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USING EMG PATTERNS FOR HUMAN GAIT CYCLE RECOGNITION[1]

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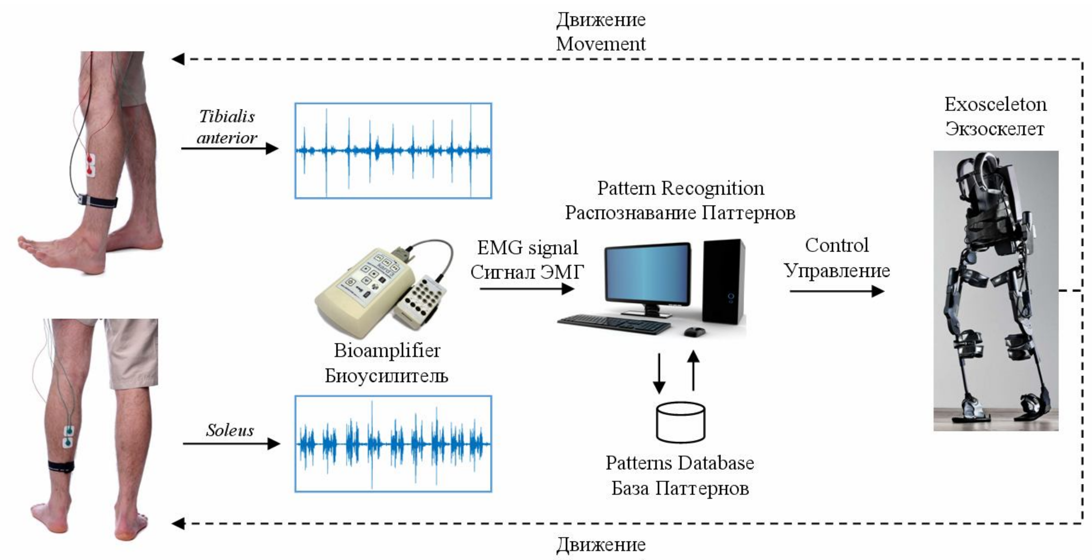
The article describes the system for human gait cycle recognition based on EMG signal processing. The analysis of electrical signals produced by lower limb muscles during gait is carried out. The correlation between EMG signal characteristics and actual leg movements during gait are researched. The method of signal preprocessing and adaptive segmentation for detection of muscle activation patterns is developed. The most informative muscles for analysis are selected basing on signal to noise ratio. The pattern sequences processing method for gait cycle coding is proposed. The algorithm is implemented in C# and has shown about 90 % recognition rate during testing. The system can be used for exoskeleton control as well as in functional diagnostics and sports medicine applications.

Keywords: electromiography, biosignal processing, pattern recognition, lower limb muscles, gait, signal filtering, functional diagnostics, movement analysis, electrophysiology

Graphical annotation (Графическая аннотация)



[1]Работа выполнена при финансовой поддержке Российского фонда фундаментальных исследований, грант №16-07-01080.

ИСПОЛЬЗОВАНИЕ ПАТТЕРНОВ ЭМГ В ЗАДАЧЕ РАСПОЗНАВАНИЯ ЦИКЛА ХОДЬБЫ ЧЕЛОВЕКА

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В статье описана система распознавания цикла ходьбы человека на основе обработки сигналов ЭМГ. Проведён анализ особенностей электрических сигналов от различных мышц нижних конечностей в процессе ходьбы. Изучены взаимосвязи характеристик ЭМГ сигнала с реальными фазами движения ног в процессе совершения шага. Разработан метод предобработки и адаптивной бинаризации ЭМГ сигнала для выделения паттернов активации мышц. Выбраны наиболее информативные для анализа мышцы на основе соотношения сигнал-шум. Предложен метод обработки последовательности паттернов для кодирования элементов цикла ходьбы. Реализован алгоритм распознавания фаз ходьбы на языке C#, при тестировании достигнут 90 % уровень верного распознавания элементов цикла ходьбы. Система предназначена для использования при управлении экзоскелетом, но может быть также использована в системах функциональной диагностики и спортивной медицине.

Ключевые слова: электромиография, обработкабиосигналов, распознавание паттернов, мышцы нижних конечностей, ходьба, фильтрация сигналов, функциональная диагностика, анализ движения, электрофизиология

Адрес видеоролика (Address of the video)
http://hi-tech.asu.edu.ru/docs/addmaterials/2016-3-1(Gait).mp4

The development of the systems, based on the biofeedback control, has been a subject of interest of many researchers during the last several years. In particular, significant progress has been made in electromiogram (EMG) signals recognition for such applications as the limb prostheses operation, functional diagnostics and sports medicine. Most of the recognition systems utilize machine learning approach (neural networks [8], Support Vector Machines [5]) to recognize the certain movements and simple gestures of a limb. This approach has been widely used and proved its efficiency, but it is actually not suitable for recognizing such complex, extended in time and subject-specific movements as strides during human walking. We have found no evidence that EMG informationfrom lower limbs has ever been successfully used for movement recognition and/or biofeedback control, such as exoskeleton [3, 6, 12]. At the same time, these applications have been implemented for the upper limb movement.

The aim of this work was to develop a robust and efficient algorithm for human stridemovement recognition. Another issue was to minimize the time delay of the recognition system, so that it could be able to operate as close to real-time regime as possible.

General characteristic of article theme. Constraint for time delay of the recognition system is essential for any biofeedback control applications. Assuch type of movement as stride is rather extended in time; there is no possibility to learn the whole history of the corresponding EMG signal in advance before processing. That's why we abandoned the idea to use machine learning methods to solve the problem and concentrated on empirical pattern recognition approach.Our method for resolve the problem can be summarized as follows.

- Filtered signals from each of the considered muscles are thresholdedinto activation and deactivation phases.
- A stride movement is described by activation pattern [5], consisting of several stages, which correspond to different combinations of activated and deactivated muscles.
- Threshold values for each muscle activation, as well as generally stable stages and the order of their occurrence for the strides, are adaptively calculated for each subject during training phase.
- During testing phase the system recognizes a stride as a set of activation patterns, occurring in the defined order.

This approach can be used for the muscle activity research for different types of movement, as well as for training a classifier for automatic recognition of these movements or their sequences, such as in [2, 10].

EMG signal processing tools. All our experiments were carried out using the Kardi3/9 wireless 9-channel amplifier with sampling rate of 1000 Hz. A subject performed series of 5 to 9 separate strides with a pause of 2–3 seconds between them. The obtained signals were passed through bandpass filter with low and high frequencies of 30 and 200 Hz respectively. Then the signal root mean square (RMS) was calculated. For gait analysis we do not need the high frequency information. So we applied a lowpass Butterworth filter with cutoff of just 1 Hz to the resulting signal. This way smooth curves, characterizing the general muscle activation in scope of several seconds, were achieved (Fig. 1).

At the first stage of our experiments the goal was to find the most informative (in the relation to the signals recognition) muscles. A wide number of muscles are involved in gait movements, but very few of them actually provide stable and reliable signals for stride phases recognition. Some of the measured signals are presented on Fig. 2. It is obvious, that although different muscles produce different activation intensities and pattern forms during strides, the actual activation of each muscle almost always happens at the very beginning of the stride and deactivation happens at its end.Exception are the muscles, which have non-zero base level – as they are activated during standing, such as Gluteus Medius. Under «activation» we mean the level of signalб which significantly distincts from noise for this muscle (over 3σ deviation).

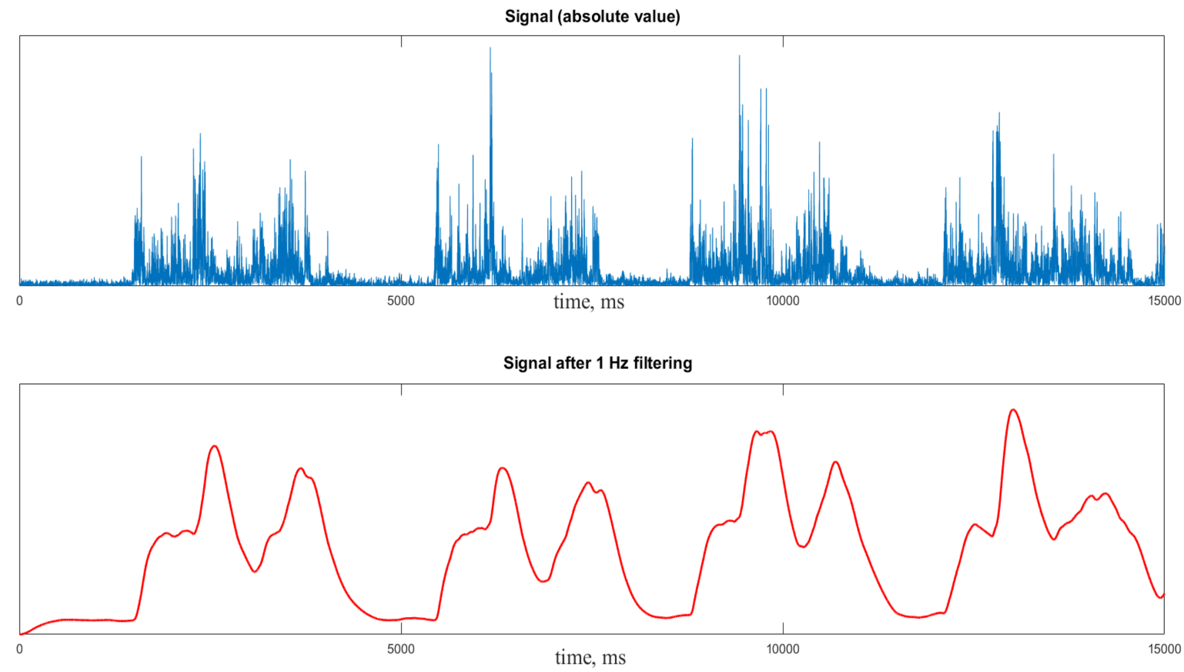

Figure 1 – Muscle activation signal sample

We have chosen *Soleus* and *Tibialis Anterior* muscles as the most informative for our task [4, 9]. The patterns generated by these muscles have proved to be rather stable during all our experiments. The former provides a single-peak activation pattern during the leg pushing off the ground.The latter remains active during the whole leg movement providingone local minimum around the push off stage and,for certain subjects,another one before the start of the support stage (when a leg is approaching the ground). The correspondence between the actual stride stages and the muscle patterns, which is shown on Fig. 3, was determined using accelerometer, attached to one of the legs.As we passed to recognition in our later experiments we utilizedonly the signals from these two muscles, from both legs.

In our experiments average voltage during activation was around 40µVfor *Tibialis Anterior* and 100µV for Soleus. With average fluctuations during rest state under 7 µV and 20 µV, both muscles provided signal to noise ratio of about 5, which is sufficient for the task.

As presented on the figures above, in ideal case it is possible to precisely extract the time periods of six stages of a stride. In practice, however, signals may contain some other local peaks or artifacts which make it difficult to judge about the gait cycle utilizing the signal form. A much more consistent, though more rough approach, is to apply adaptive signal thresholding and extract the binary activation patterns of each muscle as described below.

Signal Thresholding Method. In this paper we propose a novel algorithm for signal thresholding, which was designed to automatically distinguishthe signal features observed in our experiments.

The general aim of signal thresholding in our system is to localize the most significant and stable EMG signal phases. At the same time these signals are subject-specific as the walking movements are generally not the same for different persons [7]. Thus the threshold values for the muscles are calculated given a training sample, consisting of several strides made by subject.

The criteria for the threshold value is the following: the number of activations/deactivations should be the same for each step and should be stable enough to variations of a threshold value.

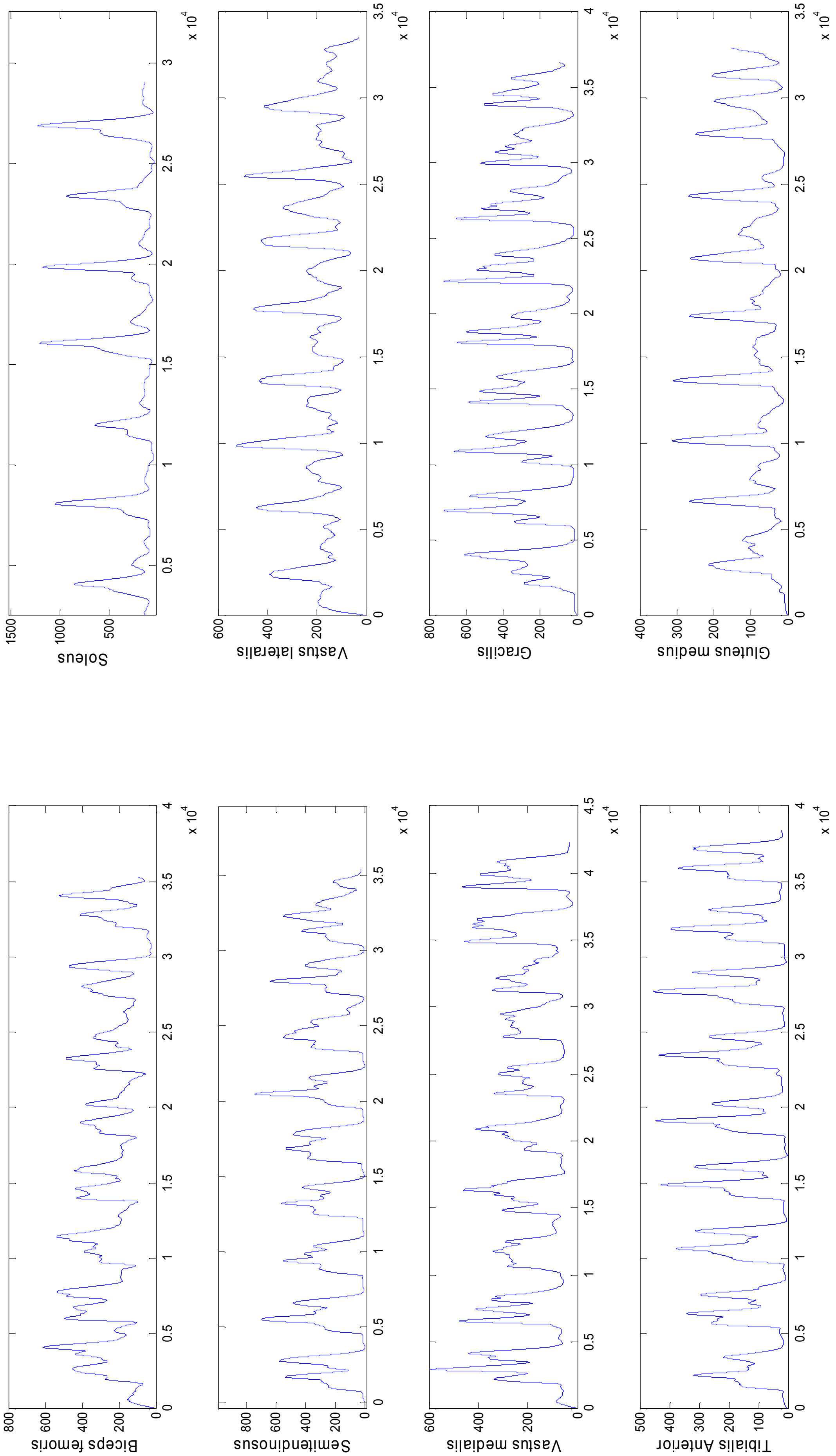

Figure 2 – EMG signals, corresponding to muscle activation during set of strides

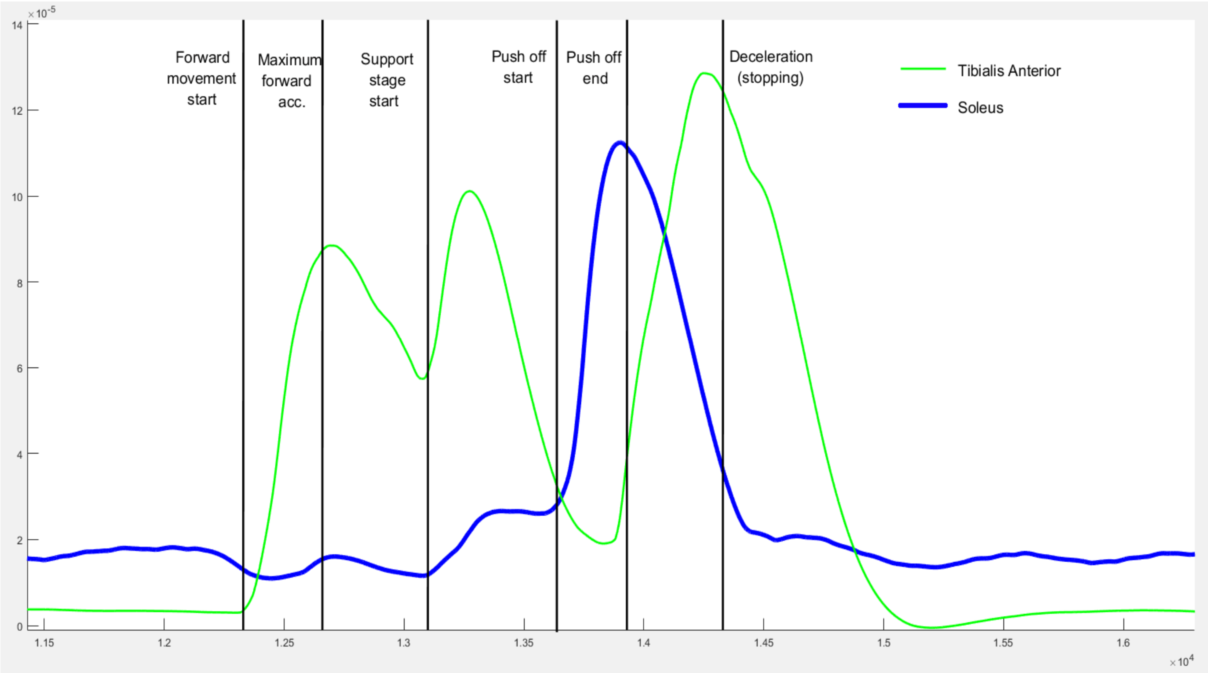

Figure 3 – Correspondence between the stride stages and the muscle activation

Given a signal $s(t)$ within a period of time $T$and number of steps in a sample n a threshold value x_t corresponds to a maximum value of $f(x, \Delta x)$ at $x = x_t$:

$$f(x,\Delta x) = \int_{x-\Delta x}^{x+\Delta x} R(x)g(x)' dx \to \max ,$$

$$g(x) = \int_0^T \left| \frac{d(sign(s(t)-x))}{dt} \right| dt ,$$

$$R(x) = \begin{cases} 1, \text{if } g(x) = k*n, \ k = 2,4 \\ 0 \ otherwise \end{cases} ,$$

where Δx is a window size. The Δx value is chosen with respect to the desired stability of a threshold chosen.

In other words, if we display the number of crossings of a signal and a threshold level line as a function of threshold value $g(x)$, the optimal value would correspond to a middle of the longest plateau of this function (Fig. 4). Such approach is not of much use in terms of muscle activity detection, but gives a good representation of some basic patterns of a particular movement.

During our experiments threshold levels were calculated independently for each muscle, using a sample signal containing from 7 to 10 strides, made by test subject.

Signal segmentation. After signal thresholding a set of activation patterns are obtained for each step as shown on Figure 5. We can introduce a *stage* as a particular combination of activated and deactivated muscles. A stage can be therefore presented in a form of a binary code. Note that the same stage may occur several times during single movement.

We have developed an algorithm, which performs automatic stage extraction from a set of activation patterns.This algorithm learning the order of patterns occurrence, their duration and their repetitiveness from stride to stride. A stage is excluded from consideration in following cases.

- If its average duration is below a specified limit (we set it as a 3% of average overall stride duration).
- If its position in stride patternsis inconsistent.
- If it is not detectable inmore than 20 % strides within the training signal.

The stages extracted during training phase are associated with particular physical movements of the legs, according to the scheme, presented on Figure 3. Depending on the test subjects from 4 to 6 consistent stages were usually detected, successfully covering the major leg movements.

As for the test mode, our system was configured to detect the stride movement as a set of stages in predefined order. During the neutral position (*0000*) the first stage is awaited. When its occurrence is detected, the second stage is awaited and so on. If a wrong stage occurs at some point of the stride the system ignores it. If a neutral stage signal *0000* occurs, the system always resets to the neutral position (an interrupted stride is declared).

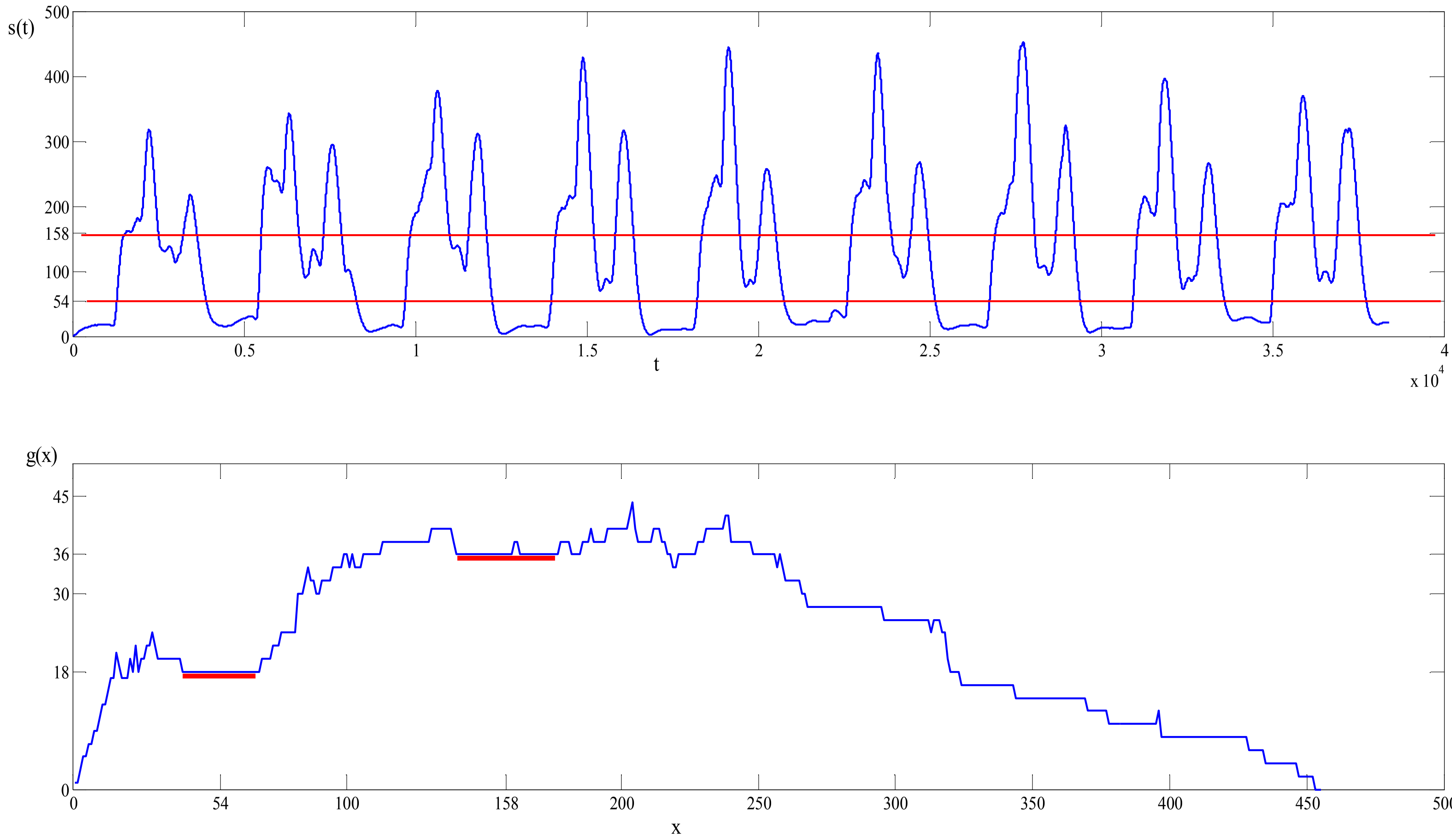

Figure 4 – Signal thresholding (*Tibialis Anterior*). A sample signal containing 9 steps can be thresholded to detect either 1 activation/deactivation per stride (18 crossings overall) or 2 (36 crossings). The second variant gives more phases for each stride but is less stable

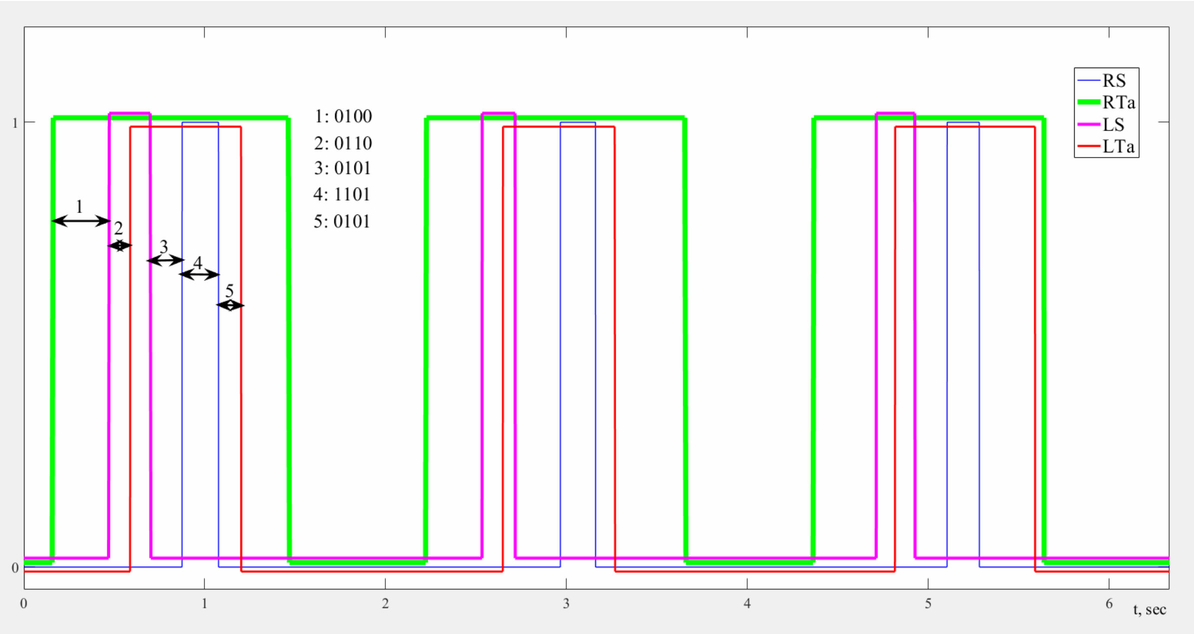

Figure 5 – Activation Patterns from two pairs of muscles (R-right; L-left; S-Soleus; Ta-Tibialis Anterior). A set of 5 consistent stages can be extracted judging on these 3 strides. Our algorithm will discard a *0111* stage between 2 and 3 as it is too short, as well as the final *0100* stage as it is almost not detectable within the 3rd stride

We tested our system on 5 subjects, each performing from 7 to 10 strides for training and about 50 strides for testing. During the experiments we achieved the recognition rate about 90 %. Actually the beginning of the movement was correctly detected for 98 % of the strides.The rest of errors were due to false interruption or mis-detection of one of the stages.The system time delay did not exceed 0,3 seconds, which we consider satisfactory for our task (it is small in comparison with the durationof theentire stride movement).

Conclusion. We have developed a system for single stride recognition, based on analysis of a filtered EMG signal of lower limb muscles. We have localized the most informative muscles and determined the relation between their EMG signal and corresponding actual leg movements during stride. Alsoauthors have developed an algorithm for adaptive signal thresholding – to generate the pattern of muscle activation/deactivation. The patterns, obtained during training, were automatically analyzed to determine their most consistent stages – the combinations of activated/deactivated muscles. A complex movement was interpreted as an ordered set of stages. This approach allowed us to efficiently recognize with relatively small time delay such a long and complex movement as a stride. The configuration, described in this paper, was used for the stride detection.However the system can also be trained and configured for any other complex movement recognition, using a desired number of EMG channels, without any major changes. This makes our approach general and flexible for different tasks.

We consider our system as a promising step in the field of biofeedback-based control system development. It could also be useful in medical applications such as functional diagnostics and rehabilitation.

In our future work we plan to use more EMG channels for obtaining more robust and accurate detection of different stride stages. Another issue is to develop a system, which could rapidly adapt for recognition of any complex movement of lower or upper limb by automatically choosing the most informative EMG channels and produce the general «map» of the particular movement and the muscles, involved in it.

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