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A Study of Computing Zero Crossing Methods and an Improved Proposal for EMG Signals

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ABSTRACT Zero crossings are a practical and efficient feature to approximate the frequency of a sampled series of data. Some research describes in different ways how to compute the zero crossings feature starting from its definition, and in some of them, a threshold is included as part of it. This research compiles a comprehensive list of description methods for zero crossings, both with or without threshold. In addition, an improvement of one method is proposed, mainly to save time resources. Moreover, it increases the precision when the objective is to perform some classification. This feature is often used as a vector of a matrix of features in signal classification. To test the different variations of the zero crossings methods, a classification of electromyographic signals was performed using support vector machines. The results obtained by the proposed method threw near to a 40% improvement in the classification compared to those approaches that do not consider a threshold and more than 7% compared to those with a threshold. The processing time of this work is shortened compared to others that also take into account a threshold.

INDEX TERMS Zero Crossings, threshold, EMG signal, signal classification, SVM, signal processing.

I. INTRODUCTION

Nowadays, the use of electromyographic signals (EMG) for the classification of movements based on pattern recognition has increased in different areas of science, mainly in those focused on prosthetic control.

In general, the myoelectric activity can be acquired by two types of sensors, namely, superficial and intramuscular. The former is placed on the surface of the skin and the latter under it. Thus, the latter are considered invasive. Sampling of these myoelectric signals generates EMG signals that can be described by different tools.

The successful classification based on pattern recognition lies in the features extracted and the classifier used [1].

It is important to describe the signals in the best possible way to be able to perform a correct classification; for this purpose, feature extraction techniques are used. The features of the signals can be analyzed in the time or frequency domain, or in the frequency spectrum, among others. The features in the time domain (TD) are very common in electromyographic control due to their computational simplicity and therefore easy to implement, since they do not need any transformation [2]. Among the most prominent techniques in the TD are the Mean Absolute Value (MAV), the Slope Sign Changes (SSC), the Waveform Length (WL), and the Zero Crossings (ZC) [3], [4].

The ZC computation for signals involves other factors in addition to the certainty of whether the signal actually went through zero or not, since at the time of the signal extraction, on many occasions, environment or line noise is also read. Therefore, this ZC value does not always yield a clear parameter with respect to the signal. When a threshold is considered, the effect of noise is reduced when the signal is characterized.

Electromyographic control based on pattern recognition requires the use of a threshold. However, there is no consensus regarding the best option to obtain an optimal threshold [2].

One of the most used methods for pattern recognition in EMG signals is the SVM technique, whose main function is to detect a n-dimensional hyperplane meant to separate a set of input feature points into different classes.

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This method has the potential to differentiate complex patterns [5]. In several comparisons, SVM has demonstrated better classification precision when compared to other classifiers such as Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA) and Particle Swarm Optimization (PSO) [5]–[10].

The key concepts underlying the SVM method are (a) separation hyperplanes, (b) the kernel function, (c) the optimal separation hyperplane, and (d) a soft margin (hyperplane tolerance).

This article presents a compilation of methods that describe how to calculate crossings by zero, with and without using a threshold, contained in Section II. Subsequently, a brief description of the SVM is given in Section II-B, and the parameters used to evaluate the performance of the classifier are described in II-C. An improvement of one method for a better classification and save processing time is also included in Section III. Then, the methods and manner in which the experiments were developed are described in Section IV. Finally, the results and conclusions are found in Sections V and VI, respectively.

II. STATE-OF-THE-ART

A. ZERO CROSSINGS DESCRIPTORS

ZC is defined as the number of times a (digital) signal crosses zero, and this feature is meant to approximate the signal frequency. However, there are different ways of calculating this value, according to different descriptions analyzed in the literature. A number of authors often mention the use of ZC in their work [2], [11]–[17], but they do not specify precisely which method was used to determine a zero crossing. As a consequence, it is not clear which description they used to perform the count; this is because of the basic definition of the ZC,

$$\mathrm{ZC} = \sum_i f_{ZC}(\cdot),$$

allows the definition of f_{ZC} to be varied. The following subsections describe different ways of defining the f_{ZC} function. In some algorithms, a threshold is used to avoid counting zero crossings due to signal fluctuations. These correspond to voltage signals read by the measuring instruments, with a relatively small amplitude compared to the rest of the signal, since they correspond to idle states; where there should be no voltage variations because there is no movement, as can be seen in Fig. 1, where the threshold is the estimated absolute value of these fluctuations, also called signal noise. The signal in Fig. 1 is an example of a signal that starts from an exciting state and ends in a resting period.

Certain research papers specify the obtained classification precision when using only ZC, for example, Roldan-Vasco [9] gets 38.25%, while Kamavualo *et al.* [18] obtain 66.5%, Phinyomark *et al.* [16] reach 71.58% and, Phinyomark *et al.* [19] 86.93%.

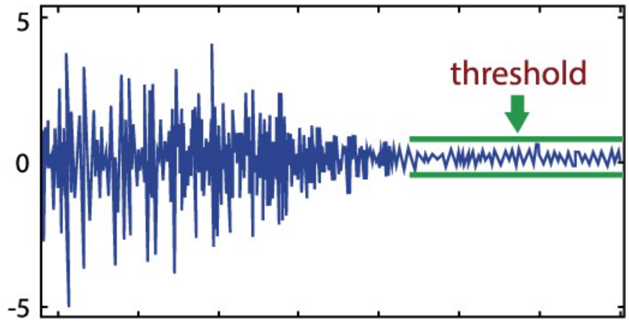

FIGURE 1. Visually estimated threshold of EMG signal.

1) METHOD 1

It is the simplest method since it consists of reviewing two continuous samples and comparing them to see if there was a zero crossing so that it can be described as:

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & x_i > 0 \text{ and } x_{i+1} < 0 \\ & \text{or } x_i < 0 \text{ and } x_{i+1} > 0, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

Unfortunately, regardless of how efficient the zero crossing is verified, this method is highly sensitive to noise.

2) METHOD 2

Mathematically, a zero-crossing occurs when two consecutive samples have a different sign. It happens when one sample is greater than zero and the other is less than zero, and so their product must be a negative number. It can be written as:

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & x_i \cdot x_{i+1} < 0 \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

Furthermore, since floating-point comparisons are expensive, some authors add a simple operation to reduce processing time at the moment of evaluating the value concerning to zero. It implies the use of the sgn function after the sample multiplication. This method is thus carried out as:

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & \mathrm{sgn}(-x_i \cdot x_{i+1}) > 0 \\ 0, & \text{otherwise,} \end{cases} \quad (3)$$

where the comparison is done with integer values.

In reference [20], in addition to performing the multiplication, they inspect if x_{i+1} is much bigger than x_i, to know if one of the samples is high due to the noise. This modifies the initial equation and can be described as follows:

$$f_{ZC}(x_i, x_{i+1}) = \sum_i g(x_i, x_{i+1}) + \sum_i h(x_i, x_{i+1}), \quad (4)$$

where

$$g(x_i, x_{i+1}) = \begin{cases} 1, & \text{if } x_i \cdot x_{i+1} < 0, \\ 0, & \text{otherwise,} \end{cases}$$

$$h(x_i, x_{i+1}) = \begin{cases} 1, & \text{if } \dfrac{x_{i+1}}{x_i} = 0, \\ 0, & \text{otherwise.} \end{cases}$$

3) METHOD 3

This method considers that, besides the change of sign between both samples, counting by the comparisons, like (1), the absolute value of the difference between these most be greater than the determined threshold T, to be considered the ZC:

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & \text{if } x_i > 0 \text{ and } x_{i+1} < 0 \\ & \text{or } x_i < 0 \text{ and } x_{i+1} > 0, \\ & \text{and } |x_i - x_{i+1}| \geq T, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

4) METHOD 4

It also considers the absolute value of the difference between samples to measure the threshold T, as in Eq. (5). Also, it combines the method 2 when using the product of samples to know when zero crossings occur. It can be described as:

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & \text{if } x_i \cdot x_{i+1} < 0 \\ & \text{and } |x_i - x_{i+1}| \geq T, \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Reference [21] instead of measuring the threshold with the absolute value of the difference of the samples, uses only the absolute value of the current sample.

Like in Eq. (2), certain works extract just the sign of the samples to simplify the computational cost of the comparison between the samples; this is calculated as:

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & \text{if } \operatorname{sgn}(x_i \cdot x_{i+1}) < 0 \\ & \text{and } |x_i - x_{i+1}| \geq T, \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

Reference [22] uses sign function with both samples and instead of comparing if the multiplication is less or greater than zero, check if it equals -1, that is:

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & \text{if } \operatorname{sgn}(x_i) \cdot \operatorname{sgn}(x_{i+1}) = -1 \\ & \text{and } |x_i - x_{i+1}| \geq T \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

5) METHOD 5

This method considers besides the previous sample x_{i-1}, and is proposed by [23]. Their method is described as follow, where T is the threshold:

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & \text{if } (x_i - x_{i-1})(x_i - x_{i+1}) \geq T \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Table 1 shows the equation used by some references related with EMG signals classification. Eq. (7) is the most utilized, followed by Eq. (6).

TABLE 1. Equation utilized by reference.

Equation	Reference
1	[24]–[26]
2	[2], [16], [27]–[29]
3	[30], [31]
4	[20]
5	[13], [32]–[35]
6	[1], [9], [18], [21], [36]–[39]
7	[19], [40]–[47]
8	[22]
9	[23]

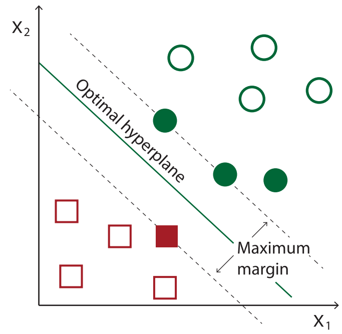

FIGURE 2. SVM geometric definition.

B. SUPPORT VECTOR MACHINES

One of the most used methods for pattern classification is SVM. The patterns can be body movements, images, sounds, etc. This theory was introduced by Vapnik and Corina in 1995 [48]. By SVM, an optimal separating hyperplane is constructed into a high dimensional feature space. It is possible to distinguish between two objects, as depicted in Fig. 2, or more, by using non-linear functions, in which the entries are mapped.

The input space is mapped into a high-dimensional feature space, and the separation hyperplane is found in this new space, to solve the nonlinear separable problem. The optimal hyperplane must discriminate different classes correctly, and so, it is necessary to find the hyperplane with maximum clearance between categories, i.e., the hyperplane that best separates them.

The training algorithm of an SVM is reformulated as a problem to solve by Quadratic Programming (QP), whose solution is global and unique. Considering input training data $(x_1, y_1), \ldots, (x_m, y_m) \in \mathbb{R}^N \times \{-1, +1\}$, where x_i corresponds to the input value and y_i to the assigned class (-1 or $+1$) to which it belongs. When data are not linearly separable; it is possible to map them by a non-linear transformation $\phi\colon \mathbb{R}^N \rightarrow \mathbb{R}^M$ inside of a new feature space $\mathbb{R}^M$ where the transformed data will be linearly separable. Thus, the obtained hyperplane that separates object types can be seen as

$$\omega \cdot \phi(x) + b = 0, \tag{10}$$

where $\omega \in \mathbb{R}^M$ and $b \in \mathbb{R}$.

The QP problem is used to construct an optimal hyperplane with a maximum value of separation and a closed error $\xi = (\xi_1, \ldots, \xi_m)$ in the training algorithm, describes as Eq. (11).

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m}\xi_i. \tag{11}$$

subject to

$$y_i(\omega \cdot \phi(x_i) + b) \geq 1 - \xi_i, \quad i = 1, \ldots, m.$$

When the data points are very nearby, it is tricky to separate them directly. Thus, a *kernel* function K must be used. That is,

$$F(\alpha) = \sum_{i=1}^{m}\alpha_i - \frac{1}{2}\sum_{j,k=1}^{m}\alpha_j\alpha_k y_j y_k K(x_j, x_k), \tag{12}$$

subject to

$$\sum_{i=1}^{m} y_i\alpha_i = 0, \quad C \geq \alpha_i \geq 0,\ i = 1, \ldots, m.$$

where $K(x_j, x_k)$ is the kernel function. The most used kernels are Radial Basis Function (RBF), a Gaussian, a polynomial, among others. The latter kernel can be linear, quadratic, cubic or of any degree d [8], and it can be described as

$$K_P(x_j, x_k) = (1 + x_j \cdot x_k)^d. \tag{13}$$

The RBF of two samples, which are feature vectors, is defined by [49]:

$$K_R(x_j, x_k) = \exp(-\gamma\|x_j - x_k\|^2). \tag{14}$$

The Gaussian function is described as [8]

$$K_G(x, \mu, \sigma) = \frac{1}{2\pi\sigma}\exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right], \tag{15}$$

where $\gamma = 1/2\sigma^2$ and σ is the standard deviation.

SVM is designed to separate only two classes, but it classifies more than two classes by two different strategies. One Against All (OAA) separates each class from the rest, and One Against One (OAO) compared the first category only against other, one by one.

C. PERFORMANCE ANALYSIS

The performance of the classification using each of the calculation equations of the ZC, was evaluated using performance indices such as precision (PRE), accuracy (ACC), specificity (SPE), and sensitivity (SEN). The formulations are described as follows:

$$\text{PRE} = \frac{TP}{TP + FP} \times 100\%, \tag{16}$$

$$\text{ACC} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%, \tag{17}$$

$$\text{SPE} = \frac{TN}{TN + FP} \times 100\%, \tag{18}$$

$$\text{SEN} = \frac{TP}{TP + FN} \times 100\%. \tag{19}$$

The parameters in Eqs. (16), (17), (18) and (19) are defined as a confusion matrix, where TP and TN are the number of True Positives and Negatives, respectively, and FP and FN the number of False Positives and Negatives, respectively.

III. IMPROVED METHOD

A. PROPOSED METHOD

To simplify operations and save processing time, this method suggests making at the same time the comparison to find crosses by zero and eliminate samples in the range of the threshold T. The T value is considered with the same amplitude up and down of the mid-line of the signal, which is, the zero line. Thus, we use

$$f_{ZC}(x_i, x_{i+1}) = \begin{cases} 1, & \text{if } x_i > T \text{ and } x_{i+1} < T \\ & \text{or } x_i < T \text{ and } x_{i+1} > T, \\ 0, & \text{otherwise.} \end{cases} \tag{20}$$

The operations avoided are:

- Multiplications, which have a high computational cost.
- Subtraction.
- Absolute value.

This description avoids the execution of an excess of operations when performing the comparison that initially was zero with the defined T. In addition, this description allows operating with different threshold values, above and below zero. However, in this research, a method to determine the T is also proposed, which is described in the next sub-section.

B. THRESHOLD

The threshold T was calculated with quadruple of the average of 10 samples of the subject in resting state because when no movements are made, there should no be voltage variation. If in the database the muscular activities start from a rest period, just take the first ten samples of every execution. Otherwise, it takes the information from the resting repetitions. The threshold T is determined as:

$$T = 4\left(\frac{1}{10}\sum_{i=1}^{10}x_i\right). \tag{21}$$

IV. METHODS AND EXPERIMENTATION

A. DATABASE

The data were collected by [24] in a database. It consists of signals extracted from five healthy subjects, three women and two men, normally limbed without muscle disorders, with an approximate age of 20 to 22 years. Four electrodes positioned in pairs and one for ground reference are the sensor system. Velocity and force of movements were removed to the will of the subject.

The sensor system was placed on the skin over the muscles by elastic bands, in Flexor Carpi Ulnaris and Carpi Radialis Extensor, Longus y Brevis muscles, with a reference electrode in the center, sensing the differential potential. Six different movements were made, with the name as corresponds to the object held in Fig. 3. Data have the following characteristics:

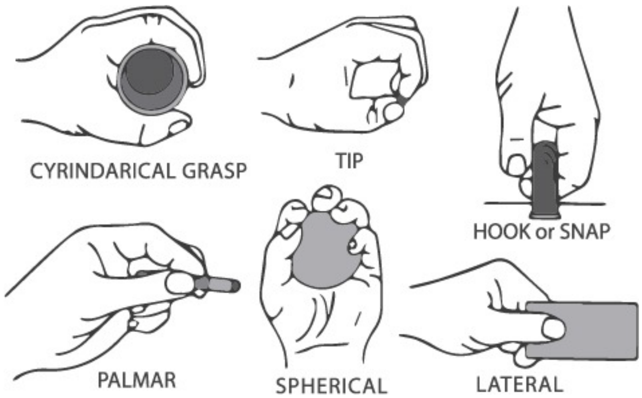

FIGURE 3. Executed movements by subjects with their names [24].

- Every movement was executed for six seconds.
- 30 repetitions of each movement were made.
- Two channels of EMG.
- Sampling frequency of 500 Hz.

B. DATA PROCESSING

For data processing, MATLAB and the LIBSVM library version 3.2 were used in this work [50]. A linear kernel was used. Two different digital filters were applied in software to remove undesirable noise from the collected sEMG signals. First, a 50 Hz Notch filter and then, a Butterworth bandpass filter between 15 and 500 Hz. The functions used were *filter*, *butter*, and *poly*.

In the training process, a feature vector was built with ZC for every channel. Then, these two vectors form the feature matrix, which is used as input to train the SVM classifier. Then, in a similar way, for the test process with the remaining samples, a feature matrix for the testing process was formed.

C. EXPERIMENTATION

The PC used for calculations has an Intel(R) Core(TM) i7 CPU at 1.8 GHz, with a RAM of 8 GB and a 64 bits operating system; with MATLAB R2015b version.

From the database, the considered window size is 500 ms, i.e., of 250 samples. The data were divided into two groups, the training, and the testing data; 10 samples for the first group, and 20 for the second. In other words, the database which is composed of 900 movements, from five different people and six different movements; 300 samples were used to train the SVM and the other 600 were used to test the classification performance. Diagram in Fig. 4, shows the general process of the experiment, starting from signal acquisition.

V. RESULTS

Eqs. (1), (2), (3), and (4) give the same classification performance; this is because they evaluate only if it exists a zero-crossing with two consecutive samples, and it does not take into account the threshold. So, the main differences are in the way to calculate if a zero-crossing occurs.

In the same way, with Eqs. (6) and (7), the classification performance is the same. In fact, in the description, also

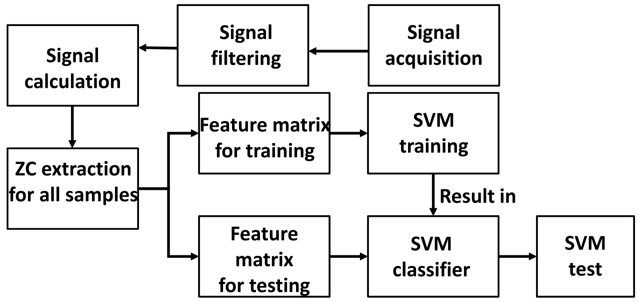

FIGURE 4. General diagram of the experiment.

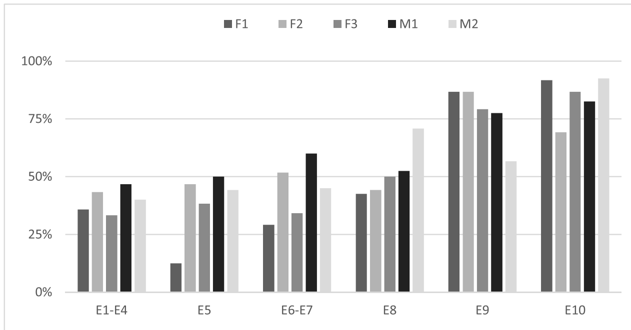

FIGURE 5. Classification precision obtained with ZC by equation. Subjects F1, F2 and F3 are females and, M1 and M2 are males.

TABLE 2. Performance analysis parameters obtained only with ZC by equation.

Subject	Equation					
	1-4	5	6-7	8	9	20
PPR	40.0 %	44.7 %	44.0 %	52.0 %	77.3 %	84.5 %
ACC	79.9 %	81.6 %	81.3 %	84.0 %	92.4 %	94.8 %
SPE	88.0 %	88.9 %	88.8 %	90.4 %	95.5 %	96.9 %
SEN	39.8 %	44.7 %	44.0 %	52.0 %	77.3 %	84.5 %

Eqs. (5) and (8) are the same that Eqs. (6) and (7), but, the result is different because some quantities are too small and by multiplying them, the total is rounded to zero by the software.

Fig. 5, shows an average view of the results. Those obtained with Eq. (9) and Eq. (20) have the best performance; however, Eq. (20) shows the best classification. Also, with equations in the first block, the acquired results are the worst. Thus, it is a better option to make the calculations of ZC using a threshold.

Also, in Table 2 are shown the parameters selected to evaluate the classification performance per equation but grouping the equations that give the same result. The last column has the result obtained by the proposed method, that is Eq. (20). The computed data throw the average of the results obtained by classifying the movements made by each subject.

The best average classification is obtained by the proposed method, with Eq. (20). Although, in terms of accuracy, the difference is not so pronounced; in precision, Eq. (20) shows the best performance, more than double of that obtained with the Eq. (1). The confusion matrix for the data

Predicted Movement

True Movement	M1	M2	M3	M4	M5	M6
M1	20	0	0	0	0	2
M2	0	19	0	0	5	0
M3	0	0	20	1	0	0
M4	0	0	0	19	0	0
M5	0	1	0	0	15	0
M6	0	0	0	0	0	18

FIGURE 6. Normalized confusion matrix for the obtained classification by Eq. (20)**, male 2 for six classes (cyrindarical grasp (M1), tip (M2), hook or snap (M3), palmar (M4), spherical (M5) and lateral (M6)).**

TABLE 3. Processing time of a sample by equation.

Equation	Processing time Average (μs)	STD (μ)
1	6.86	0.273
2	5.48	0.429
3	24.7	0.820
4	6.85	0.595
5	8.33	0.577
6	7.69	1.030
7	31.9	1.117
8	37.9	0.767
9	9.24	0.227
20	8.02	0.784

of male 2, for the classification obtained with ZC calculated by the proposed method with Eq. (20) is in Figure 6.

Table 3 illustrates the average and the standard deviation processing time obtained by a sample. This information was calculated using the *timeit* function. The minimum time by equations without threshold is 5.48 μs, and the maximum is 24.7 μs. In contrast, with equations that consider a threshold value, the minimum time is 7.69 μs and the maximum 37.9 μs, at least five more times. These results demonstrate that the proposed method is a better option when it is important to save time resources, due to the proposed method only is superior by 0.33 μs of Eq. (6); but it is better in precision with 40% and accuracy of 13.5%.

VI. CONCLUSION

This research work shows that in ZC computing it is important consider the proposed algorithm description, for two main reasons:

- If it is possible to remove all noise or it can be neglected; in ZC computing is not necessary to consider a T. Otherwise, it depends on the use of featured signal, if it is important take into account the required processing time. Eqs. (1), (2), (3) and (4) do not contemplate a threshold, so they yield the same classification precision. However, Eq. (2) provides the shortest processing time.
- When a threshold must be considered during ZC computing, it is important to deem the method through the T is calculated and the algorithm description to use. In this work, it is suggested the T calculation by the signal information read while resting state. Then, ZC computing by the proposed depiction in Eq. (20), because of this equation has the best classification precision compared to the other methods. Furthermore, it has one of the shorter processing time. Save time resources normally is important for control applications, from the operation of a prosthesis to the operation of machines made by movement.

This research work pretends to point out the improvement for ZC. Thus, in extension, it improves the precision obtained by combining it with certain features.

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