et al.*, 2017; Torbati *et al.*, 2018; Torres-Oviedo *et al.*, 2007). In this study, the HALS algorithm was used because this algorithm is fast with high accuracy and robust to noise (Torbati *et al.*, 2017).

E. Hals Algorithm (Hierarchical Algorithm Least Square)

There are some local cost functions in this algorithm. Based on the optimality requirements, the cost functions are minimized sequentially. The HALS algorithm is divided into five steps.
1. Initializing a randomity
2. Estimating X from the matrix equation:

$$A^T A X = A^T Y \tag{2}$$

By solving

$$\min_{X} D_F (Y = AX) \frac{1}{2} \parallel Y - AX \parallel_F^2 \tag{3}$$

A is an unknown Basis matrix with non-negative vectors
X is a matrix representing unknown non-negative components
3. Setting all negative elements of X to zero or a small positive value
4. Estimating A from the matrix equation $XX^T A = Y^T X$

$$\min_{X} D_F (Y = AX) \frac{1}{2} \parallel Y^T - A^T X^T \parallel_F^2 \tag{4}$$

5. Setting all negative elements of A to zero or a small positive value ε.
Y is a constructed signal with different rows and columns.

F. Determination of the Number of Synergies

The main issue is the determination of the number of synergies. To this end, R^2 criteria are used to assess the number synergy. R^2 represents the fraction of total variation accounted for by the synergy reconstruction. R^2 can calculate as follows:

$$R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_s \Sigma_{k=1}^{k_j} ||m^j(t_k) - \Sigma_i c_i^j w_i(t_k - t_i^j)||^2}{\sum_s \Sigma_{k=1}^{k_j} ||m^s(t_k) - \bar{m}||^2} \tag{5}$$

SSE is the sum of the squared residuals, and SST is the sum of the squared residuals from the mean activation vector ($\bar{m}$) (Torbati *et al.*, 2017; Torbati *et al.*, 2018). Four synergies for leg muscles were used in this investigation because R2 is consistent after four synergies. Fig. 1 depicts changes versus the number of synergies.
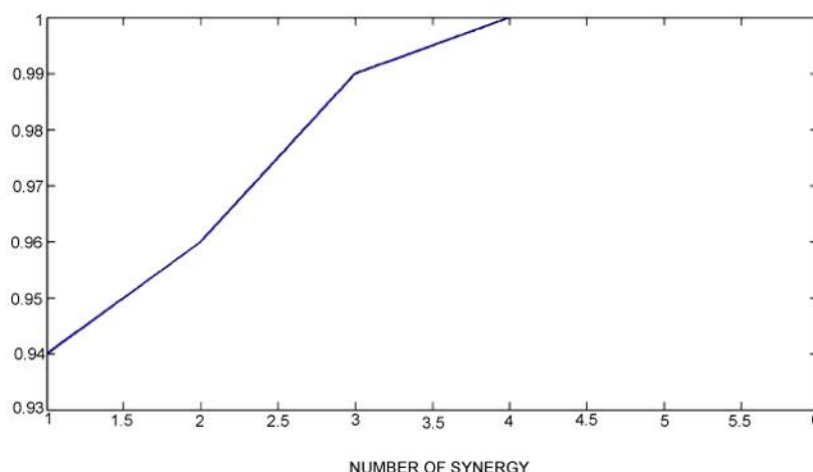
Fig. 1 Shows changes in R2 against a number of synergies.

G. Extraction of the Synergy Pattern

In the first step, raw sEMG signals were bandpass filtered (10–500 Hz). In the second step, sEMG signals were rectified. In the third step, signals were normalized to be between zero and one. Forth, the signals were filtered by the low pass filter (with a cut-off frequency of 20 Hz). Fig. 2 shows these processes.

Fig. 2 Analysis process.

Fig. 3 depicts how these steps affect the original signal. Finally, signals acquired after the low pass filter were divided into two matrixes by using the HALS algorithm.
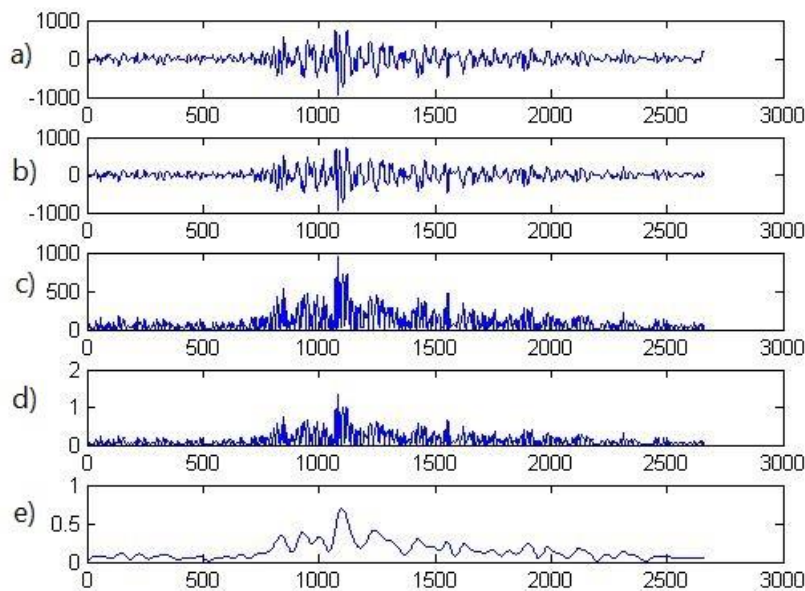

Fig. 3 a) original signal; b) bandpass filter; c) rectified signal; d) normalized signal; e) low pass signal.

III. RESULTS

Assessment of reconstructed signals extracted by the HALS algorithm was calculated. The maximum error was just 5.8 exp-9. So reconstructed signals can be considered as original signals for more analysis.

A. Evaluation Based on Muscle Synergy Pattern

Two different assessment procedures are needed. Firstly, the basis vectors of each subject were compared element by element in different trials. This comparison was executed in both situations, real and game. The whole action of participants (shooting a penalty kick) was considered as one phase of the movement.

Therefore, 60 trials of each subject were compared element by element. If the mean square error (MSE) between the elements of basis vectors were acceptable, we could claim that their muscles follow specific muscle synergy patterns. Table 2 provides information about the maximum error of professional athletes due to low errors, while Table 3 reports the minimum error of amateur players because of high errors.

As you can see in table 2, the maximum error among professional football players in each situation, real and game, were 0.48 and 0.33, respectively, which are very low relative to the range of data (5.1). In contrast, the minimum error among amateurs (table 3) in each situation was 13.18 and 18.72, which are a high amount compared with the range of data (7). Therefore, we could claim that professional athletes always, in both situations, real and game, recruit their muscles in the same way. In fact, professional athletes' muscles follow specific patterns.

TABLE II: MAXIMUM ERROR (MSE) OF REAL AND GAME TRIALS AND VALUES CALCULATED FOR EACH PROFESSIONAL FOOTBALL PLAYER

Professional football player subject	Maximum error of real trial gastrocnemius	Maximum error of game trial gastrocnemius	Maximum error of real trial tibialis anterior	Maximum error of game trial tibialis anterior
1	0.41	0.32	0.38	0.25
2	0.48	0.37	0.37	0.30
3	0.38	0.25	0.28	0.35
4	0.31	0.36	0.46	0.24
5	0.29	0.33	0.42	0.31
6	0.18	0.24	0.26	0.27
7	0.26	0.28	0.25	0.32
8	0.22	0.29	0.19	0.31
9	0.19	0.28	0.23	0.30
10	0.27	0.31	0.26	0.26

TABLE III: MINIMUM ERROR (MSE) OF REAL AND GAME TRIALS VALUES CALCULATED FOR EACH AMATEUR FOOTBALL PLAYER

Amateur football player subject	Minimum error of real trial gastrocnemius	Minimum error of game trial gastrocnemius	Minimum error of real trial tibialis anterior	Minimum error of game trial tibialis anterior
1	13.18	29.19	19.47	29.41
2	17.27	25.48	21.49	31.82
3	21.46	31.51	18.12	34.55
4	28.19	33.29	27.17	21.63
5	30.26	27.35	27.83	22.69
6	17.84	27.35	25.97	24.92
7	19.95	22.59	19.92	26.73
8	15.62	28.41	27.48	27.19
9	21.38	29.83	20.37	18.72
10	24.17	19.94	18.88	28.48

Secondly, basis vectors of participants whose muscles follow specific patterns were compared. The maximum errors were 0.72 and 0.75 for football players in real and game conditions, respectively.

Finally, the basis vectors of each professional football player in each situation were compared to each other element by element. 0.97 and 0.95 were maximum errors in real and game conditions. Table 4 provides information about maximum errors (MSE) between real and game (Xbox) measured in professional football players. These errors are very low compared with the range of data, so it might be meant that all professional athletes similarly used their muscles.

TABLE IV: MAXIMUM ERROR (MSE) BETWEEN REAL AND GAME (XBOX) IN PROFESSIONAL FOOTBALL PLAYERS

Professional football player subject	Maximum error between real and game(Xbox) trials gastrocnemius	Maximum error between real and game(Xbox) trials anterior
1	0.85	0.92
2	0.79	0.94
3	0.91	0.74
4	0.97	0.88
5	0.73	0.95
6	0.81	0.86
7	0.85	0.75
8	0.93	0.83
9	0.85	0.91
10	0.79	0.82

IV. DISCUSSION

The main purpose of this study was to design a performance analysis method that can be used to classify athletes and give them feedback during exercise. In this way, athletes and coaches can consider exercise schemes to modify and ameliorate athletes' performance.

Understanding the control of action implies understanding the motor output from the nervous system to body effectors (Shumway-Cook *et al.*, 2007). The output of the nervous system is some commands, sending to joints and muscles to organize them into coordinated movements. The CNS uses particular patterns to active joints and muscles to simplify their control. These patterns are regarded as muscle and kinematic synergies, which are essential in determining of dynamic and kinematic of the limbs (Abd *et al.*, 2021). If the process of learning for a specific task is completed in a person (motor learning), these muscle synergy patterns are always similar (Shumway-Cook *et al.*, 2007). Accordingly, extracting muscle synergy patterns of athletes provides the possibility to classify them in terms of skill based on CNS commands. So the proposed method in this work was using muscle synergy patterns. Up to now, many methods have been used to assess and enhance athletes' performance, ranging from supplements (DeGiorgio *et al.*, 2013) to engineering equipment (Thomas *et al.*, 2016). But no one has studied the relationship between CNS command signals and athletes' performance to enhance their abilities. So, this study's results present a new aspect of sports science in terms of designing training to improve athletes' performance.

The comparison of basis vectors of each participant in 60 trials (in real and game situations) proved our hypothesis about the similarity of these vectors in professional athletes. In contrast, the basis vector of amateur athletes did not follow a specific trend. More interestingly, the basis vectors of all professional athletes in each kind of condition were similar, which means they have similar synergy patterns.

The study carried out by Nowshiravan Rahatabad *et al* is the only work that used muscle synergy patterns for classifying athletes (Nowshiravan Rahatabad *et al.*, 2021). But the main advantage of current work is to have a similar analysis in a game situation.

The proposed method was safe and cheap because recording sEMG during a kicking ball was the only extra action that has been done. In addition, it can be implemented regardless of age or gender, and it is also non-fatiguing due to little needed energy for kicking a ball.

The extracted muscle synergy patterns could have several applications in sports science, including, first, designing biofeedback tools for training athletes in different levels of skill regarding the level of studying group. This is because the muscle synergy patterns of each new subject can be extracted and compared with the reference patterns and then given feedback to users on how they should change their actions. In fact, the main aim of biofeedback tools is to improve athletes' perception of the correct procedure for doing specific sports activities. However, the execution of this part needs more research and programming relative to what was done in this study. It is expected that the efficacy of biofeedback tools will be the most for children and younger generations due to motor competence of object control skills in childhood during the transition into adolescence (Costa *et al.*, 2021) and the greater level of neural plasticity in youth (Bult *et al.*, 2018). Second, in searching for talent, especially the younger generation, by comparing muscle synergy patterns of new potential subjects with professional athletes. That is to say, some talented adolescence and even children can do a task with a method that is close to professional athletes, which means their motor competence is higher than their peers. Identifying these talents and further training can give rise to outstanding results in the future. Third, designing athletic robots. Competition of athletes with robots can ameliorate their ability. Using volleyball robots in Japan's national volleyball team in the Olympic games is a piece of evidence for this claim (What'sUpJapan, 2019).

V. CONCLUSION

According to the results of this study, muscle synergy patterns of involved muscles during a sports task can be used to assess athletes' performance and classify them into different skill levels based on the CNS command signals. These patterns would be used to design a biofeedback tool for enhancing athletes' performance at various skill levels. There are many other applications ranging from talent identification to developing robotic athletes. The proposed method possesses essential factors such as a cheap, safe, and user-friendly interface and its capability to use by people with various physical features.

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CONFLICT OF INTEREST

Authors declare that they do not have any conflict of interest.

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