

## SURFACE ELECTROMYOGRAPHY BASED CORE MUSCLE FATIGUE ANALYSIS DURING REPETITIVE PLANK USING MULTIVARIATE DIMENSIONALITY REDUCTION METHODS IN BOYS AGED 12-14

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### Abstract

**The aims of the study** were: 1. To analyse the discriminative power of neuromuscular components for classifying the pre and post muscle fatigued states. 2. To examine whether the modification of neural recruitment strategies become more/less heterogeneous due to fatigue. 3. To research the effect of Erector Spinae (ES) muscle activity collectively with Rectus Abdominis (RA) and External Oblique (EO) muscle activity to identify the reduced spine stability during fatiguing Plank.

**Material and methods.** Twelve boys (age – 12-14 years, height  $148.75 \pm 10$  cm, body mass  $38.9 \pm 7.9$  kg) participated in the study. Multivariate Discriminant Analysis (DA) and Principal Component Analysis (PCA) were applied to identify the changes in the pattern of the electromyographic signals during muscle fatigue. In DA the Wilks' lambda, p-value, canonical correlation, classification percentage and structure matrix were used. To evaluate the component validity the standard limit for Kaiser-Meyer-Olkin (KMO) was set at  $\geq 0.529$  and the p-value of Bartlett's test was  $\leq 0.001$ . The eigenvalues  $\geq 1$  were used to determine the number of Principal Components (PCs). The satisfactory percentage of non-redundant residuals were set at  $\leq 50\%$  with standard value  $> 0.05$ . The absolute value of average communality ( $\bar{x} h^2$ ) and component loadings were set at  $\geq 0.6$ ,  $\geq 0.4$  respectively.

**Results.** Standardized canonical discriminant analysis showed that pre and post fatigued conditions were significantly different ( $p = 0.000$ , Wilks' lambda = 0.297,  $\chi^2 = 24.914$ ,  $df = 3$ ). The structure matrix showed that the parameter that correlated highly with the discriminant function was ES ARV (0.514). The results showed that the classification accuracy was 95.8% between fatigued conditions. In PCA the KMO values were reduced [ $0.547_{Pre\ fatigue}$  vs.  $0.264_{Post\ fatigue}$ ]; the value of Bartlett's sphericity test was in pre  $\chi^2 = 90.72$  ( $p = 0.000$ ) and post fatigue  $\chi^2 = 85.32$  ( $p = 0.000$ ); The Promax criterion with Kaiser Normalization was applied because the component rotation was non-orthogonal [Component Correlation Matrix ( $r_{CCM}$ ) =  $0.520_{Pre\ fatigue} > 0.3_{Absolute} < 0.357_{Post\ fatigue}$ ]. In pre fatigue two PCs (cumulative  $s^2 = 80.159\%$ ) and post fatigue three PCs (cumulative  $s^2 = 83.845\%$ ) had eigenvalues  $\geq 1$ . The  $\bar{x} h^2$  increased [ $0.802_{Pre\ fatigue}$  vs.  $0.838_{Post\ fatigue}$ ] and the percentage of nonredundant residuals reduced [ $50\%_{Pre\ fatigue}$  vs.  $44\%_{Post\ fatigue}$ ] from pre to post fatigue.

**Conclusions.** The variability and heterogeneity increase in the myoelectric signals due to fatigue. The co-activity of antagonist ES muscle is significantly sensitive to identify the deteriorating spine stability during the fatiguing Plank. Highly correlated motor unit recruitment strategies between ES and RA, providing supportive evidence to the concept of shared agonist-antagonist motoneuron pool or "Common Drive" phenomenon during fatigue.

**Keywords:** Myoelectric Signals, Heterogeneity, Agonist-Antagonist Co-Contraction, Discriminant analysis, Principal Component Analysis.

### Introduction

The physiological mechanism of "Muscle Fatigue" is critically diverse and difficult to understand (Merletti &

Farina, 2016). The inherent characteristics of sEMG signals are complicated, often generate inconsistent multivariate pattern during muscle fatigue. For example, the rapid and additional recruitment of the motor unit pool is a well-established phenomenon, with a more homogeneous distribution of the amplitudes. The sEMG amplitude

increases due to the increased motor unit synchronization, but Staudenmann et al. (2014) stated that the increase in sEMG amplitude has resulted from decreased not increased synchronization and homogeneity in muscle activity during submaximal isometric fatiguing contraction.

Numerous studies have reported conflicting results based on ES sEMG co-activity during Plank. Schoenfeld et al. (2014) concluded that the ES muscle activity was not significant from a co-contraction perspective for trunk stability during the Plank. While Lee et al. (2015) reported that the synchronous co-activity of antagonist lumbar ES muscle was significantly more sensitive even more than agonist RA muscle in identifying the reduced spine stability while performing the fatiguing Plank. Synchronous agonist-antagonist co-activity has not been reported consistently in previous literature. Duchateau et al. (2014) stated that researchers often reveal doubts about the validity of true antagonist sEMG due to its negligible activation level. Stokes et al. (2003) also reported that sEMG electrodes are non-reliable for analyzing lumbar ES muscle activity. But conversely Mullany et al. (2002) found a significant correlation between the normalized agonist and antagonist sEMG during muscle fatigue. Furthermore, Chen et al. (1998) also reported that sEMG activity of ES muscle showed significant discriminating power to classify low back pain patients from non-symptomatic subjects.

Alteration of Low-frequency band is considered the most important indicator of muscle fatigue, because of its spatio-temporal low-pass filtering effect. Furthermore, the low-frequency of the neural drive can provide information about the isometric force fluctuations. We previously reported that the increased phenomenon of sEMG parameters of heterogeneous muscle group were not visible equally, even manifested reduction or no significant changes were noticed, specifically for the low-frequency band activity. Using the univariate statistical technique to analyze the non-normalized sEMG activity in the previous study further makes it uncertain about the true nature of fatigue induced muscle activity and noise, specifically for antagonist ES muscle based on its non-significant and low Inter-class correlation values (Samanta & Mukherjee, 2021). It required further research, which could provide a clear understanding of the control mechanism of agonist-antagonist muscle co-activity during fatigue in pediatric subjects, therefore we extended our previous study.

Previous studies have found that multivariate statistics provide exceptionally accurate results for studying the pattern of motor development of school children (Ivashchenko, 2020). The sEMG signal waveform shows non-uniform changes during isometric fatiguing contraction, makes it critically challenging to extract 'Muscle Fatigue' efficiently from a single index through conventional Univariate analysis (Samanta, & Mukherjee, 2021; Staudenmann, van Dieën, Stegeman, & Enoka, 2014). The "Fatigue Vector" comprises of different features, therefore the multivariate dimensionality reduction methods may represent it appropriately as it also consists of multifaceted sEMG signal manifestations, particularly the homogeneous combination of time-domain and frequency-domain features to estimate variability (Rogers & MacIsaac, 2011), which requires to search for a change point with time during muscle fatigue (Merletti & Farina, 2016).

Discriminant analysis (DA) is a multivariate statistical technique used to classify groups (two or more) of observations based on linear combinations of selected parameters, measured on each experimental unit, and find the contribution of each parameter in separating the groups. DA and PCA are both used to reduce the dimensionality and noise level of sEMG data. DA provides better classification accuracy between groups by maximizing the ratio of between and within-group variance (Ivashchenko, Nosko, Bartik, & Makanin, 2020).

The PCA is a statistical technique that performs orthogonal linear transformation of the correlated variables into a set of uncorrelated scalar variables, which are named PCs. This multiple features extraction model use to reduce the dimensionality of complex sEMG data may provide a decent overview using different sEMG signal parameters in fatigue. The potential advantage of unbiased PCA application is to reduce the effects of high-dimensional, multivariate fatigue induced sEMG signal vectors and transform them into a low-dimensional space to ease the interpretation of data (notwithstanding of muscle fiber architecture, or even with the presence of volume conduction and noise contamination) (Boonstra, Daffertshofer, Van, van-der-Vlugt, & Beek, 2007)

*Hypotheses:* The authors of this present study tested a set of hypotheses, and those were:

DA:  $H_0$  = The Time to task fail ( $T_{lim}$ ) and myoelectric parameters have no significant discriminative power associated with the pre and post-fatigued conditions. Box's M tests the  $H_0$  that the covariance matrices do not differ between conditions (Roy & Oddsson, 1998).

PCA: Bartlett's test of sphericity tests the hypothesis that the correlation matrix comes from a population where the parameters are independent (Identity Matrix). A statistically significant  $p$  ( $\leq 0.001$ ) value of Bartlett's sphericity test confirms the  $H_0$  hypothesis that the pairwise correlations among parameters are equal to 0. Rejecting the independent hypothesis also confirmed the adequacy of PCA (Watkins, 2021). Some other specific outcomes were also expected to ensure the validity of the PCA: 1. significant correlation might exist among different sEMG signal parameters and the magnitude of correlation might also alter or decrease due to fatigue (Staudenmann et al., 2014). 2. Fewer components explain a considerable percentage of the cumulative variance ( $s^2$ )  $\geq 80\%$ , which might change from pre to post fatigued states (Naik, Selvan, Gobbo, Acharyya, Nguyen, 2016). The explained  $s^2$  by the 1st PC represents one of the multivariate Fatigue indices that might decrease from pre to post fatigue (Cowley & Gates, 2017). 3. The weighted loading selected the label for each component as per the predominant characteristics of sEMG parameters of the EO, RA and ES muscle at the loading position therefore loading weight might change from pre to post fatigued states (Naik, Selvan, Gobbo, Acharyya, & Nguyen, 2016).

*Objectives:* Analyzing the myoelectric activity of global axial skeleton stabilizing muscles is crucial for a better understanding of lumbopelvic stability as weakness of these muscles significantly contributes to the progression of low back pain (Lee, Kang, & Shin, 2015). To our best information about existing literature on sEMG based muscle fatigue assessment, there are no studies that enable sports experts to evaluate myoelectric manifestation of core muscle fatigue

by using multivariate DA and PCA in children during exhaustive plank test. The aims of this present study were: 1. To analyse the discriminative power of neuromuscular components for classifying the pre and post muscle fatigued states. 2. To examine whether the modification of neural recruitment strategies become more or less heterogeneous due to isometric fatigue. 3. We further aimed to research the effect of antagonist ES activity collectively with agonist RA and synergist EO muscle activity to identify the reduced spine stability while performing a fatiguing Plank.

## Materials and methods

### Study participants

Previous studies reported that less than 12 subjects are sufficient for sEMG based muscle fatigue assessment using multivariate statistical methods (Farina, Negro, Gizzi, & Falla, 2012; Ortega, Besier, Byblow, & McMorland, 2018; Rogers & MacIsaac, 2011; Staudenmann et al., 2014). Therefore a total of 12 school-going boys aged between 12 to 14 years (height  $148.75 \pm 10$  cm; mass  $38.9 \pm 7.9$  kg) were included in the study. They were selected randomly from Ramkrishna Vidya Mandir Ashrama School-Sharada Balgram (RKVM), Gwalior (M.P.), India. The study was approved previously by the Departmental Research Ethics Board of Lakshmbai National Institute of Physical Education-Gwalior (Reg. No. PH2010-114, Ref. No.-HOD/Ex.Phy./26/2018-19) and conducted following the ethical principles for human research proposed in the Helsinki Declaration. After comprehensive verbal and written explanations of the study, the RKVM school principal signed the written informed consent form. No Neuro/Myo pathological disorders and postural spinal deformities were reported during data collection. Only the dominant right handed subjects were included in this study (Samanta & Mukherjee, 2021).

### Study organization

The sEMG signals were recorded using ENCEPHALAN – MPA Autonomous Patient Transceiver-Recorder ABP-10 (Medicom MTD Ltd., Russia). The “REHACOR” and “MEDICOM” software (British Standard-Reg. No. DE/CA37/POL044A4) was used for sEMG signal processing and raw data analysis. The Bipolar (20 mm inter-electrode space) EMG/ECG Surface electrodes (Ag/AgCl sensors) were placed on EO, RA, ES muscle and the ground electrode was placed over the midline of the lumbosacral bony landmark. The sEMG linear envelope and Power Spectral Density (PSD) was calculated using Welch and Bartlett’s averaged modified periodogram (Non-parametric) method with 1024 sample analysis, 50% overlapping windows to avoid aliasing effect (Nyquist’s theorem). In the power spectral density, the sEMG frequency cut-off or the band-pass filter was 10-512 Hz. The Common Mode Rejection Ratio (CMRR) was 120 dB and noise was  $< 1.4 \mu\text{V}$  (Lee, Kang, & Shin, 2015; Ortega, Besier, Byblow, & McMorland, 2018; Samanta & Mukherjee, 2021)

It is difficult to understand specific motor unit behavior singularly from amplitude or frequency changes alone, therefore both the features extraction domain were used to assess muscle fatigue efficiently during isometric contraction.

Therefore, the  $T_{lim}$  [Sec.], Average Rectified Value (ARV) [ $\mu\text{V}$ ], sEMG SD [ $\mu\text{V}$ ], Total Spectral Power (TSP) [ $\mu\text{V}^2$ ] and Normalized Low frequency band (10-70 Hz.) (N.LF) [%] were used for fatigue analysis. Furthermore, to study the sEMG patten changes during muscle fatigue using DA and PCA, it is important to select the non-identical parameters. sEMG signals provide several complex neurophysiological information about the electrical activity of contracting muscle: 1. sEMG Amplitude: Neural drive, motor-unit recruitment/threshold, firing/discharge rate modulation or rate coding, muscle activation timing, indirect information about force generation and sharing. 2. sEMG Spectral Power and Frequency: Muscle fiber conduction velocity and motor unit synchronization (McManus et al. 2021).

Detail descriptions about fatiguing Plank were given by our previous study (Samanta & Mukherjee, 2021). Briefing, those children performed Surya Namaskara (5 times) for warming up purpose, then took rest for 5 minutes. Three times repetitive fatiguing (until exhaustion) Plank [pre-fatigue (1st Plank) and post fatigue (3rd Plank)] was performed with 3 mins. interval in between every Plank.

### Statistical analysis

IBM SPSS software for Windows 8.1, version 20.0, (IBM Corp., Armonk, NY, USA) was used for data analysis and Microsoft PowerPoint 2013 for graphical representations.

Stepwise DA was conducted to determine whether the classification was significant between pre and post fatigued states, and to assess the extent of the contribution of the sEMG signals parameters and task time, the classification is scored. The assumptions of DA are the probability density distributions are multivariate normal (Fig. 1), and equal within-group covariance matrices (Table 1). However, DA is robust to violation of these assumptions (Verma, 2013). The criterion used for the discriminant function was Wilk’s Lambda (the deviations within each condition concerning the total deviations) with corresponding p-value, canonical correlation, and classification percentage were noted. The Structure Matrix shows pooled within-groups correlations between discriminating parameters and standardized canonical discriminant function parameters were ordered by the absolute size of correlation within the function. Discriminant scores were standardized scores with  $\bar{x} = 0$  (combined groups  $\bar{x}$  on the discriminant score on that function) and  $s = 1$ . In DA the acceptable classification accuracy rate was set at  $\geq 95\%$  with the classification error rate  $\leq 5\%$ . (Iermakov, Ivashchenko, Khudolii, Chernenko, Veremeenko, & Zelenskiy, 2021; Ivashchenko, Nosko, Bartik, & Makanin, 2020).

Model for Discriminant Analysis: i. 12 (participants)  $\times$  1 (Plank 1-Pre fatigue task)  $\times$  3 (EO, RA, ES muscles)  $\times$  4 (sEMG Parameters-ARV [ $\mu\text{V}$ ], EMG SD [ $\mu\text{V}$ ], N.LF [%], and TSP [ $\mu\text{V}^2$ ])  $\times$   $T_{lim}$  (Sec.), ii. 12 (participants)  $\times$  1 (Plank 3-Post fatigue task)  $\times$  3 (EO, RA, ES muscles)  $\times$  3 (sEMG Parameters-ARV [ $\mu\text{V}$ ], EMG SD [ $\mu\text{V}$ ], N.LF [%], and TSP [ $\mu\text{V}^2$ ])  $\times$   $T_{lim}$  (Sec.). We used only Log<sub>10</sub>-transformed data for DA.

In the PCA, the value of Bartlett’s test of sphericity was set at  $p \leq 0.001$  (Broen et al., 2015). The KMO compares the extent of observed correlation to the degree of partial correlation ( $r$ ) and the value of  $KMO \geq 0.529$  was considered

acceptable (Broen et al., 2015; Kaiser & Rice, 1974). The eigenvalues ( $\lambda_i \geq 1$  [ $\lambda_i = s_i^2 / (n-1)$ ]) were used to determine the number of PCs. The total  $s^2$  equaled the total number of parameters and each parameter had the  $s^2$  of 1. Therefore  $\lambda_i < 1$  were not allowable and considered as non-functional components within the system. The acceptable value for the component loadings was set at  $\geq 0.40$  (Broen et al., 2015; Watkins, 2021). The smallest number of components that explained  $\geq 80\%$  of the total  $s^2$  was considered satisfactory (Naik, Selvan, Gobbo, Acharyya, & Nguyen, 2016). The value of 'r',  $\geq 0.80$ =very strong,  $\geq 0.70$ =comparably strong,  $0.5-0.6$ 's=moderate,  $0.3-0.4$ modest and  $r < 0.3$  were considered as a non-reliable indicator in the correlation matrix. The satisfactory percentage of nonredundant residuals were set at  $\leq 50\%$  with a standard value greater than 0.05. The absolute value for the  $r_{CCM}$  was set for Promax (oblique rotation)  $\geq 0.3 >$  Varimax (orthogonal rotation solution) (Watkins, 2021). The percentage of non-redundant residuals and  $r_{CCM}$  was applied to see the correlations between the components. The criteria for rotation was that the parameters have high loading on a few first PCs and low loading on the rest of the components. The communality ( $h^2$  – squared multiple correlation) was the proportion of  $s^2$  of one parameter, assigned to the standard components shared with other parameters. The acceptable value for  $\bar{x} h^2$  was set at  $\geq 0.6$ , which further indicated the appropriateness of PCA (Broen et al. 2015). The p value of  $\leq 0.05$  was considered significant for the correlation matrix.

The PCA are optimal decorrelation strategy for Gaussian distributed data. Further to reduce the dimensionality of multivariate sEMG parameters normalization/variance stabilizing transformation procedure is required. High variability in the non-normalized sEMG data could adversely affect the multilevel interpretation, therefore at first,  $\text{Log}_{10}$ -transformation, followed by Fisher's Z transformation was applied for all the pre and post fatigue sEMG parameters for rescaling and stabilizing the  $s^2$  ( $\bar{x} = 0, s^2 = 1$ ) before conducting PCA (Broen et al., 2015; Ivanenko, Poppele, & Lacquaniti, 2004; Gajewski & Viitasalo, 1994). Model for PCA Analysis: The sEMG parameters of all participants and conditions combined into a single signal vector yielding four different high-dimensional signal vectors: i. 12 (participants)  $\times$  1 (Plank 1-Pre fatigue task)  $\times$  3 (EO, RA, ES muscles)  $\times$  3 (sEMG Parameters-ARV [ $\mu\text{V}$ ], N.LF [%], and TSP [ $\mu\text{V}^2$ ]), ii. 12 (participants)  $\times$  1 (Plank 3-Post fatigue task)  $\times$  3 (EO, RA, ES muscles)  $\times$  3 (sEMG Parameters-ARV [ $\mu\text{V}$ ], N.LF [%], and TSP [ $\mu\text{V}^2$ ]). In the correlation matrices, the linear and partial correlations (r) among a set of interrelated parameters are called latent parameters in PCA analysis (Rogers & MacIsaac, 2011).

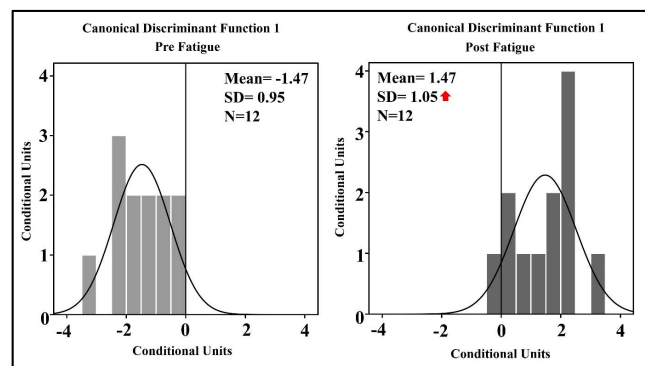
**Results**

*Tables*

**Table 1.** Test of Assumptions for Discriminant Analysis

Fatigued State	Log Determinant		
Pre Fatigue	-13.314	Box's M	13.823
Post Fatigue	-14.903	F	1.960
Pooled Within Condition	-13.480	Sig.	0.068

Box's M tests null hypothesis of equal population covariance matrices.



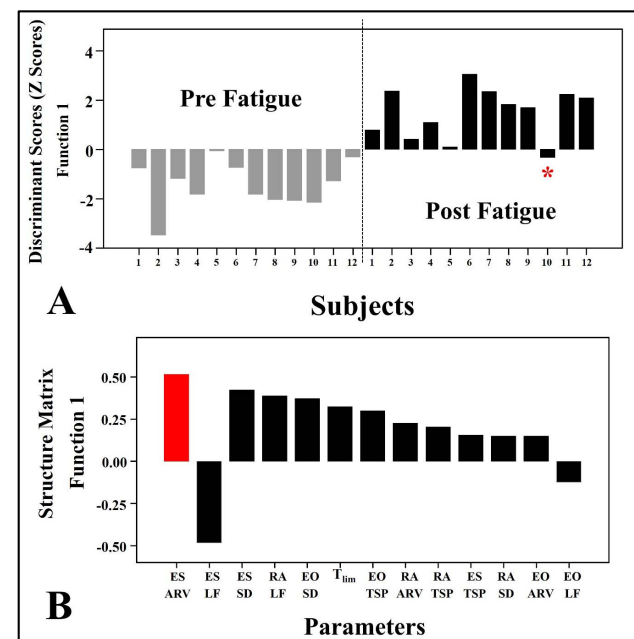
**Fig. 1.:** Canonical discriminant functions. Graphic representation of classification results of the pre and post fatigued conditions: ▲ – increased variability due to fatigue.

**Table 2.** Canonical discriminant function. Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	2.371	100.0	100.0	.839

**Table 3.** Canonical discriminant function. Wilks' Lambda

Test of Function	Wilks' Lambda	Chi-square	df	Sig.
1	0.297	24.914	3	.000



**Fig. 2. A.** Fisher linear discriminant function scores (Z scores), significantly discriminate the pre and post-fatigued states.

Negative Z scores specify pre-fatigued, and positive Z scores indicate post-fatigued condition. The Z score with \* sign in the post-fatigued condition represents false-positive classification. B. Structure Matrix plot indicates that using sEMG to assess the recruitment patterns of ES muscle (ARV) (Red bar) is necessary during fatiguing plank as it shows highest discriminating power to classify the pre and post fatigued conditions.

**Table 4.** Classification results

		Fatigued State	Predicted Group Membership		
			Pre Fatigue	Post Fatigue	Total
Original	Count	Pre Fatigue	12	0	12
		Post Fatigue	1	11	12
	%	Pre Fatigue	100.0	0	100.0
		Post Fatigue	8.3	91.7	100.0

95.8% of original grouped cases correctly classified.

**Table 5.** The correlation matrices of different sEMG parameters of EO, RA, ES muscle in pre and post fatigued states. The upper matrix consists of pre fatigue sEMG correlation values and the lower matrix consists of post fatigue sEMG correlation values.

In.	Parameters†	Pre Fatigue								
		1	2	3	4	5	6	7	8	9
1	EO-ARV (μV)	—	-0.645*	0.871**	0.75**	-0.666**	0.601*	0.708**	-0.599*	0.374
2	EO-LF (%)	-0.526*	—	-0.635*	-0.636*	0.49	-0.679**	-0.476	0.515*	-0.473
3	EO-TSP (μV <sup>2</sup> )	0.693**	-0.346	—	0.624*	-0.475	0.595*	0.746**	-0.8**	0.622*
4	RA-ARV (μV)	0.566*	-0.516*	0.277	—	-0.87**	0.9**	0.616*	-0.313	0.207
5	RA-LF (%)	-0.291	0.293	0.072	-0.563*	—	-0.791**	-0.345	0.221	-0.014
6	RA-TSP (μV <sup>2</sup> )	0.355	-0.35	0.439	0.802**	-0.389	—	0.371	-0.331	0.145
7	ES-ARV (μV)	0.63*	-0.382	0.448	0.866**	-0.218	0.737**	—	-0.621*	0.626*
8	ES-LF (%)	0.425	-0.398	0.328	-0.156	-0.132	-0.239	-0.143	—	-0.531*
9	ES-TSP (μV <sup>2</sup> )	-0.82**	0.439	-0.409	-0.268	0.257	0.025	-0.261	-0.76**	—

**Post Fatigue**

Note: The sEMG parameters are Normalized through Variance Stabilizing Transformation [Log10-transformation followed by Fisher's z transformation ( $\bar{x} = 0, s^2 = 1$ )] †,  $p \leq 0.01$ \*\*,  $p \leq 0.05$ \*. Multicollinearity in Italics. In the Correlation matrix the Normalized low frequency mostly showed negative relationship Time amplitude domain (ARV) and Total Spectral Power (TSP). The relationship between sEMG parameters were reduced mostly from pre to post fatigue, with the absolute value  $\sim 0.52$  at 0.05 significance level.

KMO test of sampling adequacy with an absolute value of  $>0.529$  (criterion range between 0-1). The pre fatigue KMO value was 0.547 ( $>0.529$ ), but the post fatigue KMO value was 0.264 ( $<0.529$ ). The Bartlett's sphericity test was  $\chi^2 = 90.72$  ( $p = 0.000, df = 36$ ) in pre fatigue and  $\chi^2 = 85.32$

( $p = 0.000, df = 36$ ) in post fatigued state, indicated the correlation matrix was not an identity matrix hence rejected the  $H_0$  that correlation matrix was a diagonal matrix.

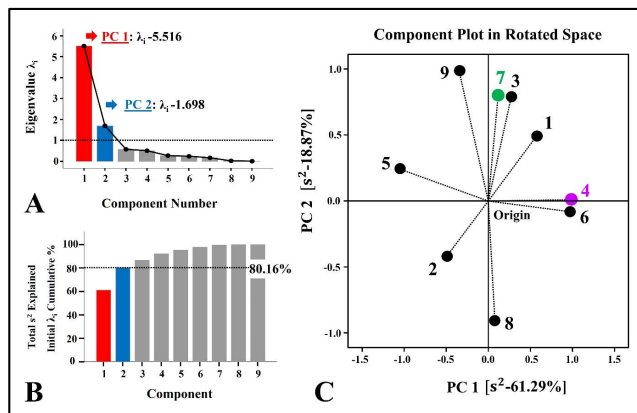
The absolute value of component loading cutoff was set at  $\geq 0.4$  (weighted components) with the corresponding  $h^2$ ,

**Table 6.** The rotated component pattern Quantitative Structure matrices (Pre and Post fatigue) after Promax rotation with Kaiser Normalization.

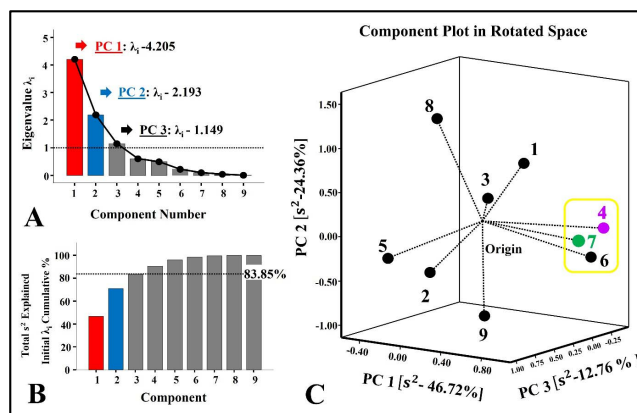
	Pre Fatigue			Post Fatigue				
	Rotated Component Loadings			Rotated Component Loadings				
	1	2	$h^2$	1	2	3	$h^2$	
RA-ARV*	<b>.968</b>	<b>.510</b>	.937	ES-ARV <sup>§</sup>	<b>.926</b>	.307	.024	.862
RA-TSP*	<b>.926</b>	<b>.422</b>	.863	RA-ARV <sup>§</sup>	<b>.918</b>	.282	-.374	.957
RA-LF	<b>-.914</b>	-.301	.876	RA-TSP	<b>.885</b>	.093	-.133	.845
EO-ARV*	.803	<b>.765</b>	.811	ES-TSP	-.255	<b>-.930</b>	.020	.884
EO-LF*	<b>-.707</b>	<b>-.671</b>	.627	EO-ARV	<b>.670</b>	<b>.856</b>	.108	.889
EO-TSP*	<b>.676</b>	<b>.921</b>	.902	ES-LF	-.129	<b>.819</b>	.026	.881
ES-ARV*	<b>.527</b>	<b>.852</b>	.735	EO-TSP*	.579	.628	.563	.830
ES-LF	-.385	<b>-.847</b>	.722	EO-LF	<b>-.504</b>	<b>-.621</b>	.205	.534
ES-TSP	.165	<b>.807</b>	.741	RA-LF	-.360	-.233	<b>.845</b>	.862

$r_{CCM} = 0.520$ †  $\bar{x} = 0.802$   $r_{CCM} = 0.357$ †  $\bar{x} = 0.838$

Note:  $h^2$  – Communality.  $\bar{x}$  – Mean communality. Predominant sEMG of muscles and Complex Component Loading\*. Absolute Component Correlation Matrix value between PCs†. Component loading  $\geq 0.4$  are bolded and arranged in hierarchical order. RA and ES ARV shows highest weighted loading in the 1st PC in post fatigue §. In the "Fatigue Vectors" extraction the negative loading for either delayed alteration or lack of neuromuscular fatigue representation.



1. Pre Fatigue



2. Post Fatigue

**Fig. 3.** 1. EO ARV ( $\mu\text{V}$ ), 2. EO N.LF (%) 3. EO TSP ( $\mu\text{V}^2$ ); 4. RA ARV ( $\mu\text{V}$ ), 5. RA N.LF (%) 6. RA TSP ( $\mu\text{V}^2$ ); 7. ES ARV ( $\mu\text{V}$ ), 8. ES N.LF (%) 9. ES TSP ( $\mu\text{V}^2$ ). The  $\lambda_i \geq 1$  were used to determine the number of PCs with corresponding explained  $s^2$  [Fig. 3 (1) and Fig. 3 (2) A] and Cumulative  $s^2$  [Fig. 3 (1) and Fig. 3 (2) B]. In pre fatigue PCA plot the horizontal (X-Axis) and vertical axis (Y-Axis) represents the 1st and 2nd PC respectively [Fig. 3 (1) C]. In post fatigue the PCA plot shows the three-dimensional vector space, hence 1st (X-Axis), 2nd (Y-Axis) and 3rd (Z-Axis) PC [Fig. 3 (2) C]. The agonist (RA ARV) is denoted with a purple circle and the antagonist (ES ARV) with a green circle. The yellow rectangular line denotes the highest loading weight in 1st PC and concurrent agonist-antagonist co-activity in the post fatigued state. The nine black dots denote the scaled PC scores, which were drawn from the variance stabilized values of sEMG parameters from EO, RA and ES muscle in pre and post fatigue. The straight black dotted line segments emerge from the origin. The Promax rotation with Kaiser Normalization applied for the rotated component pattern structure matrices [Fig. 3 (1) C and Fig. 3 (2) C].

lower values than the acceptable values both in pre and post fatigued states would be considered as non-functional and futile. The EO had salient loading on two PCs in pre fatigued state and three PCs in post fatigued state called the Complex Component Loading. Different sEMG signal domain (time amplitude, frequency and spectral power) generated by EO muscle played a predominant role during fatiguing Plank. ES ARV showed highest weighted loading in the 1st PC in post fatigue which changed from pre fatigued state weighted loading.

The satisfactory percentage ( $\leq 50\%$ ) of non-redundant residuals were calculated to assess the PCA model validity. The pre fatigue showed 18 (50%) nonredundant residuals and post fatigue showed 16 (44%) nonredundant residuals with absolute value greater than 0.05.

## Discussion

The changes in the previously mentioned multidimensional neurophysiological factors were responsible for the temporal alteration of the magnitude, variability and rate modulation properties of myoelectric signals during fatigue (McManus et al. 2021). Several other complex physiological reasons might also involved: The ATP depletion, inorganic Pi, lactate, and reactive oxygen species production; the depleted  $\text{Ca}^{2+}$  concentration in myofilaments and reduced sarcoplasmic reticulum  $\text{Ca}^{2+}$  release channels (SR- $\text{Ca}^{2+}$  RC/RyR1) sensitivity; the  $\text{K}^+$  accumulation and  $\text{Na}^+$  depletion in extracellular space in the muscle (Allen & Westerblad, 2001; Samanta & Mukherjee, 2021).

During static fatiguing contractions, the nociceptive input decreases the discharge rate of the active motor units by activating small-diameter afferents in muscle, further influencing the descending drive. In the neuronal level, the presynaptic Ia input inhibited through non-uniform excitation of Group III/IV nociceptive afferents further changed motor neuronal activity by modifying the variability in the descending neural drive and adopted a temporal reorganization strategy to reduce muscle fiber overload during fatiguing Plank (Dideriksen, Holobar, & Falla, 2016; Falla, & Farina, 2008; Farina, Leclerc, Arendt, Buttelli, & Madeleine, 2008). The increased variability in the sEMG signal (Table 6, Fig. 1, Fig. 3) might indicate the disablement of the CNS's ability to control the synaptic input efficiently. In summary, altered electric properties of the membrane, recruitment/derecruitment, firing rate in the diversely distributed motor unit types with different diameters and intramuscular pressure redistribution might affect the rate of metabolic clearance during fatigue (Farina, Leclerc, Arendt, Buttelli, & Madeleine, 2008). All of these phenomenon might alter the characteristics of the sEMG based fatigue factors and significantly discriminate the pre and post-fatigued conditions (Table 2, 3, 4; Fig. 2) (Farina, Negro, Gizzi, & Falla, 2012; Roy & Oddsson, 1998).

In the PCA model, the changes in correlation matrices (Table 5) and KMO value ( $0.547_{\text{Pre fatigue}}$  vs.  $0.264_{\text{Post fatigue}}$ ) was observed. Although some 'r' value increased between sEMG parameters [e.g. the correlation between RA ARV ( $\mu\text{V}$ ) and ES ARV ( $\mu\text{V}$ ) increased as  $r_{\text{pre fatigue}} 0.616$  ( $p < 0.05$ ) vs.  $r_{\text{post fatigue}} 0.866$  ( $p < 0.01$ )] (Mullany, O'Malley, St Clair Gibson, & Vaughan, 2002) but reduced mostly, with a reduction from the  $r_{\text{pre fatigue}} = 0.520$  to  $r_{\text{post fatigue}} = 0.357$  was observed (Table 5, 6). Therefore it was concluded that the variability and heterogeneity in temporal sEMG distribution increased during isometric fatiguing contractions (Staudenmann et al. 2014; Rogers & Maclsaac, 2011). The heterogeneity resulted from several complex physiological factors: Increased  $\alpha$ - $\gamma$  motoneuronal coactivity. Further changes in motoneuronal activities were controlled by the afferent inputs from peripheral receptors [muscle spindles, Golgi tendon organs, afferent neurons with small diameter (III and IV)] (Ortega, Besier, Byblow, & McMorland, 2018).

This afferent input further caused the discharge rate to be deteriorating progressively. The conduction velocity in muscle fiber action potential and the strength of common input related to the motor unit synchronization reduced gradually with additional recruitment of larger motor units or rate coding. However, several inconsistent results have reported by the previous literature regarding the increase in motor unit discharge rate and synchronization during submaximal isometric fatiguing contraction (Samanta & Mukherjee, 2021; Staudenmann et al. 2014). This non-uniformly increased sEMG amplitude might have resulted from the coordination or load sharing phenomenon of synergists during fatigue (Rogers & MacIsaac, 2011).

The previous study reported that in multivariate PCA the absolute value for 'r' between the Conduction Velocity with Average Rectified Value and the Mean Power Frequency was  $\geq 0.52$ , within  $\pm 0.52$ ,  $\leq -0.52$  ( $p \leq 0.05$ ) (Table 5) (Kiryu, Takahashi, & Ogawa 1997). Mild Multicollinearity might not affect the findings of PCA as only one 'r' value was 0.9 (Table 5) (Verma, 2013; Watkins, 2021). In the dominant distribution, the substantial  $\lambda_i$  had a meaningful correlation with other  $\lambda_i$  ( $\geq 1$ ). But the small  $\lambda_i$  ( $< 1$ ) showed multidirectional distribution, therefore the certainty of the relationship was relatively weak. The probability of Type I error might also increase with the number of extracted components in the post fatigued state (Fig. 3). Although in PCA the Varimax orthogonal rotation technique used most often (Ivashchenko, Prykhodko, & Cieslicka, 2018) but Temporal Promax (Pre fatigue  $r_{CCM} = 0.520$  to Post fatigue  $r_{CCM} = 0.357$ , kappa = 4) proposed a significantly accurate rotation strategy for PCA in this present study. The obliqueness is more likely than orthogonality in electrophysiological data (Dien, 2010; Watkins, 2021). In summary, re-arrangement of the sEMG parameters with the changing magnitude of the correlation among them (Table 5) and temporal redistribution of muscle activities/sEMG parameters (Table 6, Fig. 3) were observed between the pre and post fatigued states.

Each PC considered as a "Fatigue Vector" (Merletti, & Farina, 2016). The two PCs in pre fatigue [Cumulative  $s^2$  80.159%] increased to three PCs in post fatigue [Cumulative  $s^2$  83.845%]. The explained  $s^2$  (%) of 1st PC reduced from pre to post fatigue (61.287% vs. 46.72%) and the 2nd PC's explained  $s^2$  (%) inflated from pre to post fatigued states (18.872% vs. 24.363%). This similar  $s^2$  alteration tendency of the non-uniformly functional fatigue vectors was also reported by Cowley et al. (2017). The fatiguing muscles showed unique electrical activity as the hierarchical functional components loading order ( $\geq 0.4$ ) changed and reorganized the sEMG parameters (Table 6). Higher shear stress and torsional loading on the spine (intervertebral joint) might be imposed by EO as different sEMG parameters of this muscle had the Complex Component Loading (CCL) pattern in the PCA model (Table 6) while other superficial muscles (RA and ES) acted as a neutralizer/stabilizer while performing the fatiguing Plank (Ivanenko, Poppele, & Lacquaniti, 2004; Lee, Kang, & Shin, 2015). Efficient synergistic activity and agonist-antagonist co-activity were controlled by Central (CNS)/ Peripheral Nervous System (PNS) might reduce the metabolic burden, neuromuscular in-stabilization and alter loading pattern to protect the spine by optimizing force distribution. The CNS and PNS

redistributed the muscle activation by afferent signals with preferential innervation through the supraspinal descending motoneuronal drive (Barroso et al. 2014) which might alter the weighted distribution (Table 6, Fig. 3).

The acceptability of the PCA model was improved significantly (KMO value=  $0.547_{Pre\ fatigue} > 0.529_{Absolute}$ ) in the pre fatigued state when the sEMG parameters of antagonist ES muscle included jointly with agonist RA and synergist EO muscle sEMG. We also observed that despite negligible activity, the ES muscle (ARV) showed highest discriminating power to classify the pre and post fatigued conditions (Fig. 2) (Chen, Chiou, Lee, Lee, & Chen, 1998) and sensitive enough with RA and EO to identify the reduced spinal stability (KMO value=  $0.547_{Pre\ fatigue}$  vs.  $0.264_{Post\ fatigue}$ ) or nociceptive/pain induced posture impaired maintenance in children while performing the fatiguing Plank (Lee, Kang, & Shin, 2015). The percentage of non-redundant residuals reduced (50% Pre fatigue vs. 44% post fatigue) and the  $\bar{x} h^2$  increased ( $\bar{x} h^2$  Pre fatigue=0.802 vs.  $\bar{x} h^2$  Post fatigue=0.838), we further observed that the  $\bar{x} h^2$  was significantly higher from the acceptable value of 0.6 both in pre and post fatigued states (Table 6), therefore it was concluded that the validity of PCA model was satisfactory (Broen et al. 2015). We further observed that after the Kaiser Normalization applied for Promax rotation solution, both the ES ARV ( $\mu V$ ) (antagonist) and RA ARV ( $\mu V$ ) (agonist) showed highest loading weight with 0.926 ( $h^2 = 0.862$ ) and 0.918 ( $h^2 = 0.957$ ) respectively in the post fatigued state, which changed from the pre fatigue weighted loading 0.527 ( $h^2 = 0.735$ ) and 0.968 ( $h^2 = 0.937$ ) respectively in the 1st PC (Table 6, Fig. 3). This parallel increased RA-ES ARV ( $\mu V$ ) might indicate the "Common Drive" phenomenon, controlling the agonist-antagonist moto-neuronal pool and adopted similar motor unit recruitment strategies for both the RA and ES muscle. In addition with synergistic muscle, either parallel increase or constant coactivation by agonist-antagonist helped to attenuate the declined force capacity, delayed early onset of fatigue or increased time to task capacity (Samanta & Mukherjee, 2021). During fatiguing contraction, the force capacity of agonist muscle reduces, which further increases the net excitatory input to the moto-neuronal pool and recruits additional motor units. The "Common Drive" of agonist-antagonist muscles disproportionately increased the co-activity of antagonist muscle to compensate for the deteriorating joint stability during fatigue (Fig. 2, 3). Which further controlled by either supraspinal descending drive or differentiated motor neuronal pool. The altered excitability of motor neuronal pool in the antagonist muscle conventionally perceived with a substitute spinal pathway of disynaptic reciprocal inhibition from afferents of muscle spindle to the motor neurons (Duchateau & Baudry, 2014; Mullany, O'Malley, St Clair Gibson, & Vaughan, 2002).

The CCL pattern of EO, and RA-ES common drive phenomenon (Table 6, Fig. 3) could be understand extensively by their complex anatomical features. The EO maintains the lumbar spine stability through the hydraulic amplifier effect. The fused epimysial fasciae of EO and Latissimus Dorsi are extended to the posterior layer of the Thoracolumbar Fascia (TLF). Therefore, the EO fascia could transmit the tension from the EO muscle to the posterior layer of the TLF. The myofascial connections between TLF and EO, ES, RA muscles are accomplished through the aponeurosis

and fascia, which might explain the synchronized activity between ES and RA (Fan, 2018).

Further Recommendation: The multivariate statistical methods such as PCA/DA are not accepted widely in sports research due to high methodological complexity for selecting parameters and interpreting the results. The sEMG signal waveform cannot provide a valid conclusion about 'Muscle Fatigue' if we use a single parameter for a heterogeneous muscle group. In sports training, the DA and PCA is a reliable analytical tool for categorizing subjects using a set of sEMG parameters. The productivity of a training program could also be estimated by the changes in parameters of interest in a subject (Czaplicki, Śliwa, Szyszka, & Sadowski, 2017; Ivashchenko, Khudolii, Iermakov, Prykhodko, & Cieslicka, 2018). Strength and endurance training obtain opposite adaptations in motor unit discharge rates but have an indistinguishable effect on muscle fiber conduction velocity. We have a limited understanding of these training effects on heterogeneous muscle activity during fatiguing contraction. Both DA and Singular Value Decomposition/Matrix Factorization method used with PCA may anticipate a robust computational configuration to understand different training effects efficiently on muscle fatigue (Vila-Chã, Falla, & Farina, 2010). Furthermore increase sample size, items/parameters could provide a significantly accurate and reliable multivariate fatigue model.

## Limitations

Using non-maximum voluntary isometric contraction (MVIC) based non-normalized sEMG data with cautions for interpretation in a study dealing with the pediatric population is advisable due to ethical reasons (McManus et al., 2021; Samanta & Mukherjee, 2021). We also would like to address some of the other points listed below: 1. The MVIC induced sEMG amplitude normalization has some methodological limitations (e.g. 21.61% error in MVIC sEMG amplitude value which can be a potential threat to the validity and reliability of MVIC induced sEMG data, as it also depends on subject's fatigue, posture and non-cooperativeness) (Araujo, Duarte, & Amadio, 2000). 2. The previous study also reported that normalization of different sEMG parameters increase the chance to lose necessary information about neural recruitment strategies. 3. The sEMG amplitude normalization is also not suitable to understand neural drive mechanisms between muscles (Martinez, Negro, Falla, De-Nunzio, & Farina, 2018). 4. The electromagnetic interferences, crosstalk/volume conduction and artifacts by surrounding muscles might affect sEMG findings. 5. We used both PCA and DA individually in providing a better sEMG patterns alteration based multivariate fatigue model to impart a reliable solution to the insufficient sample size, high dimensionality and high redundancy problems (Prasad & Bruce, 2008).

## Conclusions

Multivariate sEMG signals undergo systematic changes with increasing magnitude and variability (phase shift) during submaximal isometric fatiguing contraction, and these changes are relatively difficult to detect with conventional Univariate analysis. A better understanding only possible by

applying the multivariate DA and PCA based on the fatiguing sEMG signal. PCA analysis revealed that the heterogeneity and variability of sEMG distribution increased, specifically from the muscles with higher geometrical diversity and a wide range of fiber type distribution during fatiguing contraction. During fatigue contraction, the distribution of muscle activity altered by CNS/PNS control, which further changed the magnitude of the correlation function among the sEMG parameters. Efficient synergistic activation, agonist-antagonist coactivation modulated by the nervous system, further reduced metabolic burden, neuromuscular in-stabilization and unwanted loading patterns on trunk structure to protect it, by optimizing force distribution and reorganized the fatigue induced load on different muscles. This efficient load sharing phenomenon of the muscles mediated by the nervous system during fatigue compensate for the fatigue induced force loss. Despite limitations, the ES muscle is highly sensitive even more than RA and EO muscle to identify the reduced spine stability while performing the fatiguing Plank. Highly correlated motor unit recruitment strategies between ES and RA, providing supportive evidence to the concept of shared agonist-antagonist motoneuron pool or "Common Drive" phenomenon during fatigue.

## Conflict of interest

The authors state that there is no conflict of interest.

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## АНАЛІЗ СТОМЛЮВАНОСТІ ОСНОВНИХ М'ЯЗІВ НА ОСНОВІ ПОВЕРХНЕВОЇ ЕЛЕКТРОМІОГРАФІЇ ПІД ЧАС ПОВТОРЕННЯ ПЛАНКИ З ВИКОРИСТАННЯМ МЕТОДІВ БАГАТОВИМІРНОГО ЗМЕНШЕННЯ У ХЛОПЧИКІВ 12-14 РОКІВ

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Авторський вклад: А – дизайн дослідження; В – збір даних; С – статаналіз; D – підготовка рукопису; E – збір коштів

Реферат. Стаття: 11 с., 3 рис., 6 табл., 42 джерела.

**Мета дослідження:** 1. Аналіз розрізняльної здатності нервово-м'язових компонентів для класифікації станів до і після м'язового стомлення. 2. Вивчити, чи стає модифікація стратегій рекрутування нейронів більш / менш гетерогенної через втоми. 3. Вивчити вплив активності м'язів Erector Spinae (ES) разом з активністю м'язів Rectus Abdominis (RA) і External Oblique (EO), щоб визначити зниження стабільності хребта під час виснажливої планки.

**Матеріал і методи.** У дослідженні взяли участь 12 хлопчиків (вік 12-14 років, зріст  $148,75 \pm 10$  см, маса тіла  $38,9 \pm 7,9$  кг). Багатоваріантний дискримінантний аналіз (DA) і аналіз головних компонентів (PCA) застосовувалися для виявлення змін в характері електроміографічних сигналів під час м'язової втоми. В DA використовувалися Лямбда Уїлкса, значення  $p$ , канонічна кореляція, відсоток класифікації і матриця структури. Для оцінки достовірності компонент стандартна межа для Кайзера-Мейєра-Олкіна (КМО) була встановлена на рівні  $\geq 0,529$ , а значення

$p$  тесту Бартлетта було  $\leq 0,001$ . Власні значення  $\geq 1$  використовувалися для визначення кількості головних компонентів (ПК). Задовільний відсоток ненадлишкових залишків був встановлений на рівні  $\leq 50\%$  при стандартному значенні  $> 0,05$ . Абсолютне значення середньої спільності ( $\bar{\chi}^2 h^2$ ) і навантаження компонентів були встановлені на рівні  $\geq 0,6$ ,  $\geq 0,4$  відповідно.

**Результати.** Стандартизований канонічний дискримінантний аналіз показав, що стан до і після втоми значно різнився ( $p = 0,000$ , Лямбда Уїлкса =  $0,297$ ,  $\chi^2 = 24,914$ ,  $df = 3$ ). Матриця структури показала, що параметром, який тісно корелював з дискримінантною функцією, був ES ARV ( $0,514$ ). Результати показали, що точність класифікації між станами стомлення складала  $95,8\%$ . У PCA значення КМО були знижені [ $0,547$  до стомлення проти  $0,264$  після втоми]; значення критерію сферичності Бартлетта було до  $\chi^2 = 90,72$  ( $p = 0,000$ ) і після втоми  $\chi^2 = 85,32$  ( $p = 0,000$ ). Був застосований критерій Promax з нормалізацією Кайзера, оскільки

обертання компонент було неортогонально [матриця кореляції компонентів ( $r_{CCM}$ ) = 0,520 Попереднє стомлення > 0,3 Абсолютна < 0,357 Втома після закінчення]. У двох ПК до стомлення (кумулятивне  $s^2$  – 80,159%) і після втоми три ПК (кумулятивне  $s^2$  – 83,845%) власні значення  $\geq 1$ .  $\bar{X}$   $h^2$  збільшилася [0,802 до стомлення проти 0,838 після втоми], а відсоток ненадлишкових залишків знизився [50% до стомлення проти 44% після втоми].

**Висновки.** Через стомлення збільшується варіабельність і неоднорідність міоелектричних сигналів. Спільна

активність ES-м'язи-антагоністи дуже чутлива для визначення погіршення стабільності хребта під час стомлюючої планки. Стратегії рекрутування моторних одиниць з високим ступенем кореляції між ES і RA підтверджує докази концепції загального пулу мотонейронів агоністів-антагоністів або феномена «Common Drive» під час стомлення.

**Ключові слова:** міоелектричні сигнали, неоднорідність, скорочуваність агоністів і антагоністів, дискримінаційний аналіз, аналіз головних компонент.

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