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Wearable Band for Hand Gesture Recognition based on Strain Sensors

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Abstract— **A novel fully wearable system based on a smart wristband equipped with stretchable strain gauge sensors and readout electronics have been assembled and tested to detect a set of movements of a hand crucial in rehabilitation procedures. The high sensitivity of the active devices embedded on the wristband do not need a direct contact with the skin, thus maximizing the comfort on the arm of the tester. The gestures done with the device have been auto-labeled by comparing the signals detected in real-time by the sensors with a commercial infrared device (Leap motion). Finally, the system has been evaluated with two machine-learning algorithms Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM), reaching a reproducibility of 98% and 94%, respectively.**

Keywords—smart wristband; strain gauge sensors; gesture recognition; wearable device; machine learning

I. Introduction

Human gesture monitoring has always been the focus of many academic studies in the biomedical and commercial field [1, 2, 3]. The main challenges are focused on achieving a reliable, high sensitive and fully wearable device that minimizes the discomfort or embarrassment of patient. Currently all the systems for monitoring the movements have strong limitations. For example, systems based on 3D infrared camera to recognize finger gestures [4] or other devices based on camera recognition [5] suffer from line-of-sight occlusions and have heavy computation requirements. Other sensors that recently become more common are devices based on electromyography (EMG) [6]. In this case, these sensors have problems detecting finer finger gestures because they use less sensitive dry electrodes, and in this way, they are susceptible to sweat and skin impedance changes over time [7].

In the last year two interest system for gestural controlling, with high performance, have been proposed. The first one is the system named *Tomo* [8], based on Electrical Impedance Tomography (EIT). This system has a high accuracy but the electrodes require a narrow contact with the skin for proper operation. The other system has been proposed by MIT laboratories [9]. This system is based on force sensitive resistors (FSRs) and exhibits a high level of reliability; however, its efficiency has intrinsic limitations due to the type of sensor. Furthermore, systems based on FSR require a close contact with the skin of the user to ensure that the movements can be detected, thus creating constriction and discomfort to the patient. Moreover, such systems are not fully wearable because, albeit flexible, they do not have the peculiarity of being extensible.

In this paper, we present a novel system for monitoring hand gestures based on polymeric strain gauge sensors. This system includes low power consumption and stretchable devices mounted on a breathable cotton wristband that maintains high reliability monitoring, making this device unique in the landscape of gestural recognition. The presented system is easy to use, since it should be only worn to start the monitoring of the movements. The wristband is constituted by one single comfortable piece with electronics embedded on it. We conducted an experiment to validate the performance of the system, using a commercial optical technology (Leap motion) to properly label each gesture. The collected hand gesture data were evaluated by two well-established machine learning algorithms Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM).

II. System

A. Wristband

The wristband system has been made by cloth tissue with a fixed number of strain sensors. The sensors have been fabricated by using a mixture of thermoplastic and nano-conductive particles; this blend is extruded into small filaments of diameter 0.7 mm and length of 1 cm. These filaments are distributed on the surface of the band at regular intervals to cover the bands tendons and muscles of interest [9]. The sensors are embedded in the tissue and, even if not in direct contact with the skin, they are able, due to their high sensitivity, to detect the movements of the hand.

This fully wearable system adopts strain sensors that transduce elastic deformation of tendons, skin and muscles into electrical signals (Fig. 1). The electrical signals are transmitted to a PC for data interpretation (in this paper we have used for convenience a USB connection, but the board is also equipped for a Wi-Fi connection to PC or Smartphone). The system is particularly innovative because it allows to obtain a breathable elastic bandage with the sensors not in contact with the skin. In this way, it is possible increase patient comfort while maintaining a high reliability in tracking the movements, obtaining at the same time a high degree of accuracy.

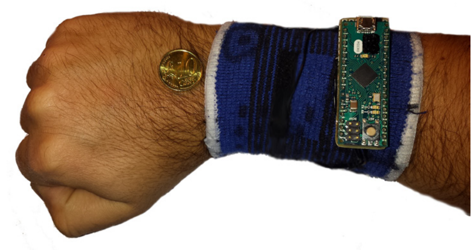

Fig. 1 A photograph of the wearable system worn on the wrist.

B. *Validation and calibration*

For the validation of the movements, a Leap Motion system has been used. This system uses infrared source and two cameras to detect and identify what kind of movement the tester is performing, thus validating the data returned by the band (Fig. 2).

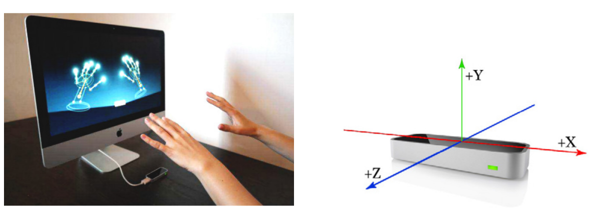

Fig. *2* A picture identifying the Leap motion system (right) and the normal position of the hand of a user (left) [*11*].

In particular, a graphical interface (GUI) has been realized by LabView software, which allows a real-time and automatic validation of the movements through the images received by Leap Motion. This program is based on vector calculus. Considering the space identified by the Leap as a Cartesian coordinate system and associating to each identified finger of the hand as vector unit, which moves in this tern, it is possible to distinguish whether the movement of interest has been recognized by the system with simple Cartesian operations. An example of such a logical process is depicted in Fig. 3, where the movement of keytap of the fingers is tested. In particular, the vectors of the fingers are classified with five vectors "i-Finger Direction" (i.fd), while the normal vector to the palm takes the name of "palm normal" (pn) [11]. The quantity identified by cosine of the dot product between the dn and pn is the discriminant for the identification of the movement. Further to complete the gesture recognition, an initial condition must be set as a threshold value corresponding to the "*rest position*", which in this case is equal to cos (θ).

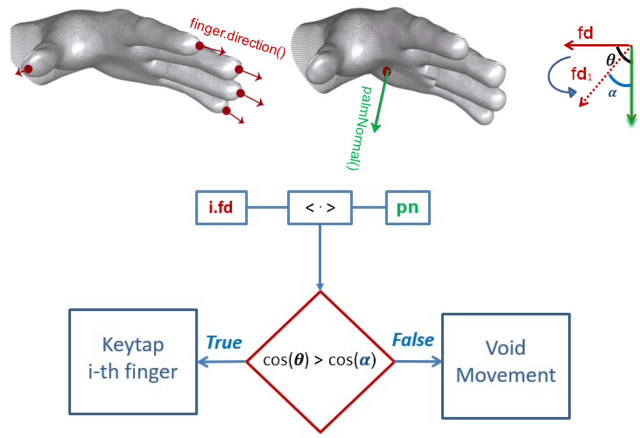

Fig. 3 The logical recognition process performed by LabVIEW software with the Leap Motion system.

III. EXPERIMENT

For the experiment, three volunteers have been recruited to perform 8 different gestures. The gestures have been divided into three groups: A) gestures 1 and 2 - extension and flexion of the hand; B) gesture 3 - Grab the hand to simulate a grasp; C) gesture 4 to 8 - keytap of each individual finger movement starting from the thumb of the hand up to little finger, as shown in figure 4. These gestures have been chosen to highlight the possibility of recognizing the movement of each individual finger (group C) and to repeat certain gestures that are usually executed during rehabilitation exercises (group A and B) [10, 12].

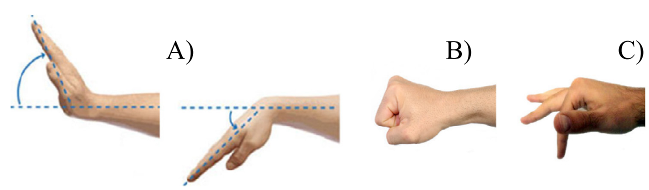

Fig. 4 Example of the different hand movements of interest.

All the participants read and signed a consent form before entering the study. The ethic form of the study has been proved by Simon Fraser University. After the wristband has been worn on the wrist of the participant, the experimenter calibrated the band. Before performing the data collecting, the experimenter demonstrated and explained the gestures to the volunteers and asked them to practice if they needed. The participant performed the 8 gestures, each repeated 5 times, in a self-paced manner. Each gesture lasted about 3-5 seconds. During the wristband test, the gestures have been monitored also by the optical validation system, based on the Leap Motion system, to automatically perform the labeling of the movements.

IV. RESULTS AND DISCUSSION

A total of 120 trials (3 subjects, each performed 8 gestures for 5 times) have been collected for data analysis. Fig.5 shows an example of the signals from 4 sensors for the first trial of each of the 8 different gestures. The 4 channels of signals show distinct patterns between the 8 gestures.

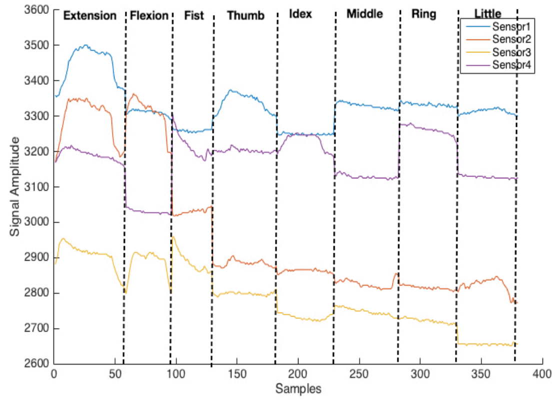

Fig. 5. An example of the sensor signals from a subject (subject 1, first trial of each of the 8 different gestures).

The each of sensor signals were normalized to scope [0 1] using the following equation (1) before being fed into the machine learning models

$$normX = \frac{X - min}{max - min} \qquad (1)$$

Where X is the vector of signal to be normalized, and max and min are the maximum and minimum values vector of the training data set. During both cross-validation and cross-trail evaluation, the training data were first normalized and the testing set data were normalized using the max and min values from the delivered normalization of the training data.

Two well-established supervised learning technologies, Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) with a non-linear Radial Basis Function (RBF) were employed to evaluate the performance of the system with the collected data. The LDA classifier used in study is from MATLAB Statistics and Machine Learning Toolbox [13] and SVM is from LIBSVM library [12] wrapped in the MATLAB.

Unlike SVM, which seeks a hyper-plane in non-linear feature space [14], LDA seeks a linear combination of features that forms the decision boundaries between different classes [13]. The ability to use simpler linear signal processing and classification methods such as LDA would indicate that the proposed wearable system could potentially be more easily embedded into a compact, low-power device that is capable of performing online classification.

We first performed 10-fold cross-validation for the whole collected data and then performed cross-repetition evaluation using both LDA and SVM. In 10-fold cross-validation, the data was randomly separated into 10 equal-sized subsets. Among the 10 subsets, one subset was retained as validation data for testing the model, and the remaining nine subsets were used for training the model. This cross-validation process was repeated 10 times (folds), with each of the 10 subsets used as the validation data. The results of the 10 repetitions were averaged as a single performance measurement. In the cross-trial evaluation, the LDA and SVM models were trained using the data recorded from the 4 of the 5 trials, and then the trained models were used to predict the rest 1 trial's gesture data. This procedure repeats 5 times to cover all the 5 trials for each of the gestures by shifting the training and testing trials. The results of the 5 repetitions cross-trial testing were averaged as a single performance measurement. All these evaluations were within-subject.

Figure 6 shows classification accuracies of 10-fold cross-validations and cross-trial evaluation for the collected data using LDA and SVM, respectively. The accuracies are very high with an average of 98% and 94% in cross-validation and 97% and 91% in cross-trial evaluation, for LDA and SVM respectively.

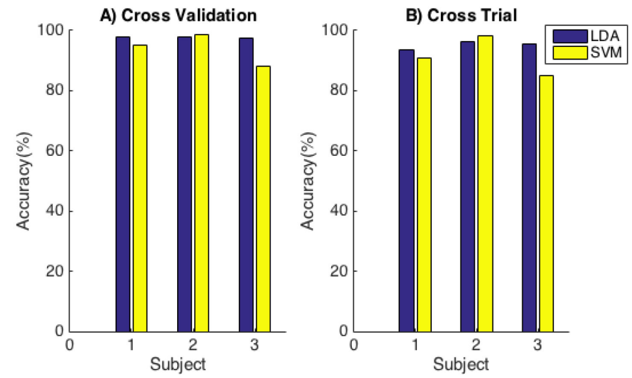

Fig. 6. Accuracies of classification of 8 classes for 3 subjects in terms LDA, SVM algorithms. The left panel is the results of 10-fold cross-validation and the right panel is the results of cross-trial evaluation.

Figure 7 shows the confusion matrix of classification using LDA in the cross-trial evaluation averaged from the 3 subjects' data; the x-axis is the predicted gesture type and the y-axis is the true gesture type. The 3 gestures -- Extension, Flexion and Fist -- achieve very high classification accuracies of over 98%. However, the 5 individual finger movement gestures have lower accuracies than those of the 3 whole-hand gestures. Among the 5 finger gestures, the accuracies of Index, Ring, and Little fingers are even lower. Interestingly, by looking into the confusion matrix (Fig.7), a majority of the misclassification of the three finger gestures is recognized as the gesture Extension. The possible reason is that the working hand of the subject extends when it tries to move one of the three fingers downward separately.

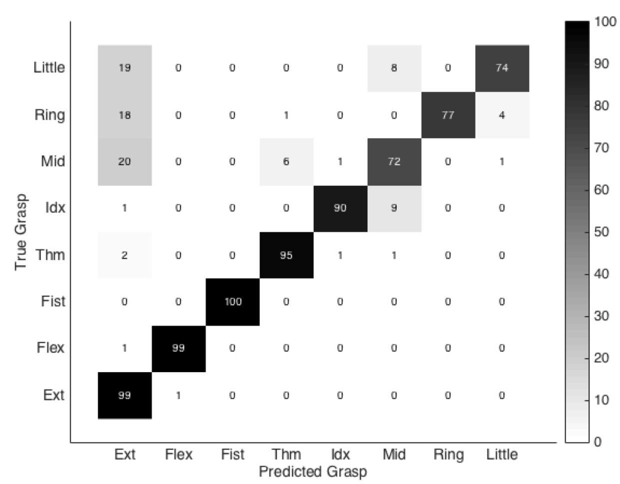

Fig. 7. Confusion matrix of classification using LDA in the cross-trial evaluation averaged from the 3 subjects' data; the x-axis is the predicted gesture type and the y-axis is the true gesture type. The number of the values in the cells is in %.

Figure 8 shows an example of the LDA model output compare to the true labels for 5 trials of 8 gestures from a subject (subject 1) in cross-trial evaluation. The blue lines are the true class labels provided by the Leap motion and the red lines are the predicted gestures by the LDA model. We can see that both trail 2 and trial 3 achieved the best performance of 100%, and the first trial of is the outline with the accuracy of 75%, where the middle finger flexion gesture has been misclassified to thumb and part of little finger has been misclassified as middle finger flexion. The rest of the misclassifications mostly happen during the transition periods.

V. CONCLUSION

A novel fully wearable system based on a comfortable wristband equipped with stretchable strain gauge sensors and

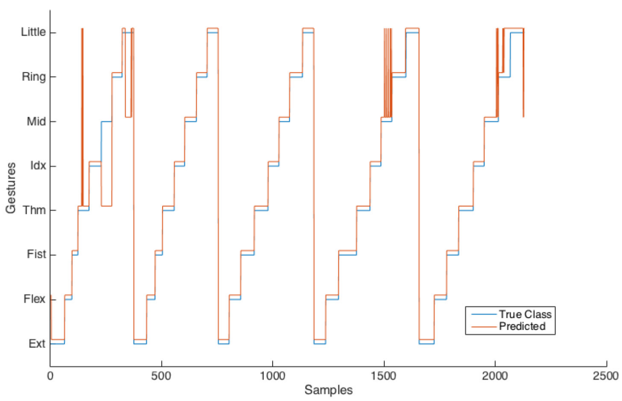

Fig. 8. An example of the LDA model output compare to the true labels for 5 trials of 8 gestures from a subject (subject 1) in cross-trial evaluation. The blue lines are the true class labels provided by the Leap motion and the red lines are the predicted gestures by the LDA model.

readout electronics have been designed and fabricated to detect with a superior degree of reliability the gestures of a hand. The system has been validated with two different methods, the first based on the comparison of the signals detected in real-time by the sensors with a commercial infrared device (Leap motion) and the second related to the implementation of the wristband results with a software of machine learning. This latter method highlights the high accuracy of the system, reaching a reproducibility of over 98% by using LDA classifier.

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