Ayse Nur Ay* and Mustafa Zahid Yildiz

The effect of attentional focusing strategies on EMG-based classification

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Abstract: Earlier studies showed that external focusing enhances motor performance and reduces muscular activity compare to internal one. However, low activity is not always desired especially in case of Human-Machine Interface applications. This study is based on investigating the effects of attentional focusing preferences on EMG based control systems. For the EMG measurements via biceps brachii muscles, 35 subjects were asked to perform weight-lifting under control, external and internal focus conditions. The difference between external and internal focusing was found to be significant and internal focus enabled higher EMG activity. Besides, six statistical features, namely, RMS, maximum, minimum, mean, standard deviation, and variance were extracted from both time and frequency domains to be used as inputs for Artificial Neural Network classifiers. The results found to be 87.54% for ANN1 and 82.69% for ANN2, respectively. These findings showed that one's focus of attention would be predicted during the performance and unlike the literature, internal focusing could be also useful when it is used as an input for HMI studies. Therefore, attentional focusing might be an important strategy not only for performance improvement to human movement but also for advancing the study of EMG-based control mechanisms.

Keywords: attentional focus; EMG classification; internal focusing.

***Corresponding author: Ayse Nur Ay**, Department of Mechatronics Engineering, Sakarya University of Applied Sciences, Esentepe Campus, Serdivan, 54050, Sakarya, Turkey, E-mail: ay@subu.edu.tr, https://orcid.org/0000-0002-4448-4858
Mustafa Zahid Yildiz, Department of Electrical and Electronics Engineering, Sakarya University of Applied Sciences, Esentepe Campus, Serdivan, Sakarya, Turkey,
E-mail: mustafayildiz@subu.edu.tr. https://orcid.org/0000-0003-1870-288X

Introduction

Many studies have been demonstrated that an individual's focus of attention have an important influence on performance and learning of motor skills [1, 2]. These studies were designed to compare the effectiveness of an internal focus (focusing on one's body movements) and an external focus (focusing on one's movement on apparatus) of attention on learner's performance [3]. In many of them, the significant differences were found between external and internal focus and external focus seemed to enhance learning skills [4, 5]. The difference between external and internal focusing was explained with *Constrained-Action Hypothesis* in 2001 [3]. According to this hypothesis, when a subject focuses externally during a performance, the subject's motor system will be more natural and self-organized, whereas an internal focus may actually constrain automatic control processes that would normally control the movement. In order to learn whether the differences would also be established at neuromuscular level, electromyography (EMG) was used by Vance et al., for the first time. Their results showed that movements were performed faster under external focus condition compared to internal focus and integrated EMG (IEMG) activity was also reduced when performers adopted externally [6]. Zachry et al. showed that focusing externally is not only reduces EMG activity but also increases movement accuracy [7]. The similar studies also showed that the muscular activity was reduced when participants focused externally [8, 9]. However, all these results are based on performances and achievements of people [10].

There are many Human Machine Interface (HMI) applications that use EMG signals to control mechanisms such as smart wheelchairs, artificial hands and prosthesis [11, 12]. The EMG activity and the resulting movement has been investigated in many studies by analyzing the duration, magnitude and amplitude of the signals [13, 14]. Nevertheless, most of the studies do not give enough importance about the environmental, physical or mental condition of a person during the measurements.

This study is based on classifying performers' EMG signals according to his/her focus of attention and predicting one's focus of attention during the performance using the EMG signal features which has great benefit when these signals are used as inputs for robotic control mechanisms. As it was explained, low EMG activity, resulted external focus, has many advantages such as enhancing the performer's motor skills and learning. However, in case of performance of HMI mechanisms, the high EMG activity, resulted internal focus, can also have several advantages such as better signal quality for extracting useful signal features for control applications. With this new point of view, the useful inputs for the HMI applications would be doubled by type of attentional focus which is going to be a novel approach.

Materials and methods

Participants

Twenty-two healthy male and 13 healthy female university students (age = 22 ± 3 years, height = 172 ± 8 cm, mass = 69 ± 12 kg) volunteered for the experiments. They were naive to the tasks and none of them were aware of specific purpose of the study. Informed consent was obtained before participation, in compliance with the university's Institutional Review Board.

Apparatus, task and procedure

In order to measure the EMG signals from the participants' biceps brachii muscles, Delsys Bagnoli™ EMG System was used (dataset) [15]. Additionally, NI-DAQmx card was connected to LabVIEW for acquiring, monitoring, processing and recording the signal. The block diagram of the study is shown in Figure 1.

The research was conducted in a quiet room. Participants were asked to perform weight-lifting (2 kg dumbbell) with their dominant hand while sitting on a chair. They were instructed to perform simply up-hold-down exercises (5 s for each position) repeated 3 times for each attentional focus conditions. The verbal instructions at the beginning of each trials for external focus were "In this trial, I would like you to focus only the dumbbell during all period." whereas "In this trial, I would like you to focus only the contraction of your biceps muscles where the electrodes are placed" for internal focus. Firstly, they have performed weight-lifting with no instructions are given (control condition). Secondly, they were asked to only focus on the dumbbell (external condition). Thirdly, they were asked to focus on the active muscle (internal condition) for entire exercise period. Here the criteria for achievement was not just lifting up and down to the dumbbell, but also performing the trial as regular as possible according to time stimuli. Figure 2 shows the representation of up-hold-down procedure of a participant.

As seen in Figure 2, 5 s intervals represent the movement steps (up-hold-down). The participants were required to complete the movements as regular as possible as a function of time for each position. Each trial was completed in consistently according to time period and since all performers were individual, all analysis were based on within subject analysis.

Data analysis

Raw EMG data was filtered using digital band-pass filter (20 –500 Hz) on NI LabVIEW. From these data, time and frequency-domain analyses were performed.

In order to extract time-domain features, the root-mean-square (RMS), mean absolute values (MAV) and Integrated EMG values (IEMG) of the data were calculated for each data sets on LabVIEW and the results are recorded for statistical analysis [16]. With the purpose of analyzing the data in frequency domain, Fast Fourier Transform (FFT) were performed on the EMG signals of each performers. From the signal, integrated FFT values were taken for statistical analysis. Figure 3 depicts the EMG signal in frequency domain of a single subject.

Both time and frequency data sets were checked for normality adopting Shapiro–Wilks and Kologorov–Shimirnov tests [17]. In both tests, the data were not found to be normally distributed. Therefore, a non-parametric Friedman test was applied to RMS, MAV, IEMG and Integrated FFT values for each group to compare conditions and Wilcoxon Signed-Ranks test (p=0.05) were computed post-hoc to test specific differences between the conditions [18, 19].

Feature extraction

In total, 105 data files (35 participant × 3 focusing type) were collected with 36,000 samples length for each file. MATLAB was used for feature

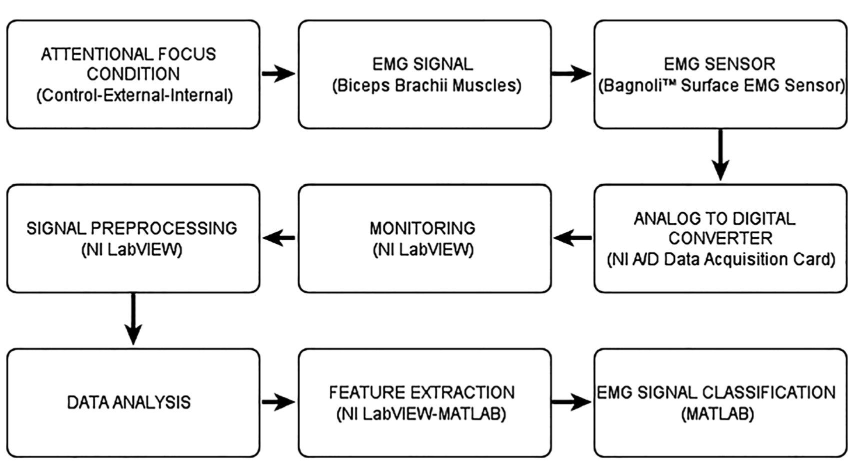

Figure 1: The block diagram of the experimental study.

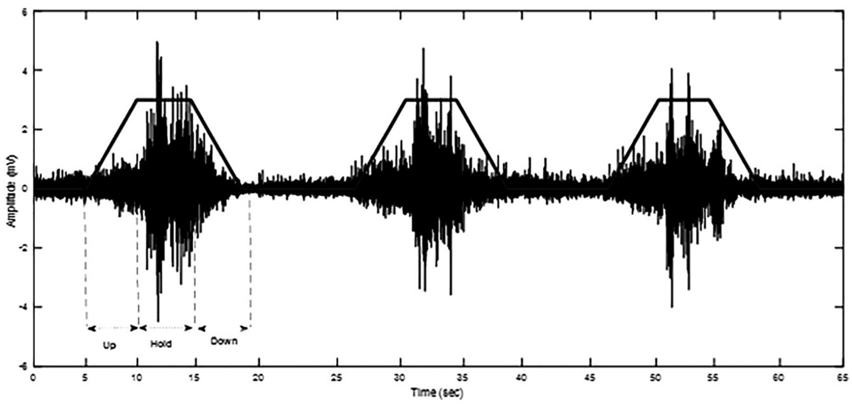

Figure 2: The representation of up-hold-down procedure of a participant.

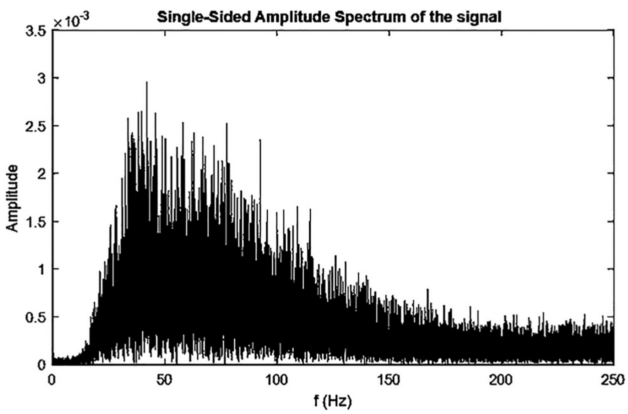

Figure 3: One of the participant's EMG signal in frequency domain during one trial.

extraction. Three type of data sets (control, external, internal) were created for 35 participants. Since the control data set consists individual preferences' results, which means it is unclear whether participants focused externally or internally under control condition, the control data were not used for signal classification. Seventy different data sets were available to distinguish the type of attention from another. The average RMS, maximum, minimum, mean, standard deviation and variance statistical features were extracted from the data sets to be used as inputs to a classifier [20–22].

Neural networks classifier

In this study the neural networks were used for classification purposes. In order to design an Artificial Neural Network (ANN) for a particular application, it is important to determine topology of the network, training algorithm and neuron activation functions [23, 24]. In this present work, two different ANNs were designed and for ANN 1 and ANN 2, six statistical features, namely, RMS, maximum, minimum, mean, standard deviation, and variance were delivered from time and frequency domain data, correspondingly. Our ANNs were feedforward trained by Levenberg–Marquardt algorithm and the output layer corresponds to the external (Class 0) and internal (Class 1) focus of attention. For both ANN1 and ANN2, the data was separated into three stages, namely, training (%70), validation (%15) and testing (%15). The sigmoid function was used as the neural activation function [25]. The performance of neural network depends on the number of neurons in hidden layer. However, there is no specific rule to obtain the number of hidden neurons for a reliable signal classification. Therefore, in this study, different number of hidden neurons were tried from 10 to 50 in ANNs for the best classification results.

Results

Statistical results

A non-parametric Friedman test results showed a significant difference between the conditions for RMS, MAV, IEMG and Integrated FFT values. The test results were given in Table 1.

The results of Wilcoxon Signed-Ranks test for all parameters showed that the main effect of attentional focus between external and internal was highly significant ($p<0.001$). Besides, the difference between control and external condition was significant ($p<0.05$) as well. However, there was no statistical difference between control and internal data. The graphical representation of average RMS, MAV, IEMG and Integrated FFT are displayed in Figure 4 and the Wilcoxon Sign-Ranks tests results are given in Table 2.

Table 1: A non-parametric Friedman test results of different parameters.

Statistical parameter	p-Value (p=0.05)	Chi-square(2) n=35
RMS	0.0032	11.4857
MAV	0.0053	10.4714
IEMG	0.0003	15.8286
Integrated FFT	0.0037	11.2100

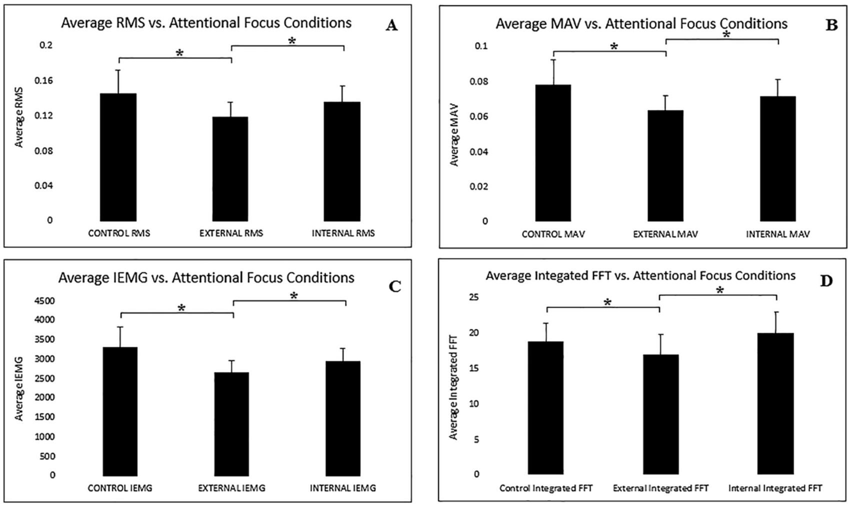

Figure 4: The average results of RMS, MAV, IEMG and Integrated FFT under attentional focus conditions. (A) Average RMS results of all data for each conditions. (B) Average MAV results of all data for each conditions. (C) Average IEMG results of all data for each conditions. (D) Average integrated FFT of all data for each conditions.
*Indicates a significant difference between the groups and error bars refer to Standard Error (SE).

Table 2: Statistical Wilcoxon Signed-Ranks tests results of different parameters for all data.

Statistical parameter	p-Value (control – External)	p-Value (control – Internal)	p-Value (external – Internal)
RMS	0.0069	0.1538	0.0012
MAV	0.0034	0.2709	0.0001
IEMG	0.0187	0.4207	0.0001
Integrated FFT	0.0079	0.1468	0.0001

EMG signal classification results

The performance of the networks was evaluated by obtaining average results of training, validation and test data. In order to make sure the consistency of classification rates, the results were calculated 3 times and their average results were compared. The summary of the EMG classification performances are presented in Table 3.

Table 3: Performance comparison of neural network for EMG classification.

Neural networks	Training (70%)	Validation (15%)	Test (15%)	Overall	Hidden layer
ANN1	64.77	70.72	75.94	67.5	10
	81.62	82.56	92.31	83.39	20
	86.87	87.67	90.32	**87.54**	30
	80.14	81.57	78.79	80.13	40
	75.38	83.42	78.29	77.09	50
ANN2	62.54	64.31	65.4	63.21	10
	80.42	79.48	77.46	79.73	20
	81.46	88.21	83.16	**82.69**	30
	72.64	68.65	77.85	73.31	40
	75.12	70.68	67.58	73.15	50

For ANN1, it was found that the neural network with 30 neurons achieved the best classification rate which is 87.54% and for ANN2, the best results were also obtained with 30 neurons which is 82.69%.

Discussion

In this study, in agreement with previous studies that are displayed in Table 4, EMG activity was reduced under external focus condition.

Table 4: Studies related to attentional focusing.

Researcher	Experimental task	Parameters	Results
Vance et al. [6]	Bicep curls	IEMG activity	External < Internal
Zachry et al. [7]	Basketball free throws	EMG activity	External < Internal
Marchant et al. [26]	Isokinetic elbow flexion	EMG activity	External < Internal
Wulf G. et al. [10]	Jump and reach	EMG activity	External < Internal
Lohse et al. [27]	Dart throwing	EMG activity	External < Internal
Lohse et al. [8]	Isometric force production	EMG activity	External < Internal
Ardakani et al. [28]	Balance task	EMG activity	External < Internal
Ashraf et al. [29]	Vertical jump task	EMG RMSE	External < Internal
Current study	Weight-lifting	EMG activity	External < Internal

Table 5: Comparison of classification results with related studies.

Researcher	Method	Classification rate
Al-Timemy et al. [24]	ANN with BPA	88 and 91%
Ibrahimy et al. [23]	ANN with trainlm	88.4%
Mane et al. [30]	ANN	93.25%
Duan et al. [31]	ANN	93.2%
Kehri et al. [32]	ANN with PCA	92.4%
Oleinikov et al. [33]	ANN	91%
Current study	ANN	87.54 and 82.69%

The results of the present study confirm and extend previous findings. Even though, in many former studies, external focus was found to result in more effective movement outcomes than internal focus, the present study was the first investigation of whether the influence of an individual's attentional focus would also be seen in his/her EMGs to be used as control signals in robotics. Even though these results were not desired in case of previous studies, in term of HMI applications, the higher EMG activity means the better signal quality thereby the signal can be classified in such way that it can be used for controlling robotic mechanisms.

In this experimental study, the EMG classification results for different attentional focusing type were presented. The results indicate that the designed algorithms ANN1 and ANN2 were successfully classified the signals and the average rates were 87.54 and 82.69%, respectively. These results that are in line with previous studies are shown in Table 5.

In the first study in Table 5, they classified the signals as they represent either myopathy or neuropathy. In the other studies, they used ANNs for hand motion detection applications [30, 31, 33]. Kehri and his colleagues used EMG signals to classify neuromuscular diseases [32].

In the present study, classification of EMG signals was achieved by means of time and frequency domain features extracted according to individual's focus of attention, and the results were 87.54 and 82.69%, respectively. Here what makes our study unique from former ones is that our origin of the EMG signal has not changed. In other words, this study is not based on differentiating EMG diseases which includes abnormal signals due to a patient's fitness. Our results were relied on healthy performers' EMG signals. Furthermore, the hand motion detection studies are also easy to classify according to their different signal outputs. However, in our study, the only difference that make the results significant was the individual's focus of attention strategy. Even though they are all healthy and performed exactly same procedure in the experiments, just by changing their focusing type, the results were changed, remarkably.

Conclusions

The findings of the present study showed that the EMG activity was reduced when the performers focused externally. Unlike previous attentional focus related studies, our study emphasizes the advantages of focusing internally. It is clear that external focus enhances motor skills and learning of people but reduces EMG activity. Nevertheless, in order to use the EMG signals in HMI applications, high EMG activity is preferred for better signal quality so that it can be used as useful inputs for robotic control purposes. Since the internal focus increases the EMG activity, one can say that, focusing internally would create more useful inputs for robotics. Besides that, with this study, the performer's EMG signals could be classified according to his/her attentional focus strategies. Therefore, one's focus of attention type would be predicted from his/her EMG activity. The previous studies used attentional focusing types to compare learning skills and motor performances of people. Here the present work, suggests that even though the origin of the signals belong to same healthy people with the same experimental task, just one's focus of attention strategy make a notable difference when these signals are used for EMG based control mechanisms.

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References

1. Shea CH, Wulf G. Enhancing motor learning through external-focus instructions and feedback. Hum Mov Sci 1999;18:553–71.
2. Lohse KR, Sherwood DE, Healy AF. On the advantage of an external focus of attention: a benefit to learning or performance?. Hum Mov Sci 2014;33:120–34.
3. Wulf G, McNevin N, Shea CH. The automaticity of complex motor skill learning as a function of attentional focus. Q J Exp Psychol Sect A Hum Exp Psychol 2001;54:1143–54.
4. Wulf G, McConnel N, Gartner M, Schwarz A. Enhancing the learning of sport skills through external-focus feedback. J Mot Behav 2002; 34:171–82.
5. Park SH, Yi CW, Shin JY, Ryu YU. Effects of external focus of attention on balance: a short review. J Phys Ther Sci 2015;27: 3929–31.

6. Vance J, Wulf G, Töllner T, McNevin N, Mercer J. EMG activity as a function of the performer's focus of attention. J Mot Behav 2004; 36:450–9.
7. Zachry T, Wulf G, Mercer J, Bezodis N. Increased movement accuracy and reduced EMG activity as the result of adopting an external focus of attention. Brain Res Bull 2005;67:304–9.
8. Lohse KR, Sherwood DE, Healy AF. Neuromuscular effects of shifting the focus of attention in a simple force production task. J Mot Behav 2011;43:173–84.
9. Ay AN, Dolukan YB, Yildiz MZ. The effect of attentional focus conditions on performer's EMG activity. Acad Perspect Procedia 2019;1:240–7.
10. Wulf G, Dufek JS, Lozano L, Pettigrew C. Increased jump height and reduced EMG activity with an external focus. Hum Mov Sci 2010;29:440–8.
11. Pan L, Crouch DL, Huang H. Comparing EMG-based human-machine interfaces for estimating continuous, coordinated movements. IEEE Trans Neural Syst Rehabil Eng 2019;27: 2145–54.
12. Shi WT, Lyu ZJ, Tang ST, Chia TL, Yang CY. A bionic hand controlled by hand gesture recognition based on surface EMG signals: a preliminary study. Biocybern Biomed Eng 2018;38:126–35.
13. Sharma S, Dubey AK. Movement control of robot in real time using EMG signal. In: ICPCES 2012-2012 2nd Int Conf Power. Control Embed Syst; 2012:1–4 pp.
14. Shobhitha AJ, Jegan R, Melwin AC. OWI-535 EDGE robotic arm control using ElectroMyoGram (EMG) signals. Int J Innov Technol Explor Eng 2013;2:282–6. https://www.ijitee.org/download/volume-2-issue-6/ number 60.
15. Ay AN, Yildiz MZ. Mendeley data - data of EMG-based attentional focus experiments [Internet]. Mendeley Data 2020. Available from: https://data.mendeley.com/datasets/grmzmpvt4c/2 [Accessed 17 May 2020].
16. Singh Y. Analaysis and classification of EMG signal using LabVIEW with different weights. [Master Thesis]. India: Thapar University; 2013.
17. Tremolada M, Taverna L, Bonichini S. Which factors influence attentional functions? attention assessed by KITAP in 105 6-to-10-year-old children. Basel: Behav Sci; 2019:9 p.
18. Schücker L, Parrington L. Thinking about your running movement makes you less efficient: attentional focus effects on running economy and kinematics. J Sports Sci 2019;37:638–46.
19. Couvillion KF, Fairbrother JT. Expert and novice performers respond differently to attentional focus cues for speed jump roping. Front Psychol 2018;9:1–9.
20. Daud WMBW, Yahya AB, Horng CS, Sulaima MF, Sudirman R. Features extraction of electromyography signals in time domain on biceps brachii muscle. Int J Model Optim 2013;3:515–9.
21. Nazmi N, Rahman MAA, Yamamoto SI, Ahmad SA, Zamzuri H, Mazlan SA. A review of classification techniques of EMG signals during isotonic and isometric contractions. Sensors 2016;16: 1–28.
22. Phinyomark A, Khushaba RN, Ibáñez-Marcelo E, Patania A, Scheme E, Petri G. Navigating features: a topologically informed chart of electromyographic features space. J R Soc Interface 2017; 14:20170734.
23. Ibrahimy MI, Ahsan MR, Khalifa OO. Design and performance analysis of artificial neural network for hand motion detection from EMG signals. World Appl Sci J 2013;23:751–8.
24. Al-Timemy AHA, Ghaeb NH, Khalaf TY. Wavelet neural network based Emg signal classifier. In: The 1st Regional Conference of Eng Sci NUCEJ; 2008:137–44 pp.
25. Oweis RJ, Rihani R, Alkhawaja A. ANN-based EMG classification for myoelectric control. Int J Med Eng Inf 2014;6:365.
26. Marchant DC, Greig M, Scott C. Attentional focusing instructions influence force production and muscular activity during isokinetic elbow flexions. J Strength Condit Res 2009;23:2358–66.
27. Lohse KR, Sherwood DE, Healy AF. How changing the focus of attention affects performance, kinematics, and electromyography in dart throwing. Hum Mov Sci 2010;29: 542–55.
28. Ardakani ZP, Abdoli B, Farsi A, Ahmadi A. The effect of attentional focus and manipulation of somatosensory on EMG of selected balance muscles in Elderly. Indian J Fundam Appl Life Sci. 2015;5: 5528. https://www.sid.ir/en/Journal/JournalListPaper.aspx?ID=222466 number 12.
29. Ashraf R, Aghdasi MT, Sayyah M, Taghibiglo N. The effects of internal and external focus of attention on children's performance in vertical jump task. Int J Basic Sci Appl Res. 2012;1: 1–5. https://dergipark.org.tr/tr/pub/turkjkin/issue/29954/326580.
30. Mane SM, Kambli RA, Kazi FS, Singh NM. Hand motion recognition from single channel surface EMG using wavelet & artificial neural network. Procedia Comput Sci. 2015;49:58–65.
31. Duan F, Dai L, Chang W, Chen Z, Zhu C, Li W. SEMG-based identification of hand motion commands using wavelet neural network combined with discrete wavelet transform. IEEE Trans Ind Electron 2016;63:1923–34.
32. Kehri V, Ingle R, Awale R, Oimbe S. Techniques of EMG signal analysis and classification of neuromuscular diseases. Adv Intell Syst Res. 2017;137:485–91.
33. Oleinikov A, Abibullaev B, Shintemirov A, Folgheraiter M. Feature extraction and real-time recognition of hand motion intentions from EMGs via artificial neural networks. In: 6th International conference on brain-computer interface IEEE; 2018:1–5 pp.