ALGORITHM FOR IDENTIFICATION OF PEDALING CYCLES FROM SURFACE EMG SIGNALS

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Abstract. *This paper presents an algorithm for identification of pedaling cycles of cyclists from signals acquired by surface electromyography (SEMG) during cycling tests. It is based on empirical measures and on the pure investigation of the SEMG energy signal envelopment in order to find each pedaling signal segment. Its logic consists of successive application of first-difference and cubic spline interpolation techniques over the SEMG energy signal. The algorithm does not require any kind of synchronization to delineate the pedaling. Thus, the instrumentation commonly used to register the start and the end of each pedaling cycle becomes unnecessary on experimental protocols. This contributes for the optimization of SEMG signal compression methods once no additional bytes are needed to recognize a pedaling cycle signal segment. As a consequence, data transmission mechanisms can be also improved and thus make easier the remote measurement procedures and the studies of performance of athletes in real conditions of training. This study segmented a 1,000,000 samples pedaling signal with the proposed algorithm and with a trigger device which delineated each pedaling cycle. Results showed that there are no significant differences between the two segmentation methods, suggesting that the algorithm is an effective way to segment SEMG pedaling signals.*

Keywords: *Cyclists training, Signal segmentation, Surface electromyography*

1 INTRODUCTION

The surface electromyography (SEMG) is a technique widely used in muscular activity studies. Its investigation can provide valuable elements to support the training of athletes. One of its most common applications is related to the evaluation of performance of cyclists (Diefenthaeler & Vaz, 2008; Duc et al., 2005; Lepers et al. 2001; Tucker et al., 2007; Soa et al. 2005; Hug et al. 2003; Bini et al. 2008; Argentin et al., 2006). The analysis of SEMG helps to understand how the biomechanical and physiological characteristics of the pedaling technique can influence on the behavior of athletes in competitions. Prilutsky & Gregor (2000) predicted muscle force patterns by pushing and pulling the pedal comparing the results with electromyographic patterns. Billaut et al. (2005) studied the muscle coordination changes during intermittent cycling sprints observing the inter-muscle coordination in fatigue occurrence through electromyographic activity. Ricard et al. (2006) compared the effects of bicycle seat tube angles on power production and electromyography of the vastus lateralis, vastus medialis, semimembranous, and biceps femoris during a Wingate test. Savelberg et al. (2003) manipulated the trunk angle in ergometer cycling and studied the effect of body configuration on muscle recruitment and joint kinematics, with respect to timing and amplitude of the SEMG signal. Li & Caldwell (1998) examined the neuromuscular modifications of cyclists to changes in grade and posture by analysis of electromyographic magnitude. Bressel et al. (1998) studied the influence of reverse pedaling and forward pedaling on the muscle activity and oxygen consumption, trough the SEMG amplitudes quantification and VO_2 analysis.

In spite of the large use of SEMG in cycling researches, most of the experimental protocols are still restricted to the use of cycloergometers (or fixed bicycles) and traditional electromyographs in a laboratory environment. This is because there are a set of care that must be take into account when SEMG signal is studied. The most of them are related to the origin of the signal, its fidelity, and its level of stationarity (De Luca, 1997). Regarding dynamic contractions, the SEMG investigation indeed requires expert operators for electrode positioning and is affected by many factors other than the physiological phenomena under study (Farina et al., 2002). Moreover, extra complexity is added to protocols if remote measurements have to be performed. Thus, the investigation of SEMG signals of cyclists in real world training conditions requires the development of compact instruments as well as the improvement of techniques of telemetry and signal compression in order to transmit data efficiently. Some researchers have studied methods of SEMG signal compression using wavelet transform (Norris et al., 2001), artificial neural networks (Berger et al., 2006), and image compression techniques (Costa et al., 2008) which have reported good compression factors. Nevertheless, an efficient segmentation procedure is needed to help the compression methods work well at real and remote conditions.

Based on all previous arguments and with focus in the segmentation problem, this paper proposes an algorithm to identify each pedaling cycle from an SEMG signal and to segment them into separated signal blocks. The logic consists of determining the envelope of the SEMG energy signal as well as finding their peaks. The SEMG signal is then segmented based only on the average distance between each peak (or each pedaling cycle). This feature optimizes the compression procedure once no additional characters of control are needed for transmission of SEMG signal. Moreover, the proposed technique simplifies the cycling test execution since no additional instrumentation (i.e. a trigger) is needed for delineating pedaling cycles. Therefore, the algorithm developed can be suggested as a good practice to be used in building experimental protocols for analyzing the performance of cyclists in real world trainings.

2 METHODS

One normal healthy adult male (33 years, 1.63 m, and 60 kg) with no history of orthopedic disease participated in this study. He voluntarily read and signed a written consent form before participating in the experiment that was approved by the University Institutional Review Board.

A cycloergometer (Biotec 1800, Cefise, Brazil) was used for the cycling test. The start and end points of each pedaling cycle were detected by a trigger composed of a magnetic key (fixed on the cycloergometer) and a magnet (fixed on the crank). The magnetic key was adapted so as to ensure an angle of 30º clockwise from upright position of crank (Fig. 1a).

SEMG signals were detected in single differential configuration during pedaling activity from the right thigh with a linear adhesive array consisting of eight silver-electrodes with 5mm inter-electrode distance. Vastus lateralis was the muscle under study. The SEMG signals and the trigger pulses (sent to the auxiliary input) were amplified by a multichannel amplifier (EMG 16, LISiN—OT Bioelettronica Snc, Torino, Italy), bandpass filtered (-3 dB bandwidth = 10–500 Hz, 4^{th} order Bessel filter), sampled at 2048 samples$\cdot$s^{-1}, and converted to digital data by a 12 bit A/D converter board. Before electrode placement, the muscle activity was assessed with a dry array of 16 electrodes (silver bars, 5mm long, 1mm diameter, 5mm inter-electrode distance, OT Bioelettronica, Torino, Italy) during 10 seconds isometric contraction with the crank fixed at the angle of 30º where the activity peak of vastus lateralis occurs (So et al. 2005). The innervation zone location and the distal tendon regions were identified by visual inspection and the region with optimal signal propagation was marked over the skin (Fig. 1b) – (Masuda et al., 1985; De Luca, 1997). The orientation of the array was also selected on the basis of visual signal analysis, choosing the angle of inclination which led to most similar potentials traveling along the array. The part of the skin where the location of the array was identified was shaved and slightly abraded. A reference electrode was placed on the right patella (Fig. 1a).

After equipment setup, the subject was asked to perform 5 minutes of cycling at 60 W for warm-up and familiarization with the equipment. For testing, he was submitted to an incremental protocol with the initial pedaling load of 150 W, cadence constant of 80 rpm, and load increment of 20 W•min^{-1}. The test was ended when the subject could not maintain the proposed cadence.

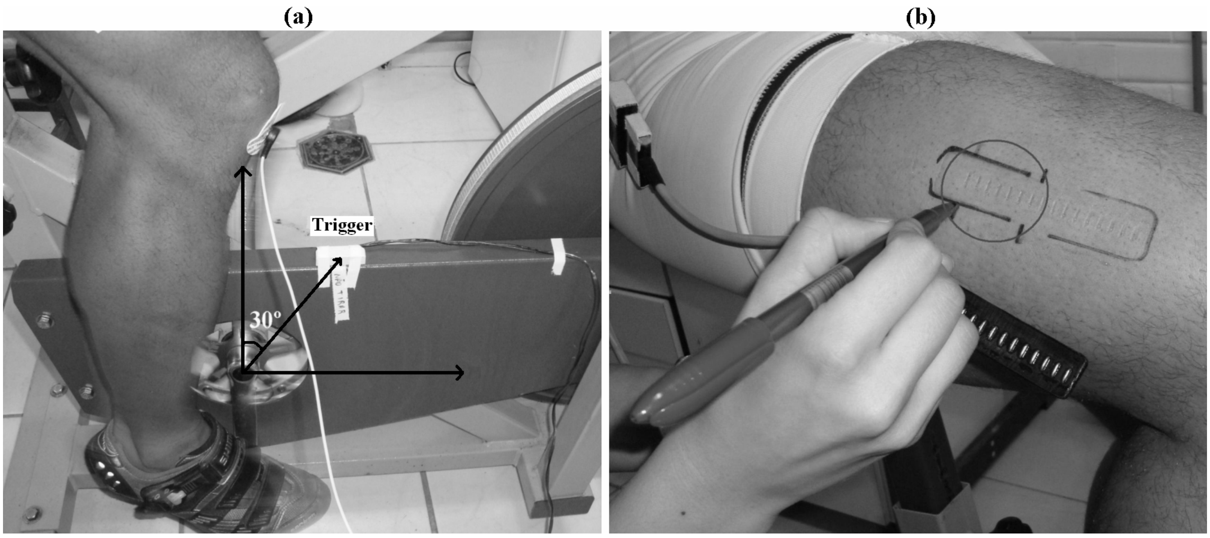

Figure 1 – a) Magnetic key of trigger device on the cycloergometer at 30º clockwise from upright position of crank; b) Optimal recording was marked over the skin.

3 PEDALING DETECTION ALGORITHM

The algorithm of pedaling cycle detection from a SEMG signal determines the envelopment of the SEMG energy signal and finds their peaks. This is achieved by the successive application of first-difference (Smith, 1998) and cubic spline interpolation techniques (De Boor, 1978). The abscissa (the “x” coordinate, in time or sample number) of each point where a peak of energy occurs is the main reference of the pedaling cycle.

3.1 The core of the algorithm

The proposed algorithm uses the first-difference technique in order to identify the inflexion points of the SEMG signal energy where the curvature is negative. These points are the basis for the envelopment construction. A rough approximation for the signal envelopment could be built by linking the inflexion points with straight segments (linear interpolation). However, a non-linear interpolation method is needed to get smoother signal envelopment. Therefore, the cubic spline data interpolation was chosen in order to better represent the SEMG energy signal behavior. Figure 2 exemplifies three iterations of the algorithm. The rough signal envelopment was shown only for illustration; it is not a required step. The envelopment found in a previous iteration is used as the input for the next iteration.

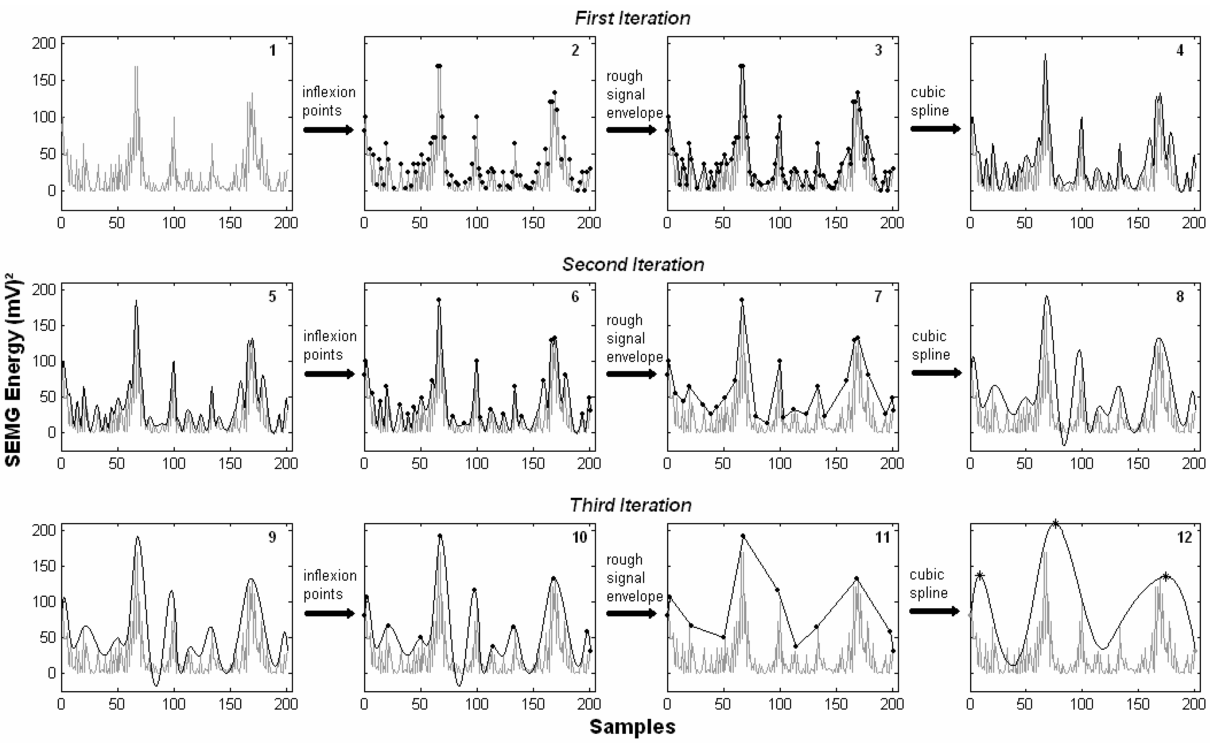

Figure 2 – A segment of the SEMG energy signal (frame 1) is submitted to three iterations of the pedaling cycle detection algorithm; the frame 12 (third iteration) shows three evidenced peaks (asterisks) which could indicate three distinct pedaling.

As the number of iterations increases, the envelopment covers a larger segment of the SEMG energy signal. Figure 3a shows that there are two pedaling cycles (surrounded by ellipses) involved by each of the envelopments of peaks 1 and 3. In order to avoid this effect, a stop condition must be defined so as to ensure that each negative curvature (or peak) has only one pedaling cycle. A first criterion to do this is to empirically determine the average length (in seconds or samples) between all pedaling cycles. Then, the iterations must continue until the distance between each found pair of successive peaks is less than the half value of this average. In addition, we need a second criterion for define what can be considered a valid peak. Empirical analysis have also shown that all negative curvatures whose amplitudes are higher than the half of the mean amplitude of SEMG energy signal can be well considered as valid peaks. Figure 3b illustrates the same segment of Fig. 3a, but now obeying the two criteria proposed.

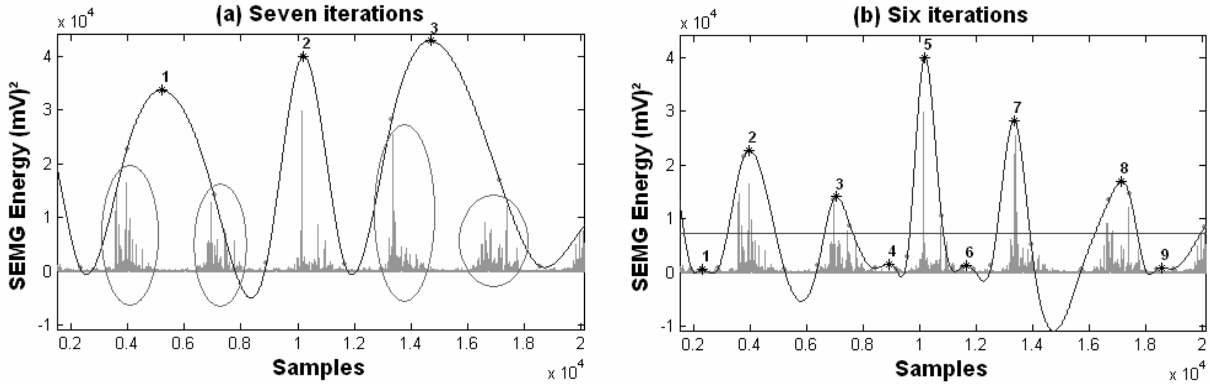

Figure 3 – a) At the seventh iteration, the envelopment of each peak does not correspond to a single pedaling; b) Valid peaks at inflexion points 2, 3, 5, 7, and 8 found at sixth iteration; straight line represents the half of the mean amplitude of SEMG energy signal.

There are nine inflexion points in Fig. 3b where the curvature is negative but only the points 2, 3, 5, 7, and 8 are acceptable peaks covering individual pedaling cycles according to the second criterion. The algorithm stopped at sixth iteration, as a consequence of first criterion, revealing five pedaling cycles. This is consistent with what can be visually observed.

3.2 Segmentation

The segmentation of SEMG signal is based on the average distance between the abscissas of points where the peaks of the envelopment of energy were found. Since the average distance was calculated, each individual pedaling segment is determined by cutting a piece of the signal with the length of the average distance so as to have the abscissa of the respective peak in the center of the segment. Only complete pedaling cycles are segmented.

Finally, the segments found can be structured in a matrix with the number of lines equal to the number of pedaling cycles, and the number of columns equal to the length (in samples) of the average distance between the abscissas. This matrix can be seen as an image structure. Therefore, techniques of image compression could be applied over this bi-dimensional signal. Figure 4 shows an example of a SEMG signal structured as an image signal.

4 RESULTS

The SEMG channel with the highest root mean square value of amplitude was chosen to the analysis. The signal had a length of 1,000,000 samples (about 8 minutes and 8 seconds) and was submitted to the proposed algorithm. After six iterations, a number of 697 pedaling cycles was identified. The distance between the abscissas of each pair of successive peaks was determined and their average value was calculated. The same was made for the abscissas of each pair of successive trigger pulses recorded during the cycling test. The SEMG signal was then segmented using both the proposed algorithm as the trigger pulses results. Figure 4a shows the segmentation of the SEMG signal made with the proposed algorithm.

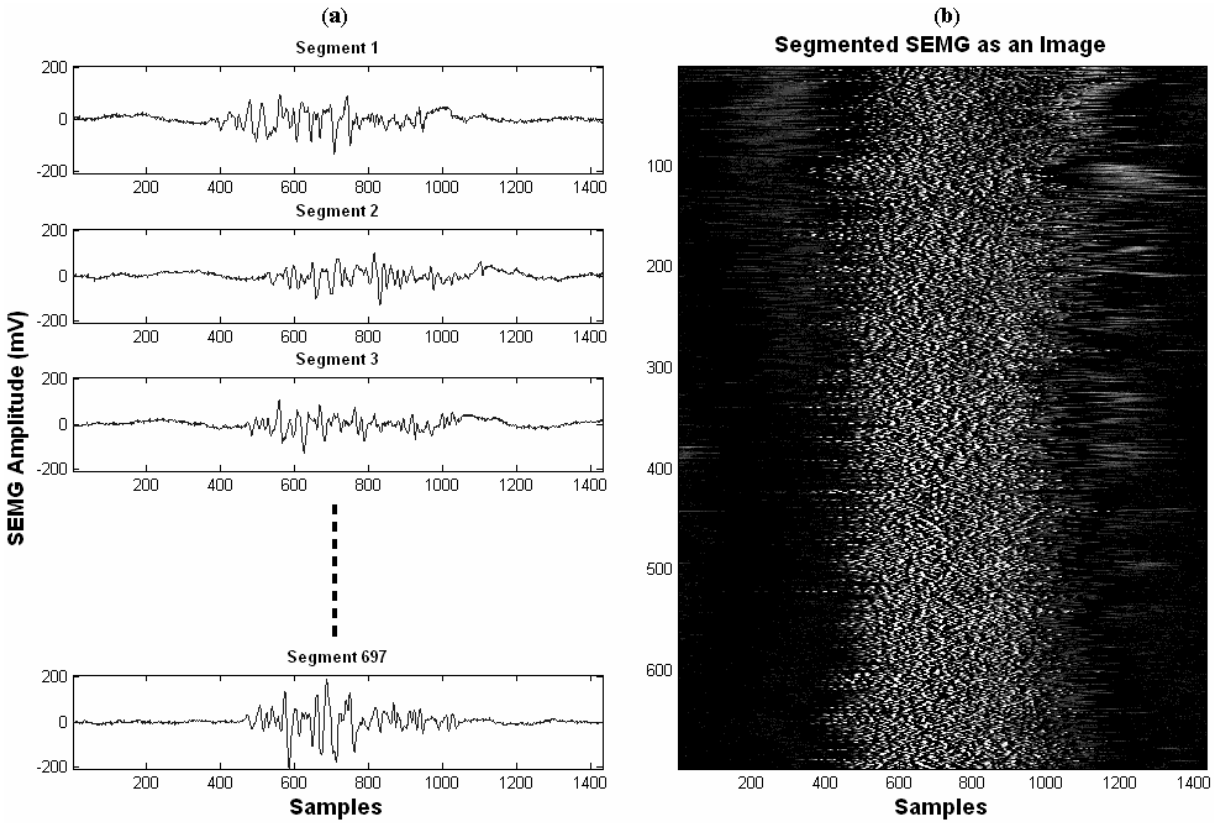

Figure 4 – a) SEMG signal segments, with a length of 1432 samples, determined by the proposed algorithm; b) Gray scale image constructed with 697 SEMG segments.

The gray scale image of Fig. 4b was constructed with the 697 pedaling cycle segments with length of 1433 samples.

After segmentation, the energy of each segment was also calculated for the two methods (algorithm and trigger pulses). The two methods were then statistically compared regarding their abscissas (of peaks and trigger pulses), the average distance, and the energy of each segment. The Kolmogorov-Smirnov normality test was applied to all variables and in just one case the normality was verified. Therefore, Wilcoxon Signed-Rank non-parametric test (De Sá, 2007) was applied to compare both methods. Table 1 summarizes the results of the comparison.

Table 1 – Comparison between the variables found using the proposed algorithm and the trigger pulses technique

Variable	Methods		
	Algorithm		Trigger
Abscissa (sample) $\cdot 10^{-4}$	49.73 ± 28.17	<	49.74 ± 28.17
Average Distance (samples)	1433.11 ± 123.56 *	=	1433.24 ± 91.50
[1]Energy of Segments $(mV)^2 \cdot 10^{-5}$	56.75 ± 15.49	<	56.76 ± 15.50
[2]Energy of Segments $(mV)^2 \cdot 10^{-5}$	55.59 ± 15.32	=	55.58 ± 15.31

Note. Values are mean ± SD.

* Significantly normal ($p > 0.05$).

[1] Values considering all the 697 pedaling cycles found.

[2] Values considering only the first 598 pedaling cycles found.

The symbols '<' and '=' are Wilcoxon Signed-Rank non-parametric tests ($\alpha = 0.05$).

5 DISCUSSION

The experimental protocol used is a traditional protocol for study of performance of cyclists. It was chosen in order to test the proposed algorithm in a standard investigation procedure of cycling tests. This enabled the evaluation of the algorithm developed in relation to a common way of pedaling cycle's identification which uses pulses generated by a trigger device.

The first analysis compares the abscissas found by both methods. The abscissas are the main reference of each pedaling cycle used for segmentation. Table 1 shows that the abscissas found with the algorithm are significantly less than the ones found with the trigger. This represents a displacement of 38 ± 61 (mean ± SD) samples on average, i.e. about 18.6 ± 29.79 milliseconds.

Despite of the abscissas displacement, the average distance is not significantly different. Therefore, the segment length calculated is the same for both methods and the size of the image matrix (as the one showed in Fig. 4b) will also be the same.

After segmentation, the energy of each segment was determined for both methods. Here a curious behavior was noted. When all pedaling cycles (697) were considered, significant differences were identified by Wilcoxon test, resulting in values for the algorithm smaller than the ones for the trigger technique. However, after further research where the cycles were removed one by one, from last to first in order to study the production of energy throughout the test, there were no significant differences between the two methods until the pedaling cycle number 598. A hypothetical reason is that the subject could be starting a critical state of fatigue at this cycle. In this situation, all the muscle motor units could be actives (Merletti & Parker, 2004) and it is possible that the displacement of the abscissas significantly interfere on the energy calculus after the cycle 598.

Regarding the use of the algorithm as a segmentation step in a SEMG signal compression procedure, we can visually observe in Fig. 4b that the image presents good correlations between all the pedaling cycles, what certainly contributes for obtaining good compression factors.

6 CONCLUSIONS

Results showed that there are no significant differences between the two segmentation methods, what suggests that the algorithm developed is effective to segment SEMG pedaling signals. The main advantage of the algorithm is that no additional instrumentation is required to identify pedaling cycles neither additional bytes to store the information of trigger pulses.

The use of cubic spline results in points of peak whose positions are balanced by the energy produced during each pedaling. This may suggest that the abscissa of each point of peak is the moment where the muscle activation is maximum. However, the results of the algorithm are different from that fund by the trigger technique which is according to (So et al., 2005) criterion of maximum muscle activation. Thus, further analyses involving a higher number of athletes are required in order to give accurate conclusions about this question.

Future works could also apply the signal compression techniques using both segmentation methods and comparing the respective compression factors.

Acknowledgements

The authors would like to express their gratitude to the Biomechanical Laboratory from the College of Physical Education and to the Group of Digital Signals Processing (GPDS), both within the University of Brasília, for all the support.

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30º CILAMCE

Congresso Ibero-Latino-Americano de Métodos Computacionais em Engenharia

Armação dos Búzios - Brasil 2009

CERTIFICADO

Certificamos que o trabalho intitulado **ALGORITHM FOR IDENTIFICATION OF PEDALING CYCLES FROM SURFACE EMG SIGNALS** de autoria de **Fabiano Peruzzo Schwartz, Francisco Assis de Oliveira Nascimento, Maria Claudia Cardoso Pereira, Marcus Vinicius Chaffim Costa,Fabiano Araujo Soares** foi apresentado no 30º Iberian-Latin-American Congress on Computational Methods in Engineering - CILAMCE realizado no período de 8 a 11 de novembro de 2009, em Armação dos Búzios, RJ.

Armação dos Búzios, novembro, 2009.

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