k-Nearest-Neighbours for EMG signal recognition applied to Sign Language

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***Abstract*—Analysis of Electromyographic signals (EMG) allows obtaining useful information to develop gesture recognition applications. Applying KNN algorithm with a correct selection of EMG features can obtain optimum results using a low quantity of training data. This paper proposes an implementation of an embedded system using FPGA De10-Standard and MYO device, which has 8 sensors to transmit EMG data in real time over Bluetooth. From this obtained data the selected feature is the RMS value of the signal. Point classifications are done every 2 seconds showing an accuracy of 95% in sign language gestures.**

***Index Terms*—Electromyography, KNN, hand-sign, FPGA**

I. Introduction

The progress and expansion of information technologies as well as it increasing acceptation by the general public have opened a huge opportunity for developers of technologies that may impact in specific parts of the community. As described in [1] improvements and additions to existing technology have made it possible for Deaf people to interact with a wider group of people and have global contact. OMS estimates that 15% of the world population, about 900 million people, are affected by any physical, psychological or sensory disability, and these disabilities difficult the personal growth and social integration say R. Koon [2]. Hand-sign language is so ancient as verbal language, but its development has changed along the time.[3] Actually, the development of applications that combine real-time operations and machine learning are the state of the art. In machine learning there are defined two types, supervised and unsupervised. In this work supervised learning is used, which is defined as the machine learning task of learning a function that maps an input to an output based on example input-output pairs.[4]

Neural networks are frequently used in common classification processes with images, text, etc. This method has become very popular and efforts to improve have resulted in better algorithms. For this work, we have chosen K-nearest neighbors, KNN, an easy algorithm to implement but powerful to observe and comprehend every stage of learning. To acquire data, we used the MYO device, developed by Canadian company Thalmic Labs, which can be worn on the arm (placed just below the elbow) to interact with the systems. The MYO is equipped with several sensors that can recognize hand gestures and the movement of the arms. It is characterized by using a process called electromyography (EMG); identifying the gesture by moving the arm muscles. Based on the electrical impulses generated by muscles, 8 EMG sensors are responsible to recognize and perform each gesture [5]. For the computational process, we used the FPGA De-10 Standard, building the cores of CPU and communication with Altera's tool Quartus Prime and the programming of the system in Eclipse.

II. Related Work

Some previous works related to classification and application of EMG data has been reviewed and analyzed to obtain useful information on this topic. In [6] it was developed a system for deaf people using an electronic gauntlet, and a 90% of minimum accuracy was achieved, all these were in an Android environment using PowerFlex as sensors. DBSCAN algorithm was used in [7], acquiring data from thirty-two superficial sensors on the forearm, testing on six participants trying to classify 9 letters for hand-signal language. Computational processing was done in Matlab and clustering algorithms in Rstudio. In this work, a big effort is done to acquire the signals and reduce noise. In the end, it concludes an accuracy rate close to 50% using K-means Algorithm. A similar work used a KNN and Bayes combination to detect 4 different gestures [8], where it was only used one EMG sensor in the forearm, achieving an accuracy of 94%. This work remarks the importance of making an initial calibration by setting different parameters for each testing subject or providing an individual training dataset each time.

III. Implementation

In this section, there will be described different stages: data acquisition, feature selection, FPGA hardware construction, initial calibration, and classification process.

A. Data acquisition

Data were acquired using the MYO device, which has 8 sensor pods symmetrically distributed around the forearm. These 8 sensor returns electromyographic data in a maximum range of 70 mV. This data comes already filtered by the technology on the device, which makes it the perfect option to obtain data and use it directly on applications without the need for pre-signal processing.

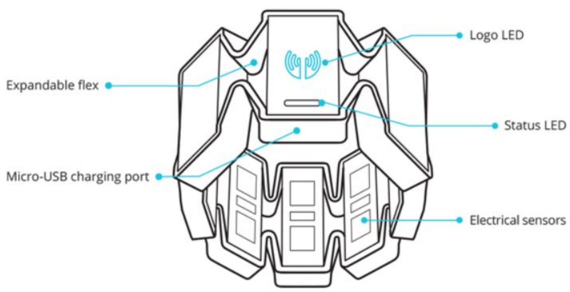

Fig. 1. MYO structure design.

EMG data is transmitted in a frequency of 200 Hz. This frequency may be changed int the data acquisition project provided by Thalmic Labs to the developer's community. MYO makes the communication process by Bluetooth 4.0 BLE and has a maximum range of 15 mts. Because of the sensibility of EMG signals to externals and environmental factors, it is advised to clean the sensor pods of the device before using every time, as well as the forearm. At the time of data acquisition the person should not make the gestures strongly or applying excessive force, this may affect the classification process because the gestures may seem like natural poses.

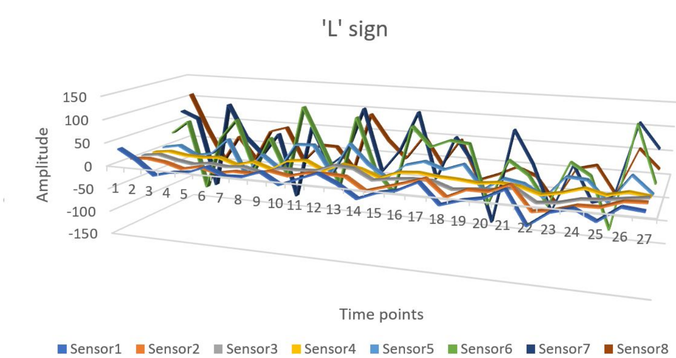

Fig. 2. Letter "L" hand-signal EMG data.

In fig.2 You may notice how sensors 6, 7 and 8 show more activity than the others.

B. Features selection

In order to get a correct representation of the signal and have enough features to work several tests were done trying features like minimum and maximum values, mean, variance, median and root main square value. The accuracy of classification was compromised at the time more features were used and the conclusion was this features mentioned above created redundant values, ruining the classification algorithm. In the end, the only selected feature chosen was the root main square value defined by the next equation:

$$Xrms = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{1}$$

This RMS value is calculated from 400 points, collected in 2 seconds periods, considering only the points when the gesture stays in a stable state. Calculating this in a transition state when moving from a gesture to another one disturbs the needed signal.

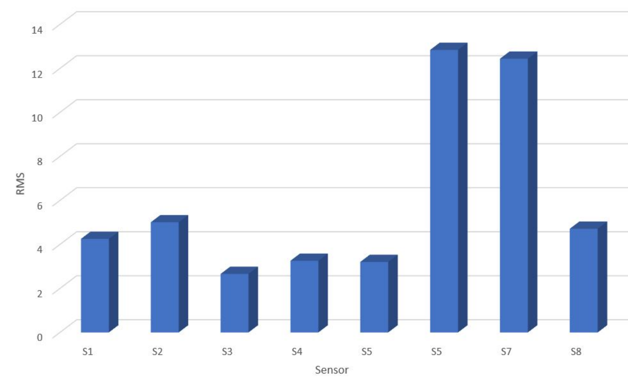

Fig. 3. Letter "B" hand-signal RMS sensor values.

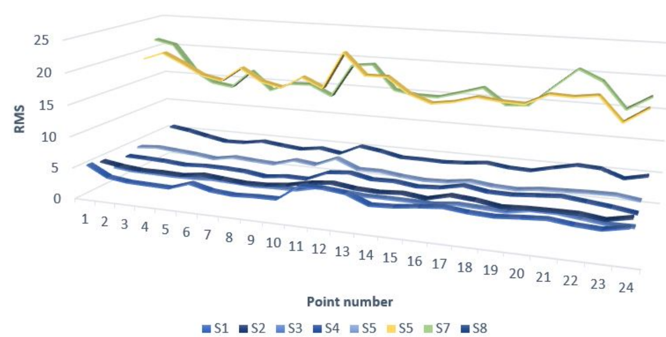

Fig. 4. Waveform of multiple letter "B" points.

In fig. 3 you can see the RMS representation for letter B, activity in sensor 5 and 7 will be crucial at the time making the classification. In fig 4 is the representation of multiple points taken at different times. The waveform may seem constant.

C. FPGA implementation

FPGA De-10 Standard was used in this work. The QSys counted with the following elements:

- Clock source.
- Altera PLL.
- Nios II processor.
- Interval Timer.
- System ID peripheral.
- JTAG UART.

- SDRAM Controller.
- UART (RS-232 Serial Port.)

FPGA De-10 Standard was used in this work. The QSys counted with the following elements: UART core had to be configured in order to receive EMG data from collecting host. This task took longer than expected because of failures in data synchronization. A mechanism to recognize when a sentence was been transmitted had to be developed, this consists in identify the first two elements, which only send act like the hello sign. The last character to be sent in every line is going to be ASCII 122, when this is detected the line is finished.

D. Initial Calibration

When the program starts it will wait to receive a 60 characters line, which indicates the FPGA to be ready to listen to de data. At this point, a welcome message is shown explaining the learning process and the instructions to follow. This calibration stage will take 9 shots of gestures, omitting the first one because this may be considered as a transitional signal. Once every group is trained the classification process begins.

E. Classification

Once the calibration is finished the result dataset is loaded on memory. Every incoming line now will create a new structure and this will be filled with the sensor data. This structure will go into the classification function, receiving also the training dataset, the number of points in the dataset and the K parameter.

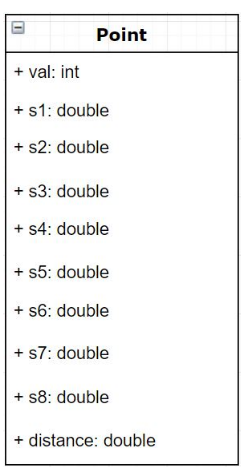

Fig. 5. Point Structure.

Basically, KNN will calculate the Euclidean distance between the incoming point against all the dataset. Once this distance is calculated the resulting points will be sorted to choose the K minor distance results. In the end, a frequency count is done by every group identifier. The group identifier with the most frequency of occurrence will be the result of the algorithm.

IV. Results

Initial tests using 5 different combined features shows that using all those features at the same time didn't represent in a correct form the signal, that's because the mean, maximum and minimum values from all signals acquired by the MYO device, in general, have the same form, that made the algorithm to not identify the gestures, probably because of the 9 point constellations fell in the same Euclidean space area.

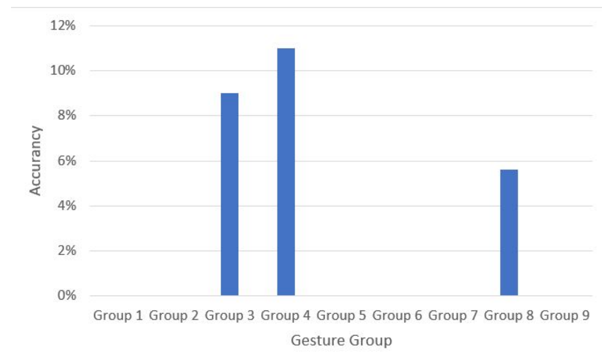

Fig. 6. Accuracy using 5 features.

At the time of only using the RMS feature, we obtained the best results, only with minimum errors in the letter "O", which classifier tends to says "P" or "U". This could be explained because of the similarity of the gestures. These experiments were run in 5 testers with 20 points to test each one. An important point is that every tester must know each letter to train very well because if there's any mistake at the training stage there's no more option than restarts the whole process.

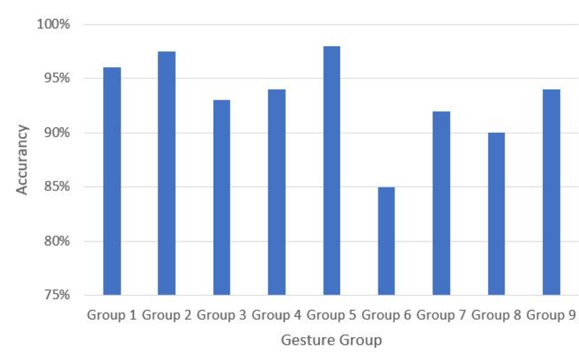

Fig. 7. Accuracy using 1 features.

Adjusting the K parameter was tested in 1 person using 40 testing points, getting a result that if K = 2 there were more probabilities for the classifier to not produce a result if the point has two nearest neighbors from different groups. Using K = 3 is more chance to achieve a result in this case.

V. Conclusions

It was possible to create the necessary hardware to process the data using FPGA, additionally, make a correct synchronization to receive data using the UART core.

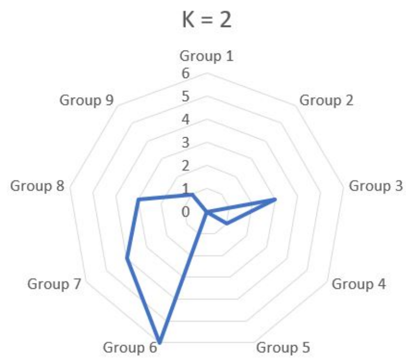

Fig. 8. Number of unclassifiable points using K = 2.

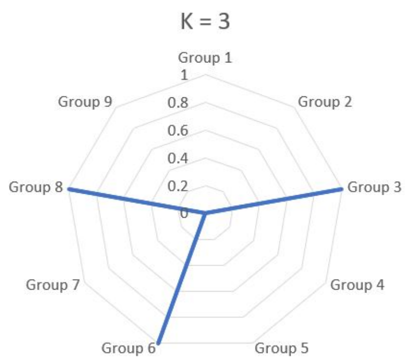

Fig. 9. Number of unclassifiable points using K = 3.

The EMG data was enough to make classifications of letters of the hand-signal language.

KNN shows to be a good algorithm to this type of application. It achieves a minimum guaranteed of 93.4% of accuracy and having less than 1% of non-classifiable points.

This systems proposed may be migrated to a mobile environment, taking advantage of the portability and ease of use of the MYO device.

VI. Acknowledgment

We thank Prof. Jose Cordova and Prof. Leonardo Munoz for their contribution to the development of this project.

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