Automatic sign language recognition based on accelerometry and surface EMG signals: An evaluation of permutation entropy as discriminate feature

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Abstract

Hearing impairment is a condition that affects the economy and more than the 5 % of the word population. Communication between deaf and hearing people is difficult due to cultural and technological barriers. In this paper, we developed an Automatic Sign Language Recongnition (ASLR) system of 12 signs of the Colombian Sign Language based on surface electromyography and accelerometry. Initially, we acquire and segment the signals using a methodology based on multi-objective optimization. Then, we assessed different signal features as Permutation Entropy (PE) and Root Mean Square (RMS). Finally, we use a Support Vector Machine to classify the signs and a grid search to select the hyper-parameters. The proposed ASLR system showed a low segmentation error of 5.8 % and a classification accuracy of 96.66 % using only the RMS. These findings suggest that our methodology is suitable to be transfer into embedded system due to its low computational cost.

Keywords: Permutation Entropy, Sign Language Recognition, Accelerometry, Electromyography

1. Introduction

The sign language is an structured communication system with visual rather than auditory codes, used mainly by the deaf population as their natural language [1]. According to the World Health Organization (WHO), more than 5% of the population (466 million) worldwide has a hearing disability, between congenital and acquired deafness and the number is expected to rise to 900 million by 2050 [2]. In addition, the WHO estimates that the cost of untreated hearing loss is USD 750,000 million per year, including assistance devices, loss of productivity, unemployment and early retirement, educational support for children, among others [3]. It is estimated that approximately 20% (72 million) of hearing impaired people could be improved with hearing aids or cochlear implants, yet global production only covers 10% of the demand in developed countries and 3% in developing countries [4]. The communication between deaf people and hearing people is affected by motivational, psychological, ideological or intercultural barriers. After studying two groups of people (a group deaf people and other group of hearing people), it was found a disinterest of both groups to learn the language of the other, due to discrimination among groups aimed by communication barriers [5].

For these reasons, in recent years, the automatic recognition of sign language has been addressed by several researchers in order to develop systems that improve the communication between deaf and hearing people.

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1.1. Related Work

The Automatic Sign Language Recognition (ASLR) has been approached in different ways by researchers, using techniques like surface electromyography (sEMG), accelerometry (ACC), videogrammetry and the implementation of deformity sensors and gyroscopes to the acquisition during the execution of the sign, the most prominent techniques are sEMG y ACC.

1.1.1. Videogrammetry

video and image processing are an alternative to deal with the problem of ASLR, that has an increasing strength in the last years. The most prominent methodology is the pure visual-based gesture, in this methodology employ detection algorithm like Canny operator or non-parametric models to segment the hands in the image [6, 7]. Applying these techniques is possible to have a classification performance above 90% with the application of typical classification methods like Support Vector Machines (SVM) or Artificial Neural Networks (ANN).

In videogrammetry there are two major acquisition and processing problems. Acquisition has drawbacks regarding the lack of robustness, clip format and the fusion of information from multiple elements (facial expression, hands and body), especially when using low-end cameras [8, 9, 10, 11]. In addition to general perceptual properties, lighting or occlusion problems and positioning relative to the camera make it difficult to capture elements within images [12, 13]. Regarding processing, there are drawbacks in Sign Language Translation, especially for grammatically complex sentences where speech entities and deixis occur a lot in the filming space, the recognition of facial expressions and in some cases the addition of new characteristics for the processing of particular subjects [14].

1.1.2. Strain sensors

The ASLR through deformation is commonly based on the use of sensors capable of capturing this phenomenon. A recent work use a data glove, with flexure sensor located at strategic points of the hand/fingers and photoplethysmography sensor to ASLR of USA Sign Language [15]. Another work, developed an ionic sensor for human motion monitoring by employing durable H-reduced graphene oxide/carbon nanotubes/Ag electrodes and an ionic polymer interlayer, then, using an smart glove with some of this sensors demonstrates its usefulness in the sign language recognition [16].

However, it has several drawbacks, such as monotonous testing signal and indispensability of additional power supply. Although some of these disadvantages can be made up by means of sensor arrays testing and portable battery supply, these means will also increase the burden of data post-processing and destroy the entire integration with wearable systems, particularly in complex motion detection. Additionally, large-scale activity detection require sensors with extreme mechanical stability [16].

1.1.3. Electromyography and Accelerometry

Surface Electromyography (sEMG) is non-invasive technique that allows to record the activation of muscle fibers in the skin. In combination with signal processing techniques, sEMG has been applied to ASLR [17]. However, has been proven that fusing sEMG information with Accelerometry (ACC) data improve the capabilities of such systems. ACC sensor are devices capable of measure the acceleration of a body in three axis and are commonly referred as inertial sensors.

In order to extract features from ACC and sEMG, is necessary to use non-linear signal processing algorithms such Sample Entropy and Empirical Mode Decomposition [18], but also simple temporal algorithm such the Root Mean Square (RMS) or frequency has been used for ASLR [19, 20, 21]. This features has been used for classification algorithm such SVM and k-Nearest Neighbors, reaching classification accuracy above 95 % [22].

In this paper we developed an ASLR system for Colombian sign language, based on SVM, sEMG and ACC, aiming to obtain a low computational cost and high classification accuracy.

2. Materials & Methods

2.1. Data acquisition

The acquisition of sEMG were taken from four forearm muscles: Flexor Carpi Ulnaris, Flexor Carpi Radialis, Extensor Digitorum Communis, Extensor Carpi Ulnaris. The ACC signals were acquired by a single inertial sensor mounted in the wrist. The gestures were performed by three right-handed subjects, two of whom were in the process of learning sign language and the other was a professional interpreter. None of the subjects reported symptoms of neuromuscular diseases. The subjects were informed about the end of the study and told what gestures they should make. Twelve words were chosen from Colombian Sign Language (CSL) about questions, family and days of the week described in Table 1, all performed with the dominant hand only. To perform the gestures, an initial position was established and the subjects were asked to return to the initial position after execute the sign. Each gesture was executed ten times by each subject.

Two devices from the company BTS Bioengineering were used for the acquisition. To capture the sEMG signal we used the BTS FREEMG, which has wireless probes and a sampling frequency of 1000 Hz. To capture the ACC signal, we used the G-WALK wireless inertial sensors which have a sampling frequency of 100 Hz. The EMG Analyzer software provided by the manufacturer, allowed the connection of the sEMG and ACC sensors simultaneously. A filtering process of the signals was not carried out because the device makes a pass-band filtering by default between 20-400 Hz.

2.2. Signal segmentation

To extract the corresponding sEMG and ACC signal of the sign execution. We conducted an activation detection process based on ACC, which is subsequently used for segmenting the sEMG signal.

Initially, was obtained the ACC vector magnitude, using the Manhattan norm, that is, the ACC vector magnitude is the sum of the components of the absolute values of acceleration of the X, Y and Z axes (equation 1), in order to unify the movement information along of the three axes.

$$Acc_{abs}[i] = |Acc_x[i]| + |Acc_y[i]| + |Acc_z[i]| \tag{1}$$

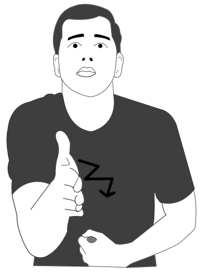
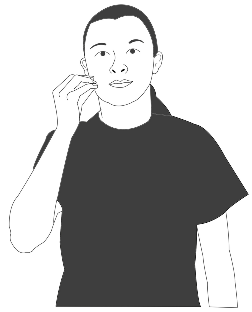
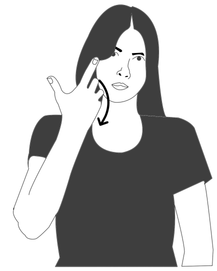
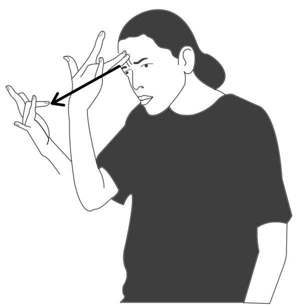
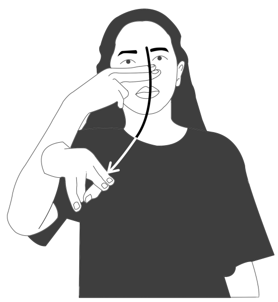
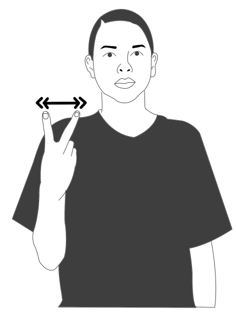
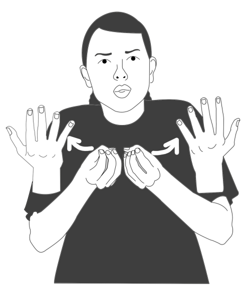
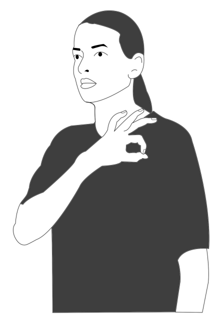
Where $Acc_{abs}[i]$ is the magnitude of the acceleration vector at point i, while $Acc_x[i]$, $Acc_y[i]$ and $Acc_z[i]$ represent the components of acceleration on the X, Y and Z axes respectively.

Subsequently, the Teager-Kaiser operator (TKEO) was computed for each signal, in order to improve the effectiveness of the segmentation process. The TKEO is calculated point by point as follows [23]:

$$\text{TKEO}[i] = \text{Acc}_{abs}[i]^2 - \text{Acc}_{abs}[i+1]\text{Acc}_{abs}[i-1] \tag{2}$$

We compute the RMS for the resulting signal TKEO[i] as suggested in [24, 25]. The RMS value is defined for an interval or window of the signal, such intervals are defined by the Window length in seconds (W_s) and the step which is a fraction of

Table 1: Description of the vocabulary and signs

Questions	**Family**	**Week days**
		
Which way?	Grandfather	Everyday
		
Why?	Son	Friday
		
How much?	Mother	Saturday
		
When?	Father	Sunday

W_s. The set of the initial position of every window is defined by $L = \{0, w_s\text{step}, 2w_s\text{step}, \cdots, nw_s\text{step}\}$, the the RMS for every window of the resulting TKEO signal was computed as:

$$\text{RMSTK}_i = \sqrt{\frac{f_s}{w_s}\sum_{j=L_i}^{L_{i+1}} \text{TKEO}[j]^2} \tag{3}$$

where f_s is the sample rate.

The region of interest was detected by the threshold method as follows [23]:

$$Acc_{Mask}[i] = \begin{cases} 1, & \text{if } RMSTK[i] > T_h \\ 0, & \text{Otherwise} \end{cases} \tag{4}$$

The threshold T_h is denoted as $T_h = \mu + h\sigma$, where μ and σ are the mean and standard deviation of RMSTK[i] respectively, while h is a constant that sets the level of the threshold.

Afterwards, we carried a search of the hyperparameters W_s and the step for the calculation of RMSTK, as well as the h value for the threshold method, with variations of 10 ms to 70 ms, 20% to 50% of the window and 0.01 to 0.1 respectively.

The parameters selection has an effect on signal segmentation, for example, a small threshold T_h or a large window, it could lead to an over-segmentation of the signal, i.e, would include signal segments that do not correspond to the sign. In contrast, a large threshold or a short window could lead to a sub-segmentation, causing information loss about sign execution.

Therefore, the performance was evaluated taking into account the length of the segmented signals. In this sense, a search for atypical lengths was performed by applying the Interquartile Range (IQR) method, which can be computed as $IQR[z] = Q3[z] - Q1[z]$, being $Q1$ and $Q3$ the first and third quartile respectively, and z represent the set of lengths of the signals to be analyzed, then the number of outliers (noutliers) is computed as follows [26]:

$$\text{num\_outliers} = \sum_{j=0}^{N} (z_j < (Q1 - 1.5\ \text{IQR}[z]) \vee z_j > (Q3 + 1.5\ \text{IQR}[z])) \tag{5}$$

N is the number of samples contained in z.

Atypical detection was conducted independently for each subject and sign (word), due to signal length on these two factors.

We selected the segmentation parameters to optimize 3 criteria: (1) Minimize the number of atypical signals, (2) Minimize the standard deviation of the signal length and (3) Minimize the average absolute difference between the signal length and the mean signal length.

In this purpose, we employed the concept of Pareto Optimality [27]. This concept stands that the solution to a multi-objective optimization problem is a set of non-dominated solution called Pareto front [28]. Figure 1 shows two examples Pareto fronts in different optimization problems.

As established before, the Pareto front is a set of solutions, so, in order to obtain a single solution, we took the solution in the front closer to the origin, after vector normalization.

2.3. Automatic Sign Language Recognition based on machine learning

In order to retrieved information from segmented sEMG and ACC signals, we characterized the signals using Permutation Entropy (PE) proposed by Bandt & Pompe in 2002 [29]. PE is a complexity measure that uses symbolic dynamics, allowing

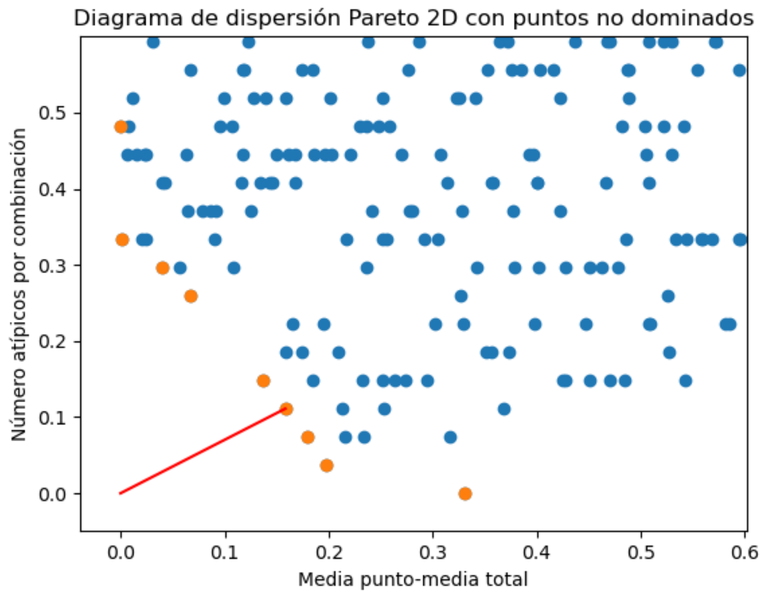


Figure 1: Pareto fronts examples

to compute entropy from long time series, to include the effect of the temporal evolution of a time series and to reduce the computation cost [30]. For these reasons PE is a simple and robust complexity measure.

Given a time series $X[i]$, $i = 1, 2 \ldots N$ and sequences of length m (Embedded dimension), PE is computed as [29]:

$$H(\Pi) = -\sum_{j=1}^{m!} p(\pi_j) \log p(\pi_j) \tag{6}$$

being $\Pi = \{\pi_1, \pi_2, \pi_3 \cdots \pi_{m!}\}$,the set of all possible ordinal patterns (permutations) of m-order. The ordinal patterns are computed from signals segments $S_i = \{X[i], X[i+\tau], X[i+2\tau] \cdots, X[i+(m-1)\tau]\}$, whose points are dispersed by τ time units (Time delay), in this way, the ordinal pattern $\pi_z = \{r_1, r_2, \cdots r_m\}$, is the rank order of the signal segment sorted ascending as $X[i+\tau r_1] < X[i+\tau r_2] < X[i+\tau r_3] < \cdots < X[i+\tau r_m]$. Lastly, $p(\pi_j)$, is the relative apparition frequency of the pattern j in X.

Determining the best embedding parameters m and τ it is a previous step to implement PE effectively. In this regard, we computed the entropy of each segmented signals with values of m between 2 and 12, and $\tau = \{\frac{0.4}{f_s}, \frac{0.6}{f_s}, \frac{0.8}{f_s}, \frac{1}{f_s}\}$. The selection of the best embedding parameters is based on PE performance to discriminate the different signs, we used a SVM with a lineal kernel, a cross-validation strategy and 10 repetition. The election of embedding parameter was conducted independently for sEMG and ACC, in addition, it was carried a SVM parameters tuning using a grid search.

SVMs are supervised classifiers. Proposed by Vapnik in [31], their ability to find a hyperplane that separates the classes with the largest margin is what greatly differentiates them from other classification algorithms such as neural networks [32].

Given a training data set $U = \{(x_1, y_1), (x_2, y_2), \cdots (x_l, y_l)\}$, where $y_i \in \{-1, 1\}$ is the class of the input vector x_i, the purpose of the SVM is to find a function that satisfies the expression $f(x_i) \approx y_i$ for all training data. Such function can be founded solving an optimization problem in its dual form (Equation 7), this allows us to simplify the SVM solution in order to find only the Lagrange multipliers α_i.

$$\min \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j (x_i \cdot x_j) - \sum_{i=1}^{l} \alpha_i$$
$$\text{Subject to:} \begin{cases} \sum_{i=1}^{l} y_i \alpha_i = 0 \\ \alpha_i \in [0, C] \end{cases} \tag{7}$$

$C > 0$ is the cost constant controlling the penalty of errors; therefore, a larger C assigns a higher penalty to errors [32]. f can be represented as follows

$$f(x) = \sum_{i=1}^{n} \alpha_i (x_i \cdot x) + b, \tag{8}$$

which is known as the support vector expansion. The most remarkable property of SVM is that f can be extended to nonlinear functions just by replacing the dot product $(x_i \cdot x_j)$ in Equation 7 and $(x_i \cdot x)$ in Equation 8. This is possible for a kernel function $\Phi(x_i, x_j)$ because Φ retrieves the pairwise dot product, in a high-order dimensional space without explicitly mapping the data.

Several kernel functions have been reported. However, the most widely used are the radial basis function kernel (RBFK), where γ is free parameters that control the kernel's behavior.

$$\phi(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2} \tag{9}$$

In order to develop an ASLR system. We employed SVM, using as input features the PE of sEMG and ACC signals, as well as temporal features as RMS. Initially, we compute the PE and RMS of the signals splited in three equal windows, in order to obtain the temporal evolution.

Then, we conduct three experiments, whereby we train several models, the first one using only PE features. The second using only RMS features, and the final model, using the combination of both groups of features. The models were trained using a 10 fold cross validation. We carried on a comparison between 2 different kernel (Linear and RBK), and we use grid search for hyperparameter selection, the employed grid are described in Table 2.

Table 2: Grid search parameters for SVM optimization

Hyperparameter	**Minimum**	**Maximum**	**Step**
C	10^{-2}	10000	×10
Gamma	10^{-5}	10000	×10
Kernel	RBFK, Linear		
Decision function shape	One vs One, One vs All		

The evaluation of the operation of supervised classifiers was done through performance measures. Such measures allow us to know the behavior and effectiveness of the algorithm during the training and validation process.

Several performance measures like *recall*, *presicion*, $F1score$ or *accuracy* are been proposed to assessed different aspects of classification systems. In order to define these metrics we implemented the next abbreviations: True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN) [33].

Accuracy represents the success rate of the model and it is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{10}$$

Recall or also known as sensitivity is the probability that the label classified as false is actually false, it is defined as:

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

Precision is the probability that the label classified as true is actually true, it is defined as:

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$F1score$ is the harmonic mean between *Recall* y *Precision* and it is computed as:

$$F1score = 2\frac{Presicion.Recall}{Presicion + Recall} \tag{13}$$

Taking into account that SVM is bi-class classifier, and our classification problem is multiclass (12 classes). We compared different decision functions shape as One vs All and One Vs One, such decision function can be seen in figure 2. One vs All, consist in training a classifier for every class against the remaining classes, and the final decisions is based on the largest probability between classifiers. One vs One classification instead, consisting in training a classifier between every pair of classes, and the final decision is based on the most voted class among the classifiers. The advantage of One vs All classification is that only have to train s classifiers (s is the number of classes), but have the problem of balance between classes, because in most of cases, the union of reaming classes represent a largest portion of the training data. In other hand, One vs One classification has no imbalance problems but have to train more classifiers ($s(s-1)/2$).

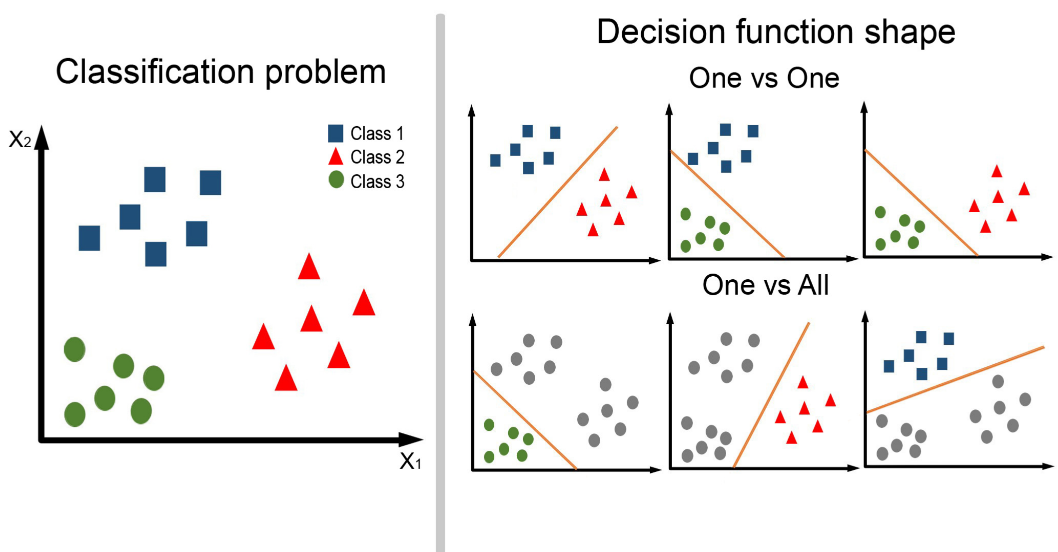


Figure 2: Decision function shape types

3. Results and discussion

3.1. Data acquisition

Samples were taken from three subjects with no symptoms of neuromuscular disease, with ages between 22-30 years old, two women and one man. We successfully acquired 360 signals from the 12 LSC gestures and 10 repetitions per each. Obtaining, 4 channels of sEMG from the muscles Flexor Carpi Ulnaris, Flexor Carpi Radialis, Extensor Digitorum Communis and Extensor Carpi Ulnaris. In addition, of the three accelerometry axes. Obtaining as a result a total of 120 signs execution with 7 signals.

3.2. Signal segmentation

Figure 3 illustrate the segmentation process results in every step of proposed segmentation methodology based on Threshold and TKEO. Pareto optimality allowed to identified 10 non-dominated solutions (Figure 4), the solution closer to the origin was a Window Length of 60 ms, steps of 20% and h of 0.09 to compute the threshold. For this solution, the IQR analysis report 21 miss-segmented signals, we found visually in those signals a significant noise levels at the beginning, however, during sing execution the signal quality were fine and were manually segmented.

These findings suggest that the proposed segmentation process was successfully and only in 5.8% of the signals were miss-segmented. Other works using TKEO and RMS to segment EMG are reported successfully results [24, 25], we found that such methodology could be applied in other signals like ACC. In addition, we show that use Pareto optimality is an easy and efficient criterion to select best segmentation parameters.

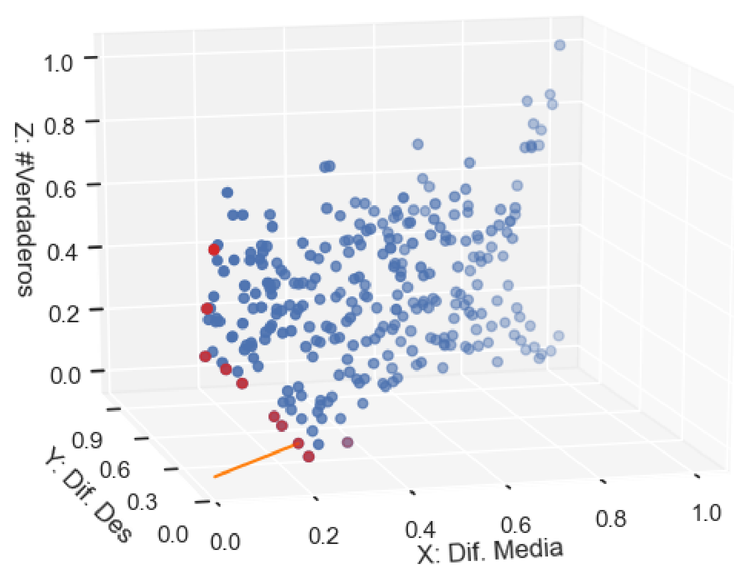
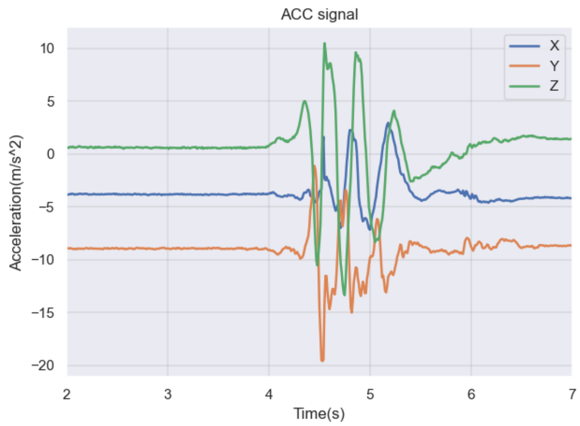
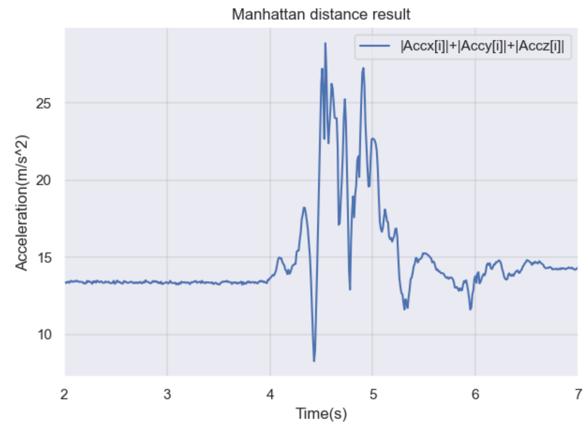


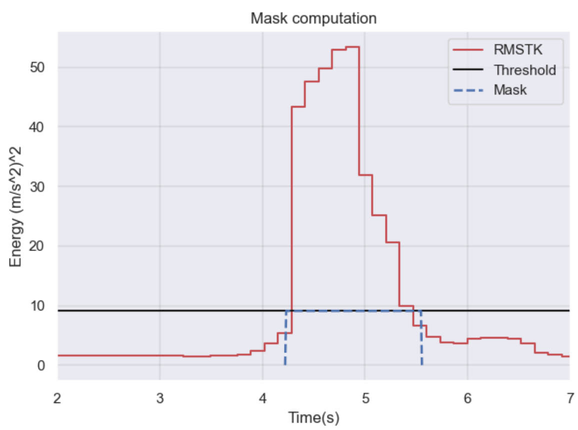
Figure 4: Frente de Pareto



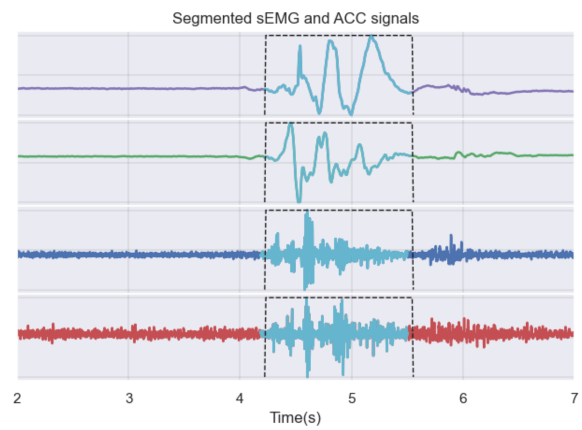
(a) Subfigure a



(b) Subfigure b



(c) Subfigure c



(d) Subfigure c

Figure 3: Subfigures

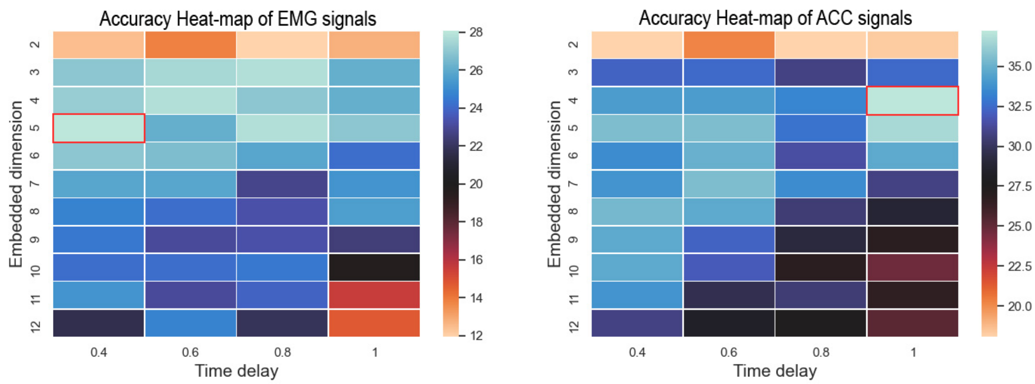
3.3. *Automatic Sign Language Recognition based on machine learning*

Figure 5 shows the results obtained after the search for the best embedding parameters to apply PE, we foud that m=5 and τ=2.5 ms where the best embedding for sEMG and m=4 and τ=10 ms for ACC.

Figure 6 illustrate the performance of the ASLR system based on SVM on the three proposed experiments. The best results in the signs recognition, were obtained using the RMS of the ACC and sEMG signals, obtaining an Accuracy and F1-Score of 96.66% and 96.60% respectively, versus 67.5% and 65.31% using PE, and 95.83% and 95.64% when both features were used. These results strong suggest that PE is not an informative feature to ASLR, since it does not allow the optimal signs differentiation by itself, and not provide additional information when it was used in combination whit RMS, on the contrary, it slightly decreases performance.

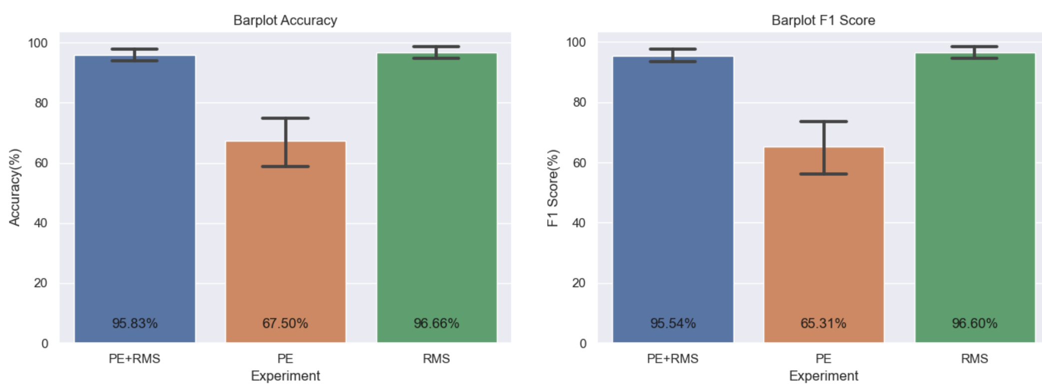
The SVM hyperparameters C, gamma, kernel and decision function shape parameters of the best ASLR system were 100, 1, RBFK and one vs one respectively. After classification performing, the results were 96.66% accuracy and 96.60% F1 score. This suggests the appropriateness of the SVM to perform the discrimination among the twelve problem classes.

In this work, as can be seen in Table 3 the vocabulary size it is not too extensive like in other studies [18, 22, 19, 37], however, due to the fact that this work includes professional interpreters and sign language learners as subjects. This add



(a) sEMG signals (b) ACC Signals

Figure 5: Heatmaps of classification accuracy based on PE of EMG and ACC signals



(a) Accuracy (b) F1-score

Figure 6: Classification performance of the 3 experiments

variability, due to professional interpreter performs the sign in a faster and less descriptive way compared to learners. In terms of segmentation, in [35] TKEO is used for the segmentation of the signals without reporting the effectiveness of the same, our work provides a methodology more objective to find the best parameters of TKEO, reducing error caused by subjectivity of the carrying out this action in a visual way.

ASLR system involves a high dimensional input space (over 5 features) [19, 35, 38, 39], while our study achieves a performance of 96.66% using only RMS on three windows (see Table 3). This is a positive result towards a reduction of computer costs to deploy the ASLR system into an embedded system.

We proposed the use of PE to characterize the signals, however, in the obtained classifications performance suggest that PE is not an appropriate metric for ASLR task. Although PE has been used effectively for sEMG signals, in other applications such as muscle fatigue, fall and neuropathic disease detection [40, 41, 42]. Moreover, on ACC signals PE has allowed to failure analysis of rotating machines [43]. It is possible, that the low sensibility of PE to sign recognition is because the duration of the gesture (sign) to be classified is too short and no produce a significant change in entropy. In contrast other complexity measures like Sample Entropy has achieved a performance of 92% in ASLR [44], this suggest that amplitude based entropies are more effective to ASLR task.

Table 3: performance comparison of ASLR

Paper	Number of Signs	Number of features	Techniques	Performance (%)
Our approach	12	1	sEMG, ACC	96.66
C. Savur [17]	26	10	sEMG	91.73
J. Wu [19]	80	20	sEMG, ACC, Gyroscope	96.16
R. Gupta [34]	10	12	sEMG, ACC	87.50
S. P. Y. Jane [35]	48	10	sEMG, ACC, Gyroscope	93.27
S. A. Khomami [36]	20	5	sEMG, ACC, Gyroscope	96.13

Finally, the proposed ASLR system shows promising results taking into account that experiments were carried out inter-subject, this mean that eventually that the ASLR system could be used for any user without the need of previous personalize training.

4. Conclusion

This paper presents an approach to automatic recognize 12 word of Colombian sign language with an accuracy of 96.66 %, based on 4 channels of sEMG and 3 axis accelerometer. Using the RMS and the TKEO of ACC signal to segment signals allow us to properly identify sign execution and using the multiobjective optimization processes help us to select proper thresholds and windows length.

On other hand, Permutation Entropy showed a low sensitivity to identify signs. This could be due to execution time of the signs are too short and do not represent a change in the entropy levels. Moreover, the RMS of sEMG and ACC signal were high informative to detect the signs, with a low number of windows over the signals. This represent a low computational resources, which could result in an easy transition to real time applications.

Support Vector Machines using Radial Basis Function Kernel exhibited a high accuracy to detect the signs, when One vs One decision functions shape is used, however, when the vocabulary is high the number of classifiers increase exponentially, this have to be taken into account when this method would be applied in real time applications.

In future works a more extensive vocabulary have to be consider and a reduction of the sEMG channels.

Conflict of interest

The authors have no conflicts of interest to report.

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