Human-Sitting-Pose Detection Using Data Classification and Dimensionality Reduction

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***Abstract*— The research area of sitting-pose analysis allows for preventing a range of physical health problems mainly physical. Despite that different systems have been proposed for sitting-pose detection, some open issues are still to be dealt with, such as: Cost, computational load, accuracy, portability, and among others. In this work, we present an alternative approach based on a sensor network to acquire the position-related variables and machine learning techniques, namely dimensionality reduction (DR) and classification. Since the information acquired by sensors is high-dimensional and therefore it might not be saved into embedded system memory, a DR stage based on principal component analysis (PCA) is performed. Subsequently, the automatic posed detection is carried out by the k-nearest neighbors (KNN) classifier. As a result, regarding using the whole data set, the computational cost is decreased by 33 % as well as the data reading is reduced by 10 ms. Then, sitting-pose detection task takes 26 ms, and reaches 75% of accuracy in a 4-trial experiment.**

Keywords—chair position; embedded system;knn; pca

I. INTRODUCTION

The area of analysis and detection of sitting-pose during workdays and in classrooms has been explored by several studies that uses electronic devices and a wide range of sensors. Mostly, such studies are aimed at detecting static sitting poses and determining their influence on the normal development of daily activities [1] [2]. In [3], authors explain that keeping bad/incorrect postures habits may cause attention missing, and loss of motor and brain skills for problem solution and decision making, as well as physical health problems such as muscle rigidity, fatigue and muscle pain [4]. The recognition/detection of sitting poses can be conducted by following mainly two approaches: Image-processing-based and sensor-based approach [5]. The latter requires pressing sensors able to be located on different weight-supporting surfaces by taking into account the pressure distribution over the whole surface.

The most common human sitting poses have been categorized in different manners. For instance, in [6], after performing several experiments, it is determined that there are 10 typic poses. Another study [5] considers 5 poses to develop the detection system. Despite that different systems have been proposed for sitting-pose detection, some open issues are still to be dealt with, such as: Cost, computational load, accuracy, portability, and among others.

In this work, we present an alternative approach based on a sensor network to acquire the position-related variables and machine learning techniques, namely dimensionality reduction (DR) and classification. To design our detection system, we start with a comfortable chair that helps a user to readily reach a good posture so that his/her body keeps the natural state wherein the spin position and the space between the vertebrae do not change and the muscles of the waist and back relax. Otherwise, when changing to an incorrect position, intervertebral discs are narrowed and ligaments are stressed causing pain and discomfort [7].

The selection is done of set of poses is highly dependent on the detection system design. Particularly, we set 4 poses.

Once data are acquired by installed sensors, we perform a data analysis stage using machine learning techniques. Such a stage involves a classification step using the well-known K-Nearest Neighbors (K-NN) classifier that depends of a metric used for the calculus of the Euclidian distance between two points for select the k neighbors nearest in terms of p attributes [11]. As well, due to the high dimension of acquired data, we perform a DR step based on Principal Component Analysis (PCA) [8]. To implement our system, we opt by an Arduino platform because it is not only a powerful embedded system but is by construction highly versatile. In addition, there is a great amount of free code available at internet [9] [10] [12]

The proposed system is aimed at detecting different poses that student may make during studying time. It works as follows: we use strength and ultrasonic sensors, which send the information to an embedded system. Such sensors are appropriately located and distributed on the chair. To process the acquired data, we first apply PCA to represent the initial data – arranged into a data matrix - in lower-dimensional space [13]. Subsequently, we perform the KKN [14] [15] algorithm on the reduced data matrix. Doing so, we determine the poses that users (students) have made during a pre-established time period. To assess the accuracy of our system, we perform quantitative comparisons with a standard system running the same algorithms over the original higher-dimensional data matrix. As a result, regarding using the whole data set, the computational

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cost is decreased by 33 % as well as the data reading is reduced by 10 ms. Then, sitting-pose detection task takes 26 ms, and reaches 75% of accuracy in a 4-trial experiment.

The remaining of this paper is structured as follows: Section II, on one hand, presents the design of the electronic systema and explains the data acquisition process. On the other hand, it outlines the data analysis made to detect sitting poses. Section III gathers the obtained results. Finally, Section IV draws the concluding remarks and future work.

II. MATERIALS AND METHODS

The design of the sitting-pose detection system proposed in this work can be divided into two main stages: Acquisition and data analysis. An explaining diagram of the proposed system is shown in Fig. 1.

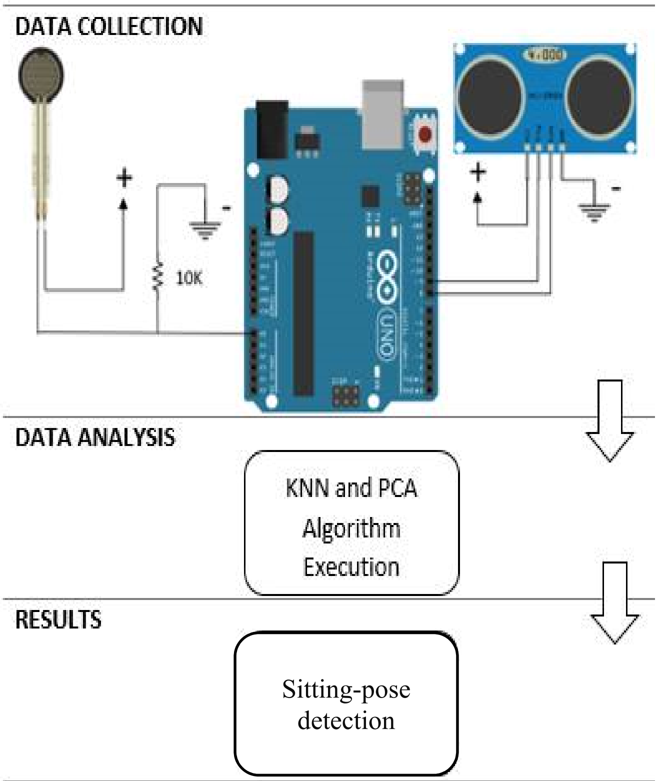

Fig 1. Explaining diagram of the proposed system. It mainly involves stages for data collection and analysis.

A. Considered sitting poses and data settings

To establish the poses to be considered for our study, we use direct observation for setting the types of sitting made by a study group. The analysis is done over a University student group, who are monitored during their studying activities at library, as shown in Fig. 2. As a conclusion, we find that there is a sitting pattern evidenced in 4 poses, similarly as proved in another study [16].

Fig 2. Sample picture of the student's type of sitting. Four poses are determined: Upright (red), leaning forward without back support (yellow), bowed forward (green), and tilted backwards (blue)

Table I gathers the name and description of all the considered poses. Fig1. Comparatively, Poses 1 (in red) and 3 (in green) are better than the remaining ones since they have lumbar support, preventing from extra loads on the intervertebral discs of the spine, while relaxing the hip and back muscles.

TABLE I. Considered poses

#	Pose	Brief description
1.	Upright	The back and thighs form an angle of 90◦.
2.	Leaning forward without back support	The lower back have no support. Slope of up to 40º.
3.	Bowed forward	It has lumbar support. Slope of up 40º.
4.	Tilted backwards	Upper back against the chair backrest. Relaxed.

Data are acquired from observing 7 students (4 men and 3 women). Each of them is monitored for a while and making the 4 considered poses depicted in Fig. 3. For classification purposes, we set poses 1 and 3 as the target classes, while poses 2 and 4 as non-target ones. Our system linearly picks samples over a period of 1 minute.

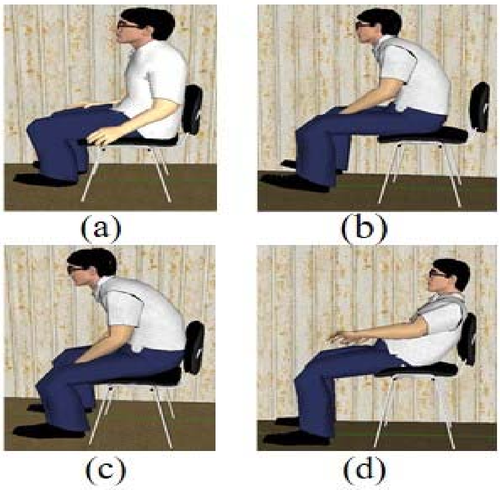

Fig 3. Sitting poses to be performed by the students from study group.

B. *Electronic system design*

We design the circuit using as a main element the Arduino 1 R3 as embedded system. Three strength sensors (FSR-402) and one ultrasonic sensor (HCSR-05) are connected to Arduino through a transmission line that carries data while the user is sitting on sensor surface. Sensors are utilized as follows: Strength sensors are placed together on the chair being adapted to a piece of fabric, while the ultrasonic sensor is placed on top of backrest as shown in Fig 4.

(a) (b)

Fig 4. Sensor distribution on the chair. The figure shows the front (a) and backhand (b) view of fabric.

C. *Data analysis*

The acquired data are arranged into a data matrix ***M***, which is m x n, where m is the number of samples or data points and n is the number of attributes or variables representing each data point. Initially, since 4 sensors are used, we get n = 400 and m = 4 for the higher-dimensional matrix. Then, such a matrix is reduced by using PCA [10]. Particularly, we extract a new, 2-dimensional matrix. Over the reduced matrix, we run a K-NN classification algorithm. It depends on a metric used as a distance to measure how similar are the data points. Here we consider the Euclidean distance [11].

Since strength sensors tend to be very sensitive, during data collection, the outliers must be clearly identified, especially those generated in the descent to the chair and sitting movements before establishing a fix sitting pose. We perform a manual outlier removal procedure. A total of 100 data points per position are considered for training the system. PCA is used to find the most relevant variables following a variance criterion. We obtain that sensors 3 and 4 represents the 86.66% of the data representation (see Fig. 6). To perform the DR procedure, we set the resultant dimension as 2. So, we can draw 2D scatter plots as shown in Fig. 7.

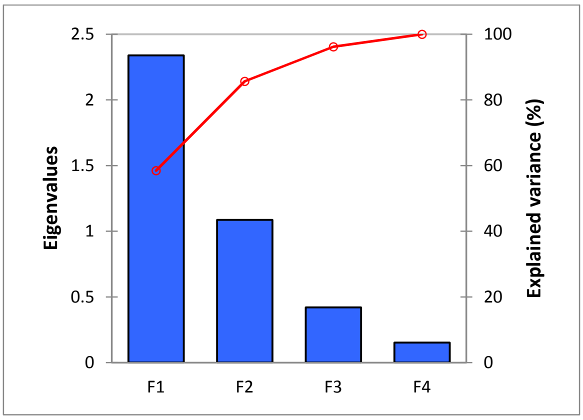

Fig 6. Eigenvalues bar diagram and explained variance plotting for the original higher-dimensional data matrix.

The considered variables are those for the strength sensor s3 and proximity sensor S4. Another matrix size reduction should still be performed to prevent from saturating the RAM of the microcontroller [17] [18]. Following a K-NN scheme the number of rows (samples) can be reduced by excluding the data points being close from the average data distribution. Doing so, we get that the new number of rows becomes 80. Here we name the new, reduced matrix is named ***S***.

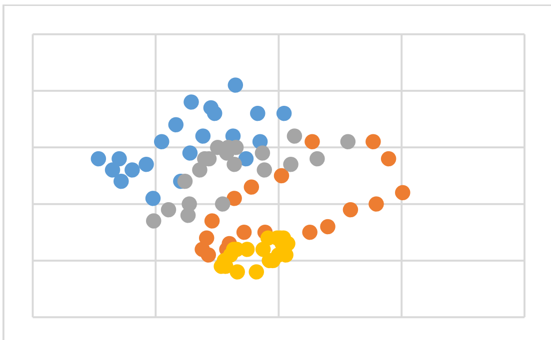

Fig 7. Scatter plot of reduced matrix. Each color represents one of the considered classes (poses) as follows: Pose 1 in blue, pose 2 in orange, pose 3 in gray and pose 4 in yellow.

The flow diagram of the implemented approach is graphically described in Fig. 8.

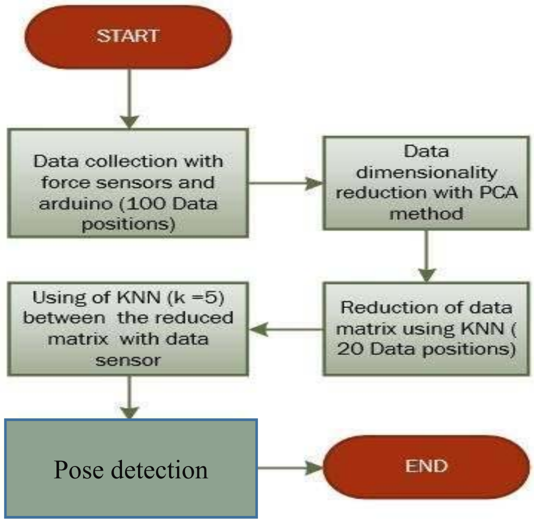

Fig 8. Flow diagram of the proposed data classification approach used for sitting-pose detection.

III. RESULTS

The tests were conducted on both a standard computer (PC) and the proposed system. Ten data points per pose taken at random were tested considering the matrices ***M*** and ***S***. The former matrix is only tested on the PC.

Results were obtained for all the analyzed poses a. Using matrix ***M***, for pose 1, an average accuracy rate (AAC) of 72% success rate was reached. Likewise, for poses 2, 3 and 4 the AAC was 86%, 63% and 77%, respectively. Fig. 9 shows the ACC boxplots. Given its simplicity, the system outcomes are comparable with those reported in literature. As a result, the rules for x and y to reduce the dimension were:

$$x = \sum_{i=0}^{t} (-0.0945 * i) + (0.7541 * i) + (0.6487 * i) + (-0.0384 * i)\,,$$

and

$$y = \sum_{i=0}^{t} (-0.0232 * i) + (0.0274 * i) + (0.0239 * i) + (\,0.9991 * i)\,.$$

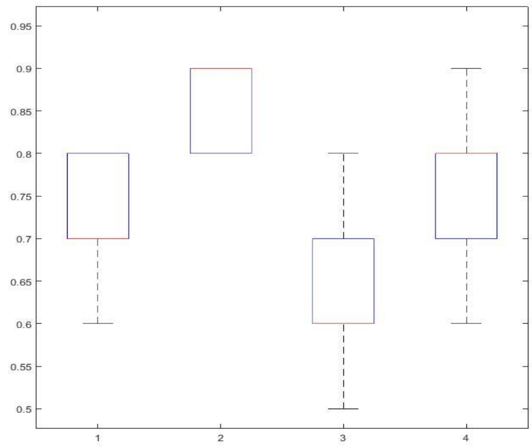

Fig 9. Boxplots of accuracy rate using matrix ***M***.

Using ***S***, AAC is of 68% for pose 1, 83% for pose 1, 67% for pose 3 and 83% for pose 4. These results can be graphically appreciated in Fig. 10.

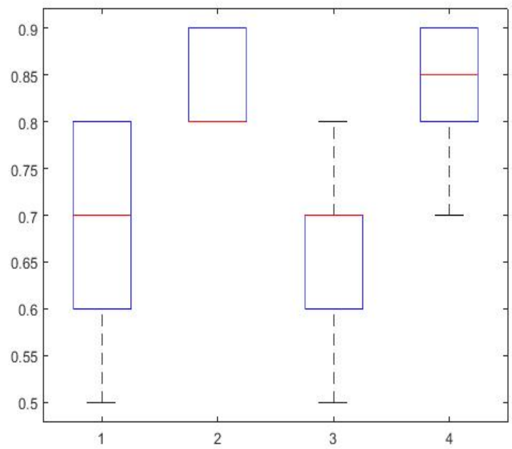

Fig 10. Boxplots of accuracy rate using matrix ***S***.

Results regarding memory usage of the embedded system processor are significant good. When inputting the higher-dimensional matrix ***M*** 99% of the flash memory of 8Kbytes is used, and therefore there would not be enough space for typing more script lines. On the contrary, using the lower-dimensional matrix ***S***, only the 30% of the memory is used, leaving enough to add lines of programming space. As a result, regarding using the whole data set, the computational cost is decreased by 33 % as well as the data reading time is reduced by 10 ms. Then, sitting-pose detection task takes 26 ms, and reaches 75% of accuracy in a 4-trial experiment.

IV. Conclusions and future work

This work presents an alternative approach to deal with the problem of sitting-pose detection, which is based on a sensor network to acquire the position-related variables and machine learning techniques. Particularly, dimensionality reduction (DR) and classification techniques are considered. In this regard, both K-NN and PCA show to be suitable.

For future work, other issues are to studied such as real-time applications, computational load optimization and the use of different classification techniques to reach better performance.

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