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Case Study: Influence of Muscle Fatigue and Perspiration on the Recognition of the EMG Signal

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Abstract: EMG data processing and muscle activity recognition has become the most popular method for upper limb prosthetics. The high sensitivity of EMG sensors with respect to external disturbances and other factors prevent from accurate muscle activity recognition. The aim of the paper is to investigate robustness of window recognition method with respect to muscle fatigue and perspiration of the forearm skin. The current experiment was carried out using Arduino nano microcontroller connected to EMG sensors. The subject under study is a healthy man of 26 years old with an average build. The subject was asked to do physical exercises, thereby loading the muscles of the fingers of the hand to achieve partial or complete fatigue and perspiration. During the whole process, EMG sensors have installed on the subject and transmitted the signal to the computer using Arduino. All signal processing is done directly on the computer with a pre-recorded signal. Experimental results have been shown that with the appearance of external factors during prosthesis operation recognition accuracy may degrade to unsatisfactory. False positives occur with perspiration of skin surface and complete muscle fatigue. An algorithm for automatic self-correction of the boundaries of motion detection zones has been introduced. Instead of identification of causes that leads to performance degradation, we use correction scheduling started by timer. Experimental results have shown that proposed automatic adaptive correction is effective. Despite higher recognition delay, proposed auto-tuning method provides satisfactory muscle activity identification and feature extraction in real-time.

Keywords: sensors, electromyogram, myoelectric control, prosthetics, pattern recognition

1. INTRODUCTION

In recent decades, and especially in recent years, much effort has been made to implement efficient control algorithms based on processing of electromyographic (EMG) signals [1]. EMG signals provide easy and non-invasive access to the physiological processes that cause muscle contraction. That is why EMG technique is extensively used in control of upper limb prostheses. Since the first attempts in the late 1940s [2], several EMG-based algorithms have been developed to improve the functionality and ease of use of hand prostheses [3]. Currently, EMG signal processing is the most common approach used to manipulate prosthetic hands. Limitations in prosthetic mechanics and EMG data processing are currently the main restriction to the development and implementation of a complete bioelectric prosthesis [4–7]. Moreover, when it comes to recognizing myoelectric patterns, the big problem is that statistical properties of EMG signal change over time. This leads to the fact that control systems become unstable or difficult to use after a certain period of time [8].

In practice, it is very important to maximize EMG data efficiency. To do this, it is necessary to assess the condition of the end user of the prosthesis, observing the condition of

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the skin, tissues, skeletal anatomy, muscle strength and activity, as well as the range of motion. Also, an important factor is monitoring the shape, amplitude, frequency of the signal. Only after a complete study of the user it is possible design the system for correct receiving and recognizing of EMG signal [9].

The high sensitivity of EMG sensors with respect to external disturbances and other factors prevent from accurate muscle activity recognition. Such factors are investigated in [5]. Among them:

1. Muscle fatigue during work [10, 11].
2. Perspiration of the skin.
3. Displacement of sensitive elements [12–14].
4. Physiological characteristics of a person [15, 16].

Factors such as muscle fatigue and perspiration can lead to incorrect muscle activity recognition and feature extraction. The researchers argue that the accumulation of sweat under the sensor leads to a decrease in amplitude and filtering of high frequency components [17–20]. However, little is known about the amount of sweat above which a number of problems can arise. Many authors also study the effect of muscle fatigue on recognition. [21] argue that with muscle fatigue, both the amplitude and frequency of the EMG signal change. It was found that muscle fatigue is usually quantified as a decrease in maximum muscle strength or power, resulting in different recordings of signals from EMG electrodes over time [22]. Various traits were examined to assess muscle fatigue, such as the wavelet transform [23, 24], the number of zero crossings [25], and autoregressive coefficients [26]. It is important to note that muscle fatigue identification commonly is carried out in frequency domain. This is cased by EMG spectrum shift towards lower frequencies [5].

In this paper, we investigate influence of muscle fatigue and perspiration at feature selection accuracy performed by window method developed and presented in [27]. Additionally, fail-safe correction to prevent false recognition is introduced. In the proposed method fatigue or perspiration identification technique is not used. This is caused by low computational requirements and real-time implementation of the algorithm. Instead of identification of causes that leads to performance degradation, we use correction scheduling started by timer. The rest of the paper is organized as follows. Sect. 2 describes experimental details and some necessary information on hardware and software equipment. Sect. 3 presents main result of the paper. Some conclusive remarks and future works are emphasized in Sect. 4.

2. PRELIMINARIES

2.1. Hardware Description

The current experiment was carried out using Arduino nano microcontroller connected to EMG sensors. Arduino nano was selected due to its low cost and low power consumptions. The microcontroller itself is connected to the computer. All signal processing is done directly on the computer with a pre-recorded signal. Matlab software is used for processing and analysis received data.

To read the muscle activity we use EMG sensors from DF Robotics. These sensors combine the filter circuit and the amplifier circuit. EMG sensor amplifies the minimum electron diffraction signal within 1.5 mV by a factor of 1000 and suppress noise (especially frequency interference) using a differential input and an analog filter. The output signal is analog, which takes 1.5 V as the reference voltage. Output voltage range 0–3 V. The signal level depends on the intensity of muscle activity. The output signal indicates muscle activity and contributes to the analysis and study of the EMG signal.

For laboratory experiment, sensor surface has been cleaned and degreased at each sensor. After that, 5 electrodes are placed on the upper and lower parts of the forearm in the correct order. Most of the electrodes were located near the forearm (see Fig. 2.1), since the flexors

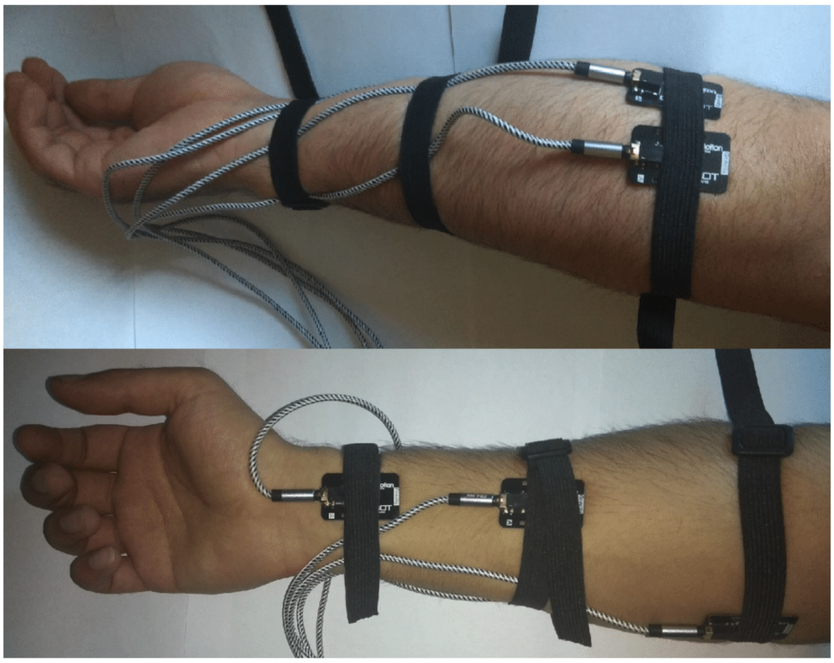

Fig. 2.1. Location of EMG sensors.

and extensors of all fingers except the thumb are mainly located in this area. These muscles are oriented mainly parallel to the axis between the elbow and the wrist. Unlike wearable band or sleeve such kind of electrode location provides better EMG signal recording.

2.2. Software Tools

Before evaluating the influence of various factors on recognition, it is worth to briefly explain an EMG signal recognition window method software. This algorithm is given and described in [27]. We try to recognize finger movements as close to its physiological behavior as possible. To this end we selected three levels of finger states. They are defined as follows:

$$\mathrm{G} = \begin{cases} 1, & \text{the muscle is relaxed,} \\ 2, & \text{the muscle is in half tense,} \\ 3, & \text{the muscle is in full tense.} \end{cases}$$

In last expression, value $\mathrm{G} = 1$ corresponds to straightened finger while values $\mathrm{G} = 2$ and $\mathrm{G} = 3$ correspond to half and fully bent finger respectively.

Briefly, this algorithm can be summarized as follows:

1. Preparation of the sensor and signal reading.
2. Signal preprocessing and normalization. Preprocessing consists of sliding MAV calculation within the window of length N. Here N is chosen experimentally to provide satisfactory accuracy. Normalized signal is calculated as absolute difference between sliding MAV and current measurement.
3. Boundary values a_i and b_i identification.
4. Depending on the area in which the processed signal is located, a decision is made on the value of G as:

$$\mathrm{G}(X_{max}) = \begin{cases} 1 & \text{if } a_1 < X_{max} \leq b_1, \\ 2 & \text{if } a_2 < X_{max} \leq b_2, \\ 3 & \text{if } a_3 < X_{max} \leq b_3, \end{cases} \tag{2.1}$$

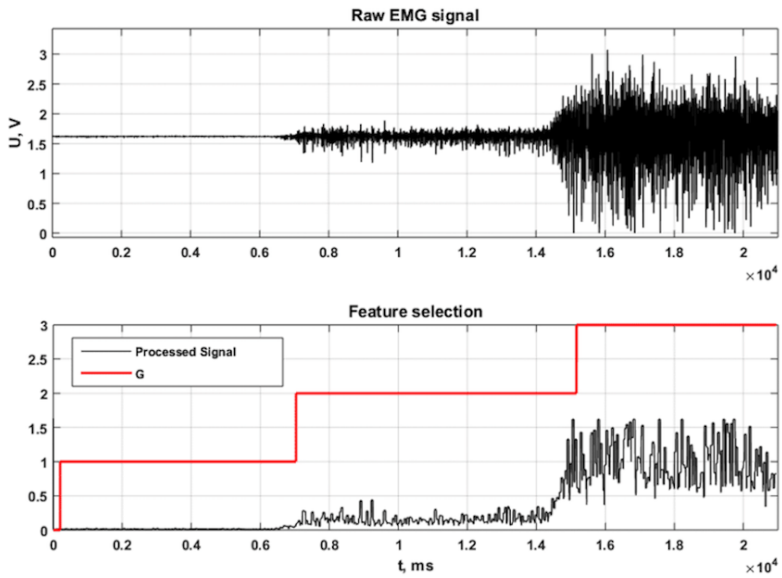

Fig. 2.2. EMG data processing: a.) Raw signal. b.) Results of muscle activity recognition using window method.

where X_{max} is a maximum value of normalized signal at the window of length N counts.

The result of muscle activity recognition using window method is depicted in figure 2.2.

Window algorithm has been tested for quality and correct operation under normal conditions. Also, the window method was compared with artificial neural networks, which made it possible to conclude about benefits of this method [27].

2.3. Methods

Identification algorithm, described in [27], was tested at 28 healthy people both males and females from 20 to 55 years old. Identification error for both hands is depicted in Figure 2.3. Analyzing the data obtained during the experiment, it was found that there are no substantial differences in identification depending on age. Female muscle activity is defined a little bit better than male. In view of this, it was decided to select a healthy man of 26 years old with an average build for further experiments.

The subject was asked to do physical exercises, thereby loading the muscles of the fingers of the hand. During the whole process, EMG sensors have installed on the subject and transmitted the signal to the computer using Arduino. We note that EMG sensor data for different sensors have the same waveform. So, the further investigation and illustrations are carried out at one selected sensor dataset. The subject, due to physical exertion, led the muscles of the finger to partial fatigue. After that, a signal was recorded with three types of finger states. When the subject led to complete fatigue signal values for three types of finger states was also recorded. After that these signals were analyzed. Another experiment was to test the effect of perspiration on the EMG signal. For this, the subject was placed in a special room with a high temperature where he also performed physical exercises. After that EMG data recording was carried out similar to previous experiment. All the results of these experiments are discussed below.

3. MAIN RESULT

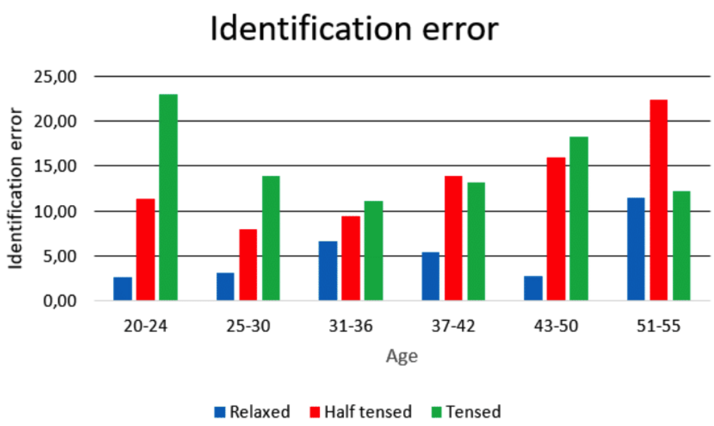

Fig. 2.3. Identification error statistics.

3.1. *Muscle fatigue*

The term muscle fatigue is used to describe a temporary decrease in one's physical capacity of performing motions. Several researchers investigate the impact of muscle fatigue using time domain or frequency domain characteristics of EMG signal such that maximum amplitude or power spectrum density [23]. Many efforts have been made to identify the level of fatigue. In order to mitigate for the effects of fatigue research focuses on collecting data from multiple levels of fatigue and utilizes the abundance of information. This requires recording more data than a simple classification case and creates different computational requirements to the system. Window method described in previous section also may suffer from muscle fatigue. Further we investigate effect of muscle fatigue on feature extraction by window method.

In this experiment, the subject performed physical exercises with chest expander to load the muscles with work until muscle would be tired. Experiment is stopped when muscle has reached a complete fatigue. During all of the process, EMG recording was carried out. We are interested in states of partially tired and completely tired muscles. EMG pattern of all three finger positions is depicted in figure 3.4.

Figure 3.5 shows the raw EMG signal on an enlarged scale. One can see the difference between two states, namely untired hand and completely tired one. Both signals indicate relaxed muscles. It is noticeable that noises appear in the channel with accumulation of fatigue. However, it can also be concluded that noises are not significant and can be neglected. The root mean square (RMS) value is also not much different. RMS for ideal conditions is equal 1.53 while partially tired and tired muscles gives RMS value equal to 1.51 and 1.53 respectively. The number of crossings of the mean square value is also the same. However, the number of changes in the sign of the function and its amplitude are significantly different due to the appearance of noise.

We should note that the best recognition accuracy is reached only when muscle is untired. Partially tired muscles also provides satisfactory recognition. However, activity of tired muscle cannot be recognized correctly. In figure 3.9 one can see that half tensed muscle recognized with incorrectly almost in 50% cases.

3.2. *Perspiration*

Now let's check how the system will behave if, during operation, the subject in the places where the sensing element is placed is wet due to perspiration. For this, EMG data were collected from the subject, after which he performed a series of physical exercises for perspiration. The measurement result can be seen in figure 3.7.

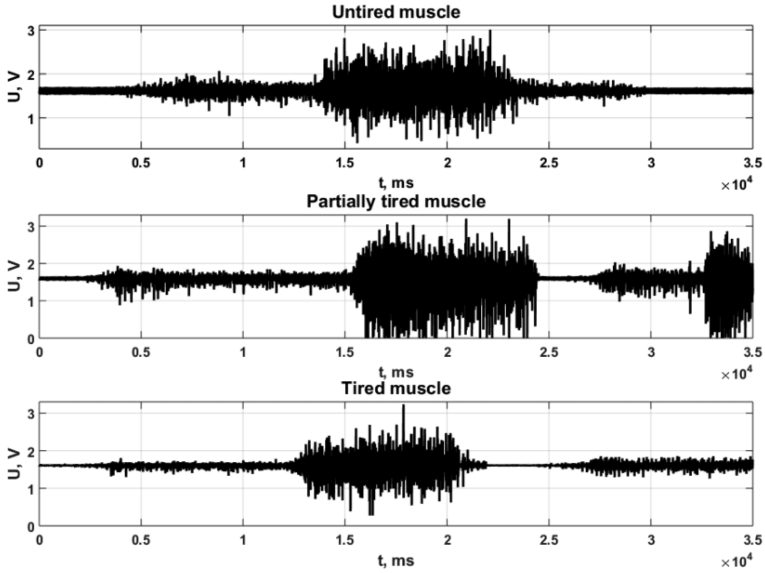

Fig. 3.4. Comparison of muscle fatigue charts: a.) untired muscle; b.) partially tired muscle; c.) tired muscle.

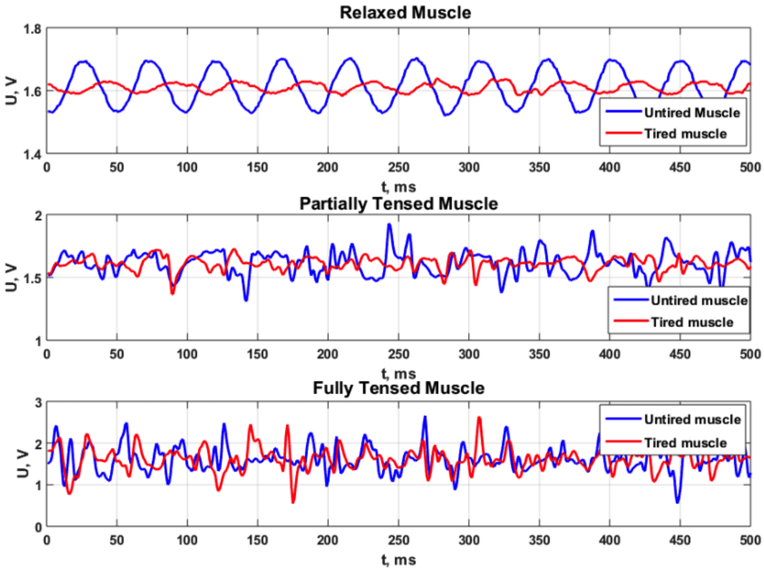

Fig. 3.5. Comparison of EMG shapes of untired and tired muscles.

It is shown that EMG signal has sufficiently distorted. In particular, the amplitude decreased and the number of changes in the signal sign increased. The RMS has not changed much. It is equal to 1.52. However, the number of RMS crossings has been increased. With such strong interference, there is a possibility of false triggering of the recognition algorithm. Figure 3.8 illustrates recognition results after perspiration. One can see that algorithm provides false recognition during operation if parameters a_i and b_i are not corrected.

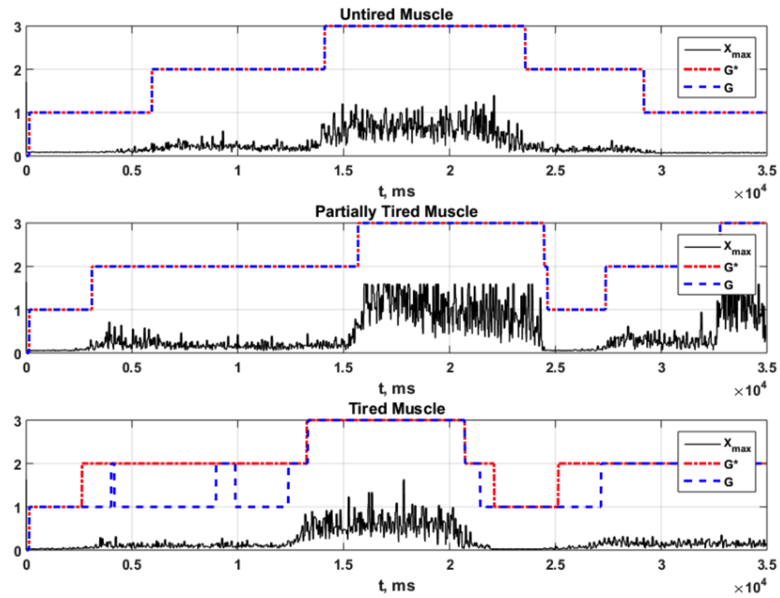

Fig. 3.6. Results of muscle activity recognition for muscle fatigue: a.) untired muscle; b.) partially tired muscle; c.) tired muscle.

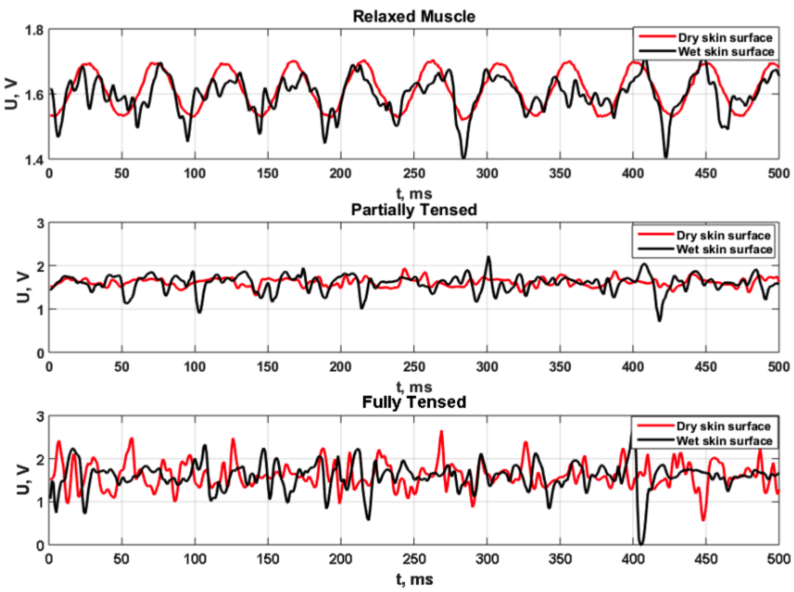

Fig. 3.7. Comparison of waveforms with perspiration.

Results of muscle activity recognition under sweat skin surface has shown high probability of false recognition. Figure 3.8 clearly shows that the boundaries that were

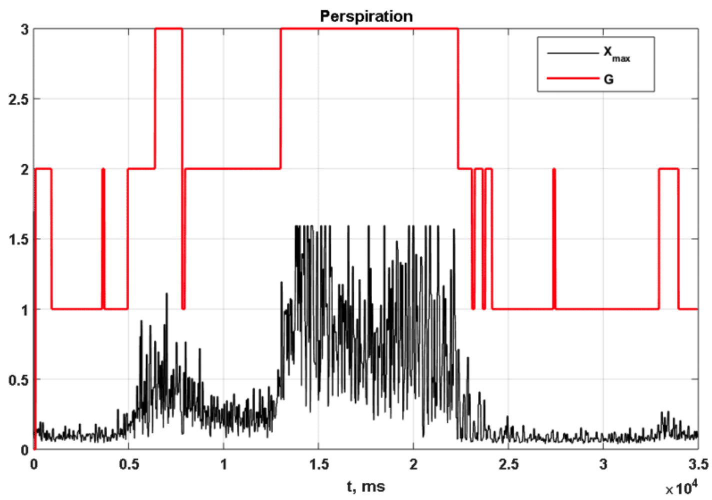

Fig. 3.8. Results of muscle activity recognition operation for perspiration.

calculated before perspiration are no longer suitable and during operation, if the boundaries are not automatically corrected, the user will lose control of the prosthesis.

3.3. Malfunction Correction

Experimental results have been shown that with the appearance of external factors during prosthesis operation recognition accuracy may degrade to unsatisfactory. Therefore, it is required to develop correction algorithm that performs correction of boundaries a_i and b_i to provide fail-safe recognition. The most interesting case is automatic recalculation to perform fail-safe recognition without manual mode even during active operating of the prothesis.

We propose the following boundary values correction strategy. The program code for recalculation of new boundaries starts every 5 minutes in automatic mode without user interaction. The 5 minutes time interval has been selected empirically after several experiments. Time interval can be changed individually for each patient. The correction process is a cycle in which the system inspects the user's activity. After initialization of the boundary correction, the system is switched to waiting mode and wait for muscle activities. After activity detected, the correction algorithm collects about 150 measurements for each type of muscle activity. When data for three types of muscle activity are collected, correction step is carried out between contiguous movements, for example, between relaxed and half tensed muscle. New boundaries are defined by the following relations:

$$
\begin{aligned}
&a_1 = 0,\\
&a_2 = b_1 = \frac{\sum_{i=1}^{N} X_i^{\text{relaxed}} + \sum_{i=1}^{N} X_i^{\text{half}}}{2N},\\
&a_3 = b_2 = \frac{\sum_{i=1}^{N} X_i^{\text{half}} + \sum_{i=1}^{N} X_i^{\text{full}}}{2N},\\
&b_3 = \frac{\sum_{i=1}^{N} X_i^{\text{full}}}{N} + 2.5,
\end{aligned}
\tag{3.2}
$$

where X_i^{relaxed}, X_i^{half}, and X_i^{full} are maximum window value for relaxed, partially tensed and fully tensed muscle respectively, N is a number of counts for calculating the average value ($N = 150$).

Table 3.1. Recognition accuracy of window method.

Muscle activity	Relaxed	Half tensed	Tensed
Fatigue no correction, %	12	52	28.8
Fatigue with correction, %	3.5	8.2	2.5
Perspiration no correction, %	24	19.5	6
Perspiration with correction, %	12	9.8	4.5

Results of muscle activity recognition before and after correction are given in table 3.1. It is easy to see that correction algorithm allows to improve accuracy of window method. Also we should note errors correspond to the transient process between states of muscle activity. It has been experimentally obtained that overall delay in recognition between two states of muscle activity may be increased up to 100 ms. This is satisfactory value for real-time operations.

Additionally, we derive boundaries for ideal conditions (untired muscle and dry skin surface) and corrected values for each type of deflection. Boundaries for ideal conditions are defined in (3.3), corrected values for tired muscle are defined by (3.4), and corrected values for sweaty skin are given by (3.5).

$$
G = \begin{cases} 1 & \text{if } 0 < X_{max} \leqslant 0.11, \\ 2 & \text{if } 0.11 < X_{max} \leqslant 0.42, \\ 3 & \text{if } 0.42 < X_{max} \leqslant 3.3. \end{cases} \tag{3.3}
$$

$$
G^*_{\text{fatig.}} = \begin{cases} 1 & \text{if } 0 < X_{max} \leqslant 0.03, \\ 2 & \text{if } 0.03 < X_{max} \leqslant 0.3, \\ 3 & \text{if } 0.3 < X_{max} \leqslant 3. \end{cases} \tag{3.4}
$$

$$
G^*_{\text{persp.}} = \begin{cases} 1 & \text{if } 0 < X_{max} \leqslant 0.12, \\ 2 & \text{if } 0.12 < X_{max} \leqslant 0.45, \\ 3 & \text{if } 0.45 < X_{max} \leqslant 3.5. \end{cases} \tag{3.5}
$$

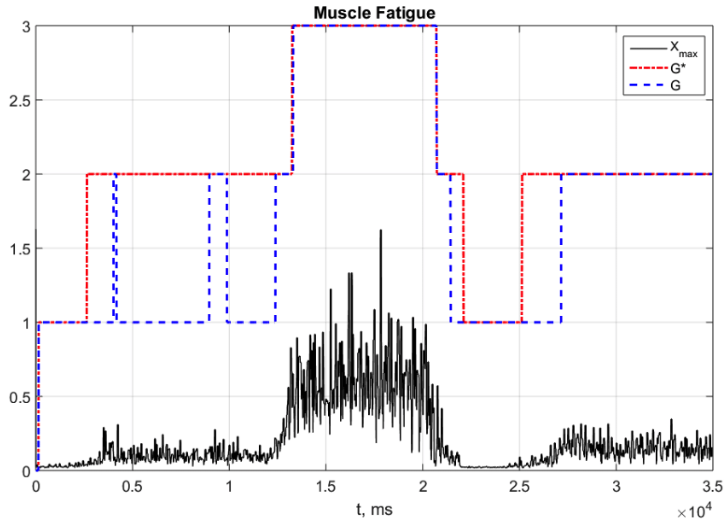

Fig. 3.9. Algorithm operation after border correction for muscle fatigue.

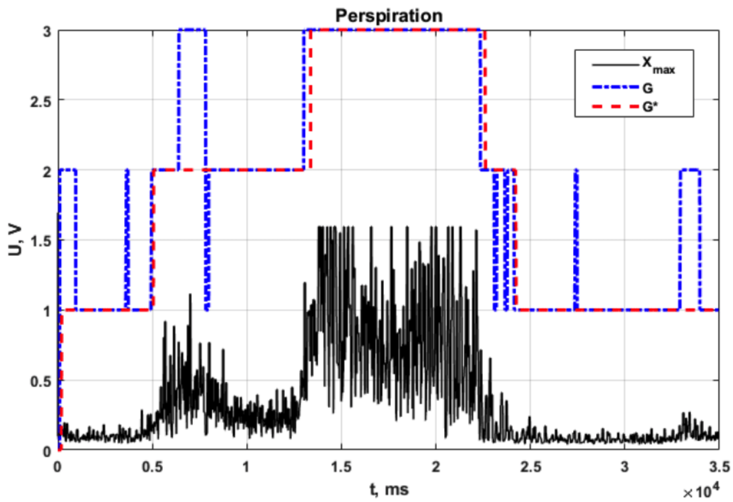

Fig. 3.10. Algorithm operation after border correction for perspiration.

One can see that for tired muscle corresponding boundary values are less than ideal ones while corrected boundaries for sweaty skin surface are larger than ideal. The operation of the algorithm after border correction can be seen in figures 3.9 and 3.10. It is shown that proposed correction procedure provides improved recognition without substantial fails during operation.

4. CONCLUSION

The paper presents an experimental investigation of the influence of muscle fatigue and perspiration on the recognition of muscle activity using EMG signal. A number of experiments have been carried out. During study of the perspiration and muscle fatigue, it was found that complete fatigue may increase identification error to unsatisfactory (over 50%). Perspiration as well as fatigue leads to performance degradation. To improve identification accuracy, automatic correction method has been proposed. Experimental results has shown that proposed solution allows to improve working precision of the amplitude-based window identification under perturbing factors. It has been shown that when deflection from ideal conditions occurs, the algorithm adapts to changes.

The future works is focused on:

1. Study of other factors for EMG signal recognition.
2. Complex tests on several subjects with different parameters of external disturbance.
3. Development of rehabilitation strategy for amputees to provide prosthetic hand operation.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest

The authors declare that there is no conflict of interest.

Ethical standard

The participant signed an informed consent before the experiment. The study was conducted in accordance with the Declaration of Helsinki. The protocol was approved by the V.A. Trapeznikov ICS RAS Institutional Review Board.

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