Study of the Muscular Force/HOS Parameters Relationship from the Surface Electromyogram

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Abstract— **The aim of the present study is to investigate a possible relationship between High Order Statistic (HOS) parameters and muscle force. In fact, it is guessed that Motor Unit (MU) recruitment during contraction has an influence on surface EMG (sEMG) amplitude distribution shape. For this purpose, skewness and kurtosis are used to monitor variation of monopolar sEMG data according to contraction level. First, a simulation was performed to evaluate the sensitivity of both proposed parameters to physiological and instrumental parameters. Then, 3 healthy young males took part to an experimental protocol on the biceps brachii muscle. The sEMG and force data were recorded and analyzed for different voluntary contraction levels. According to the results obtained, a relationship between HOS parameters and muscle force appears to exist. However, HOS parameters are sensitive to the tested parameters.**

Keywords — **Motor unit recruitment; Surface EMG; Twitch/Force; HOS.**

I. INTRODUCTION

Extracting information about Motor Unit (MU) recruitment schemes during muscle contraction from the analysis of surface EMG data is a challenging task [1], [2]. In fact, temporal and spatial recruitment of the MUs, driven by the Central Nervous System (CNS), are fundamental mechanisms for generating sEMG signal and force by the studied muscle [1], [2]. The evaluation of the relationship between neural command and sEMG/Force data is essential for the comprehension of complex processes underlying muscle contraction [1],[2]. Several studies, based on simulation and human experiments demonstrate this relationship [1], [2]. From the sEMG signal, typical descriptors usually investigated are amplitude and frequency information [1], [2]. However, it has been reported a poor discriminative ability of these descriptors in the evaluation of MUs recruitment scheme [1]. Furthermore, these descriptors are sensitive to clinical variability (anatomical, instrumentation, etc...) [1]. In the present study, we propose to investigate the relationship between Force and High Order Statistics (HOS) parameters extracted from monopolar sEMG signal. Indeed, HOS parameters are sensitive to shape variation of the sEMG amplitude distribution. Moreover, these shape variations are supposed to occur following temporal and spatial MUs recruitment. A recent study [3], using a shape modeling formalism based on simulation, has shown the ability of this formalism to separate several contraction force levels, according to sEMG amplitude distribution shape. Following this idea, two parameters, skewness and kurtosis, will be tested in the present study by using simulation as well as human experimentation. Previous studies [4], [5] have already used skewness to detect MU firing synchrony during fatigue.

For this purpose, a first study based on simulation is reported using a sEMG/force model. This simulation focused on the evaluation of the force/HOS parameters relationship for three contraction levels. Influence of the MUs recruitment strategy, fat thickness, and electrode distance from the innervations zone, is investigated. The second step is to perform an experimental study on three young healthy subjects to extract HOS parameters according to the same three contraction levels of the biceps brachii muscle. Finally, the obtained results are discussed.

II. MATERIAL AND METHODS

A. sEMG/Force model

The simulations were based on a commonly used recruitment model of a population of MUs [2]. In this model, each MU activation is tuned by a motoneuron firing rate which increases linearly with the force level, from recruitment threshold toward the peak firing rate level as in [6]. In fact, each MU has its own firing/force slope. To provide a better physiological realism, different firing rate ranges were imposed according to MU type (see Table. 1). The InterPulse Interval (IPI) probability is supposed to have normal distribution (SD=15%) [1]. A layered volume conductor model proposed by [7] is considered. It includes muscle, fat and skin tissues, electrodes (shape and configuration), finite length fibers, etc… Mathematically, it consists in applying two-dimensional filters to the input current density function, derived from the intracellular action potential [7]. The muscle is assumed to have a circular section (20 mm diameter). The mean length of the muscle fibers is 120 mm (L1=55mm, L2=65mm), as in human biceps brachii [5]. Ends of the fibers were scattered uniformly within a 18 mm range. The overall width of the innervation region was 30 mm [5]. For each individual MU, the end plate region width was set to 10 mm as in [5]. Other anatomical properties of MU and fibers are shown in Table.1. Signal was recorded from one monopolar circular electrode (10 mm diameter) located above the longer semi-length, 20 mm away from the middle of the innervation zone. Calculation of the conduction Velocity (CV) for each fiber belonging to a given MU was performed following the same equation (linking CV to the fiber diameter) and using a reference CV=4 m/s as reported in [5].

Table 1 Main MU and anatomical parameters (mean±maximal deviation)

MU Type	Number of MUs	MU diameter (mm)	Number of fibers	Fiber diameter (µm)	Firing Rate (Hz) Fmin - Fmax
S	50	5 ± 1	100± 10	45±5	8 - 20
FR	25	5.5± 1	150± 15	50±5	10 - 25
FIN	25	6± 1	200± 20	55±5	15 - 30
FF	50	6.5± 1	250± 25	60±5	20 - 35

When an action potential arrives at muscle fibers, the contractile response appears and is named “twitch.” It is the mechanical response of the fiber. The MU twitch (the mechanical response of a MU to a single neural impulse) has a specific bell shaped that is dependent on the MU type: fast twitch fatigable (FF), fast-twitch fatigue resistant (FR), intermediate (FIN), slow-twitch (S), and is analytically described in [8]. In all simulations, the total muscle forces are obtained from the summation of individual MU forces computed as in [8] and depending on the recruitment strategy (see Figure.1).

B. HOS analysis

In this work the HOS descriptors (Skewness, Kurtosis) were used to evaluate the shape variation of the sEMG amplitude distribution according to contraction level. The SEMG signal can be considered as a stochastic process whose amplitude variation is related essentially to summation of MUAPs (MU Action Potentials) of a large number of active MUs according to the level of muscle activation. The activation of the corresponding MUs follows stochastic discrete processes [4]. It is guessed that sEMG amplitude distribution shape is strongly dependent on the activation of the MUs during contraction [8]. The asymmetry of the distribution can be described by using the skewness statistic (normalized 3rd order central moment), which is defined for a random variable X as:

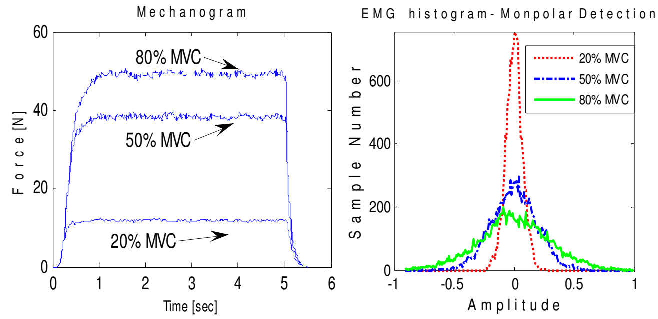

Fig.1 Simulated Force/SEMG Amplitude histograms for 3 contraction levels

$$\gamma_1 = \frac{E[(X-\mu)^3]}{\sigma^3} \quad (1)$$

A normal distribution has a skewness equal to 0. A positive skewness corresponds to an important right tail. A negative value is due to an important left tail of the distribution. Elsewhere, another parameter is used for the quantification: the kurtosis of the distribution of a random variable X, which is defined as:

$$\gamma_2 = \frac{E[(X-\mu)^4]}{\sigma^4} \quad (2)$$

Kurtosis statistic (normalized 4th order central moment) is linked to the degree of peakedness of a distribution. We substract 3 (normal distribution value) from the computed value, so that the normal distribution has a kurtosis of 0. However, a positive value corresponds to a peaked distribution and a negative one to a flattened distribution.

C. Experimental Protocol

Three healthy males participated to this study (age=27±5.0 year, height=173.6±8 cm, weight=81±12 kg). After preparing the skin of the subject, the sEMG activity was recorded (sampling frequency 3 kHz) by TeleMyo 2400 G2 PC interface of Noraxon telemetry system; with monopolar electrode (10 mm diameter) placed along the longitudinal axis of the Biceps Brachii of their right arm, at a distance of 1cm away from the middle of the belly toward the elbow. A reference electrode was placed on the elbow. The sEMG activity and the associated force developed were simultaneously measured for the different contraction levels investigated. Testing was performed on the right arm. The elbow was maintained at 90 degrees with the palm up. A maximal isometric voluntary contraction (MVC) of the Biceps Brachii was developed in isometric conditions as fast as possible and maintained for three seconds. Two MVCs were performed with two minutes rest between trials. The best attempt was recorded as the participant’s

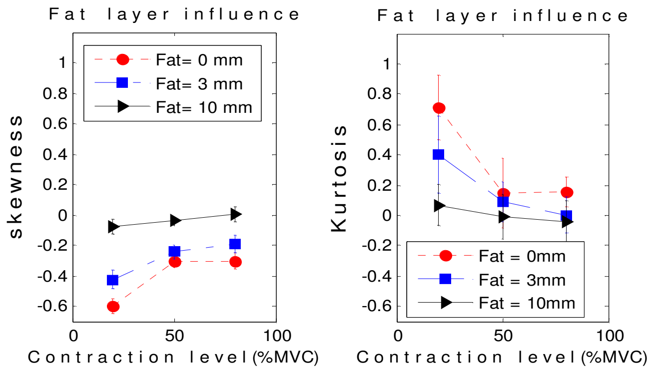

Fig.2 Fat layer influence with (R2) Recruitment strategy

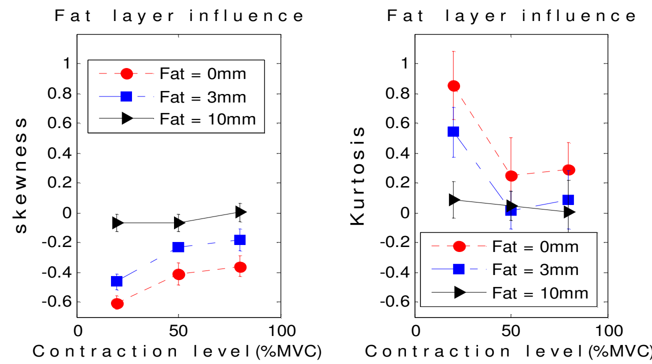

Fig.3 Fat layer influence with (R1) Recruitment strategy

MVC score for the day. Then subject were instructed to maintain a torque corresponding to 20, 50 and 80% MVC for five seconds with a visual feedback of their voluntary torque developed. A minimum of 90 sec of rest was given between contractions. Two trials were done for each contraction level. To avoid changes due to circadian rhythm, for each subject 3 testing sessions were conducted at the same hour for 3 different days, with 1 to 3 days rest in between testing sessions, to assess reproducibility of the used method.

D. Simulation protocol

To evaluate the sensitivity of the proposed approach to clinical variability, different simulation sets (according to the same random location of different MUs in the muscle) were generated (see Figure 1), by using the model described in Section II.A, with a Gaussian noise (20 dB, SNR). We used each combination of the following parameters:

(1) The same muscle anatomy with three different fat layer dimensions (0, 3, and 10 mm) using R2 recruitment strategy (see below).

(2) Two different recruitment strategies, (R1) as depicted in [2]. The MU increased its firing rate with force in a linear way, with the same slope for the whole MUs, min and max firing rate for each MU are used as Fmin=8 Hz, Fmax=35 Hz. The (R2) strategy is an improvement of [6] with different MU firing/force slope according to Table.1 (see Section II.A).

(3) Three electrode positions (10, 20, 40mm) from the innervation zone, with fat thickness equals to 3 and 10 mm. For each simulation, 5 contractions of 5 seconds for each force level (20, 50, 80 %MVC) are modeled.

The average skewness and kurtosis were calculated by segmenting the sEMG signal into 4 epochs of 1 sec. duration.

III. RESULTS

A. Simulation study

On Figure 2 and 3, we can observe clear tendencies concerning the HOS parameters with force level: an increase of the skewness from negative value toward zero and a decrease of the kurtosis from a positive value toward zero. Indeed, whatever the recruitment strategy considered (R1 or R2), both parameters are sensitive to fat layer with less dynamic according to thickness increase. Concerning force relationship, this can be explained by two phenomena occurring during contraction. The first phenomenon is more visible at low contraction level and consists on the influence of the MUAP amplitude distribution on the overall signal. In fact, monopolar MUAP recording is asymmetric with high negative peaks. At low contraction level, few MUs are recruited and MU superposition is not important. For this reason, skewness is negative. In the other side, the kurtosis is positive due to an important number of small values in the signal. The second phenomenon is the increase in MU superposition with force level. In fact, and following the central limit theorem, superposition of random variables tends to normal distribution. For this reason, an increase and decrease of the skewness and kurtosis respectively, toward zero value (normal distribution). Both recruitment strategies (R1, R2) give almost the same tendencies for skewness and kurtosis. Concerning the strong influence of the fat layer thickness on the HOS parameters, this is mainly due to the spatial filtering induced by increasing thickness. For a large thickness of the fat layer, the HOS parameters are less sensitive to different levels of contraction especially the skewness.

Concerning the electrode position, for a fat layer of 3mm, the influence on the HOS parameter tendencies is small (see Figure 4) for the three positions (10, 20, 40 mm). For a larger thickness (10 mm), the influence is greater especially for the distance of 40 mm as presented on Figure 5.

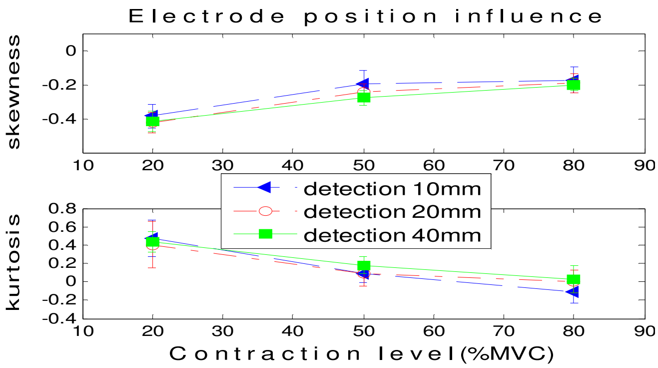

Fig.4 influence of detection position with fat layer = 3mm

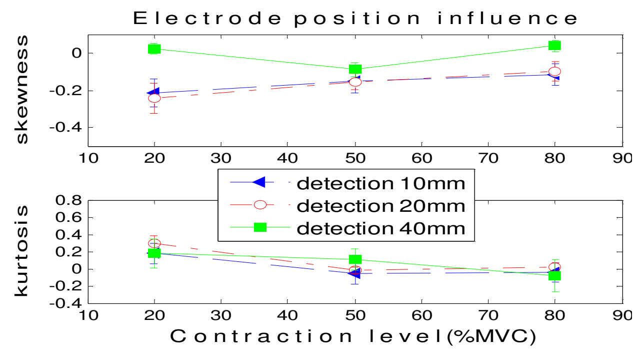

Fig.5 influence of detection position with fat layer = 10mm

B. Experimental study

In experimentation, we can observe interesting results on Figure 6. As for simulation, we show an increase and decrease of the skewness and kurtosis respectively. But, the tendencies are not so clear as in simulated results. In fact, an increase toward positive skewness values is observed. This is mainly due to errors in the placement of the electrode according to the innervations zone, and to the influence of the fat thickness and muscle anatomy. The subcutaneous fat tissue influence is clearly shown in subject 1. In fact, his BMI was 34 instead of 23 for subjects 2 and 3. For subject 1, it becomes difficult to extract any tendency for skewness and the range of variation is small. In the other side, the tendencies are more pronounced and the variation range is larger for subjects 2 and 3.

IV. CONCLUSIONS

The present study investigated High Order Statistic (HOS) parameters to evaluate muscle force. HOS parameters (skewness and kurtosis) were used to study possible relation between variations of the sEMG amplitude distribution shape, due to MU recruitment, and isometric contraction levels. First, a study by simulation has been proposed to evaluate HOS parameter tendencies and robustness against clinical and instrumental variability. It appears that a relationship with force seems to exist. But it shows a great sensitivity to fat thickness and electrode position. For experimental results, the same tendency seems to occur in the evolution of HOS parameters, but with less clarity. This is mainly due to errors in electrode placement according to innervation zone, and also to the presence of muscle anatomy variability. Finally, this study is part of a preliminary study and further investigations are needed to precisely demonstrate the capability of HOS parameters to track force variations despite the presence of several sources of variability.

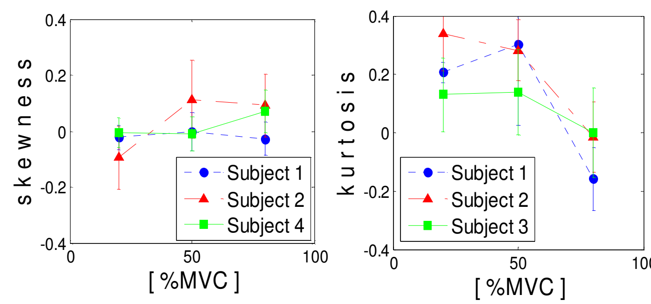

Fig. 6 experimental results for 3 subjects.

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