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COMPARISON OF FEATURES FOR SEMG BASED DETECTION OF HAND MOVEMENT INCEPTION USING A WEARABLE DEVICE

Astrid Rubiano, Jose Luis Ramirez and Robinson Jiménez Moreno
Faculty of Mechatronic Engineering and Industrial Engineering Nueva Granada Military University Bogotá, Colombia
E-Mail: astrid.rubiano@unimilitar.edu.co

ABSTRACT

In the present paper, we introduce a methodology for movement inception detection based on superficial Electromyography Signals (sEMG). Consequently, a mathematical model using feature extraction and feature flow is proposed, selected features are Mean Absolute Value (MAV), Root Mean Square (RMS), and Entropy (H). The first two are chosen due to the low computational cost, and the last one is chosen due to its outstanding behavior to recognize movements. Moreover, an experimental assessment is carried out using a wearable device so-called MyoArmband bracelet, during experiments three subjects execute grasp (close hand) and release (open hand) movements. Finally, experimental results show that entropy and entropy flow are suitable for detecting movement inception and for further classification of movement, and our methodology allows detecting movement inception in 245.9ms, out of laboratory conditions.

Keywords: movement Inception, feature extraction, electromyography signals, entropy.

INTRODUCTION

Several works in state of the art have been carried out aiming to detect or predict movement intention of patients. There is evidence that Electromyography Signals (EMG) plays a crucial role in the identification of movements. The previous statement arises from two facts: i) EMG signals are a measure of electrical activity produced by muscles during movement, and ii) these signals are composed by a superposition of individual muscle action potentials, generated by irregular discharges of active motor units in a muscle fiber, which contains information about movement intention.

Therefore, according to state of the art, analyzing and processing sEMG can lead to the estimation or prediction of body motion through the analysis of sEMG signals (Reaz *et al.*, 2006).

Mainly, sEMG signals produced by the forearm's muscles are suitable to recognize hand motions. State of the art presents several studies aiming at the recognition of movements, analyzing the following gestures: 1) keeping the hand straight (Oskoei & Hu, 2008), 2) tip, 3) hook, 4) lateral, 5) point, and 6) spherical (Wang 14 et al., 2013).

Regarding open hand movement authors are mainly studied EMG signals from extensor digitorum muscle (Chu *et al.*, 2007; Kaufmann *et al.*, 2010; Phinyomark*et al.*, 2013a, 2014), Flexor Carpi Ulnaris (Chu *et al.*, 2007; Kaufmann *et al.*, 2010; Phinyomark *et al.*, 2013a) and Flexor Carpi Radialis (Kaufmann *et al.*, 2010; Phinyomark *et al.*, 2013a, 2014). Concerning signal treatment, there are many methodologies to process sEMG signals with the aim of movement recognition, the most commonly used methodologies follow three steps: 1) filtering signals, 2) extracting features from signals, and 3) classifying in feature space to recognize movements. However, much uncertainty still exists about the choice of a methodology to work out the relationship between movement and sEMG signals. One of the main drawbacks is the lack of a method for movement inception identification, which represents the starting time of movement, and is essential for movement recognition using only sEMG signals, avoiding the employ of motion tracking systems.

Implementation of movement recognition based only on sEMG signals, dodging the employ of motion tracking systems, can lead to the development of human-machine interfaces, suitable to work out of laboratory conditions. Consequently, finding a methodology to detect movement inception is a crucial milestone in recognition of movements. Therefore, we introduce an innovative method, allowing the accurate detection of movement inceptions. The method is based on the variation rate analysis of features and considers the most used features in the field of sEMG based movement recognition.

The overall structure of the study takes the form of three chapters, including: 1) Detection of movement inception: presenting the mathematical model of features that are used in the study, the feature flow calculation, and movement inception detection. 2) Experimental assessment of the method: presenting the experimental set-up, the used wearable device Myo Armband™, and the data capture technique. 3) Experimental Results: presenting the result of the analysis carried out with experimental data. Finally, a conclusion is presented, reviewing the primary outcomes of the work, and highlighting the advantages of the entropy-based analysis of movement.

DETECTION OF MOVEMENT INCEPTION

As mentioned before, relevant information about body movements is embedded into sEMG signals (Arief 40 *et al.*, 2015; Oskoei & Hu, 2008), for this reason, movement intention could be obtained from sEMG extracting features. A feature is a scalar value extracted from the EMG signal in time or frequency domains that contains relevant information that could be linked with motion. Thus, features are suitable to identify the produced movements, as a function of the measured electrical activity (Rubiano *et al.*, 2015a, b). Table-1

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summarizes typically used features for sEMG based movement recognition

Table-1. Most used features in recognition of movements.

Feature	Abbr.	Reference
Mean Absolute Value	MAV	(Alkan & G¨unay, 2012; Chu *et al.*, 2007; Oskoei & Hu, 2008; Tenore *et al.*, 2009)
Willison Amplitud	WAMP	(Oskoei & Hu, 2008; Phinyomark *et al.*, 2014; Tenore*et al.*, 2009)
Variance	VAR	
Autoregresive Coefficients	AR2 or AR6	(Al-Timemy *et al.*, 2013; Oskoei & Hu, 2008; Zecca *et al.*, 2002)
Root Mean Square	RMS	(Oskoei & Hu, 2008; Phinyomark *et al.*, 2014)
Waveform Length	WL	(Oskoei&Hu, 2008; Tenore *et al.*, 2009)
Zero Crossing	ZC	(Oskoei & Hu, 2008; Phinyomark*et al.*, 2013b)
Slope Sign Changes	SSC	
Independent Component Analysis	I CA	(Naik *et al.*, 2009, 2010; Tenore *et al.*, 2009)
Fractal Dimension	FD	(Naik *et al.*, 2009; Tenore*et al.*, 2009)
Power Spectrum Dimension	PSD	(Oskoei& Hu, 2008)
Frequency MeaN	FMN	
Frequency Median Dimension	FMD	
Principal Component Analisys	PCA	(Castellini*et al.*, 2009)
Normalized Difference variance value	NDAMV	(Kim *et al.*, 2011)
Sample Entropy	SampEn	(Phinyomark*et al.*, 2013a)
Wavelet packet transform	WAVET	(Chu *et al.*, 2007)
Difference Mean Absolute Value	DMAV	(Phinyomark *et al.*, 2014)
Difference Variance Value	DVARV	
Difference Absolute Standard Deviation Value	DASDV	
Myopulse Percentage Range	MYOP	

As presented by Micera *et al*. (2010), a critical criterion for choosing a feature is the computational cost that is why in several studies features as Mean Absolute value (MAV) or Root Mean Square (RMS) are used. Nevertheless, as presented by Rubiano (2016), entropy H has shown an outstanding behavior to recognize movements, and consequently to detect movement inception. Therefore, in this paper, we experimentally assess the three features, aiming to validate the efficacy of the method for movement inception detection. Subsequently, mathematical models for extracting selected features is presented.

A. Mathematical model of selected features

First, it is necessary to consider that for feature extraction, each sample of sEMG signal results from the combination of a finite number of Motor Units Action Potentials (MUAPTs) ui(k). Thus, the samples are directly related to muscular activity and movements. In vectorial notation, a sEMG signal obtained from the ith electrode of a group of sensors, with a total number of samples W, is defines as: $s_i = \{s_{1,i} \ldots s_{w,i}\}^T$.

a) Mean Absolute value MAV: The mathematical model of MAV is described in equation (1) [13], where $s_{k,i}$ represents the *k-th* sample of the *i-th* sEMG signal, and W is the number of samples in segment.

$$MAV(s_i) = \frac{1}{W}\sum_{k=1}^{W}|s_{k,i}| \quad (1)$$

b) Root Mean Square RMS: The mathematical model of RMS is described in equation (2) (Phinyomark *et al.*, 2013c), where $s_{k,i}$ represents the *k-th* sample of the *k-ths* EMG signal, and W is the number of samples in segment.

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$$RMS(s_i) = \sqrt{\frac{1}{W}\sum_{k=1}^{W} s^2{}_{k,i}} \quad (3)$$

c) Entropy H: The procedure is based on the analysis of a quantity H that measures at what rate the information, embedded in a sEMG signal, is produced during a movement (Rubiano, 2016). Likewise, sEMG signals' samples are mapped into a set of finite events, whose probabilities of occurrence $P_l$arep_1, $p_2, \dots, p_{Ni}$, being $N_I$the numberoffinite events. Consequently, the quantity H is calculated examining the signal samples in a segment of the signal. Furthermore, to measure how much information is produced, the quantity H is required to be: 1) continuous in the *pl*, 2) a monotonic increasing function over the number of samples if all *pl* values are equal to 1/*Ni*, and 3) the weighted sum of the individual values of H if a choice is broken down into two successive choices. The only H quantity satisfying the above assumptions is of the form:

$$H = \sum_{L=1}^{N_I} p_l log p_l \quad (4)$$

The form of H is recognized as entropy which is defined in formulations of statistical mechanics, in Boltzmann's H–theorem and in the Shannon's entropy from information theory *(Cover & Thomas, 2006)*. Consequently, for a group sEMG signals $s_i$si, the entropy will be written as H(si); thus $\boldsymbol{s_i}$ is not an argument of a function but a label for a number, to differentiate H(s1) (first signal of the group) from H(s2) (second signal of the group). The entropy has several interesting properties and two of them characterize its maximum and minimum values: 1) H is zero if and only if one of all probabilities of occurrence pl is almost equal to zero and 2) for a given number of events Ni, entropy is a maximum H = log(Ni), when all pl = 1/Ni. The last property represents the most uncertain situation. In our case, since we use binary digits the selected base is 2. As a result, the entropy for an sEMG signal fragment s with W samples is given by:

$$H(S_I) = \sum_{L)1}^{N_I} P_L log_2 p_l \quad (5)$$

The probabilities of occurrence p_1, p_2,…, p_{Ni} is estimated based on the absolute occurrence frequency f_l normalized by the total of events as:

$$p_l = \frac{f_l}{N_i}, \text{for } l = 1,2, \dots, N_i \quad (6)$$

Classically, absolute occurrence frequencies fl are described as the amount of favorable outcomes over the number of all possible outcomes. In that case, we consider favorable outcomes as the number of signal samples belonging to one discrete event l, and the number of all possible outcomes as the total number of discrete events Ni. Taking into account that sEMG signal is acquired using the MyoArmband bracelet, which is provided by an 8-bit (1-byte) analog to digital converter, it is reasonable to set the total number of discrete intervals Ni to 256. Likewise, to evaluate if a sample belongs to a particular discrete interval l, the following membership function is introduced:

$$\epsilon(s_k, l) = \begin{cases} 1 \text{ if} \frac{l-1.5}{N_i-1} \leq s_{k,i} < \frac{l-0.5}{N_i-1} \\ 0 \end{cases} \quad (7)$$

where $s_{k,i}$ is the *k*th sample of the sEMG signal captured from the *i*th electrode. Thereupon, absolute occurrence frequencies f_l, for a sEMG signal with W samples, are calculated as:

$$f_l = \sum_{k=1}^{W} \epsilon(s_{k,i}.l), \text{forl})1,2, \dots, N_i \quad (8)$$

d) Feature flow and movement inception considering that features are scalar values representing embedded information in sEMG signals, we analyze it to identify or predict movement inception. These variations are extracted through the calculation of the feature flow, e.g. for a feature $\boldsymbol{F}$(a feature $F(si) = \{F1, i \dots FW, i\}^T$ is the result of the application of equations (2), (3), or (5) to the *i*-thsEMG signal of the group, and can be considered as a data series containing feature behavior over the time)we calculate$\dot{F}(s_i)$, which corresponds to the first derivative with respect to the time of the feature.

In consideration of the discrete nature of the sEMG signals, an thus the features, we consider to use a numerical approximation of the derivative, thus we adopt the following discrete-time differential operator *D*.

$$D = \frac{\delta}{(\mu\delta T+1)} \quad (9)$$

Where $\delta/(\mu\delta T + 1)$, z is the usual shift-operator, and T is the sampling period.

The parameter μ is any real number, and it is usually chosen between three options: i.) μ = 0 if the derivative is on future and current values using forward difference, ii.) μ = 1/2 if the derivative is computed in a middle point between two samples and is operated using future or past values merged with the current measures. The method is typically known as Tustin or bilinear transform, and iii.) μ = 1 if the derivative is on the past and present values using backward difference.

In the present study, the parameter μ is set to 1, assuring that the derivative is causal (*i.e* it is calculated based on the past and current values, and not on future values of entropy).

Consequently, the discrete time differential operator is rewritten as $D = (1 - z^{-1})/T$. In time series analysis, application of the shift operator z leads the *k*th sample of a time series to produce the following $(k + 1)$th element. When the shift operator is raised to negative power, e.gz^{-1}, it lags the *k*-th sample of a time series to produce the previous $(k - 1)$th element. Therefore, when the D operator is applied to a discrete feature DF(s_i), the numerator$(1 - z^{-1})F_{k,i}$ becomes $F_{k,i} - F_{k-1,i}$. As a result,

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the first derivative of the feature $\mathbf{F}(s_i)$ can be written as follows:

$$\dot{\boldsymbol{F}}(S_i) = \frac{F_{k,i} - F_{k-1,i}}{T} \quad (10)$$

Finally, if the Feature **F** shows fluctuations, as a result of the produced movement, analyzing critical shifts in the behavior of the feature flow $\dot{F}$, we can accurately obtain the movement inception. In the following chapters, the experimental assessment approach used to validate our methodology, for detection movement inception, is presented.

EXPERIMENTAL ASSESSMENT OF THE METHOD

One of the main obstacles in the classification or recognition of human movements, out of laboratory conditions, is related to the uncertainty of the movement occurrence time. To solve this problem, we have introduced a methodology based on the analysis of the features flow, which allows detecting the movement inception. Thus, in the following, we present an experiment that aims to verify the performance of the proposed methods in the classification of two grasping patterns, that are grasp (close hand) and release(open hand).

Experimental setup

The proposed methodology is tested using MyoArmband bracelet, and the experiment is carried out using a software developed in C++. In the beginning, the software gets connected to the MyoArmband; then it captures sEMG signals form eight electrodes of the MyoArmband™. Finally, sEMG signals are stored for post-processing using MATLAB.

In this study, we consider three healthy subjects that execute grasp (close hand) and release (open hand); each subject executes three trials of grasp and three trials of release. For each movement, we measured sEMG signals of muscles in contact with the MyoArmband bracelet. It is important to note that each subject is informed about the way the bracelet should be wearing, and subjects place the bracelet in the forearm by themselves.

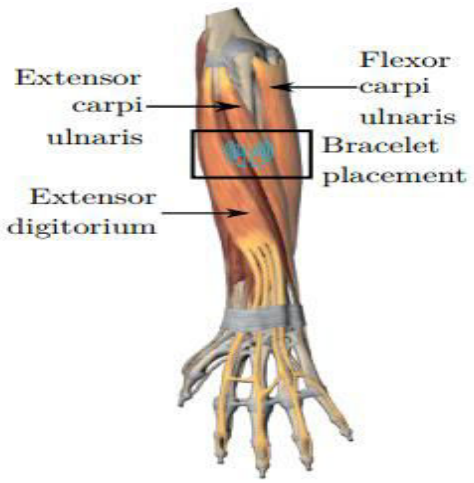
A. Wearable device

In this study, we consider three healthy subjects that execute flexion and extension movements, the first, second and third subject execute one, four and six trials, respectively. For each movement of flexion and extension, we measured EMG signals of the triceps and the biceps (due to their high electrical activity during these movements [7]) and tracked the upper limb motion.

Human interface devices are proposed with the aim of having an interpreter between human and machines in real-time. Thus, wearable human interface is a device which is attached to the user as a piece of clothing *(e.g.* smart watches, jewelry and intelligent eyewear). Those devices have multiple applications, for instance, blind persons assistance (Tapu *et al.*, 2014), ambulation, transportation, exercise, fitnessand military activities (Lara & Labrador, 2013). Measuring several attributes such as motion, location, temperature and vital signals. Similarly, new innovative devices have been developed not only for measuring the patterns but also for identifying motion and more specifically gestures, considering gestures as a non-verbal communication(Pomboza-Junez & A. Holgado-Terriza, 2015).

For the present research work, we use the Myo Armband bracelet, which is a wearable device for gesture recognition. It comprises a set of eight sEMG sensors and one inertial measurement units' sensors that are composed by: i.) a three axis gyroscope ii.) a three-axis accelerometer and iii.) a three-axis magnetometer. Inertial measurement units are used to sense motion in all directions, obtaining the reference position using Euler angles and Quaternions formulation. Data from sEMG sensors and movements are transmited through a bluetooth connection. Furthermore, it is equipped with a low consumption ARM Cortex-M4 microprocessor. The MyoArmband electrodes are labeled with IDs from 1 to 8 and are disposed as shown in Figure-1.

Figure-1. sEMG sensors of Wearable device MyoArmband™ and muscles closer to the sensors.



(a) Frontal muscles.

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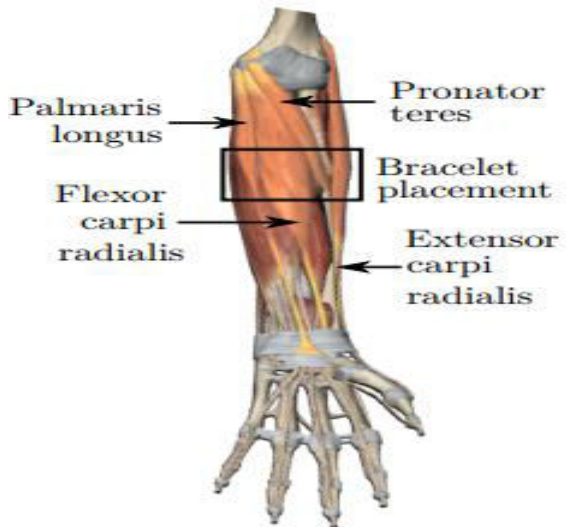

(b) Posterior muscles.

Figure-2. Muscles closer to the MyoArmband sensors.

Once a subject is wearing the bracelet, sEMG sensor is located radially around a circumference of the forearm. The fourth electrode (CH4) is identified with a blue marker, and is placed in lower forearm followed by third electrode (CH3) in clockwise direction and fifth electrode (CH5) in counter clockwise direction. The sampling frequency is 200Hz.

According to the placement of the bracelet, different muscles can be measured. Thalmic Labs suggest sliding bracelet into the forearm until it is just below the elbow. Following this instruction, the muscles closer to the sensors are those presented in Figure-2.

B. Software for data capture and store

The software, developed for the experiment, is composed of: 1. a connection with bracelet via Bluetooth, 2. a graphic interface to display the hand gesture, and 3. a principal cycle that iterates every 5 ms. In the beginning, the software gets connected to MyoArmband, display the first gesture, and initializes with zero all parameters. Once the cycle is active, the sEMG signals acquisition is started, each received sample produces an increment of discrete-time stamp k.

EXPERIMENTAL RESULTS

As discussed before, the experiment is carried out by three healthy subjects that execute grasp (close150 hand) and release (open hand). As a result, we built a set of sEMG signals, corresponding to the executed 151 movements. It is important to highlight that for each movement eight signals are stored (one signal per 152 electrode of the MyoArmband). Figure-3 exemplary shows stored sEMG signals of subject 1, for three 153 trials of grasp and release.

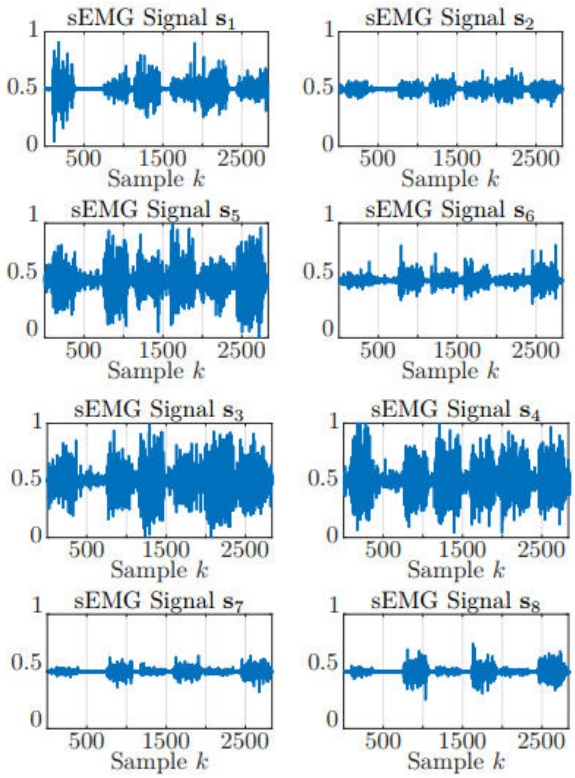

Figure-3. sEMG signals of subject 1.

Furthermore, features are extracted from sEMG signals, applying equations (2) to (5). As a result, a time data series is obtained for each feature, i.e., one data series for entropy, one for MAV, and one for RMS. Consequently, Figures 4 to 5b show: 1. behavior of features with respect to the time, on the top side, and 2. feature flow, on the bottom side. It is important to note that vertical bands labeled with letter Rmatch occurrence time of release movements, and vertical bands labeled with letter G match occurrence time of grasp movements.

According to the obtained experimental results of (entropy and entropy flow), after a lag time tl, positive peaks of $\dot{H}(s_i)$ match movement inception, considering all trials of grasp and release movements. Likewise, negative peaks match movement termination. Figure-4 exemplary shows entropy flow peaks rising after movement inception, and falling during movement termination.

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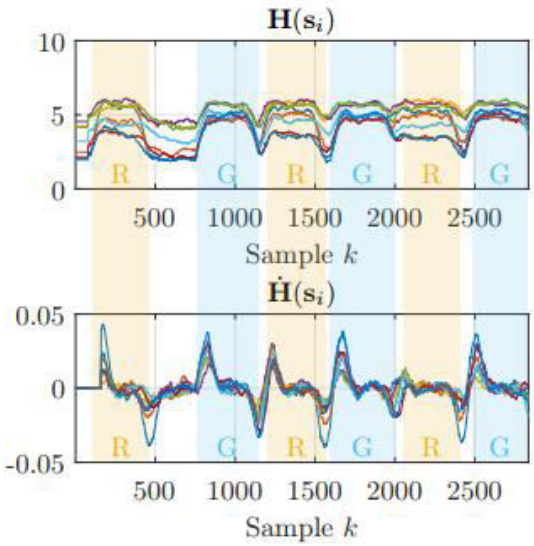
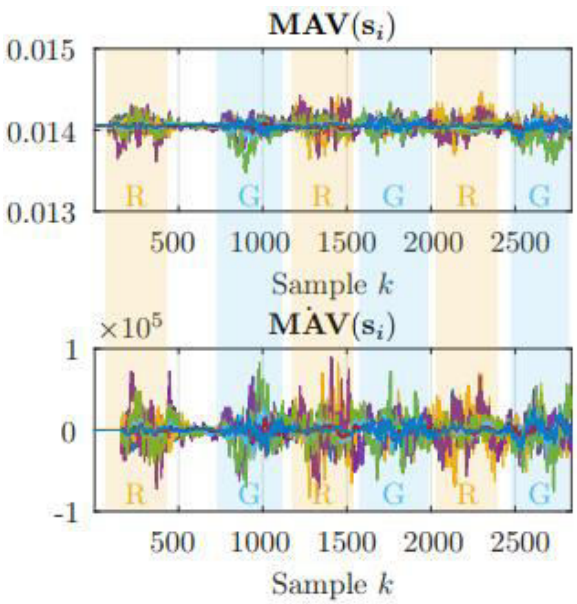


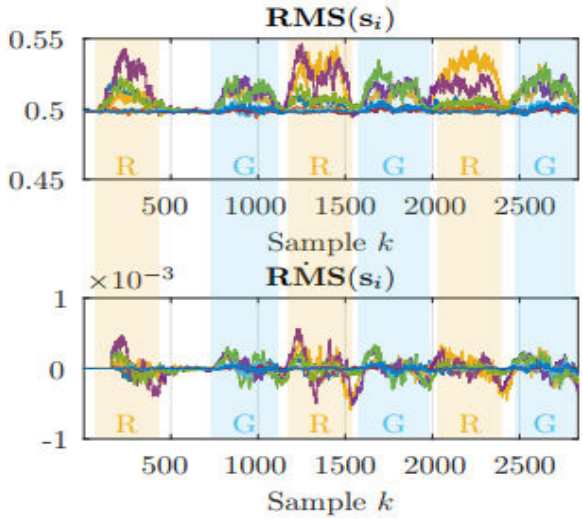
Figure-4. Entropy behavior and Entropy flow.

On the other hand, analyzing experimental data is right to infer that there is not an apparent relationship between movement inception and flow of MAV and RMS. Figure-5a exemplary show the behavior of MAV feature $\mathrm{MAV}(s_i)$ and MAV flow$\dot{MAV}_I(s_i)$. Likewise, Figure-5b exemplary show the behavior of RMS feature $\mathrm{RMS}(s_i)$and RMS flow $\dot{\mathrm{RMS}}_I(s_i)$.

Consequently, concerning MAV flows$\dot{MAV}_I(s_i)$. and RMS flow$\dot{\mathrm{RMS}}_I(s_i)$, no pattern or property could be used to detect movement inception. Therefore, even the lag of time, entropy $H(s_i)$ (and entropy flow$\dot{\mathrm{H}}_i(s_i)$) is the only suitable feature for detecting movement inception, which is useful for further classification of movement, out of laboratory conditions.



(a) MAV behavior and MAV flow



(b) RMS behavior and RMS flow.

Figure-5. Behavior and flow of MAV and RMS features.

Regarding the lag time $t_l$of the entropy flow's positive peak, it can be considered as: 1. the rising timerequired for the entropy to achieve its steady state value from a stable reference or 2. The time required to identify the presence of a movement inception. In both cases, this lag will have a considerable influence for further classification of movements. The value of $t_l$is measured directly from the experimental data as:

$$t_l = t_{pa} - t_{sa} \tag{11}$$

where $t_{pa}$is the peak occurrence time and $t_{sa}$is the sEMG signal activation start.

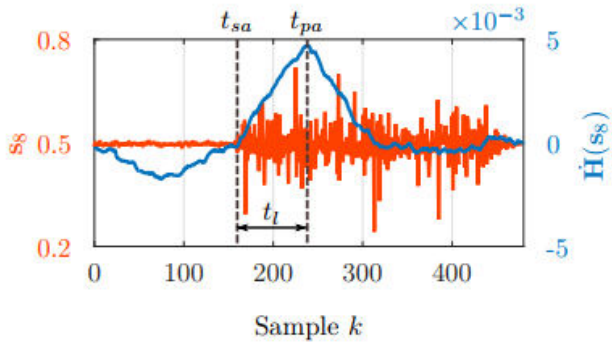


Figure-6. MAV behavior and MAV flow.

Figure-6 shows the measures of $t_{sa}$and t_{pa}based on the 8th sEMG signal of subject 1 during trial 1. Thereafter, $t_l$is measured for the ten trials (five for grasp and five for release) performed for each subject applying equation (11). Taking into account that the lag, t_l depends on several phenomena (e.g. during a specific movement, the dominant muscle has less slack than the auxiliary ones, as explained by Rubiano (2016)), the lag is measured over all signals captured from different muscles.

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The lag obtained from the different muscles are averaged to obtain three quantities per subject: 1. The mean value during grasp trials, 2. the mean value during release trials, and 3. the overall mean value considering grasp and release trials. As a result, the global mean value of lag is, t_l= 91.58 with a standard deviation of σ = 19.792. The mean value during grasp trial is, t_l = 87.941 with a standard deviation of181 σ = 16.042. The mean value during release trials is, t_l= 91.589 with a standard deviation of σ = 17.65. Allvalues are measured in number of samples. Considering that the sampling frequency of the MyoArmband™ is 200Hz, the maximal lag time obtained from the different muscles and trials is, t_l = 457 with a standard deviation of 98ms. According to the results, introduced by Rubiano (2016), an sEMG signal rise 212ms before the movement inception. Therefore, we can consider that our methodology allows detecting movement inception in 245.9ms, out of laboratory conditions.

CONCLUSIONS

In this paper, we have presented a new method for movement inception detection, which is based on: 1. the utilization of a wearable device, so-called MyoArmband, for capturing sEMG signals, 2. the analysis of entropy measured over sEMG signals produced during movement, 3. the analysis of entropy flow, 4. and finally the detection of movement inception. The method is tested using two more features, mean absolute value (MAV) and root mean square (RMS). Those features are chosen due to their low computational cost. Nevertheless, analyzing experimental data is right to infer that there is not an apparent relationship between movement inception and flow of MAV and RMS. Finally, the proposed methodology is tested through an experiment in which three subjects have participated. As a result, our methodology allows detecting movement inception with a delay of 245.9ms, out of laboratory conditions.

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