Relationship between body composition and postural control in prepubertal overweight/obese children: A cross-sectional study

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- Keywords: Obesity, Children, Body composition, Postural control

ABSTRACT

Background: Excess body weight during childhood causes reduced motor functionality and problems in postural control, a negative influence which has been reported in the literature. Nevertheless, no information regarding the effect of body composition on the postural control of overweight and obese children is available. The objective of this study was therefore to establish these relationships.

Methods: A cross-sectional design was used to establish relationships between body composition and postural control variables obtained in bipedal eyes-open and eyes-closed conditions in twenty-two children. Centre of pressure signals were analysed in the temporal and frequency domains. Pearson correlations were applied to establish relationships between variables. Principal component analysis was applied to the body composition variables to avoid potential multicollinearity in the regression models. These principal components were used to perform a multiple linear regression analysis, from which regression models were obtained to predict postural control.

Findings: Height and leg mass were the body composition variables that showed the highest correlation with postural control. Multiple regression models were also obtained and several of these models showed a higher correlation coefficient in predicting postural control than simple correlations. These models revealed that leg and trunk mass were good predictors of postural control. More equations were found in the eyes-open than eyes-closed condition.

Interpretation: Body weight and height are negatively correlated with postural control. However, leg and trunk mass are better postural control predictors than arm or body mass. Finally, body composition variables are more useful in predicting postural control when the eyes are open.

1. Introduction

The prevalence of overweight and obesity in children and adolescents has increased substantially; from 16.9% and 16.2% (boys and girls, respectively) in 1980 to 23.8% and 22.6% in 2013 (Ng et al., 2014). This situation being more accentuated in the developed countries, although this trend has been stabilised in the last decade (Jackson-Leach and Lobstein, 2006; Ng et al., 2014). There is a large amount of evidence supporting the hypothesis that the excess of body weight in children is related with cardiovascular-hormonal and musculoskeletal diseases (Fabris de Souza et al., 2005; I'Allemand et al., 2008; Taylor et al., 2006; Tsiros et al., 2014) and increased mortality (Must et al., 2012; van Dam et al., 2006). Moreover, higher body weight produces an increase in body segment weights and alterations in body geometry (Dutil et al., 2013), which causes reduced motor functionality and increases the probability of injuries during daily physical activities in subjects with obesity (Fjeldstad et al., 2008; Wearing et al., 2006).

Obesity and overweight also cause problems in postural control (Villarrasa-Sapiña et al., 2016). From a mechanical point of view, increased body weight can pose a higher risk of falls and injuries (Fjeldstad et al., 2008), as it is necessary to generate faster and greater moments of force in the ankle for balance control (Corbeil et al., 2001; Peterka, 2002). The greater risk of falls in individuals with obesity and overweight has been demonstrated empirically (McGraw et al., 2000), as has their reduced postural control as compared to those of normal weight (Menegoni et al., 2009; Villarrasa-Sapiña et al., 2016). Postural control alterations have also been found in children with obesity (Goulding et al., 2003; Villarrasa-Sapiña et al., 2016). Nevertheless, it seems that if adults, and probably children, with obesity and overweight reduce their body mass, they can obtain better postural control (Handrigan et al., 2010; Teasdale et al., 2007) although one study showed contradictory results (Cieślińska-Świder and Błaszczyk, 2016). Some studies have found that, apart from body weight, the body fat percentage, waist and hip circumferences, height and maximum foot width (among others) are also important predictors of balance in adults (Alonso et al., 2012; Błaszczyk et al., 2009; Chiari et al., 2002; Hue et al., 2007). Regarding children, some studies have pointed out that high BMI, waist circumference, fat percentage are related with poorer motor skills (Goulding et al., 2003; Kemp and Pienaar, 2013; Okely et al., 2004). In fact, an inverse relationship of fat mass ($r = -0.37$) and waist circumference ($r = -0.33$) has been found with the Bruininks/Oseretsky balance test (Goulding et al., 2003).

However, although these variables are good postural control predictors, it has only been studied using information from the entire body and, the implication of the composition of each corporal segment on postural control, has not been shown to date. There is a rationale to study this issue due to the fact that, following the inverted pendulum theory, an excessive accumulation of mass in the trunk could advance the position of the centre of mass leading to a more challenging balance control situation. Moreover, waist circumference is a predictor of postural control in adults and children (Alonso et al., 2012; Goulding et al., 2003). Therefore, there is evidence showing that the distribution of body composition among body segments could be important predictor of postural control, but this topic needs further consideration.

Although the influence of the distribution of body tissues (i.e., fat and fat-free mass) in people with obesity on their postural control still has not been proven, obtaining this knowledge would facilitate the study and prediction of the influence of obesity on children's postural control. The main objective of this study was therefore to establish the relationship between the composition of different body regions and postural control in overweight or obese children. We hypothesized that not only body weight, but also the accumulation of fat mass and fat-free mass in the trunk would be positively related with the postural control of these children.

2. Methods

2.1. Study design

A cross-sectional design was used to establish the relationships between body composition variables and postural control variables obtained during bipedal eyes-open (EO) and eyes-closed (EC) conditions. For each postural control condition, time and frequency domain variables were obtained by means of centre of pressures (CoP) signals acquired from a force plate. Body composition variables provide information about height and body composition distribution in the legs, arms, and trunk. The body composition data were used as predictors in multiple regression models to estimate each postural control variable.

2.2. Participants

Caucasian pre-pubescent children with overweight and obesity of both sexes were recruited by the convenience non-probabilistic sampling method at the Obesity and Cardiovascular Risk Unit of the Valencia General Hospital (Spain). The inclusion criteria were: i) presence of overweight or obesity (by using BMI percentile ranking obtained from the Centres for Disease Control and Prevention website), and ii) absence of any neuro-muscular, psychological or neuro-physiological pathology that could affect their motor control. Twenty-two children participated in the study (7 females, 15 males; 3 overweight children, 19 obese children). The subjects' characteristics were: age = 12.04 (1.25) years old, height = 156.91 (10.46) cm, weight = 69.37 (14.8) kg and body mass index = 27.92 (3.48) kg/m^2. The Institutional Ethical Committee of the University of Valencia approved the study. Written informed consent forms were obtained from parents prior to their children's participation.

2.3. Body composition measures

The children's height was measured to the nearest 0.5 cm using a fixed calibrated stadiometer (Scale-Tronix, Wheaton, IL). Body weight was recorded to the nearest 0.1 kg with the use of a standard beam balance scale with the subjects wearing light indoor clothing and no shoes. Body composition measurements were performed by dual-energy x-ray absorptiometry (Hologic Discovery Wi, Hologic Inc., Bedford, MA, USA) on the whole body. The subjects were asked to lie still in a supine position. Post-acquisition analysis was completed using the children whole body software module (QDR v.12.3). Test–retest reliability for this type of measurement and equipment showed

ICC values between 0.98 and 0.99 (Covey et al., 2008). The mean mass, mean fat mass and mean fat-free mass of the arms, legs, trunk and whole body were calculated. Height, BMI, fat mass/height^2, android/gynoid ratio and trunk/extremities fat mass ratio were also obtained.

2.4. Postural control measures

A force plate was used to measure postural control (Dinascan/IBV, Biomechanics Institute of Valencia, Valencia, Spain). The platform was placed on a stable surface and the subjects stood barefoot and relaxed with their arms by their sides. The same foot placement was adopted in all the trials (i.e., heels separated by the width of the shoulders and toes pointing outward at an angle of 20° from the sagittal midline), according to the manufacturer's specifications. A point of reference (5 cm in diameter) was placed opposite the subject at eye level at a distance of 2 m. All the subjects were informed of the importance of maintaining this posture and were asked to stand as still as possible. Two 30 s tests were performed under each of two conditions: (i) bilateral stance with EO, (ii) bilateral stance with EC. Although 60-s trials have been recommended for adults to increase the reliability of postural control variables (Carpenter et al., 2001), it is possible that children around 12 years old may not be able to focus on the task for this length of time. A previous study has shown good-to-excellent reliability indexes in typically developed children who performed 3 10-s trials (De Kegel et al., 2011). Two 30-s trials therefore seemed to be an appropriate duration to obtain valid postural control measurements in children of this age. The order of the conditions was counterbalanced. During each postural trial, signals were recorded at a frequency of 40 Hz using an amplified analogue-to-digital converter.

2.5. Data analysis

The CoP displacement data, in both the medio-lateral (ML) and the antero-posterior (AP) directions were obtained using NedSVE/IBV software (Biomechanics Institute of Valencia, Valencia, Spain). The data were analysed using Matlab R2013a (Mathworks Inc, Natick, USA). The CoP signals were low-pass filtered using a Butterworth IIR filter (cutoff frequency 12 Hz). The cutoff frequency was set at 12 Hz, as previously used (Bonnechère et al., 2016), since 99% of the power spectral density was below this frequency. The first and last 5 s of each trial were removed to perform feature extraction. Using the selected period of time, the root mean square (RMS), mean velocity, ellipse area, temporal sway and fractal dimension based on the 95% confidence circle were computed. A Fast Fourier Transformation was applied using the ‘periodogram’ Matlab function (without overlap). The energy of the power spectral density was then divided into three bands: i) low frequencies (i.e., ≥ 0.15 and < 0.5 Hz), ii) medium frequencies (i.e., ≥ 0.5 and < 2 Hz) and iii) high frequencies (i.e., ≥ 2 and < 6 Hz). The energy bands were expressed as a percentage of total energy. The median frequency was also obtained. Excluding area features, each variable was computed in the AP and ML directions as well as the resulting distance [$RD = \mathrm{sqrt}(AP^2 + ML^2)$].

A sway density plot analysis was also conducted (Baratto et al., 2002). For each value of the centre of pressures signal the number of consecutive samples inside a circle of 3 mm radius was computed. A signal in which the x-axis represents time and y-axis represents number of points was then obtained. This signal can be transformed into a time/time curve by multiplying the value of the signal at each time point by the sampling period. The next step is to perform peak detection, which was improved by filtering the signal in both direct and reverse directions using a fourth order low-pass Butterworth filter with a 2.5 Hz cutoff frequency. The peaks of the sway density plot were averaged to obtain the mean peak (MP) value. The mean distance (MD) was calculated as the distance covered by the centre of pressures between two consecutive peaks of the sway density plot. Finally, the mean time (MT) between consecutive peaks was computed. A detailed explanation of this analysis is available in Baratto et al. (2002) and Villarrasa-Sapiña et al. (2016). Finally, 26 postural control variables were computed for each visual condition.

Mann-Whitney U test were performed to analyse a possible sex effect on postural control and body composition variables. As no significant differences were found between males and females, both were analysed together in a subsequent analysis. Secondly, the assumption of normal distribution was checked (K-S test). Pearson correlations were then applied to establish the relationships between postural control and body composition variables. In order to avoid potential multicollinearity problems in the multiple linear models, we applied principal component analysis to body composition variables to obtain 17 uncorrelated principal components (PCs). Body composition variables with an arbitrary 0.25 threshold were selected to represent each PC.

Multiple linear regression analyses were performed to determine the best model to estimate postural control variables by means of the PCs obtained from body composition variables. The forward-stepwise procedure was used to include variables as the predictors in the model. The maximum p-value for a predictor being added was 0.05 (i.e., entrance tolerance), while the minimum p-value for a predictor being removed was 0.10 (i.e., exit tolerance).

3. Results

The correlation between body composition features and postural control variables are shown as Supplementary Material. The body composition variables that showed the greatest number of the significant correlations with postural control variables were height (the highest correlation for 14 postural control variables) and leg mass (the highest correlation for 6 postural control variables).

Regarding PCs, eigenvectors higher than 0.25 (arbitrary threshold) are shown in Table 1. The eigenvectors represent the importance of each body composition variable in computing each PC. The higher the absolute value of the eigenvector, the greater the importance of that variable in computing the PC.

Table 2 gives the multiple linear regression equations found to estimate postural control variables during EO using the PCs obtained from body composition variables as input variables. The PCs that appeared most frequently in these equations were PC1 (10 times), PC4 (8 times) and PC14 (6 times). As can be seen in Table

1, PC1 are composed of information on mass, fat mass, fat-free mass and height. On the other hand, PC4 are mainly calculated by using trunk mass, trunk fat mass and the android/gynoid ratio. The variables that gave the most information to compute PC14 were: total, arms, legs and trunk mass, as well as arm and leg fat mass. The regression models obtained increased the |r-value| in the relationship to simple correlations (Table 2) by at least 0.2 in 12 variables (i.e., mean velocity in AP, temporal sway, fractal dimension in RD and AP and almost all frequency domain variables).

The regression models for postural control variables during EC condition are shown in Table 3. PC1 appeared most frequently in these equations (9 times). As mentioned above, PC1 describes mass, fat mass, fat-free mass and the height of participants. It should be noted that the multiple linear model increases |r-value| in relationship to simple correlations (Table 3) by at least 0.2 only in 4 variables in the EC condition (i.e., fractal in RD, MT, high frequency band in ML and median frequency in AP).

There were no significant regression models in 11 of 26 postural control variables in the EC condition, while only 1 postural control variable could not be estimated using PCs in the EO condition. Nevertheless, using simple correlations, there were 20 postural control variables with no significant correlations with body composition features in EO. In EC, there were no significant correlations between 17 postural control variables and the body composition features.

4. Discussion

The present study is the first to provide results that support the influence of the distribution of the different body region tissues on postural control and stability in overweight or obese children. According to the correlations between the variables, height showed the highest relationship on postural control variables, which means that lower postural stability and more active postural control are associated with greater height, as has been found in previous studies (Chiari et al., 2002). Moreover, leg mass was found to be the second most influential body composition factor on postural stability, so that the greater the mass of the lower limbs, the lower the postural stability.

However, the multiple regression models obtained by using the PCs as predictors increased the amount of the explained variance for most of postural control variables. It was found that PC1 and PC4 are the components that provided most information on predicting postural control in OE. Information on PC1 was obtained from many body composition distribution variables (Table 1) but PC4 provides information on mass and fat mass of trunk and the android/gynoid ratio. With these results it is therefore possible to highlight the negative influence of trunk mass on postural control in overweight/obese children with their EO. A potential explanation of why this variable was not correlated with postural control in the EC condition is discussed below. These findings are in agreement with previous results in which the waist circumference was found to be highly correlated with body weight and to have a significant negative influence on postural control (Goulding et al., 2003; Hue et al., 2007). Thus, the inverted pendulum biomechanics model seems to be appropriate in estimating the effect of the distribution of body weight among body segments. High trunk mass advances the centre of mass, which leads to a more challenging condition because the subjects must generate muscle torques of greater magnitude to maintain balance (Corbeil et al., 2001).

PC14 and PC16 also appeared in several regression EO models (6 and 5 times, respectively). As can be seen in Table 1, PC14 is composed of all body mass variables (positively) and fat mass of arms and legs (negatively). However, PC16 is composed of arm mass (positively), leg and trunk mass (negatively), as well as fat and fat-free arm mass (negatively). The effect of arm mass (including fat mass and fat free mass) was inconsistent in this PC (positive and negative influence), although there was a clear negative influence of the trunk and leg mass. Observing the equations in Table 2 in which these PCs appeared, the negative influence of trunk mass as well as mass and leg fat mass should be considered on postural control and stability. As has been pointed out previously, the excess of trunk mass is consistent with the inverted pendulum model, although there could be another explanation to justify the effect of leg mass on postural control of overweight/obese children. At this point, two hypotheses could be drawn: firstly, leg mass could have a physiological, but not a mechanical influence, on the systems involved in postural control, e.g. excessive leg mass may have an effect on the leg proprioceptors. Secondly, a higher leg mass could be an indicator of a lack of physical activity, leading to lower neuromuscular competence. Future studies should identify the mechanism underlying the effect of leg mass on postural control, since the present results are not conclusive.

On the other hand, when visual information is restricted (i.e., EC condition) solely PC1 was involved in several equations. Therefore, body composition variables were found to have a higher influence in EO than EC (Tables 2 and 3). The influence of body composition factors is therefore more important in postural control when the children have their EO and are using the visual system. However, previous studies did not find these differences in the relationship between body weight and postural control when adults maintained balance with EO and EC (Chiari et al., 2002; Hue et al., 2007). As children are more dependent on visual cues to maintain balance (Rival et al., 2005), the functional difficulty of bipedal standing with EC is higher in children than in adults. This fact could suggest that in postural tasks with high functional difficulty the body composition distribution variables could have less importance than physiological factors such as sensory reweight or muscle synergies and could thus be responsible for the poor relationship between corporal composition distribution variables and postural control observed in children but not in adults when standing with EC. In this sense, antagonistic muscle synergies in challenging postural tasks are more frequently used than anterior, posterior and core synergies (García-Massó et al., 2016). The higher antagonistic synergies could increase joint stiffness, so that fewer active torques would be required during this more challenging condition, reducing the influence of body mass on postural control.

The results of this study thus suggest a number of recommendations on interventions aimed at improving postural control of overweight and obese children. Physical activity should be focused on reducing trunk and leg mass as far as possible. Scotto di Palumbo et al. (2017) recently found localized fat reduction in the lower limbs when explosive leg resistance training was performed before endurance training (Scotto di Palumbo et al., 2017). This suggests that overweight children should perform programs with both trunk and explosive lower limb resistance before endurance training. Combined with a dietary intervention, this exercise would help to reduce fat in the trunk and lower limbs while maintaining lean mass, leading to better postural control and lower impact forces when walking (Villarrasa-Sapiña et al., 2017).

Regarding the study's limitations, the choice of these simple tasks is one of the most important issues in our study. Nevertheless, as no studies had previously been published analysing the effect of the distribution of body tissues among the body segments on postural control of overweight children, EO and EC conditions were chosen because they are the most frequently used tasks in quiet standing studies. Future studies should include more difficult postural conditions to determine the effect of obesity on stability during complex tasks. It would also be of interest to increase the sample size as well as to include normal-weight participants in order to generalize the current results with a larger population. In the present study, distribution of body tissues was assessed by means of dual-energy x-ray absorptiometry that used ionizing radiation, with its potentially harmful health consequences. Children of normal weight were thus not included because we did not want to evaluate completely healthy children due to ethical considerations. Finally, the multiple linear models obtained by >2 predictors (i.e., 6/26 with eyes open and 1/26 with eyes closed) should be considered with caution because of possible overfitting due to the small sample size.

5. Conclusions

Although height was the individual factor that explained the highest amount of variance of the postural control variables, the multiple linear models showed that the distribution of the different tissues in the different body regions is also important in predicting postural control in overweight or obese children. Trunk and leg mass were found to be the best body composition predictors for postural control in these children.

Conflicts of interest

The authors have no conflict of interest to report.

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TABLES

Table1.

Eigenvectors of each principal component.

Variable	Zone	PC$_1$	PC$_2$	PC$_3$	PC$_4$	PC$_5$	PC$_6$	PC$_7$	PC$_8$	PC$_9$	PC$_{10}$	PC$_{11}$	PC$_{12}$	PC$_{13}$	PC$_{14}$	PC$_{15}$	PC$_{16}$	PC$_{17}$
Mass	Body	0.30	–	–	–	–	–	–	–	–	–	–	0.45		0.42	–	–	0.65
	Arms	0.29	–	–	–	–	0.39	–	0.26	–	–	–	–	–	0.41	–	0.58	−0.32
	Legs	0.28	–	–	–	–	–	–	–	–	−0.31	–	–	–	0.45	0.53	−0.35	
	Trunk		0.27		0.35	–	–	–	–	–	–	–	–	–	0.26	−0.53	−0.40	−0.27
Fat mass	Body	0.28	–	–	–	–	–	0.31	–	–	–	−0.37	0.46	−0.46	–	–	–	−0.36
	Arms	0.25	−0.27	–	–	–	0.55	−0.30	–	0.31	–	–	–	–	−0.25	–	−0.35	–
	Legs	0.25	−0.31	–	–	–	–	0.34	–	−0.40	−0.43	0.25	–	–	−0.30	−0.31	–	–
	Trunk			0.32	0.68	0.34	–	–	–	–	–	–	–	–	–	0.32	–	–
Fat-free mass	Body	0.28	–	–	–	–	–	–	–	–	–	–	0.37	0.67	–	–	–	−0.36
	Arms	0.27	–	–	–	–	–	–	0.79	–	–	–	–	–	–	–	−0.29	–
	Legs	0.27	–	−0.30	–	–	−0.35	–	–	0.67	–	–	–	–	–	−0.25	–	–
	Trunk	0.26	0.25	–	–	−0.34		−0.31	−0.29	−0.36	–	–	−0.35	–	–	0.34	–	–
Others	Height	0.25	–	−0.34	–	–	0.35	0.26	−0.32	–	0.53	0.41	–	–	–	–	–	–
	BMI	–	–	0.31	–	–	−0.38	–	–	–		0.63	–	−0.27	–	–	–	–
	Fat mass/ Height^2	–	−0.38	0.36	–	–	–	–	–	–	0.50	−0.32	−0.42	0.33	–	–	–	–
	Android/ gynoid ratio	–	0.28		−0.53	0.74	–	–	–	–	–	–	–	–	–	–	–	–
	Trunk/ extremities fat ratio	–	0.44	0.48		−0.37	–	0.52	–	–	–	–	–	–	–	–	–	–

PC = principal component; BMI = body mass index.

Table 2

Regression models for eyes open condition.

Variable Value	Direction R^2	Equation MSE	R- MAE			
RMS (mm)	*RD*	$Y = 6.00 + 0.30x_1 + 0.73x_4$	0.77	0.59	1.27	0.90
	AP	$Y = 3.83 + 0.17x_1 - 84.29x_{14}$	0.62	0.38	0.98	0.80
	ML	$Y = 4.55 + 0.25x_1 + 0.60x_4$	0.72	0.52	0.95	0.78
Mean velocity (mm/s)	*RD*	$Y = 11.64 + 0.48x_1$	0.53	0.28	6.24	2.06
	AP	$Y = 6.71 + 0.30x_1 - 108.14x_{14} - 505.84x_{16}$	0.79	0.62	1.18	0.87
	ML	$Y = 8.00 + 0.31x_1$	0.47	0.22	3.47	1.48
Ellipse area(mm^2)		$Y = 316.55 + 29.48x_1 + 74.15x_4 + 109.82x_6 - 9888.37x_{14}$	0.86	0.74	7890.91	73.36
Temporal sway (mm^2/s)		$Y = 20.86 + 1.89x_1 + 4.29x_4 + 6.29x_6 + 9.19x_7 - 594.74x_{14}$	0.88	0.77	26.43	4.23
Fractal dimension	*RD*	$Y = 1.73 - 0.04x_4 - 0.59x_{11} + 5.24x_{14} - 26.63x_{16}$	0.79	0.62	< 0.01	0.04
	AP	$Y = 1.73 - 27.97x_{16}$	0.50	0.25	< 0.01	0.05
	ML	$Y = 1.61 - 20.82x_{16}$	0.44	0.19	< 0.01	0.05
MD (mm)		$Y = 3.81 + 0.21x_1 - 100.49x_{14}$	0.64	0.41	1.26	0.85
MP (s)		$Y = 1.66–0.11x_1$	0.51	0.26	0.34	0.46
MT (s)		$Y = 0.66$	–	–	–	–
Low frequency band (%)	*RD*	$Y = 0.63 - 0.12x_7$	0.50	0.25	0.01	0.06
	AP	$Y = 0.73 + 0.04x_4$	0.47	0.22	0.01	0.07
	ML	$Y = 0.71 + 0.03x_3 - 0.34x_{10} + 0.77x_{11}$	0.72	0.52	< 0.01	0.04
Medium frequency band (%)	*RD*	$Y = 0.34 + 0.11x_7$	0.48	0.23	< 0.01	0.05
	AP	$Y = 0.26 - 0.04x_4$	0.47	0.22	0.01	0.07
	ML	$Y = 0.27 - 0.03x_3 + 0.33x_{10} - 0.70x_{11} - 2.00x_{13} - 16.86x_{16}$	0.86	0.74	< 0.01	0.03
High frequency band (%)	*RD*	$Y = 0.03 + 0.01x_7$	0.46	0.21	< 0.01	0.01
	AP	$Y = 0.02 - 0.02x_9$	0.52	0.27	< 0.01	< 0.01
	ML	$Y = 0.02 - 0.08x_{11}$	0.46	0.21	< 0.01	0.01
Median frequency (Hz)	*RD*	$Y = 0.38 + 0.06x_5 + 0.09x_7$	0.67	0.45	< 0.01	0.04
	AP	$Y = 0.33 - 0.03x_4$	0.44	0.19	< 0.01	0.05
	ML	$Y = 0.32 - 1.69x_{13}$	0.46	0.21	< 0.01	0.03

RD = resultant distance; AP = antero-posterior; ML = medio-lateral; MSE = mean square error; MAE = mean absolute error; MP = Mean Peaks; MD = Mean distance; MT = Mean Time. x_n represents the n principal component.

Table 3

Regression models for eyes closed condition.

Variable	Direction	Equation	R-Value	R2	MSE	MAE
RMS (mm)	*RD*	$Y = 8.42 + 0.49x_1$	0.51	0.26	7.14	2.36
	AP	$Y = 5.47 + 0.50x_1$	0.57	0.32	5.29	2.04
	ML	$Y = 6.16$	–	–	–	–
Mean velocity (mm/s)	*RD*	$Y = 17.52 + 0.95x_1$	0.45	0.20	36.47	5.40
	AP	$Y = 9.68 + 0.59x_1 - 34.19x_{11}$	0.62	0.38	10.23	2.76
	ML	$Y = 12.49$	–	–	–	–
Ellipse area (mm^2)		$Y = 651.13 + 77.89x_1$	0.52	0.27	166,119.70	359.21
Temporal sway (mm^2/s)		$Y = 46.80 + 5.18x_1$	0.52	0.27	763.06	25.04
Fractal dimension	*RD*	$Y = 1.76 - 1.22x_{11}$	0.52	0.27	0.01	0.07
	AP	$Y = 1.79$	–	–	–	–
	ML	$Y = 1.64$	–	–	–	–
MD (mm)		$Y = 6.52 + 0.49x_1$	0.47	0.22	8.91	2.49
MP (s)		$Y = 1.12 - 0.07x_1$	0.44	0.19	0.24	0.39
MT (s)		$Y = 0.70 + 0.10x_9 + 1.37x_{13} - 2.43x_{14}$	0.73	0.53	< 0.01	0.02
Low frequency band (%)	*RD*	$Y = 0.61$	–	–	–	–
	AP	$Y = 0.75$	–	–	–	–
	ML	$Y = 0.67 + 0.04x_2$	0.47	0.22	0.01	0.10
Medium frequency Band (%)	*RD*	$Y = 0.36$	–	–	–	–
	AP	$Y = 0.23$	–	–	–	–
	ML	$Y = 0.31 - 0.04x_2$	0.48	0.23	0.01	0.09
High frequency band (%)	*RD*	$Y = 0.03$	–	–	–	–
	AP	$Y = 0.02$	–	–	–	–
	ML	$Y = 0.02 - 0.01x_5 + 1.73x_{15}$	0.67	0.45	< 0.01	0.01
Median frequency (Hz)	*RD*	$Y = 0.41$	–	–	–	–
	AP	$Y = 0.32 - 0.01x_1 + 0.19x_8$	0.63	0.40	< 0.01	0.05
	ML	$Y = 0.36 - 0.03x_2$	0.43	0.18	0.01	0.09

RD = resultant distance; AP = antero-posterior; ML = medio-lateral; MSE = mean square error; MAE = mean absolute error; MP = Mean Peaks; MD = Mean distance; MT = Mean Time. x_n represents the n principal component.