Linear correlation between fractal dimension of surface EMG signal from Rectus Femoris and height of vertical jump

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1. Introduction

1.1. Review

Fractal dimension (FD) was proved to be a useful quantifier for the structure of a wide range of idealized and natural occurring objects, from pure mathematics, through physics and chemistry, to biology and medicine [1,2].

The fundamental characteristic of fractal objects is that their measured metric properties (such as length, area or volume) depend on the scale of measurement. A great number of physical, biological, even economical systems tend to present similar behaviors on different scales of observation. This phenomenon is often expressed by statistical scaling laws in time domain or spatial domain, such as the power-law behavior of real-world physical systems [3].

FD is a quantifier that measures the rate of addition of structural details with increasing magnification, scale or resolution. The fractal dimension works therefore as a quantifier of complexity [1,2].

Espinoza-Valdez et al. [2] built and validated a fractal model of the renal arterial tree, for which they used the box counting method to compute FD and correlated the fractal dimension of the biological structure to its physiological functionality. In other words, fractal dimension might determine whether a renal vascular structure is capable of performing physiological functions [2].

Since many signals produced by biological systems, first of all the human body, shows complex chaotic patterns

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and irregular behaviors, exactly as the stock exchange time series, it is interesting to study these signals in terms of complexity using FD.

Analysis of complexity of such a signal helps to study the system itself, in particular dynamics of transitions between discrete system's states [4]. The FD, that is characteristic of the complexity of the curve, can be computed directly in the time domain by using some algorithms specifically developed [1,3,4].

Some of these algorithms are explained in detail by Lopes and Betrouni in their review [3].

For planar curves and one dimensional signals, the fractal dimension ranges between 1.0 (straight lines) and about 1.5 (highly spiked waves) [5,6]. The more complex the curve, the higher the FD.

It should be kept in mind that FD is not interesting as an absolute measure, but as a relative measure. This means that to identify events in the signal, we shall look to time variations of the FD value [1,4,7,8].

Fractal dimension has been widely used as a nonlinear technique to study different biological signals, such as Electroencephalography (EEG), Electromyography (EMG), Surface Electromyography (sEMG), heart rate, etc. that are well known to exhibit an irregular and chaotic behavior. Some examples can be found in the work of Accardo et al. [7] who studied the FD of EEG time series by applying the time-domain algorithm proposed by Higuchi in 1988 [9]. Accardo found that the FD approach allowed to identify EEG events. Some easily detectable events through FD were: epileptic seizures, identified by a lower FD of the EEG signal, eyes opening and closing and speech, characterized by a higher FD of the respective EEG signal. Accardo [7] found that FD variations corresponded to power spectrum variations. I.e. in case of epileptic seizures, the lower FD of EEG signal corresponded to an increase in alpha band power of the same EEG signal.

A similar work on EEG was performed by Klonowski [4]. He showed that the events of eye opening and eye closing produced variations in the FD of the respective EEG signal (channel P4-O2). Klonowski found also that FD was able to detect EEG events in case of application of magnetic fields to the brain or while performing phototherapy [4].

As the EEG signal is well known to have a complex chaotic behavior, detecting events into the signal is extremely useful for medical purposes. Events may be macroscopic changes of the signal pattern associated to transitions such as changing of the state of consciousness, epileptic seizures, etc. Recent studies showed that an event can also be identified by a sequence of short time transitions, or intermittency, in the EEG pattern [10–12]. Also intermittency patterns can be associated to the level of cooperation of different areas of the brain [11]. Allegrini et al. [11,12] adopted a fractal model to describe intermittency and pattern change in EEG signal. Paradisi et al. [10] found that intermittency is connected to changes in the state of consciousness and reflected to the computed value of FD. Therefore changes in the FD correlate with changes in the state of consciousness and FD is extremely useful for pattern recognition and clinical interpretation of EEG [8,10].

Tagliazucchi et al. [13] computed FD on 2D images of the brain obtained by functional magnetic resonance (fMRI). They used box counting method to compute FD and found that FD may help to identify active areas of the brain and cooperation between neurons. Another study was conducted by Fingelkurts et al. [14] that studied brain mechanisms of perception and consciousness in terms of behavior of local neuronal assemblies. They adopted a chaotic-fractal approach to study the structure of EEG signal, for which the construction of a dynamical model is not easy [14].

Another interesting work is the one made by Cimolin et al. [15]. They used the box counting method [3] to compute FD of Center of Pressure (CoP) trajectory and showed that the FD approach provided useful information in addition to the traditional analysis of CoP trajectory. CoP is the projection to the ground of the Center of Mass of the body, and its trajectory can be obtained by a static posturography analysis. CoP trajectory is a measure of the whole body dynamics and represents various neuro-musculoskeletal components acting at different joints level [15]. CoP trajectory is difficult to interpret clinically and there is need of reliable approaches to extract useful information [15]. The study [15] was based on the comparison between pathological subject and control group and the FD was proved to be able to discriminate between the two groups. In fact, the pathological subjects were characterized by higher values of FD than the control group and the FD was indicative of the complexity of the stabilometric track during postural maintenance.

Analysis and interpretation of EMG signals are interesting as today this kind of signals are widely used in the clinical practice for diagnosis of neuromotor disorders and to study muscular condition, neuromuscular lesions and reflex responses [16]. In other words, EMG allows to determine ON–OFF activation status of a muscle and timings. Actual research is studying methods to extract more information from this complex signal. EMG is also used for other engineering applications such as the feedback control of prosthetic devices and control of rehabilitative robotics [16].

EMG is a voltage signal that represents the electrical activity of muscles. The signal is produced by the membrane of the motor units during muscular contractions. The electrical signal is generally collected by needle electrodes inserted directly into the muscle while the patient is asked to perform a contraction. This highly invasive method allows to collect electrical charge directly from the membrane of the motor unit and allows a detailed study of motor units recruitment [16]. A less invasive method consists in the use of disposable surface electrodes, based on Ag/AgCl conductive gel, applied directly on the skin over the muscle and fixed by adhesive tape. The gel allows electrical coupling between the anatomical tissues and the metal electrode. The surface electrode is placed on a specific position over the muscle, as defined by SENIAM recommendations [17] and allows to collect the overall electrical signal produced by the contraction of the muscle. This technique is named surface EMG (sEMG). It is obviously less accurate than standard EMG but it is non-invasive and can be used in studies involving motion of the subject, heavy physical activity and it can be easily synchronized with motion capture instrumentation

[18–21]. E.g. the sEMG was used to study gait patterns of subjects with spastic paraparesis and diplegia [22].

The sEMG generally requires a complex post-processing due to noise superimposed to the signal. Rectification, integration and power spectrum computing are required to extract information about activation and timings [20,21]. Alternative processing algorithms, based on fractal dimension, were developed. These algorithms work on the raw signal and do not require pre-filtering [1,3,5,7].

Gupta et al. [23] studied the fractal dimension of sEMG signal from the biceps during isokinetic flexion–extension of the arm and different loading conditions. They used Katz's algorithm [5] to compute fractal dimension of the signal obtained from electrodes placed over the biceps. The subjects were keeping different loads in the hand and were asked to flex–extend the arm at different speed. Gupta et al. [23] found that FD increased with increasing load and increasing flexion–extension speed. The FD was the lowest when the subject had no load placed on the hand and the flexion–extension time was the highest, while FD was the highest when the subject had the highest load in the hand and the flexion–extension time was the lowest. The correlation between FD and hand load was linear. Gupta et al. [23] concluded that the increase in EMG signal irregularity, measured by fractal dimension, indicated an increase in activation level of the muscle.

Liu et al. [6] also studied fractal dimension of EEG signals. They acquired human EEG signals while the subjects were holding a force measurement device. Each subject exerted handgrip at different force levels. The study resulted in the finding that computed FD of EEG had a linear correlation with the measured force exerted. Liu et al. [6] also tested different computation algorithm for FD and they concluded that Katz's algorithm was the most sensitive to signal variations and the most able to quantify motor-related signals.

Other studies showed that fractal dimension of EMG is sensitive to magnitude and rate of muscle force generated and also fractal dimension correlates to the muscle's potential in athletics. The better the athlete the higher the fractal dimension. The fractal dimension is representative of the training level [24].

1.2. Aim of the study

The purpose of this work is to study, in terms of Fractal Dimension, the surface EMG (sEMG) produced by the Rectus Femoris during a vertical jump. As the Rectus Femoris is the main erector muscle of the leg, it plays a relevant role in vertical jump and we expect to find a correlation between the FD of the sEMG from Rectus Femoris and the height of the jump.

2. Materials and methods

2.1. Subjects

The subjects included in this study were 20 healthy subjects, 8 males and 12 females, without any motor skills disorders or dyspraxia. The inclusion criteria were: male or female subject, aged above 10 years old, without any neuro-motor related disorder and without any postural problem. The subject should not have undergone any kind of musculoskeletal surgery.

Every subject was evaluated by a physiatrist and by a physiotherapist right before the trials.

The mean age of subjects was 22 years with st. dev of 6.2 and range from 11 to 28. The mean height was 160 cm with st. dev of 15 cm. The mean weight was 57 kg with st. dev of 18 kg.

2.2. Equipment and data acquisition

Motion and biomechanics data were acquired in the GaitLab of IRCCS San Raffaele Pisana, Roma, Italy. The lab was a gym of about 100 m^2 designed for rehabilitation purposes and supervised by a physiotherapist. Kinematic data was recorded by and an optoelectronic motion capture system, composed of 12 TVC and synchronized video recording system (BTS ELITE, by BTS Italy). sEMG was recorded by a wireless 8 channel surface EMG recorder (BTS Pocket EMG, BTS Italy). EMG and kinematics data recordings were time-synchronized.

EMG was recorded through pre-gelled electrodes (Ag/AgCI gel, Kendall Disposable Surface EMG/ECG/EKG Electrodes) applied on the skin of the subject and connected to the EMG recorder through electrical probes. The electrodes and electrical probes were securely fastened to the skin by using adhesive tape, in order to reduce noise due to motion of the cables and in order to do not interfere with subject's motion. sEMG electrodes were positioned on the Rectus Femoris of both legs, according to SENIAM directions [17]. The sampling frequency was 1000 Hz.

Kinematic data was acquired by an IR-reflecting spherical marker (diameter 10 mm) applied on the skin of the subject, over the sacrum bone. The optoelectronic system recorded the motion of the subject by reconstructing the 3D coordinates (x, y, z) of the marker in a 3D virtual space. Kinematics data was recorded at a sampling frequency of 100 Hz with a calibrated volume of about 8 m^3.

In every session of data acquisition, the subject was asked to stand still in the center of the calibrate volume for a few seconds, in order to record the reference position. Then the subject was asked perform sequentially three vertical jumps at three different heights (a small jump, a medium jump and the highest they could). During the whole trial, the subjects were asked to keep their hands fixed on the sides of the pelvis, in order to inhibit the effect of the arm motion on the jump [25].

For each subject, from 5 to 7 sessions were recorded, with a resting time of about 3 min between consecutive sessions, in order to avoid fatigue effects. We therefore had at least 15 jumps for each subject.

2.3. Data processing

Data was processed by using BTS ELITE and BTS Track-lab (BTS, Italy) software in order to reconstruct and track the absolute 3D coordinates of each marker.

The marker on the sacrum was rigidly coupled with the pelvis so it allowed an approximate reconstruction of the center of mass (COM) trajectory during the jump [26]. The height of the jump was computed as the difference between the maximum value reached by the vertical component of the sacrum marker, and the value found during rest (standing) conditions. Track of the sacrum was then imported in MATLAB and processed by ad-hoc built scripts.

The raw sEMG signal was also imported in MATLAB and fractal dimension was computed directly on the raw signal as directed by Katz's algorithm. The Katz's algorithm [5] was chosen because it was demonstrated to be the most sensitive and most appropriate to identify and quantify complexity variations in biomedical signals, especially for signals related to motion analysis [6,27].

Katz's algorithm was implemented as directed by [5] and is briefly explained in the following:

The general definition of the fractal dimension, FD, of a planar curve is:

$$FD = \frac{\log(L)}{\log(d)} \tag{1}$$

where L is the total length of the curve, and d is the diameter (the planar extent) of the curve.

For waveforms, which are ordered sets of (x, y) point pairs, the total length L is the sum of the distances between successive points:

$$L = \sum dist(i, i+1) \tag{2}$$

where $dist(a, b)$ means the distance between two point pairs $a = (x, y)$ and $b = (u, v)$.

As waveforms have a natural starting point, the planar extent can be considered to be the farthest distance between the starting point (point 1) and any other point (point i) of the waveform:

$$d = \max(dist(1, i)) \tag{3}$$

For discrete domain waveforms, fractal dimension computation needs to be normalized to the average step or the average distance (a) between successive data points. With the previous considerations the formula (1) can be adapted to discrete domain one dimensional waveforms as follows:

$$FD = \frac{\log\left(\frac{L}{a}\right)}{\log\left(\frac{d}{a}\right)} = \frac{\log(n)}{\left(\log(n) + \log\left(\frac{d}{L}\right)\right)} \tag{4}$$

where $n = L/a$ is the number of steps in the curve.

Processing algorithm was implemented according to formulas (2)–(4).

For the planar curves (waveforms) that proceeds "forwards" monotonically, the fractal dimension ranges between 1.0 (straight lines) and about 1.5 (highly spiked waves). True waveforms can never become sufficiently convoluted to fill a plane, thus waveform will never have a fractal dimension approaching the dimensionality of a plane (2.0) [5].

To compute FD changes over the time, the signal was segmented into windows composed of 250 samples, corresponding to a time window of about 250 ms at a sampling frequency of 1000 Hz, as suggested by Accardo et al. [7]. Katz's algorithm was then applied to the window. The window was moved along the signal with an overlapping of 50% and a new FD vs time signal was composed.

The FD was computed for both left and right Rectus Femoris sEMGs. Peak values of FD were detected for each jump and then averaged between left and right.

2.4. Statistical analysis

For each subject the maximum height reached in each jump and the maximum value of respective fractal dimension were collected and tabled. This was repeated for every jump made by each subject. Statistical analysis was conducted by using MS Excel data analysis tools. A scatter plot was obtained for each subject by plotting fractal dimension versus height of the respective jump. Least squares linear regression and its relative R^2 coefficient was computed for each plot by using Excel functions in order to study correlation between FD and height of the jump. The R^2 coefficient is a measure of the strength of the linear relationship and correlation between two variables. R^2 ranges from 0 to 1. As R^2 approaches 1, it means that there is a strong correlation between the variables. On the contrary, if R^2 approaches 0, it means that there is no correlation between variables.

Analysis was repeated for each subject and results were reported into a table.

2.5. Study approval

This study was approved by the Institutional Review Board at the IRCCS San Raffaele Pisana, Roma, Italy. All subjects (and/or their parents for underage children) were informed and signed consent prior to the participation.

3. Results

Fig. 1 shows signals acquired and processed for a subject. On the 1st row the vertical component of sacrum is plotted against time. The three jumps can be observed: they begin with a loading phase, followed by a rising phase where the maximum height is reached, then the descending phase and stabilization phase. On the 2nd and 3rd rows are shown the sEMG signals recorded from left Rectus Femoris and right Rectus Femoris. The bursts represent the contraction of the muscles. On the last row is shown the average fractal dimension obtained by averaging the fractal dimensions of the left channel and right channel EMG. The maximum value of FD corresponds to the maximum eccentric contraction of the muscle that corresponds to the end of loading phase and the beginning of upwards movement. These results are similar for every subject.

Maximum value of fractal dimension and maximum height reached in each jump were compared for correlation. A sample result (subject 1 in Table 1) is shown in Fig. 2. On the vertical axis the fractal dimension is represented, on the horizontal axis the height of the jump is represented. Each dot represents a different jump recorded for the same subject.
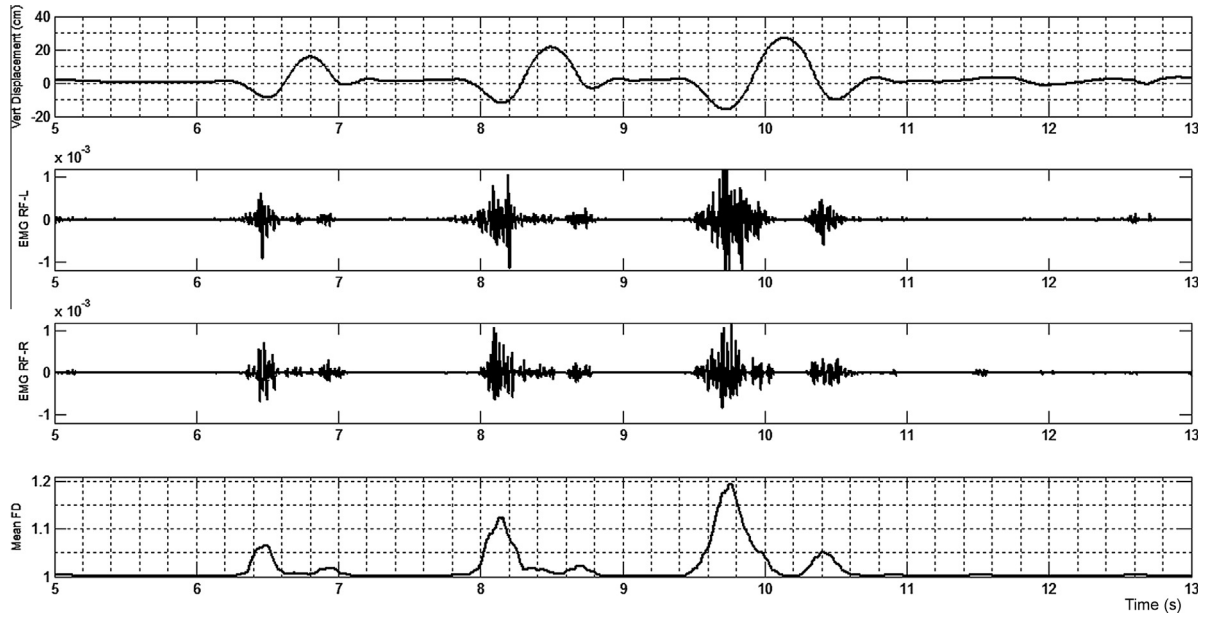
Fig. 1. Example of a trial recording. On the 1st row: the vertical displacement of sacrum. On 2nd and 3rd rows: sEMG signal from left and right Rectus Femoris. On 4th row: average fractal dimension of both sEMGs.

Table 1
Average height and fractal dimension for low, medium and maximum jumps. Mean values were obtained by averaging values of the same level of jump in different trials. R^2 correlation coefficient for each subject is also shown.

Subject	Low jump			Medium jump			Maximum jump			R^2
	Mean height (cm)	SD (cm)	FD	Mean height (cm)	SD (cm)	FD	Mean height (cm)	SD (cm)	FD	
1	18.6	1.7	1.0841	22.1	2.7	1.1176	29.9	1.3	1.1741	0.9406
2	15.6	1.3	1.0619	20.0	3.1	1.1059	26.9	1.7	1.1969	0.8887
3	16.6	1.5	1.0934	23.1	1.2	1.1717	27.5	1.1	1.1997	0.8964
4	25.2	2.4	1.0345	31.8	2.9	1.0833	37.4	3.4	1.1251	0.9214
5	16.4	3.7	1.0795	27.0	2.8	1.1614	33.5	1.7	1.1701	0.8769
6	14.3	1.3	1.0268	19.6	1.1	1.0645	26.4	1.0	1.1087	0.9265
7	11.9	2.4	1.0448	18.7	3.0	1.0911	24.9	2.8	1.1349	0.8548
8	18.5	1.4	1.0285	25.3	0.6	1.0686	32.0	0.2	1.1358	0.936
9	11.0	4.6	1.0470	19.0	4.6	1.0925	28.3	3.2	1.1518	0.9276
10	12.4	2.5	1.0968	13.3	2.3	1.1043	15.9	2.6	1.1578	0.6053
11	16.2	1.0	1.0305	22.2	2.6	1.0885	28.6	1.0	1.1825	0.9436
12	14.8	1.4	1.0870	21.0	2.4	1.1597	25.6	1.0	1.2290	0.8965
13	20.0	0.7	1.0476	28.7	1.9	1.0796	35.4	0.5	1.1020	0.8482
14	17.9	1.7	1.0482	32.5	2.1	1.1031	50.1	3.1	1.1998	0.9116
15	18.6	0.6	1.0288	25.4	0.2	1.0706	31.9	0.1	1.1377	0.9669
16	16.7	1.5	1.0321	22.3	1.6	1.0394	28.1	1.5	1.0503	0.8349
17	19.8	1.8	1.1259	26.9	2.1	1.1846	37.1	3.8	1.2851	0.7751
18	19.8	2.7	1.0632	24.5	1.9	1.0994	26.2	0.9	1.1250	0.8651
19	16.8	2.0	1.0607	22.6	2.0	1.1576	28.8	2.3	1.2697	0.8079
20	13.1	2.5	1.0342	19.7	2.1	1.0837	26.4	0.3	1.1295	0.9353

In Table 1 detailed results are reported for each subject with the respective value of R^2. Overall average of R^2s is 0.8779.

4. Discussion and conclusion

The fractal dimension of sEMG, acquired from Rectus Femoris, was determined while the subject was performing different jumps at different heights.

By examining Fig. 1 we can observe that the maximum muscle contraction, represented by the maximum sEMG burst, was time-located at the beginning of the upwards rising phase of the jump.

The fractal dimension, computed over the whole sEMG signal, and then averaged between left and right channels, reached its maximum at the beginning of the rising phase, when the maximum muscle contraction is expected. Also we can observe that the fractal dimension adjusted with
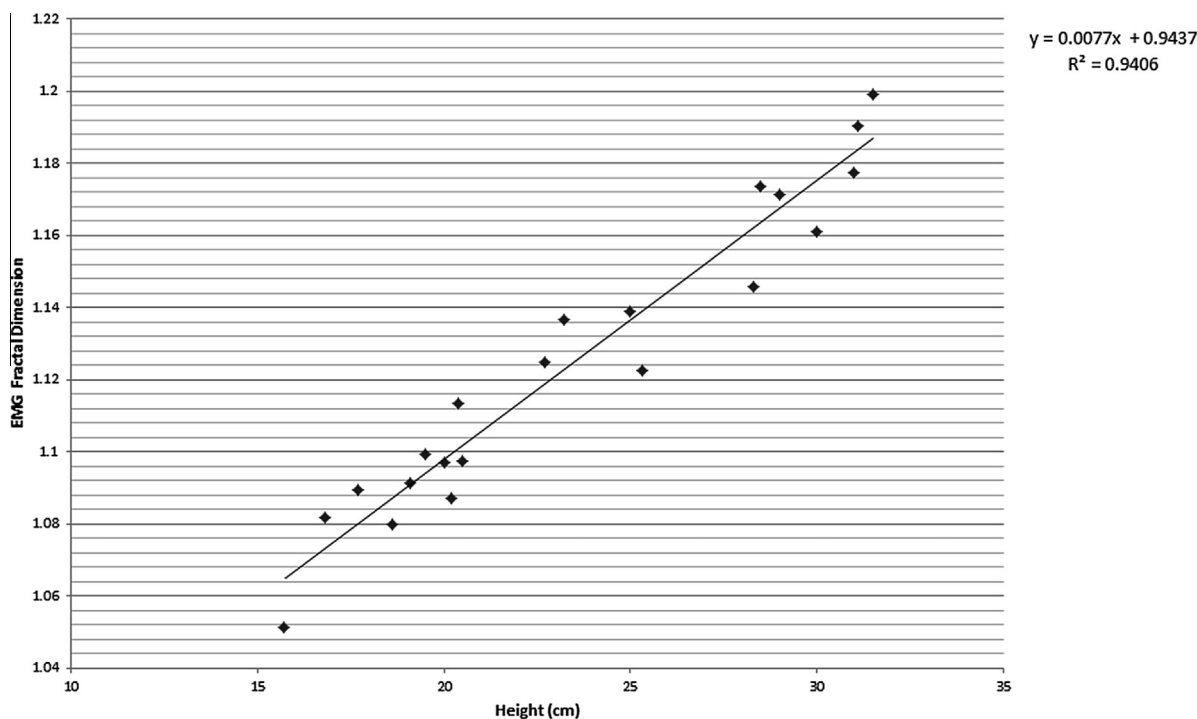
$$y = 0.0077x + 0.9437$$
$$R^2 = 0.9406$$

Fig. 2. Example of a data plot for a studied subjects. Each dot represents a jump for a total count of 21 jumps. Black line represents the correlation between fractal dimension and height of the jump.

the increase of the height of the jump. The higher the jump, the higher the force exerted by the muscle, the higher the fractal dimension of sEMG.

Repeating the jumping task within the same subject allowed to record data from many jumps. Fractal dimension and height of each jump showed a very high linear correlation (see Fig. 2 and Table 1). The correlation was very high for subjects of both sexes as shown by the correlation coefficients reported in Table 1.

These results are compatible with the results of Gupta et al. [23] that measured the fractal dimension of sEMG from the biceps under different loading conditions and found linearity between the fractal dimension and the load applied.

Despite the fact that there was a high correlation within the same subject, results were not comparable between different subjects. This may be due to differences in EMG signal and differences in jump performance due to different body mass, height and jump strategy of the subjects. Surface EMG power may also be affected by fat surrounding the muscle. Anyway other studies [1,4,7] advise to use fractal dimension only as a relative measure to make comparison within the same subject.

Fractal dimension of EMG can therefore be used together with the temporal and frequency domain analysis to characterize the EMG signal and can be considered to be representative of muscular activation. In fact, the sEMG signal can be considered the result of superimposition of many pulse trains produced by the asynchronous firing of motor units. The more motor units are engaged, the more complex is the resulting sEMG trace. Since more

pulse trains are produced when the muscle is activated and exerts force, the resulting sEMG complexity increases as the muscle contracts, and the FD increases as well. In other words, sEMG complexity can be seen as the level of cooperation and synchronous activation/deactivation of motor units. The fractal dimension analysis applied to physiological signals can therefore be interpreted as an index of the self-organization abilities of the system under study, and it could be seen as the emergence of a strong cooperation.

Thus fractal dimension may be an useful indicator of a subject training and increasing in performance (e.g. athletes) or indicator of muscle recovery after surgery or other treatments or, more in general, an indicator of motor units recruitment.

The main limitation of this study is the use of surface EMG that is affected by noise, cross-talk and is not able to discriminate the signal produced by the single motor units. Further study should involve the use of invasive EMG to study the possibility of a correlation between the FD value and the number of motor units involved and cooperating. Further studies may also involve testing sEMG and EMG fractal dimension variations in subjects affected by neuromotor pathologies or patients undergoing recovery or rehabilitation.

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