A Generation Model for Surface EMG Signals

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***Abstract*— Modeling of physical phenomena has contributed significantly in research. In fact; several investigation and results have been found basing on Modeling. In this work, we proposed a model to generate an electromyographic (EMG) signal detected on the surface of the muscle. Nowadays, surface EMG (SEMG) signal is used in many clinical applications due to its easier detection technique which is non invasive. Information carried by this signal is referred to its generation mechanism and muscle properties. In this paper, the model is based on multi-layer planar analytical model proposed in last few years by Farina which allows just the simulation of single fiber action potential (SFAP). We have generalized this model to get motor unit action potential (MUAP) which is the base of the simulated SEMG signal.**

Key word— Modeling, Surface electromyography, Motor unit action potential, Single Fiber Action Potential.

I. INTRODUCTION

MUSCLES consist of long cells named fibers. Fibers which are innervated by the same α-motoneuron via the peripheral nervous system constitute what we call motor unit (MU). The MU is the functional element of the muscular contraction. Depending on the required force, MUs are recruited in order to produce the needed force [1][2]. When the nervous impulse reaches the neuro-muscular junction (NMJ) of the fiber, an intra muscular action potential (IAP) is generated and propagates towards tendons junction with a conduction velocity (CV). The IAP represents a depolarization of the potential action of fiber which was polarized negatively at rest. This propagation of the IAP along the fiber creates a current flow around the fiber that can penetrate the fat and skin layers and reach the surface. Due to the conductivity of the medium around fibers (conductor volume), this electric activity can be detected at the surface using suitable electrodes [3]. The electric activity in the muscle medium is governed by the Poison's equation (presence of current) and by Laplace's equation when current is null, case of the fat and skin layers. The muscle medium is anisotropic because the conductivity in direction of fiber is bigger than the conductivity in the other directions, this anisotropy makes the Poison's equation difficult to solve. Dario et al [4][5] have presented an analytic solution for mentioned equations to find the action potential of single fiber at the surface (SFAP). This result of the action potential was considered as response of a linear and invariant time system (LITS) exited by the current accompanying the IAP. The IAP was mathematically modeled for the first time by Rosenfalk [6].The LITS is represented by the transfer function of the conductor volume in cascade with the transfer function of the detection system.

In this work, we will not repeat the mathematic method to get the SFAP as it describe in details in [4]; but we focus on how SEMG signal which is generated from many MUs can be obtained in case of isometric contraction . The mechanism of recruitment of MUs in relation with the contraction level, their firing rates and their number; will be the object of this work. Some results of SEMG signals will be presented and discussed.

II. SEMG GENERATION MODEL

Several SEMG models have been proposed for many purposes [7-10].The generation of the SEMG signals adopted in this work is based, on the one hand, on the modeling of the fiber action potential proposed by Farina et all [4] [5] and, on the other hand, on the structure of the muscle model adapted to the abductor pollicis muscle according to Disselhorst-Klug's work [11] in case of the MU morphology in which fibers overlap all muscle territory (model 2) and on the work of Stashuk [7] in which MU is considered as cylinder (model 1) . The model of the muscle is depicted in the figure 1. Most anatomical and physiological parameters have taken from literature (Table I).

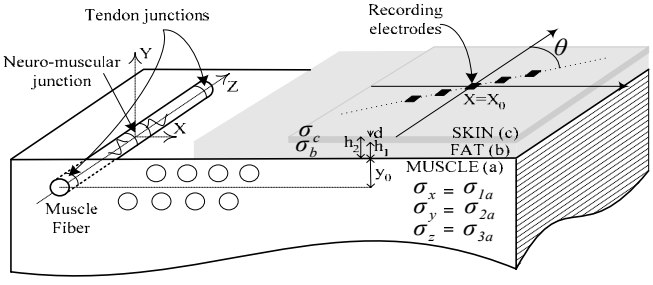

Fig.1. Planar multi layer model of muscle.

Fibers of each MU are parallel and can be distributed randomly (uniform probability density function) either in a cylinder (model 1) of radius RMU depending on the size of the MU or in all muscle territory i.e. one MU territory occupies most parts of the muscle (model 2).
In isomeric muscular contraction, such muscle produces the same force during a period of time. To maintain this force, recruited MUs have to be activated continuously via the α-motoneuron by train of impulses. The resulting action potential in this case is called the motor unit action potential train (MUAPTs). Each MU has a firing rate that depends on

the contraction level indicated by the percentage of the maximum voluntary contraction (MVC). Figure 2 represents six MAUPTs for six different MUs. MUs are different in many characteristics namely are:

- The size i.e. the number of fibers that constitute it. It is from 600 to 1000 fibers uniformly random distributed over the MUs.
- The conduction velocity. MUs have CV equals 3.5± 0.5 m/S, normally distributed.
- The radius which depends on the number of fibers to keep the density of fibers in muscle constant (232/mm^{-2}). This is in case of the cylindrical form of MU (model 1). In the other case i.e. fibers of a MU overlap all muscle territory (model 2); MUs differ from each other in occupied zone.
- The depth of MU in case of model 1and the position of fibers in the model 2.
- The position of innervations zone (zone contains the NMJ of different fibers) which is more a less in the middle of fibers, but change position from MU to another.
- The tendon limits. Fibers that constitute a MU have not the same length. Limits are uniformly distributed in a tendon zone which equals to 1 mm. but each MU has their proper limits.
- The firing rate which depends on the contraction level and on the size of the MU.

TABLE I
PARAMETERS VALUE USED IN SIMULATION

Description	Value
Number of MUs in muscle	29
The maximum depth of muscle (mm)	8
Length muscle (mm)	50
Density of fibers muscle (fibers mm$^{-2)}$	232
Number of fibers in MUs (fibers /MU)	800±200
Thickness of skin layer (mm)	0.5
Thickness of fat layer (mm)	1.5
Tendon zones widths of muscle (mm) *TRm=TLm*	2.5
Innervation zone width of muscle (mm) *Wim*	2.5
Innervation zone width of MUs (mm) *IZ*	0.5
Tendon zones widths of MU (mm)	1
Conductivity of muscle ($\Omega^{-1}m^{-1}$)	0.2574
Conductivity of fat ($\Omega^{-1}m^{-1}$)	0.045
Conductivity of skin ($\Omega^{-1}m^{-1}$)	0.01
Conduction velocity in single MU (ms^{-1})	3.5±0.5
Firing rate of MUs (Hz)	5-30
Standard deviation STF (%of firing rate)	10
Radius of circular electrode (mm)	0.25
Inter-electrode distance *IED* (mm)	2.5
Filter location center *Ze* (mm)	15
Sampling frequency (Hz)	4096

The detection at the surface is performed using spatial filters 2 D. There are many different spatial filters that allow getting selective signal in order to be easier for interpretation. The theoretical aspect of the spatial filters has been studied by Reucher [12][13]. Here is, in bellow, examples of spatial filters. Values are the linked weighs to electrodes.

$$M_{SD} = \begin{pmatrix} 1 \\ -1 \end{pmatrix} \qquad M_{DD} = \begin{pmatrix} 1 \\ -2 \\ 1 \end{pmatrix}$$

$$M_{NDD} = \begin{pmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{pmatrix} \qquad M_{IB^2} = \begin{pmatrix} 1 & 2 & 1 \\ 2 & -12 & 2 \\ 1 & 2 & 1 \end{pmatrix}$$

These are the masks of the single differential, the double differential (DD), the normal double differential (NDD) and, the *IB2* filters respectively.

The simulated SEMG signals represent isometric contractions for different contraction levels. These signals are the contribution of all recruited MUs which obey the Hennman principle [14-16].The principle states that recruitment of MUs within a muscle proceeds from small MUs to large ones. In other words, MUs are recruited in orderly sequence, from those that produce the smallest forces to those that exert the largest forces [17].

It is known that a force level is reached by the nervous system which adjusts two terms, the MUs number (MUN) that will be recruited and the modulation of their coding rate.

This mechanism of recruitment is very complicated and change from muscle to muscle [2]. From many studies, the firing rate of recruited MUs increases with increasing of force level [1][17]. Once a MU is recruited…smaller MUs discharge at a higher firing rate that large ones. According to the Kukulka's work [18], about the abductor pollicis muscle, table II has been proposed to indicate the relationship between the contraction levels and the recruited MUN with their corresponding firing rate range.

Our simulations are based on the general approach of the rate coding organization which indicates that the low-threshold MUs attain higher firing rates than later recruited MUs [15]. Once a MU has been recruited, its firing rate will increase with increasing force. The new recruited MUs take the lower firing rate as function of their corresponding size. For the third level, (15 %MVC) 16 MUs have to be recruited with a firing rate ranges from 5—12 Hz, the first recruited MU (the smallest one which was recruited at 5%MVC) fires at 12Hz and the last recruited MU fires at 5Hz. Sixteen firing rates are generated randomly (uniform law) from 5 to 12Hz and attributed to MUs as function of their size from the largest (last recruited) to the smallest one (early recruited). The firing rate of each MU has a standard derivation of 10% (STF) around its mean value with uniform law. All MUs (29 MUs) are recruited at 50%MVC.

TABLE II
RECRUITED MUS AND THEIR FIRING RATE AS FUNCTION OF CONTRACTION LEVEL.

MVC (%)	MUN	Firing rate (Hz)
5	8	5—8
10	12	5—10
15	16	5—12
20	18	5—15
25	22	5—17
30	25	5—20
35	26	5—25
40	27	5—28
45	28	5—29
50	29	5—30

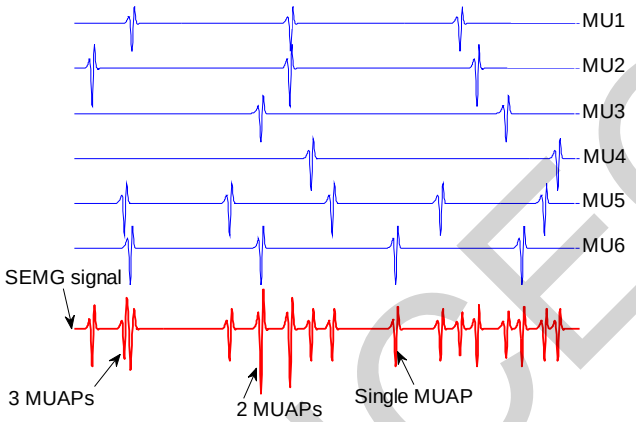

Fig.2. SEMG signal with its MUAPTs for six different MUs detected by the NDD detection filter.

III. RESULTS OF SIMULATION

The model is governed by several and different parameters, consequently; results can be also many and different. In this section, some results are presented to show the usefulness of the SEMG generation model. Figure 3 and 4 represent examples of SEMG signal detected by NDD filter in both configurations (model 1 and model 2). Three contraction levels have been adopted in these examples of simulation which are 10, 25 and 25% MVC. In front of each signal, the power density spectral (PSD) is depicted. As we can note from figures, the SEMG signal has low band frequency. The PSD is very similar to the PSD of real signals; furthermore, these PSDs are correlated like it was found by researcher concerning real signals. We note a small difference between the two PSDs in the two models. Indeed; the PSD in the model 2 is slightly larger than the PSD in the model 1. This is due the concentration of fibers in a cylinder (model 1) which make a crisp (narrow) MUAP in time domain that leads to a large PSD in frequency domain. The energy associated to SEMG signal is dependant of the contraction level. Signals have more energy when the contraction level is important. Signals in the model 1 have more energy than signals simulated in model 2. This is due to the distribution of fibers in both models; there are more fibers near to the surface in model 2 than those of the model 1.

The effect of the interelectrode distance (IED) of the detection filter on the morphology of the SEMG signal is shown in the figure 5. This morphology is investigated via some classical parameters which are:

- RMS root mean square.
- ARV average rectified value.
- MDF median frequency.
- MNF mean frequency.

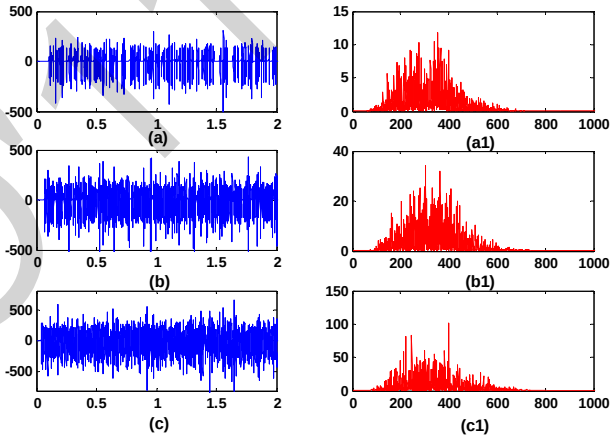

Fig.3. SEMG signals with corresponding PSD in case of fibers overlap all muscle territory (model 2). (a) an a1) SEMG with its PSD at 10% MVC. (b) and b1) SEMG with its PSD at 25% MVC. (c) and c1)SEMG signal with its PSD at 50% MVC.

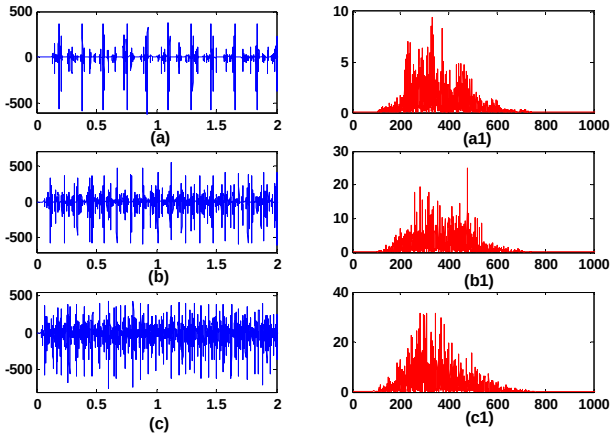

Fig.4. SEMG signals with corresponding PSD in case of cylindrical MU (model 1). (a) and (a1) SEMG with its PSD at 10% MVC. (b) and (b1) SEMG with its PSD at 25% MVC. (c) and (c1)SEMG signal with its PSD at 50% MVC.

From figure 5 (a), both ARV and RMS increase when the IED increase in both models. This result means that each time the IED increase, the conductor volume increase and more fibers are contributed to the detection at the surface. The figure 5 (b) indicates that the MDF and the MNF decrease when the IED increase. This is in both models and due to the widening of the MUAP when the conductor volume increases by increasing of the IED. Both results in figure 5 were confirmed by researchers of the domain.

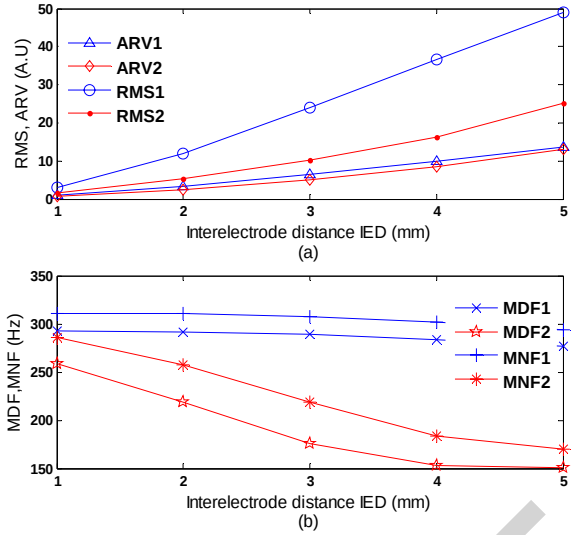

Fig.5. Behavior of indicated parameters of the DD detection SEMG signal as function of the interelectrode IED for both model 1 and model 2. (a) Average rectified value (ARV) and root mean square (RMS). (b) Median frequency (MDF) and mean frequency (MNF).

Our generation SEMG model permits us also to simulate a muscular or neural disorder (disease). In clinical applications, SEMG signal can be a good indicator about the state of a given muscle (healthy or ill). Figure 6 shows an example of simulation of a muscular disorder that many patients suffer from it. It is the Duchene disease that manifests by loss of muscle fibers due to biological anomaly. This result represents progressive loss of muscle fibers in different MUs. Signals are normalized to the maximum negative peak of the original signal (no loss of muscle fibers, 0% i.e. healthy subject). The reduced number of muscle fibers belonging to one MU decreases the amplitude of peaks. With progressive of the loss of muscle fibers, the single peaks become more and more difficult to recognize in the signal. Figure 7 represents the RMS of the different SEMG signals, already simulated, with respect to the percentage of loss muscle fibers. RMS decreases linearly with the increase of the loss of muscle fibers. The present result can be exploited by clinicians, so they may ask patient to exercise a force from a given muscle and compare its SEMG signal with of healthy muscle. Of course each muscle has their proper characteristics. Clinicians should also know these characteristics in order to identify such disorder.

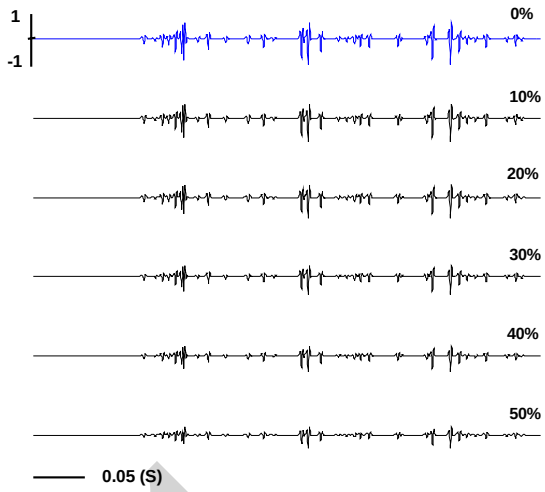

Fig.6. Normalized NDD detection SEMG signals to the max peak of the original signal (no loss muscle fibers i.e. 0%) as function of percentage of loss muscle fibers related to the maximum number of fibers of the original signal. Original signal is at 10% MVC contraction level (model 1).

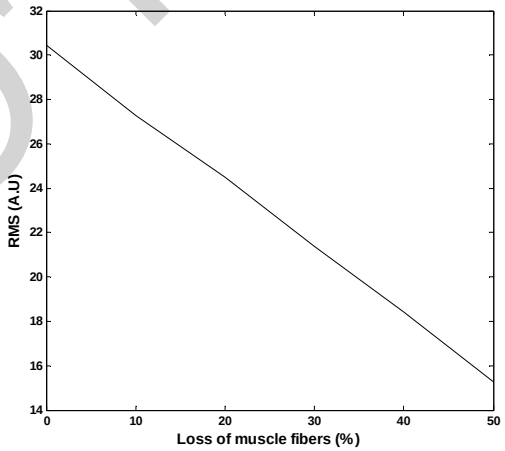

Fig.7. Root mean square RMS of SEMG signals (Fig. 6) as function of percentage of loss muscle fibers related to the number of fibers of signal without loss fibers.

IV. Conclusion

In this paper, a model to generate SEMG signal has been presented. The modeling taken in accounts most anatomical and physiological muscular parameters. Two configurations of MU morphology have been considered. The mechanism of recruitment of MU is also considered to generate voluntary isometric contraction. The SEMG signals are very similar to those found by many researchers. In this paper, some results concerning the behavior of the SEMG signal according to the detection filters, to the contraction levels, to the interelectrode distance and to the muscular disorder were presented. This modeling has precious utility and will permits us to study and investigate many aspect of the SEMG applications such as the

decomposition, the detection of the neuro-disorder muscular, the estimation of the force from SEMG signal, the control of prostheses and the discovery in biology and physiology discipline.

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