Electromyography Signals Processing for Gait Phase Recognition

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***Abstract*—Gait phase recognition systems are widely used in medicine to control devices aimed at restoration of patients' motor functions and have an increasing interest in scientific society. Use of electromyography as a source of information for such systems gives considerable advantages in comparison with other data sources at the cost of complex signal processing needed. In this paper, the author outlines these advantages and suggests a method that uses discrete wavelet transform to retrieve muscle activity shape and a novel double-threshold detector to find the regions of activity. Then a robust statistical treatment is performed following a dimensionality reduction. As a result, a set of classification objects is retrieved that are suitable for further use in various clustering and classification techniques. The introduced method was tested in the Movement Physiology Laboratory of I. P. Pavlov Institute of Physiology, Russian Academy of Sciences and proved its applicability on real electromyography data.**

I. Introduction

Gait phase can be used as an integral time characteristic of complex body and limb movements during the walk. Therefore, in medicine gait phase information can be used to control exoskeletons [1]–[4] or provide stimuli for spinal cord or muscles so as to restore patient's motor functions [3], [5]–[7]. Nowadays, there are various techniques for gait phase recognition that differ mainly in the data source they are based on. This paper addresses the use of electromyography (EMG) signals for this purpose in the context of developing a gait phase recognition software.

The author suggests a method that uses discrete wavelet transform to retrieve muscle activity shape and a novel double-threshold detector tolerable to amplitude hopping to find the regions of activity. Then a robust statistical treatment based on interquartile range calculation is performed following a dimensionality reduction. This results in a set of classification objects that are suitable for further use in various clustering and classification techniques. In his bachelor thesis [8], the author used end-to-end approach which included fuzzy C-means clustering and classification using adaptive neuro-fuzzy inference system (ANFIS). Although fuzzy techniques are a reasonable choice for EMG signals since their nonstationary nature, the method suggested in this paper does not set any limitations that would impede other classification techniques that are typically used for EMG-related tasks (support vector machines (SVM), linear discriminant analysis (LDA), artificial neural networks (ANN) etc) [9], [10].

A. *EMG as Data Source for Gait Phase Recognition*

The process of gait phase recognition is built around sensors that are used to retrieve the data during walk. According to the overview [11] by Muro-de-la-Herran et al. sensors for gait analysis can be divided into wearable and non-wearable groups of devices. The latter "require the use of controlled research facilities where the sensors are located and capture data on the gait while the subject walks on a clearly marked walkway" [11]. In contrast, wearable sensors make it possible to capture gait information during the person's everyday activities. Thus the systems that are based on wearable sensors can be used outside the laboratory which is the crucial advantage of the wearable approach.

When capturing the data during walk, different physical quantities can be measured. Based on such quantities one can divide wearable sensors into lots of categories: accelerometers, gyroscopic sensors, magnetometers, force sensors, extensometers, goniometers, EMG sensors etc. [1], [11].

This paper addresses the use of electromyography to retrieve the information about gait phase. The benefits provided by this approach include the following:

- the least response time to the start of muscle activity [12] since the electrical activity is measured by EMG sensors directly whereas other sensors measure the physical quantities that change as a consequence of movements caused by that activity (according to Wentik et al. the use of EMG allows to predict movements "up to 138ms in advance in comparison to inertial sensors");
- the ability to detect movement intention [13], [14] as electrical activity in muscles exists even if its power is insufficient to initiate the movement (e.g. as a result of nervous connection injury);
- the possibility to use EMG sensors for amputees because, in most cases, EMG signals of large muscles can be measured from patient's stump [12].

The main disadvantage of using EMG is the need for high-quality instrumentation as EMG signals "are invariably very small (in the order of 0.00001 to 0.005 of a Volt)" [11] and thus are strongly influenced by noise.

Considering all the pros and cons, electromyography signals appear to be a reliable and rich data source for gait phase recognition systems. To prove this concept the software pack-

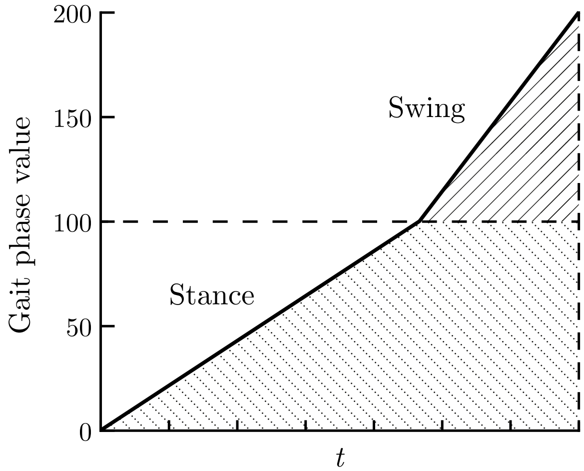


Fig. 1. Gait phase representation within the limits of a gait cycle.

age was developed and tested [8] on real electromyography data showing promising results which are discussed later in this paper.

Some researchers have already used EMG for solving gait phase recognition [15], [16], movement pattern classification [17], [18] or locomotion mode identification problems [9], [19]. Typical techniques incorporate extraction of such aggregate features as mean absolute value, root mean square, number of zero crossings etc in a moving window and forming a feature vector via combination of these features extracted from several EMG-channels. Some authors [17] have successfully used wavelet transform to extract numerical features related to wavelet-coefficients. The resulted classification objects were then used in conjunction with ANN, SVM, LDA and other classification techniques.

EMG processing technique proposed by the author produces essentially different classification objects. Not only a combination of some aggregate values calculated from EMG samples are they but also an image in the feature space that describes EMG fragments containing muscle activity by their shape in the time-domain. The basis of this approach is stated in the next sections of the paper.

B. Paper Structure

The paper structure is as follows:

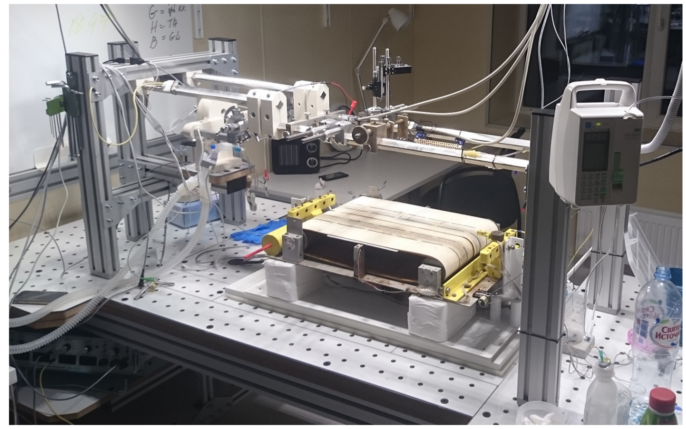
- Gait phase representation.
- Experimental setup and raw data analysis.
- Preparation of classification objects:
  1) retrieval of muscle activity shape;
  2) muscle activity detection;
  3) statistical analysis;
  4) dimensionality reduction.
- Results and discussion.

II. Materials and Methods

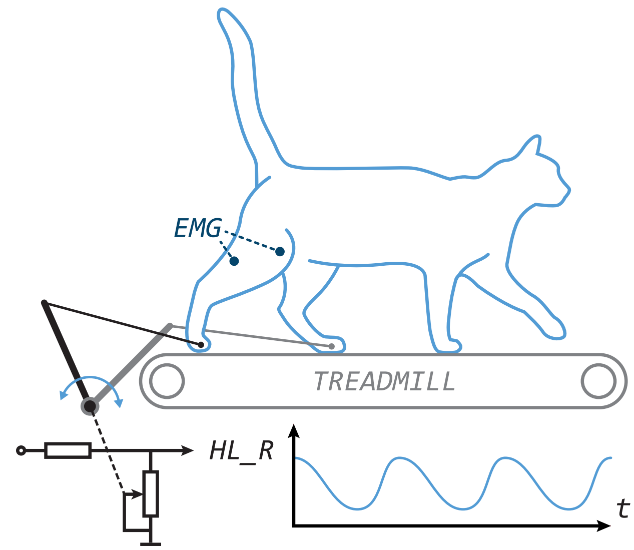
A. Gait Phase Representation

Within the limits of a gait cycle gait phase can be represented as a continuous monotonically increasing function of time. It is important to fix the transition from stance to swing hence the representation showed on Fig. 1 was chosen: gait phase is measured in conventional units from 0 to 200 where range 0-99 applies to the stance phase and the range of 100-200 applies to the swing phase.

Such a representation is very useful to detect transitions between steps and between stance and swing phases within a step, as well as it can be easily constructed and efficiently processed since its linear nature.



(a)



(b)

Fig. 2. Experimental setup and HL signal acquisition: real setup (a) and its schematic representation (b).

B. Experimental Setup and Raw Data Analysis

Electromyography data used in the research was acquired in the Movement Physiology Laboratory of I. P. Pavlov Institute of Physiology, Russian Academy of Sciences in the course of acute experiments on healthy and decerebrate cats. Their locomotion was aroused by epidural stimulation of the spinal cord (dorsal surface) with the optimum frequency (5-10 Hz) [20] for stepping pattern.

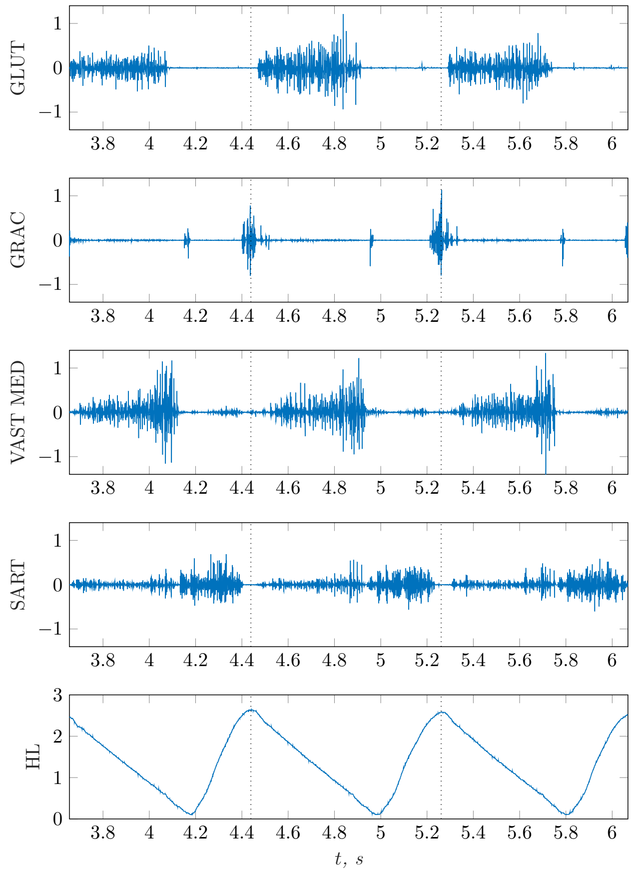


Fig. 3. Raw experimental data example. Dashed lines mark step boundaries. Y-axes labels are names of EMG channels. HL signal has its maxima at step boundaries and its minima at transitions between stance and swing. This very feature was used to construct the reference phase line.

Raw data used in the research was acquired using experimental setup showed at Fig. 2. Electromyographic activity was taken from healthy and decerebrate cats that were walking on a treadmill during the experiment. The following muscles were observed: lateral gastrocnemius, tibialis anterior, adductor, gluteus, gracilis, sartorius anterior, vastus medialis, rectus femoris and muscles of back. Bipolar electrodes used for EMG acquisition were implanted bilaterally into the hind limbs. Amplification of signals was performed using differential amplifier (A-M Systems Model 1700) in the range from 30 Hz to 10 kHz. Analog-to-digital conversion was done with the help of an ADC by National Instruments.

Apart from EMG there also were used some other signals. The most important one is the signal of hind-limb potentiometer (HL signal) that represents the position of a foot endpoint in the sagittal plane (Fig. 2, 3) [21]. The shape of this signal makes it possible to unambiguously detect step boundaries and transitions between stance and swing phases. As a result, some reference phase line can be constructed according to the chosen representation (Fig. 1).

Electromyographic signal consists of separate "batches", i.e. intervals in the EMG where muscle activity presents and the power of EMG signal has an increase. These batches have different shape and duration depending on a channel. However, within a channel each batch has roughly the same duration and position relative to the step boundaries. The shape of a batch is defined by the temporal distribution of power during muscle activity, its beginning and ending (according to some threshold) times depend on the biomechanics of gait which has a stereotyped nature.

Thus one can draw a conclusion that the beginning or ending time of a batch (within the limits of a gait cycle) can be determined based on the shape of that batch. The gait phase that takes place on that time can be registered using the HL signal. As a result, a definite gait phase dependence on the shape of the EMG signal can be established. This idea leads to the gait phase recognition method based on classification of batches taken from the EMG signal.

C. *Preparation of Classification Objects*

According the suggested concept, muscle activity batches should be divided into some clusters. Each cluster of batches is supposed to correspond to some gait phase value that is derived from EMG signal during the learning stage of a gait phase recognition system.

Therefore, in order to be used as an inputs for a classifier, i.e. classification objects, muscle activity batches must undergo some preparation. Steps of this preparation are described below.

1) Retrieval of Muscle Activity Shape: The first step of the suggested gait phase recognition method consists in retrieval of muscle activity shape meaning some raw EMG signal processing that will facilitate the following steps of muscle activity detection and dimensionality reduction.

This paper suggests using discrete wavelet transform (DWT) [22] to expose muscle activity shape. At the beginning of the process the EMG signal is rectified. Then the exposure is done in the following way:

1) perform DWT to a high level of decomposition so as to extract large-scale components of the signal;
2) discard wavelet-coefficients of the lower levels;
3) reconstruct the signal using the remaining wavelet-coefficients.

As a result, there will be constructed a smooth curve – an envelope – that correctly [23] describes the shape of a batch preserving the most powerful peaks while not containing the high-frequency spectrum region. In this research the best results were achieved using the 3rd Coiflet (coif3) as the mother wavelet and decomposition was performed at level 7. The low-frequency nature of the envelope makes it possible to perform decimation on the subsequent steps of the gait phase recognition method.

In author's previous work [8] the comparison was performed between DWT and other methods that can be used to retrieve muscle activity shape. As a result of this comparison, the approach based on DWT was considered as the most flexible and accurate.

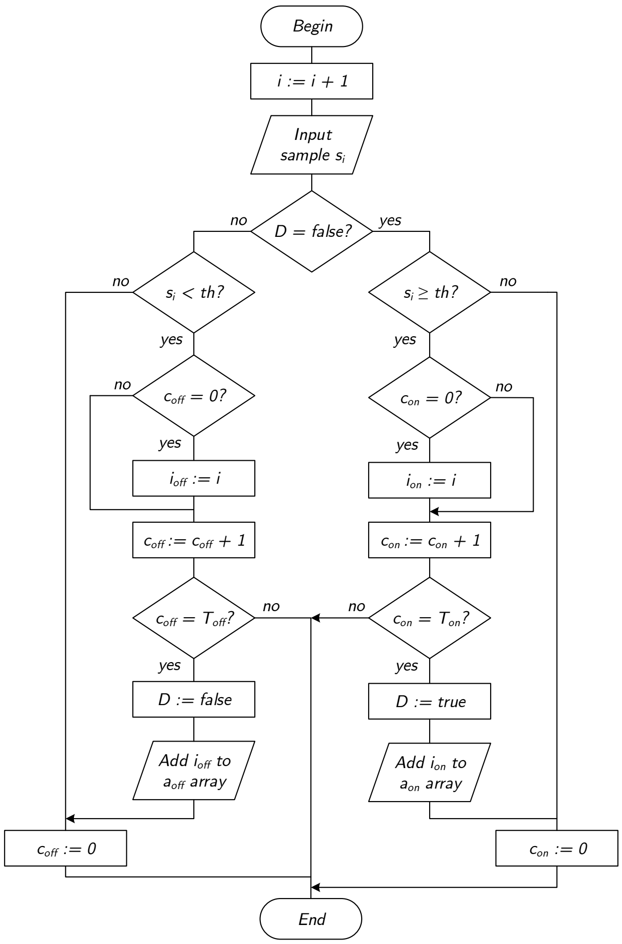


Fig. 4. Flow chart describing the algorithm (loop body) of the double-threshold detector implementation introduced in this paper. Variables that are used in symbols: th – the 1st threshold (defined as amplitude), T_{on} – time duration when input signal must exceed th so as to batch beginning is registered, T_{off} – time duration when input signal must *not* exceed th so as to batch ending is registered, c_{on} and c_{off} – time counters in the states where batch beginning and ending are pending, a_{on} and a_{off} – arrays to store beginning and ending times of detected muscle activity batches, these are the output variables for a learning stage. Boolean variable D is used as an output when gait phase recognition system is functioning in real-time.

Fig. 5. Comparison of three detectors used on a sample of rectified EMG signal. (a) Single-threshold detector ($th = 0.1$ V) has detected 636 regions of activity. (b) Simple double-threshold detector ($th_1 = 0.1$ V, $th_1 = 0.2$ V) has detected 308 regions of activity. (c) Double-threshold detector with amplitude and time thresholds ($th_1 = 0.15$ V, $T_{\text{on}} = 1$ ms, $T_{\text{off}} = 100$ ms) has detected 5 regions of muscle activity which is the correct result.

2) Muscle Activity Detection: In order to perform clustering and classification of the muscle activity batches it is essential to detect these batches in the EMG signal. Constructing an envelope on the previous step makes detection much simpler than if a raw EMG signal was used as an input for a detector.

According to Reaz et al. one should use double-threshold methods to detect motor-related events in EMG signals [23]. Single-threshold approach was shown to produce generally unsatisfactory results [24]. Moreover, using a double-threshold method one “can tune the detector according to different optimal criteria, thus, adapting its performances to the characteristics of each specific signal and application” [23]. This tuning ability is especially useful as EMG channels have decent differences in muscle activity shape and power.

In this research a novel implementation of a double-threshold detector is introduced: the author suggests to define the second threshold in the time domain (instead of amplitude) and make it use two possibly different values - one to detect beginning of a batch, and another one to detect the ending.

The use of a time-domain threshold as described above makes the detector much more tolerable to amplitude hopping in the middle of a batch and hence its low probability of false detections. A flow chart of the detecting algorithm is shown at Fig. 4.

Fig. 5 illustrates a comparative test of three detectors performed on a sample of raw EMG signal: a single-threshold (with $th = 0.1$ V), a simple double-threshold ($th_1 = 0.1$ V, $th_1 = 0.2$ V) and the one suggested by the author ($th_1 = 0.15$ V, $T_{\text{on}} = 1$ ms, $T_{\text{off}} = 100$ ms). The latter has detected all activity regions without false positives while others have given unsatisfactory results: instead of five continuous regions they have produced hundreds of narrow intervals. Despite the fact that, being applied to an envelope instead of raw EMG, the simple detectors are likely to produce acceptable results, the advantage of the novel detector shown in the unfavourable conditions makes it much more suitable for gait phase recognition systems based on EMG signals.

3) Statistical Analysis: Detected batches of muscle activity need to be adjusted to the single length (in samples). This requirement follows from the fact that all classification objects must be described as a feature vectors that belong to the feature space of a fixed dimensionality. This is not required for all classification algorithms but facilitates the application of the typically used ones (SVM, LDA, ANN, ANFIS etc) [9], [10].

After the previous step, there is a selection of batches that form a statistical sample that needs to be conditioned before performing adjustment to the single length. The conditioning implies omitting outliers that are usually incorrectly detected batches or some artefacts in the EMG signal. These outliers, if present in the sample, differ greatly from the majority of batches in their length even considering natural variation in

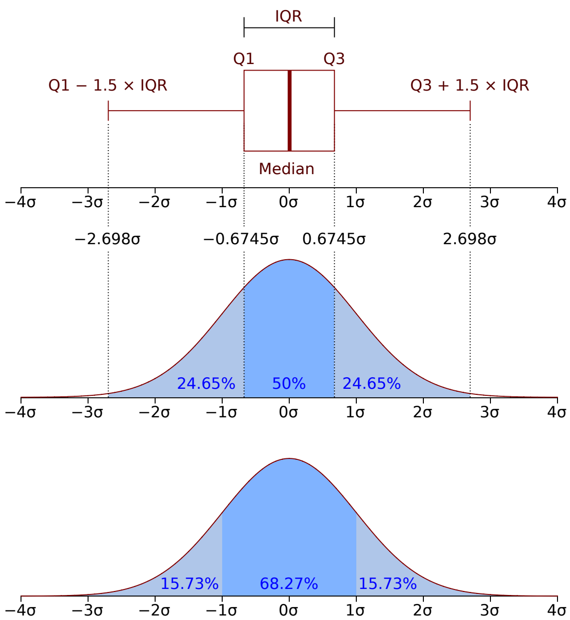


Fig. 6. Illustration of the IQR-based rule in comparison with three sigma rule. The author suggests using the former to make the conditioning of batches robust and independent of the distribution of their lengths.

the duration of step and its phases [8].

A common method of omitting outliers is estimation of the standard deviation across the sample and using the three sigma rule to set the acceptable parameter bounds (length of a batch). However, the author suggests to use interquartile range (IQR) as a robust alternative to the three sigma rule because the latter rule is based on the assumption that the sample is distributed normally. In contrast, using IQR makes it possible to find and discard outliers even in case the sample does not comply to the normal law.

When the IQR is computed, the acceptable value bounds are defined as:

$$\left(Q_1 - 1.5\,IQR,\ Q_3 + 1.5\,IQR\right), \tag{1}$$

where Q_1 and Q_3 are the estimates of the 1st and the 3rd quartiles respectively. This rule is illustrated at the Fig. 6.

After omitting the outliers, the single length of batches is chosen as the maximum across the remaining elements in the sample. Then the adjustment of all remaining batches to that length is performed.

D. Dimensionality Reduction

The final step in the process of preparation of classification objects is their decimation in order to reduce dimensionality of the feature space. The decimation is possible because batches are represented by the envelope that does not contain high-frequency spectrum region.

Raw data used in this research was captured with sampling frequency of 1 kHz and the batch length was 500 samples on average. An envelope constructed after DWT in II-C1 had only low-frequency components of 10-20 Hz so the decimation factor was chosen to be 20. As a result, a feature space dimensionality was reduced to the value of 25 that is acceptable for further use in clustering and classification.

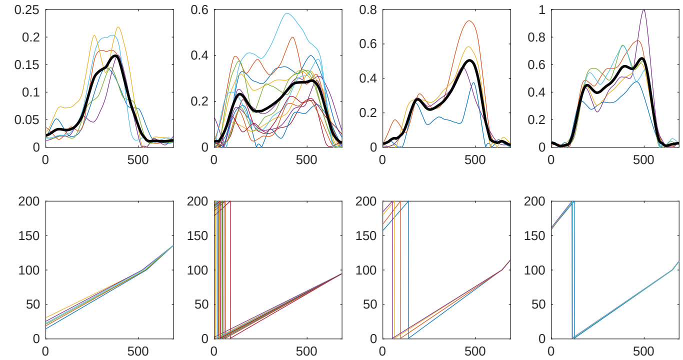


Fig. 7. Example of clusters (in columns) that were found in the resulting set of batches produced by the suggested EMG processing method. In the top row there are batches represented by the fragments of envelope constructed using DWT, thick black curve stands for the average muscle activity shape for each cluster. In the bottom row fragments of gait phase line are presented that took place at the same time with the batches above, the rightmost phase value is assigned to each cluster and can used for training a classifier.

III. Results and Discussion

Gait phase recognition systems which are based on electromyography require complex processing of EMG signals. This paper has covered steps of such processing that result in a set of classification objects derived from the EMG and suitable for the following use in clustering and classification.

Fig. 7 shows an example of clusters that were found in the EMG of the gluteus muscle. One can see the shapes of this muscle activity fragments (batches) that were retrieved via the method suggested in II-C1 before decimation. As a consequence of natural nonstationarity, these batches keep substantial variations in shape even inside a cluster so there is a need for wise decisions on classification methods to use [25].

In [8] a gait phase recognition software based on EMG was developed utilizing adaptive neuro-fuzzy inference system (ANFIS) as classifier. The results of classification, matching phase value and its derivative, were used to construct an approximate phase line in accordance with an ad-hoc algorithm. Fig. 8 shows a comparison between real (blue) and approximate (red) phase lines on a time interval spanning three consecutive steps. Data from 6 EMG-channels (coinciding with the muscles listed in II-B) and a sample consisting of 35 locomotor cycles were used there.

The accuracy of the developed system was estimated using the normalized integral criterion (2) and a set of qualitative measures (3)–(5) of time misalignment:

$$\varepsilon = \frac{\sum_{i=1}^{N}\left(P_{\text{real}}(i) - P_{\text{approx}}(i)\right)^2}{\sum_{i=1}^{N} P_{\text{real}}^2(i)}, \tag{2}$$

where P_{real} – samples of the real phase line, P_{approx} – samples of the approximate phase line, N – total number of samples;

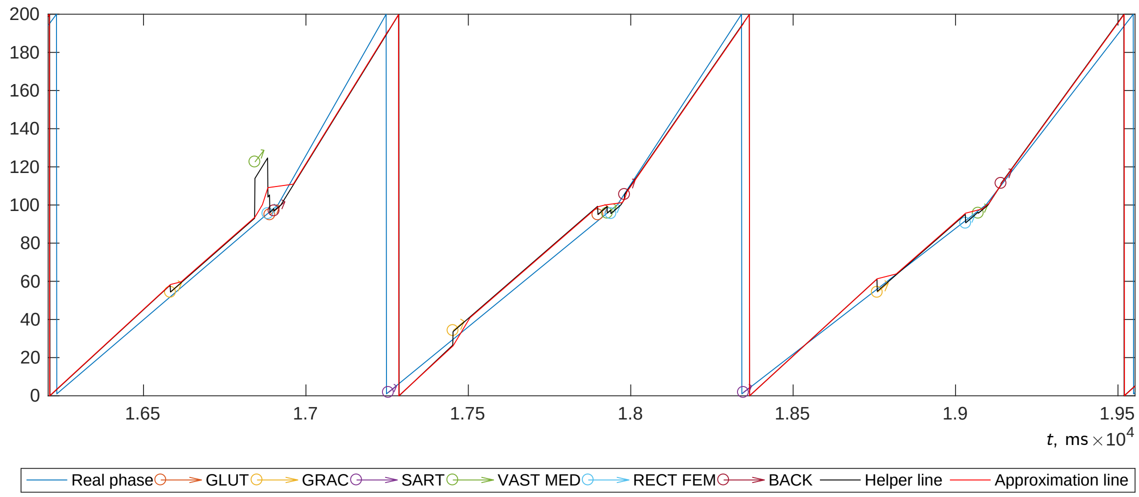


Fig. 8. Gait phase line construction in the system based on the EMG processing method suggested in this paper. Circles point out gait phase values calculated by the classifier and arrows represent values of phase derivatives at those points. These values were used to construct the approximate phase line (red) using an ad-hoc algorithm. The blue line representing the real gait phase is quite close to the approximate proving the functionality of the system and applicability of the suggested method.

TABLE I
TIME MISALIGNMENT ESTIMATES ACHIEVED USING THE SUGGESTED EMG PROCESSING METHOD

Absolute estimates		Relative estimates	
Estimate	Value	Estimate	Value, %
δ	13 ± 14 ms	δ/a	1.3 ± 1.4
δ_{abs}	42 ± 8 ms	δ_{abs}/a	4.2 ± 0.8
$\langle\delta_{\text{max}}\rangle$	60 ± 20 ms	$\langle\delta_{\text{max}}\rangle/a$	6.0 ± 2.0
$\langle\delta_{\text{min}}\rangle$	-36 ± 11 ms	$\langle\delta_{\text{min}}\rangle/a$	-3.6 ± 1.1
δ_{max}	210 ms	δ_{max}/a	21.0 ± 0.8
δ_{min}	-132 ms	δ_{min}/a	-13.2 ± 0.5
		ε	11.6

$$\delta = \frac{1}{n}\sum_{i=1}^{n}\delta_i \qquad \delta_{\text{abs}} = \frac{1}{n}\sum_{i=1}^{n}|\delta_i| \tag{3}$$

$$\langle\delta_{\text{max}}\rangle = \frac{1}{n}\sum_{i=1}^{n}\delta_i^{\text{max}} \qquad \langle\delta_{\text{min}}\rangle = \frac{1}{n}\sum_{i=1}^{n}\delta_i^{\text{min}} \tag{4}$$

$$\delta_{\text{max}} = \max_i \delta_i^{\text{max}} \qquad \delta_{\text{min}} = \min_i \delta_i^{\text{min}}, \tag{5}$$

where δ_i, δ_i^{min} and δ_i^{max} equal to mean, minimum and maximum time misalignment within a gait cycle respectively; n is the total number of steps.

The values of (3)–(5) are also of interest relatively to the mean duration of a gait cycle (for the examined experimental subject) which was equal to $a = 1000 \pm 40$ ms (with the confidence probability of $q = 0.90$). The results obtained by the author in [8] are presented in Table I.

One can see that all mean estimates by their absolute value are not greater than 60 ms which is 4–8% of the mean gait cycle duration. The integral criterion value that is equal to 11.6% also proves good approximation of the gait phase.

The above-mentioned results were achieved to a considerable degree with the help of the EMG processing method suggested in this paper. The constructed classification objects enabled the system to train on and analyse real EMG data which resulted in successful gait phase recognition [8].

Since assessment of the proposed technique with respect to the state of the art can be of interest, the author has made a comparison between the results achieved in his own work [8] and that presented in four other papers [9], [15]–[17] considering mean classification error as the quality estimate that can be compared with the normalized integral criterion (2). In general, one cannot directly compare results achieved by different researchers since they use dissimilar gait phase representations and sometimes solve problems which are closely related to gait phase recognition but are not exactly the same. However, use of classification makes it possible to compare EMG processing techniques indirectly via comparison of mean classification errors. The results of the comparison are presented in Table II.

In sum, the suggested method gives accuracy at the level of other state-of-the-art techniques but it has some crucial advantages over them, viz. automatic moving window size choice (as a result of statistical analysis), flexible and reliable detector, robustness to artefacts in EMG and potential to utilize classification techniques used in image recognition since the structure of feature vectors produced by the suggested method.

IV. CONCLUSION

As a result of the research covered by this paper, an EMG signal processing method was developed that facilitates the use of electromyography for gait phase recognition systems. The suggested method makes it possible to retrieve classification objects from raw EMG data and can be used during learning stage of the gait phase recognition system as well as the stage of its real-time functioning.

TABLE II
COMPARISON WITH OTHER GAIT RECOGNITION SYSTEMS

Authors	Features extracted from EMG	Classification method used	Number of used EMG channels	Mean classification error, %
Huang et al.	MAV, ZC, WL, SSC, RMS, AR and other	Linear discriminant analysis	6*	14.0
Li et al.	MAV, Variance	Support vector machine	4	11.2
Meng et al.	MAV, WL†	Hidden Markov model	8	8.5
Yu et al.	DWT-based aggregates	Artificial neural network	9	10.0
G. Zhemelev	DWT-based activity shape	Adaptive neuro-fuzzy inference system	6	$\varepsilon = 11.6$

The abbreviations are defined as follows: MAV – mean absolute value, ZC – zero crossings, WL – waveform length, SSC – slope sign changes, RMS – root mean square, AR – autoregression coefficients, DWT – discrete wavelet transform. * In the research of Huang et al. experiments with 6, 8, 10 and 16 EMG channels were conducted. Here the result for 6 channels is shown to match the number used by the author. † Meng et al. studied different combinations of features, here presented the one that led to the best results.

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