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ORIGINAL ARTICLE

Assessment of Waveform Similarity in Electromyographical Clinical Gait Data: The Linear Fit Method

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Abstract
The assessment of waveform similarity is a crucial issue in gait analysis for the comparison of electromyography (EMG) and kinematic patterns with reference data. A typical scenario is in fact the comparison of a patient's EMG pattern with a relevant physiological pattern. Many methods have been proposed for a quantitative comparison of the two patterns, suggesting the absence of a gold standard. A recently proposed method for comparing kinematic patterns is the linear fit method (LFM). This study aims at testing the applicability of this method on data of EMG. The validity of LFM was tested in terms of appropriateness, sensitivity, specificity, and reliability, by comparing 20 EMG pathological gait patterns (obtained by a group of patients with Parkinson's Disease) and 20 EMG physiological gait patterns (obtained by healthy subjects). When gastrocnemious and tibialis anterior EMG activity was analyzed, the appropriateness of LFM in discriminating pathological patterns resulted of 97.5%, with a sensitivity of 95% and a specificity of 100%. The reliability was good for 2 out of 3 parameters in each group of subjects. The LFM resulted a simple method suitable for analysing the waveform similarity in gait EMG clinical analysis.

Keywords Gait analysis · Electromyography (EMG) · Muscle activity · Parkinson's Disease · Rehabilitation

1 Introduction

Walking is a complex function involving multiple interactions between different muscle groups that need to be well synchronized in order to guarantee an efficient, symmetrical, stable and harmonious locomotion at different speeds or on different surfaces [1]. Gait patterns are usually impaired in people with muscular deficits [2], as well as in people with dysfunction of the Central Nervous System (CNS), such as stroke [3] or Parkinson's Disease (PD) [4]. Instrumented gait analysis allows gathering quantitative information about electrical activity of muscles (electromyography, EMG), joint kinematics and kinetics during walking. The conventional output of gait analysis are curves obtained from data normalized with respect to the gait cycle [5]. A curve obtained from a patient is usually compared with a reference curve, typically obtained by averaging data of a group of healthy subjects. Clinical information can be obtained by visual comparison of the two curves, but a more powerful approach should be an objective quantitative assessment of the deviation of pathological patterns via an analysis from the physiological one through the estimation of few meaningful indices [6–9].

In the literature, quite a few methods have been proposed for a quantitative comparison between pairs of gait curves, such as the use of Pearson Correlation Coefficient (R, which allows for quantifying their shape similarity [10, 11]), the Root Mean Square Error (*RMSE*, which provides a positive global index [10]), the Coefficient of Multiple Correlation (*CMC*, which is helpful when the reliability of a group of curves is under analysis [12, 13]),

Another simple approach consists in computing the difference between parameters assumed to be representative of the entire curve, such as the amplitude (that could be assessed in terms of its range or using its maximum) or the timing, in terms of gait cycle percentage at which a particular event

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may occur, such as the maximum of an EMG signal. Several indices have also been proposed in order to assess the difference between two muscle patterns during gait, based on principal component analysis [14], pattern recognition techniques [15] and neural networks [16]. Another approach for comparing two EMG curves is to assess their overlap, or in terms of percentage of gait cycle [3] or in terms of the area of an enveloped overlap [17] (for a review about some of the proposed methods see Rosa et al. [18]).

A more simple method proposed for assessing the waveform similarity of gait curves is the Linear Fit Method (LFM) [19]. Strengths and attractiveness of LFM are based on its easy mathematical implementation and a straightforward clinical meaning of the obtained parameters, as shown by results obtained by comparing gait curves among subjects with cerebrovascular accident and healthy subjects [19] or among different laboratories [20]. The LFM has been previously proposed and tested for kinematic patterns, but not for EMG patterns.

The aim of this study is to assess the applicability of the LFM to EMG-data, in particularly those of medial gastrocnemius and tibialis anterior in order to compare pathological walking patterns and physiological ones. Analogously to the validation of LFM for kinematic gait data [19], the validation of LFM for EMG data was tested in terms of appropriateness, accuracy, sensitivity, specificity and reliability.

2 Materials and Methods

2.1 Validation of LFM

To validate the LFM application to EMG data-sets, we tested if this method may answer to the following criteria (questions): appropriateness (does it provide different results for patients when compared to healthy subjects? It represents the ability of LFM to provide parameters having values with a statistical significant difference between healthy subjects and patients), accuracy (does it provide results able to correctly identify patients and healthy subjects?), sensitivity (is LFM able to detect as pathological only actually pathological patterns?), specificity (is LFM able to detect as physiological only actually physiological patterns?), reliability (can the measures be accurately repeated?). For this purpose, twenty EMG curves obtained from subjects affected by Parkinson's Disease were compared with twenty curves obtained from a group of healthy subjects.

2.2 Gait and EMG Analysis

Gait datasets were acquired using a 6-camera motion capture system (Smart-D system, BTS Bioengineering, Milan, Italy) to reconstruct the 3D position of 21 retro-reflective spherical markers located on the subject's skin according to the conventional Davis' protocol [21], during level walking in barefoot conditions at self-selected speed.

We compared 20 physiological EMG patterns obtained from two trials of left and right legs of 5 healthy subjects (mean age: 33.2 ± 6.2 years) and 20 pathological EMG patterns obtained from two trials of left and right legs of 5 patients with Parkinson's Disease (mean age: 74.6 ± 5.5 years). Because the aim of the study was to test the LFM when it is used to compare pathological EMG-data vs. physiological ones, we enrolled a group of young healthy subjects for obtaining physiological reference patterns. Age-matched comparison is usually more helpful from a clinical point of view, but this is beyond the scope of this methodological study in which the reference curves should be representative of physiological patterns.

Instrumented kinematic gait analysis has been performed using a stereophotogrammetric system (SMART system, BTS Padua, Italy) with 6 infrared cameras, an acquisition frequency of 50 Hz, and a resolution of 640 × 286 pixels [22]. Twenty-one retroflective markers were located on subject skin in the body landmarks defined by the Davis' Protocol [21]. According to the purpose of this study, the data extracted by the stereophotogrammetric system has been used to define the spatio-temporal parameters of walking, and in particular the gait cycle on respect to which the EMG curves have been normalized. In particular, this system has been used for time-normalizing the data between two selected events, such as two consecutive foot-strikes of the same limb which define the gait cycle [5]. We recorded on each subject 4 walking trials, and analyzed the two steps performed in the center of stereophotogrammetric workspace. We excluded the first two trials because of adaptation to the environment, and analysed the last two.

The EMG signals were obtained using four wireless sensors (FREEEMG 300 System, BTS, Padua, Italy) with a sample frequency of 1000 Hz and positioned on left and right anterior tibialis and left and right medial gastrocnemious of the subjects according to the SENIAM protocol [23]. We used a FREEEMG 300 System with four wireless miniaturised probes (mass of 7.5 g) and one receiving unit using a PocketPC platform. Each probe consisted of a mother electrode and a satellite electrode (both with a diameter of 17 mm) connected via a flexible cable for optimizing the electrode distance (between 16 and 66 mm). In the mother electrode there is the preamplifier, the A/D converter, the antenna and battery. The input impedance was higher than 10GΩ the common-mode rejection ratio higher than 110 dB at 50–60 Hz.

On EMG signals it has been applied a 4th order Butterworth pass-band filter (30–450 Hz, [24]). Then, the filtered EMG-signal was rectified and its envelopment was obtained with a 4th order Butterworth low-pass filter with a cut-off

frequency of 5 Hz [25]. Finally, the obtained signal has been interpolated for reporting it with respect to the gait cycle identified by stereophotogrammetric system and enveloped averaging data with a mobile window of 50 ms. In particular, the identification of foot strikes was performed analyzing kinematic data by the identification of downward peak of the position of lateral malleolus markers [26].

2.3 Brief Analytical Description of the Linear Fit Method

The analytical extended description of the LFM has been provided in Iosa et al. [19], and briefly summed up in what follows in order to describe applications on EMG-data given a reference curve **X**, representative of a physiological pattern, and a curve **Y** of a subject to analyse (such as that of a patient). Since **X** and **Y** are normalized with respect to the gait cycle, they result in two arrays of real numbers of the same length. Hence, it is possible to plot **Y** against **X**, to define a set of points in a Cartesian coordinate system, where **X** values correspond to values of horizontal-axis of the Cartesian system and **Y** to those of vertical-axis (Fig. 1). The LFM method is based on applying a linear fit to this set of points. This fitting minimizes, in a least squares sense, the sum of the square vertical distances between the points and the fitting line (regression line, right plot of Fig. 1):

$$\mathbf{Y}_1 = a \cdot \mathbf{X} + b,$$

where $\boldsymbol{Y}_1$ represents the linear function which approximates **Y** values by means of a linear transformation of values of **X**; a is the angular coefficient and b is the intercept of the fitting line. The goodness of the fit can be easily assessed by the coefficient of determination R^2 that coincide with the square of the Pearson's correlation coefficient R.

The LFM relies on the interpretation of the values of R^2, a and b for assessing curve similarity between **Y** and **X** in terms of shape similarity, offset and amplitude scaling factor [19]. It should be noted that if $\mathbf{Y} = \mathbf{X}$ then the values of LFM parameters are $a = 1$, $b = 0$, $R^2 = 1$, that represent the theoretical situation in which the Y curve is perfectly physiological. In real data, and especially in pathological cases, a could be lower or higher than 1, b could be higher or lower than 0 and R^2 could be lower than 1.

In this study, we firstly applied the LFM on healthy subjects' data in which Y was one of the 20 EMG-curves obtained by 5 healthy subjects per 2 trials per 2 legs. The obtained parameters formed the data for healthy groups (summarized in mean ± standard deviation in Table 1).

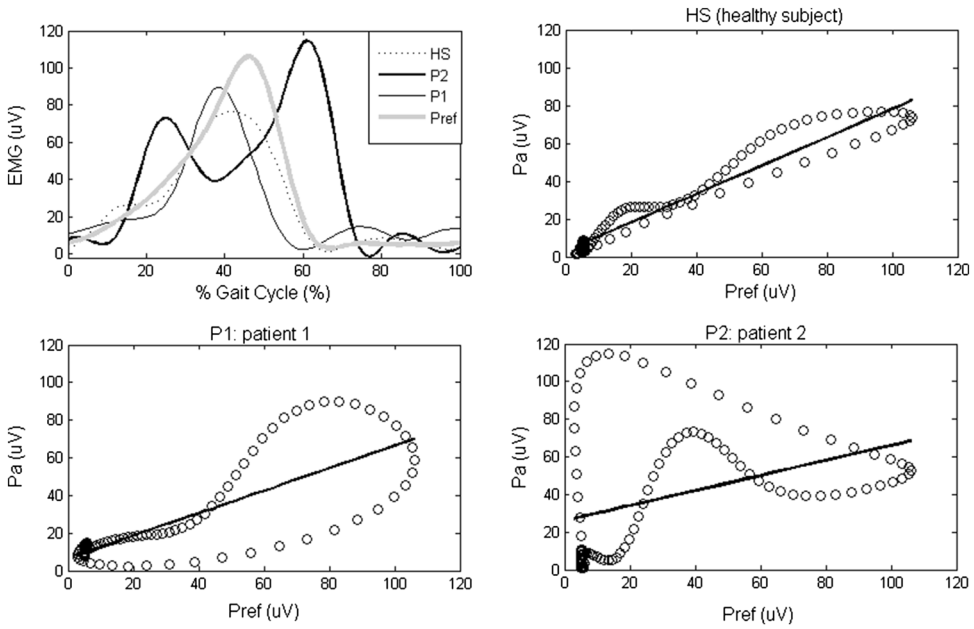

Fig. 1 EMG data (left above graph, expressed in microvolt) for a healthy subject (HS, dotted curve), patient 1 with mild Parkinson's Disease (P1, thin black curve), patient 2 with severe Parkinson's Disease (P2, bold black curve), and reference data (Pref, grey curve). In the other plots, each one of the subjects' curve (Pa) were compared with reference data (one-hundred circles) and the regression line (bold black line) shows the application of LFM on these data

Table 1 Mean and standard deviation for the LFM parameters computed for PG (patients' group) and HG (healthy subjects' group), with the p values of *t* test

Muscles	Gastrocnemious			Tibialis anterior		
Groups	A	b	R^2	a	b	R^2
HG	1.0 ± 0.39	0.0 ± 7.1	0.76 ± 0.17	1.0 ± 0.54	0.0 ± 14.3	0.52 ± 0.30
PG	0.31 ± 0.22	18.5 ± 7.4	0.27 ± 0.25	0.06 ± 0.54	52.7 ± 26.4	0.04 ± 0.04
p values	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$

Then, we applied LFM to the patients' data, using as Y one of the 20 EMG-curves obtained by 5 patients per 2 trials per 2 legs. These data formed those of patients' group (Table 1). For both the groups, the X-curve, that is the reference physiological curve, was obtained as the average curve of the 20 EMG-patterns of healthy subjects. This approach was performed for medial gastrocnemius data, as well as for tibialis anterior data. Figure 1 reports the example of this approach for the EMG-patterns of one healthy subject and two different patients.

2.4 Statistical Analysis

Mean and standard deviation of the LFM parameters were computed for describing data. Kolmogorov–Smirnov test, applied with the Lilliefors significance correction, revealed normal distribution for all the analyzed data-sets ($p \geq 0.108$ for all of them), allowing the use of parametric inferential tests. To assess the LFM appropriateness, the values of parameters extracted by LFM obtained from physiological data were compared with those obtained from pathological data by means of unpaired 2-tailed t-tests. For this and all the other statistical tests applied in the present study the threshold for statistical significance was set at 0.05.

LFM accuracy, sensitivity and specificity were assessed performing a Wilk's lambda discriminant analysis computed on the above described real data. This analysis was carried out to assess the capacity of LFM to cluster each one of the 40 analyzed EMG-datasets as physiological or pathological. Wilk's lambda discriminant analysis was performed not using the information about the number of data to include into two categories (it means it was applied without imposing to classify 20 datasets as physiological and 20 as pathological). Then a confusion matrix using a 2×2 table has been defined counting the number of patterns correctly classified as physiological (true negatives, TN), correctly classified as pathological (true positives, TP), incorrectly classified as physiological (false negatives, FN) and incorrectly classified as pathological ones (false positives, FP). Accuracy has been computed as the general ability to well classify the patterns: $(TP + TN)/(TP + TN + FP + FN)$; sensibility as the ability to detect true positives on all the pathological patterns: $TP/(TP + FN)$, specificity as the ability to detect true negatives on all the physiological patterns: $TN/(TN + FP)$. Further, graphical description of sensitivity and specificity parameters was shown for the two muscles by means of ROC-curve (Fig. 2).

The reliability of LFM was evaluated by computing the intra-class correlation coefficient (ICC(2,1)) between two trials of the same subject. The absence of interaction factors leaded to a coincidence between the evaluated ICC and the Cronobach's alpha value [27]. According to literature [28], the meaning of ICC value was defined as follows: between 0 and 0.01 no reliability, between 0.01 and 0.20 slight reliability, between 0.21 and 0.40 fair reliability, between 0.41 and 0.60 moderate reliability, between 0.61 and 0.80 substantial reliability, between 0.81 and 1 almost perfect reliability.

3 Results

3.1 Exemplificative Application of the Linear Fit Method

Figure 1 shows an exemplificative application of the linear fit method when applied to medial gastrocnemious EMG data for a healthy subject, a mildly affected patient, and a severely affected patient compared to the reference curve. The linear fit showed a very good association between reference and healthy subject's data, with $R^2 = 0.94$, $a = 0.75$, $b = 3.2$. The mild affected patient 1 showed a curve quite different from results, as also shown by LFM parameters: $R^2 = 0.63$, $a = 0.60$, $b = 26.2$. A completely different shape was found for the severely affected patient, also confirmed by the results of linear fit method: $R^2 = 0.15$, $a = 0.40$, $b = 6.75$. In this last, extreme case, the a and b parameters lost their significance because R^2 was lower than 0.20 (that is the minimum value still statistically significant for two vectors of 100 elements).

3.2 Appropriateness

LFM has been applied to analyze the EMG signals of Patients' Group (PG) vs. healthy subjects' group (HG). Means and standard deviations of the LFM-parameters (a, b, R^2) were reported in Table 1. For healthy subjects, the mean a and b resulted equal to ideal values 1 and 0, respectively, whereas the mean R^2 was close to its ideal value for gastrocnemious EMG signal and lower for tibialis anterior. All the relevant values computed for patients resulted significantly lower than those obtained for healthy subjects, as shown by p-values reported in Table 1.

3.3 Accuracy, Sensitivity and Specificity

LFM sensitivity and specificity was assessed performing a Wilk's lambda discriminant analysis on the three parameters of LFM for the two muscles analyzed at the same time. This analysis was carried out to assess the capacity of LFM of clusterizing as pathological or physiological each one of the 40 analysed EMG curves (5 subjects per 2 groups per 2 muscles per 2 trials). The confusion matrices evaluated using data of both muscles together or separately are reported in Table 2.

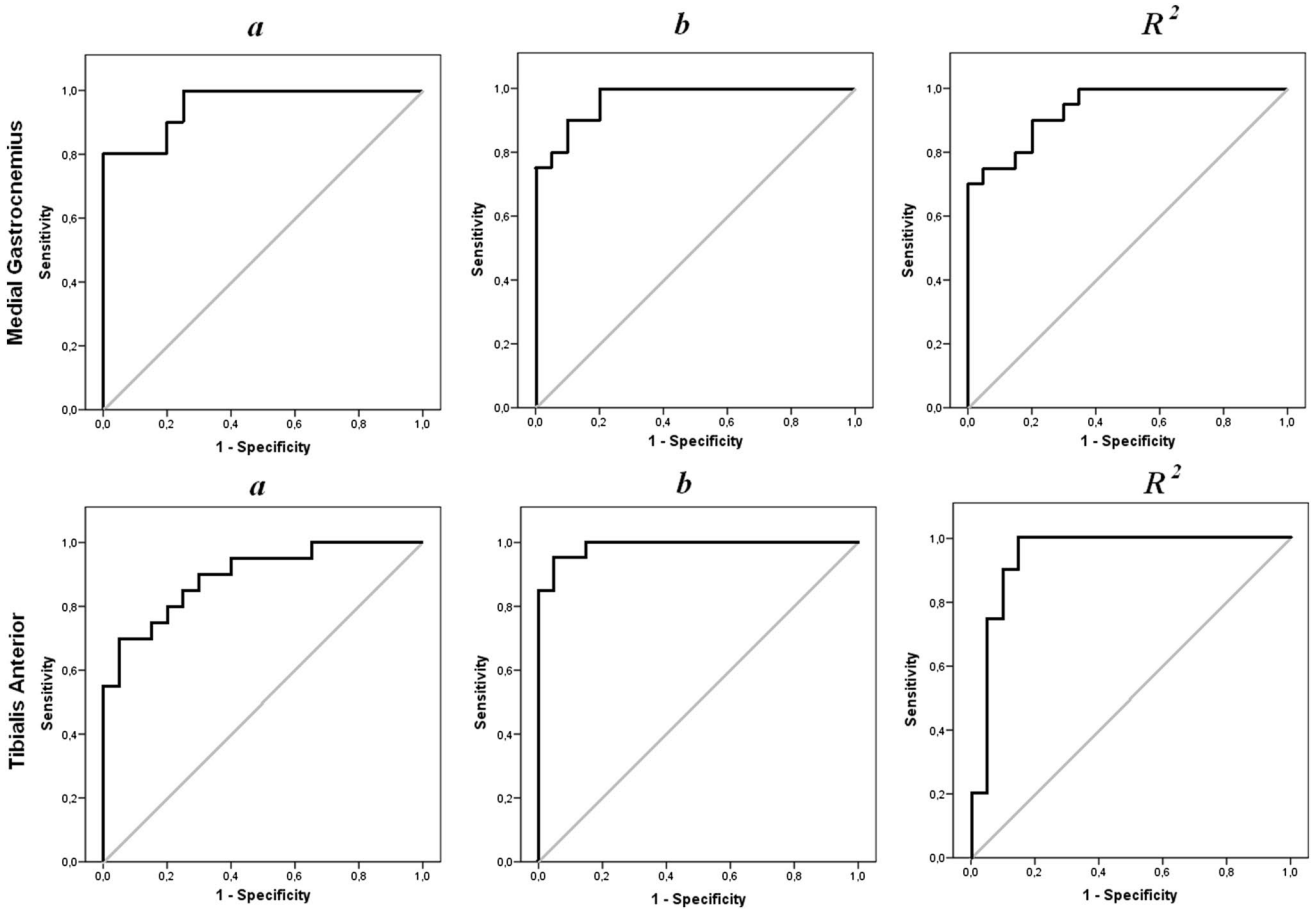

Fig. 2 ROC curves for the three LFM parameters computed for medial gastrocnemious (above) and tibialis anterior (below)

Table 2 Confusion matrices obtained using Wilk's lamba discriminant analysis on data of both muscles together or separately analyzed for patients' group (PG) and healthy subjects' group (HS)

Muscles		Gastrocneumious and tibialis anterior		Gastrocnemious		Tibialis anterior	
Groups		Estimation (%)		Estimation (%)		Estimation (%)	
		Pathological	Physiological	Pathological	Physiological	Pathological	Physiological
Actual groups	PG	19	1	18	2	20	0
	HG	0	20	2	18	3	17
Accuracy		97.5		90		92.5	
Sensitivity		95		90		100	
Specificity		100		90		85	

As shown, most of the EMG signals were correctly classified. Accuracy ranged from 90 to 97.5%, sensitivity from 90 to 100% and specificity from 85 to 100%. As expected the best results were obtained when the EMG of both muscles were analyzed together in the Wilk's lambda discriminant analysis. Figure 2 reports the ROC curve when the three parameters were separately analyzed.

3.4 Reliability

The reliability of LFM was evaluated by computing the intra class correlation coefficient (ICC(2,1)) estimating the absence of any interaction effect, so that the reported ICC-values coincide with the values of Cronbach's alpha. The ICC values evaluated for *a, b,* and R^2 resulted for HG: 0.715, 0.628, 0.389, and for PG: 0.119, 0.707, 0.638. So, a

substantial reliability was found for four out of 6 parameters, close to moderate reliability for R^2 in HG, and slight reliability for a in PG.

4 Discussion

The aim of our study was to validate the Linear Fit Method for assessing the similarity between electomyographical curves relative to gait datasets. This assessment is usually the basis of gait analysis, both for clinical and research purposes. Such as for kinematic gait data comparison [19, 20], the meaning of *a, b*, and R^2 is respectively related to amplitude differences, offset differences and shape differences. As for kinematic data, the linearity of the model allowed to obtain the theoretical values of a and b for healthy subjects ($a = 1, b = 0$). Continuing the similarity with the application of LFM to kinematic data, also for EMG-data the R^2 values were < 1, and those of HG defined the physiological reference. Finally, also in EMG-signals, when these parameters were computed on pathological patterns the values resulted far from theoretical ones, and significantly different from those of healthy subjects. However, the clinical meaning of these parameters obtained from EMG-signal is different from that in kinematic analysis. We found for patients a-values < 1 and b-values > 0, that represent an incorrect activation ($a < 1$) of muscle and a diffuse muscular rigidity related to a hypertone ($b > 1$). The R^2-values were very low for patients, especially for tibialis anterior, showing that the pathological curves had a quite different shape of activation with respect to physiological ones.

The values of the LFM-parameters easily allowed identifying pathological patterns with respect to physiological ones. The numbers of false positives and false negatives were in fact very low, leading to high values of accuracy, sensitivity and specificity. It should be noted that, for being closer to real clinical situation, we applied the Wilk's lambda discriminant analysis without using the information on the number of cases for each category (physiological vs. pathological). Although we did not perform any a-prioristic assumption on the categorization that could facilitate the discriminant analysis, the results were very satisfying, especially when data of both muscles were analysed together.

The reliability of these parameters resulted good, but with the exception of a in PG. Also, the R^2 in HG shows only a fair reliability, but it could be related to the fact that the ICC compares inter-subject variability to intra-subject variability, but being physiological patterns very similar among healthy subjects, the within-subject variability could be similar to the between-subject variability [7]. For PG, a good variability should be required for validating the method. At the same time, it is well known that the high variability of muscular activity from trial to trial in Parkinson's Disease (such as other neurological diseases) is a common sign of the motor control deficits [29].

When we applied to EMG data, the parameters of LFM can be easily computed, as for kinematics data. Other methods [14–16] need a disadvantageous more complex computation, especially during clinical routine.

At the same time, the proposed LFM have some limitations which should be considered and which can bind its fields of application. Firstly, we compared 20 patterns of patients with Parkinson's Disease (PD) vs. 20 patterns obtained from healthy subjects. Despite the number of patterns was adequate to identify statistically significant differences, the number of subjects and trials from which these patterns were obtained is small. However, we would highlight that the aim of this study is methodological and not clinical, and hence the aim was to show the appropriateness of application of LFM method even on small data-sets, more than clinically studying pathological patterns that needed a higher number of subjects and an age-matched control group. In this study the healthy group was composed by adults and not by elderly people in order to obtain physiological patterns; however, it may have introduced a bias and further studies should compare patients' patterns with those of age-matched healthy subjects. Then, the values of a and b may reduce their meaning when the linear relationship between pathological and physiological curves is poor (for low value of R^2). Further, we compared EMG-patterns of patients walking at slower speed than healthy subjects; however, it may have introduced a bias because, in physiological condition, higher speeds are associated to higher muscular activity. Then, we applied the LFM on EMG-data just filtered but not normalized. Many different methods have been proposed to normalize EMG-data with the aim of facilitating comparison between subjects (such as peak dynamic method [30], mean dynamic method [31] or dividing data for maximum voluntary contraction [32]). We did not apply any normalization with the idea that if LFM works for not normalized data, it will be easier that it works also for normalized data independently by the selected normalization method, but further studies should verify this assumption.

Another potential limit of this study is the absence of comparison with another method, such as for example the Root Mean Square [10] or the Coefficient of Multiple Correlation [12, 13] or statistical methods for assessing co-contraction [33, 34], but too many methods exists in the literature, without one well acknowledge as the gold standard. This requires a new method, such as LFM, that is easy-to-use and with a clear clinical meaning of its parameters. Although it has been recently proposed, the LFM has already been applied in many studies on gait kinematics: for comparing curves among different laboratories [20], for assessing the repeatability and reproducibility of foot- gait analysis protocols [29], for assessing the reliability of gait kinematics in

obese subjects [35]. Further studies could investigate if LFM could be applied also to investigate relationship of muscular activity with functional patterns such as gait harmony [36], and/or to other physiological curves, for example for assessing the similarity between electroencephalographic curves [37].

The present study supports the idea that the LFM can also be successfully applied to EMG-data and it can be appropriate to differentiating pathological from physiological patterns with a very high accuracy, sensitivity and specificity, and with a moderate reliability that is strictly related to and affected by the intrinsic variability of EMG-signals recorded in patients with neurological disorders.

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