Intelligent System for Identification of Wheelchair User's Posture Using Machine Learning Techniques

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Abstract—**This paper presents an intelligent system aimed at detecting a person's posture when sitting in a wheelchair. The main use of the proposed system is to warn an improper posture to prevent major health issues. A network of sensors is used to collect data that are analyzed through a scheme involving the following stages: selection of prototypes using condensed nearest neighborhood rule (CNN), data balancing with the Kennard–Stone algorithm, and reduction of dimensionality through principal component analysis. In doing so, acquired data can be both stored and processed into a micro controller. Finally, to carry out the posture classification over balanced, pre-processed data, and the K-nearest neighbors algorithm is used. It turns to be an intelligent system reaching a good tradeoff between the necessary amount of data and performance is accomplished. As a remarkable result, the amount of required data for training is significantly reduced while an admissible classification performance is achieved being a suitable trade given the device conditions.**

Index Terms—**Embedded system, Kennard-stone, K-nearest neighbors, principal component analysis, posture detection.**

I. Introduction

PEOPLE using wheelchairs may have either a physical, mental and/or sensory disability that limits their everyday activities. Around the world, approximately 15% of the population has some type of mobility problem [1], [2] and market research studies forecast a growth in manual wheelchair expenditure from $ 1.8 billion US in 2011 up to $ 2.9 billion US in 2018 [3]. While using wheelchair has been shown to increase the quality of life of users by enabling mobility, occupation and social interaction, among others [4]–[6], the health condition of wheelchair users is strongly affected by sitting posture. In particular, bad posture on a wheelchair leads chronic pain, sclerosis, kyphosis, skin and respiratory problems, loss of brain skills, some physical health problems such muscle rigidity, fatigue and muscle pain, among others [7], [8]. The causes can be: lack and imbalance muscle, lack of exercise, bad position of wheelchair pillows and usual functional activities carried out in the same way every day. In some cases the user lacks a feeling of pain until its health has been seriously compromised [9]. On the other hand, multiple benefits are achieved when the user shows the habit of sitting right: pain intensity decreases and the probability of ulcers formation is reduced [10]. Among the different parts of the wheelchair, the seat stands out in providing health benefits. It determines the user's stability and distributes uniformly the user's weight on the largest possible area [7]. When the seat is shorter than what the user needs, an increase in pressure is applied on the buttocks. On the contrary, when it is longer that needed, an increment of pressure is then applied in the knees. Unbalanced seat bending will make the user feel a lack of symmetry and cause the thighs and knees to be pushed. This in turn will result in excess of pressure and friction, affecting in long term the hip, as displayed in Fig. 1.

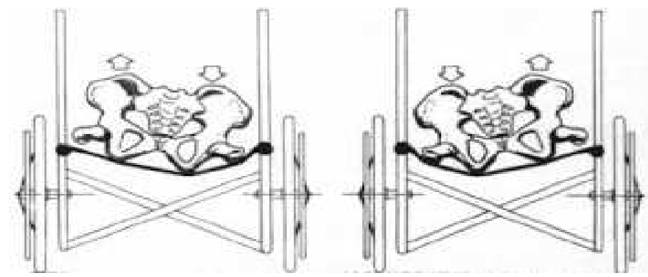

Fig. 1. Asymmetrical stress on hips due to unbalanced sitting posture on a wheelchair.

When the user holds an adequate sitting posture, the hip angle formed by the thighs and the trunk stabilizes the pelvis. An angle of 90° has been found optimal for most of everyday activities. The best way to achieve this angle is by using a customized cushion, adapted to the human shape, located behind low back in order to accommodate the buttocks shape.

Some related works [10], and [7] have developed studies on the manners that people typically sit and their consequences. But they lack intelligent posture classification solutions. A related study, [11] performs a similar work of posture selection, but over conventional chairs and therefore does not take into account the affections of hip imbalance. In the

Manuscript received October 12, 2018; revised November 28, 2018; accepted November 29, 2018. Date of publication December 6, 2018; date of current version February 6, 2019. The associate editor coordinating the review of this paper and approving it for publication was Prof. Kazuaki Sawada. *(Corresponding author: Paul D. Rosero-Montalvo.)*

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Digital Object Identifier 10.1109/JSEN.2018.2885323

context of sensor use and configuration, [12] and [13] explain main uses and applications of a broad variety of sensors. Albeit not being researches focused on the detection of postures, they do provide with guidelines for the selection, location and reading ways of sensors. Also, other studies [14], [15] have proved the benefit of using k-NN and sensors to classify human activities, mainly in the detection of sign language, reaching a classification performance around 80% (under ideal non-realistic environments). In addition, they stress the fact that using k-NN in electronic systems results adequate given the computational limitations of the processor.

In this paper, we present an intelligent system to inform in real time the wheelchair user about the correct sitting posture. The system is based on a pressure sensor network embedded in the seating and back cushion of the wheelchair, used to acquire the position related variables, and on classification machine learning techniques. To design our system, we took with various commercial wheelchair types and we integrated the sensors in the seat and the backrest for data acquisition. This allows for determining the user sitting posture with high accuracy [16]. The position readings were collected in a high-dimensionality database, having reading variations/errors on raw data. The data were filtered by performing a prototype selection procedure through a Condensed Nearest-Neighbours (CNN) algorithm [17]. Subsequently, the Kennard-Stone (KS) method was employed to balance the classes' distribution into the database, as well as a Principal Component Analysis (PCA) process was applied to further reduce the number of variables to feed the micro-controller [18]. Finally, a k-NN automatic learning algorithm was implemented to classify position readings. On doing so the final user will be warned in case deviations from the optimal, on-wheelchair sitting posture. The k-NN classification algorithm activates through the micro controller a series of vibrators that signal to the wheelchair user the areas in the seating displaying pressure excess, thus allowing for a posture correction and enhancing the userś health state. The system has -in average- a high level of accuracy in classification performance.

The remaining of the paper is organized as follows: Section 2 presents the electronic design, database settings and data analysis. Section 3 holds the conducted tests and obtained results. Finally, Section 4 gathers the final remarks as conclusions and future work.

II. Materials and Methods

The intelligent embedded system is designed to be conformed by three main stages: (a) design of the electronic device for location and data acquisition using sensors, (b) database configuration, and (c) data analysis, namely, prototype selection, classes balancing, dimensionality reduction, and classification algorithm.

A. Design of the Electronic Device

Fig. 2 shows a wheelchair view displaying the pressure sensors (red circles) and the vibrator devices (blue circles) on the seat, as well as the micro-controller and another pair of sensors (grey circles) at the backrest. The figure also shows the hardware connection and the incoming and outgoing communication between the microprocessor and sensors/actuators [19], displayed by red and yellow arrows, respectively.

Three pressure sensors are employed for data acquisition and located inside the seat filling. Their position is selected to fit the ideal place just under the coccyx and the legs. Besides, an ultrasonic sensor was used in order to determine the distance between the back and the wheelchair backrest. The analog signals obtained from the sensors were digital converted with an Arduino nano micro-controller with Ohm's law of resistance sensing technique [20]. Table I shows the description of each electronic element.

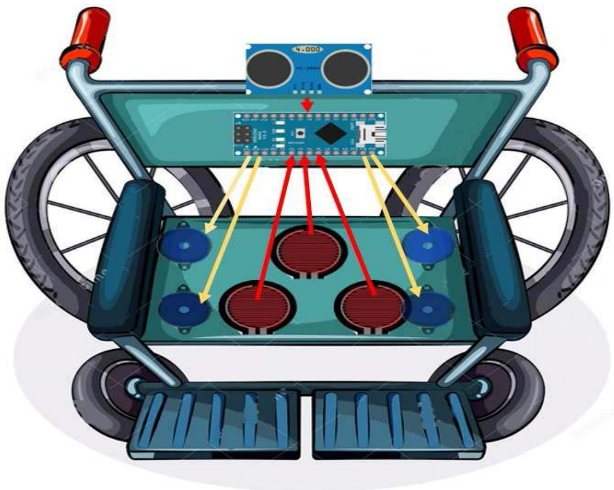

Fig. 2. A view of the wheelchair displaying the embedded system using diagram blocks for the sensors and actuators. Pressure position sensors and actuators are represented by red and blue circles on the seating, respectively. Black circles display ultrasound sensors in the backrest, yellow arrows show output peripheral, and red arrows indicate peripheral input into the analog-digital converter.

TABLE I
Electronic Elements Description

Element	Description	Available at
Pressure sensor	This is a force sensor with a round, 0.5" diameter, sensing area. This sensor will vary its resistance depending on how much pressure is being applied to the sensing area. The harder the force, the lower the resistance.	https://www.sparkfun.com /products/9375
Arduino nano	The Arduino Nano is a small, complete, and breadboard-friendly board based on the ATmega328 (Arduino Nano 3.x)	https://store.arduino.cc/ usa/arduino-nano
Ultrasonic Sensor	This is the HC-SR04 ultrasonic ranging sensor. This economical sensor provides 2cm to 400cm of non-contact measurement functionality with a ranging accuracy that can reach up to 3mm	https://www.sparkfun.com /products/13959
Vibration Motor	With a 2-3.6V operating range, these units shake crazily at 3V	https://www.sparkfun.com /products/8449

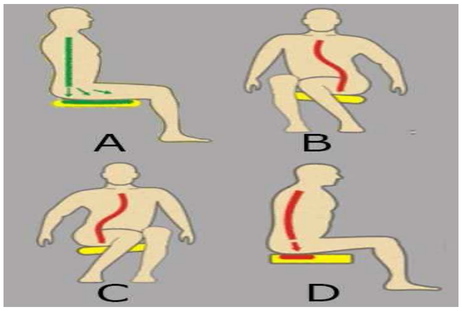

Fig. 3. Most common on-wheelchair postures: their effects at the spinal column and weight distribution on the seat surface.

TABLE II
LABELS AND EFFECTS OF DIFFERENT SITTING POSTURES ON A WHEELCHAIR

Position label	Description	Possible health problems
A	Right position	No harm
B	Higher pressure on right side	Respiratory issues, muscle imbalance stress on liver, stomach and right kidney
C	Higher pressure on left side	Respiratory issues, muscle imbalance stress on spleen and left kidney
D	Higher forward pressure	Knee issues, back pain, and stress on abdomen

In this work, sensor location was carried out by performing an electronic, data reading analysis, which consists of: (i) Voltage loss analysis in each sensor, and (ii) data readout stabilization by analog conversion between 0 to 1023.

As final important considerations on how to implement the electronic system, we highligth the following ones: (i) It is implemented in a single system within a wheelchair, communication between sensors, actuators and the system is done with connection cables. A LiPo battery of 4.7 volts and 700 mA is initially used. (ii) A library of k-NN classification algorithms was developed, which is called after having received 10 readings from the sensors and finding their average to avoid errors. (iii) Due to the system conditions, the library runs parallel to the RAM of the system. Therefore in some cases it is necessary to perform general resets to avoid saturating the system. (iv) The system uses approximately 70% of the available memory of the micro controller (32KB available), this percentage varies in relation to the training matrix stored in the system.

B. Database Settings

To ascertain the typical sitting postures on a wheelchair in order to label the acquired readings (henceforth called samples) for solving our classification problem, we take advantage of a conventional taxonomy recommended by physicians and physiotherapists expert at this topic. As a result, four common sitting postures together with the effect on the backbone were identified, as depicted in Fig. 3 and Table II describes their related potential health issues.

The data acquisition protocol utilized in this work is as follows: We consider 5 individuals asked to keep every single selected posture (A, B, C and D) during two minutes (average time needed to reach a reliable sample). When the system detects a bad posture in a wheelchair, it waits for a 2 minutes.

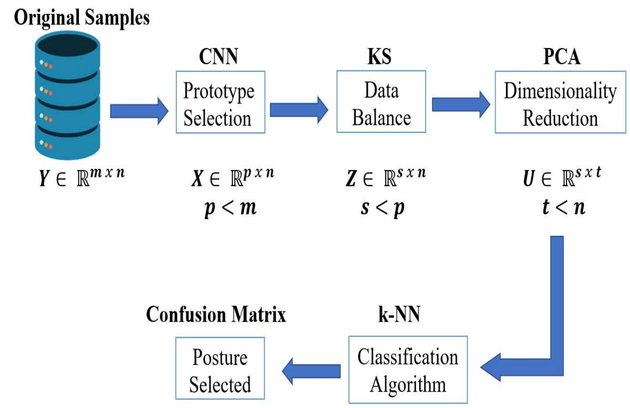

Fig. 4. Data analysis framework: it starts with the raw database matrix $\boldsymbol{Y}$. Then, such a matrix undergoes a progressive dimension reduction by using prototype selection and data balance (reducing the number of samples) as well a data representation procedure (reducing the number of attributes). Finally, a classification algorithm is used to assign a final posture label.

In the absence of new information, the system activates the actuators inside the seat that indicate through vibration the points where there is an excess of pressure. Upon activation of this alarm signal, the user is pointed to change sitting posture until correcting the pressure distribution exerted on the seat. At that moment the vibrators power supply is switched off.

Each individual repeated 25 trials per posture. Then, since 4 sensors are used, a total of 2000 data points (500 samples $\times$ 4 sensors) are obtained.

C. Data Analysis

The acquired data are stored into a matrix $\boldsymbol{Y} \in \mathbb{R}^{m \times n}$ order, where **m** is the number of samples and $\boldsymbol{n}$ amounts the number of sensors (that is to say, the number of attributes representing each sample). Meanwhile, $\boldsymbol{L} \in \mathbb{R}^{m \times 1}$ is a vector holding the sample labeling. In this case, $\boldsymbol{m}$=500 and $\boldsymbol{n} = 4$. Proposed data analysis framework involves the following stages: (1) prototype selection using CNN, (2) data balancing with KS algorithm, (3) dimensionality reduction via PCA, and (4) data classification. An explaining block diagram of the data analysis process is shown in Fig. 4.

Following are explained the considered stages:

1) Prototype Selection: As well-known, in pattern recognition, supervised classifiers need a labeled dataset of information to feed the algorithms in the training stage. Due to limitation in computational resources, resource optimization is a major issue to ensure proper functioning in embedded systems [21]. In practice, not all data are useful, therefore irrelevant data should be discarded. This process is called *prototype selection*, and allows for reducing the size of the training data set. A remarkable advantage of prototype selection is the decrease of execution times, space complexity, and computational cost, besides eliminating noise [17]. Works as those presented in [22]and [23] use prototype selection in many data sets reaching training set size reduction about 87% and 97% of the total amount of instances, respectively. Besides, they explain how the combination PS with classifiers algorithms works in a multi-class environment. Along with this, noise elimination algorithms are studied, which a are aimed at filtering boundary points staying out of pre-established neighborhoods, and thus yielding soft decision boundaries [22].

Our choice for prototype selection algorithm follows from the so-called CNN. It algorithm determines two subgroups, called $\boldsymbol{S}$ (training set) and $\boldsymbol{T}$ (test set), and it eliminates the data that the algorithm cannot properly classify [17]. Indeed, similar k-NN based approaches have been used successfully in other applications such as gases analysis [24]. In practice, prototype selection allow us to reduce the noise between data assigned to the four labels, A to D, corresponding to the 4 different sitting postures displayed in Fig. 2 and table I, and obtain the matrix $\boldsymbol{X} \in \mathbb{R}^{p \times n}$ with $\boldsymbol{p}$ less than $\boldsymbol{m}$.

2) Data Balance Regarding Classes: An important issue faced at data acquisition stages when using embedded system is the ability to balance uniformly the training data for each label. Data acquisition rate is strongly correlated to the sensor reading speed, highly dependable on the wheelchair user action. KS algorithm allows balancing the data set in relation to the four labels [25]. We thus obtain the lower dimensionality matrix $\boldsymbol{Z} \in \mathbb{R}^{s \times n}$. Despite this data reduction, there are still too much data to be fed into the micro controller ($\boldsymbol{s}$ is less than $\boldsymbol{p}$).

3) Dimensionality Reduction: Representing a set of high dimensional data increases the complexity in the user's understanding and the information can become abstract and intricate [18]. Dimensionality reduction (DR) is one of the approaches to convert the data into a simpler and more compact way. DR methods thus enable to represent large volumes of information at optimal processing times, maintaining the same properties of complex high-dimensional data. One of these methods is the so-called PCA, that makes a projection on the variables that can better represent the data set in terms of least squares fits [26]. Application of PCA algorithm to $\boldsymbol{Z}$ matrix further reduces the volume of information and results into a lower order matrix called $\boldsymbol{U} \in \mathbb{R}^{s \times t}$ with $\boldsymbol{t}$ less than $\boldsymbol{n}$.

4) Classification: Finally, a classification algorithm is implemented. k-NN is one of the non-parametric algorithms most used for machine learning due to its simplicity and effectiveness, considered one of the 10 best methods of automatic learning [22]. k-NN is simple to implement since it uses the euclidean distance between the entire training set to sort new incoming data. Its aim is to isolate a small group of information, which allows predicting its class with the same quality as the initial set of data. k-NN algorithm has been shown to be computationally effective for this system when analyzing an non-hardly-separable-classes database (as that obtained with the aforementioned dimension reduction stages) [19]. The new incoming data classification is then performed by a k-NN algorithm in real time when wheelchair users are requested to sit down adopting one of the four different postures.

III. Results

To assess the behavior and benefit of every single system stage, we will first discuss over some results related to the dimension reduction (regarding the used training set) procedure. Then, the outcomes of the classification algorithm (in terms of both performance and processing time) are described to state the whole system performance.

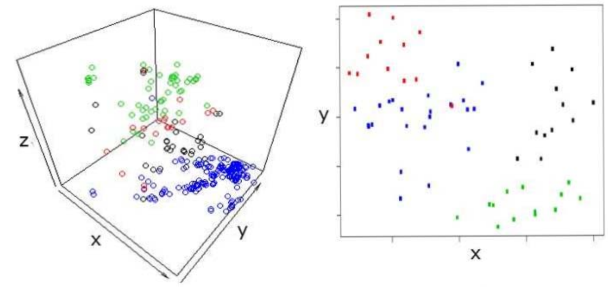

Fig. 5. Scatter plots for original data matrix **Y** (at left) and reduced data matrix **U** (at right). Scattering colors correspond to the four characteristic, sitting postures. Colors green, blue, red, and black correspond respectively to posture label A, B, C, and D.

TABLE III
PCA Summary Method Applied to **Z** Matrix

Component indicators	PC1	PC2	PC3	PC4
Standard deviation	223.66	171.77	112.89	11.24
Proportion of variance	0.5414	0.3193	0.1379	0.0014
Cumulative proportion	0.5414	0.8607	0.9986	1.00

A. Training Set Reducing Results

The proposed system yields a considerable reduction of the training matrix (namely, 88%) while keeping the same classification performance. In this way, the micro-controller can perform the classification process in optimal times (less than one minute) without overburdening its resources such as RAM, work registers, cycle counters, among others. It should be mentioned that the classifier has some drawbacks from the data acquisition form. To overcome such drawbacks, the classification process is performed once the sensors are installed in the wheelchair, and users are asked for adopting postures being not ideal to acquisition data. As a result, the training matrix becomes highly noise. The dimensions of input database matrix $\boldsymbol{Y}$ are $\boldsymbol{m} = 500$ and $\boldsymbol{n} = 4$. Upon application of prototype selection using the CNN algorithm with neighbor $\boldsymbol{k} = 1$, the resultant matrix $\boldsymbol{X}$ is $\boldsymbol{p} \times \boldsymbol{n}$ dimensional, with $\boldsymbol{p} = 260$. Subsequently, the balance data stage using the KS algorithm results in a matrix $\boldsymbol{Z}$ in size of $\boldsymbol{s} \times \boldsymbol{n}$, being $\boldsymbol{s} = 80$.

Fig. 5 shows the scatter plot for the original data matrix at left, and the matrix $\boldsymbol{Z}$ at right. Marker colors are given correspondingly to the established four labels (the four considered sitting postures).

Table III holds the PCA summary in terms of the component indicators, namely, the standard deviation, proportion of variance and cumulative proportion. A significantly smaller value for the standard deviation is observed for PC4, which corresponds to a sitting posture with the back leaning forward in the wheelchair. We attribute this reduction in the deviation to the lack of data stemming from the ultrasound sensors at the backrest of the wheelchair. As will be further discussed, the lack of these data will impact the accuracy of the prediction performance by the classification algorithm for this

TABLE IV

CLASSIFICATION PERFORMANCE USING DIFFERENT TRAINING SET

Training Set representation	Pos. A (mean ± std)	Pos. B (mean ± std)	Pos. C (mean ± std)	Pos. D (mean ± std)
matrix $\mathbf{Y}_{(500\times4)}$	85.45 ± 4.25	82.28 ± 4.8	78 ± 5.68	63.5 ± 8.2
matrix $\mathbf{X}_{(260\times4)}$	88.45 ± 3.28	80.21 ± 4.12	78 ± 4.32	65.5 ± 5.11
matrix $\mathbf{Z}_{(80\times4)}$	83.28 ± 2.45	80.21 ± 3.75	78 ± 3.77	66.5 ± 4.89
matrix $\mathbf{U}_{(80\times2)}$	81.58 ± 1.89	77.50 ± 2.14	78 ± 2.55	67.14 ± 3.04

TABLE V

USED MEMORY AND CONSUMED ELECTRICAL CURRENT TESTS

Training Set representation	Used % Memory	Exec. time Simulation	Exec. Time Real	Current
matrix $\mathbf{Y}_{(500\times5)}$	NN	NN	NN	NN
matrix $\mathbf{X}_{(260\times5)}$	95	1.71s	3.5s	359mA
matrix $\mathbf{Z}_{(80\times5)}$	65	1.25s	2.2s	267mA
matrix $\mathbf{U}_{(80\times2)}$	42	1.1s	1.5s	202mA

sitting posture. As a final PCA result, we obtain a matrix $\boldsymbol{U} \in \mathbb{R}^{s\times t}$, with $\boldsymbol{t} = 2$.

Following from the the standard deviation weight given by the applied PCA procedure, the equations to reduce of 4 dimension to a 2 dimension ($\boldsymbol{x}$ and $\boldsymbol{y}$ axes) representation are:

$$\mathbf{x} = \sum_{i=0}^{\mathbf{s}} (0.6125 * i) + (0.5228 * i) - (0.592 * i) + (0.019 * i), \tag{1}$$

$$\mathbf{y} = \sum_{i=0}^{\mathbf{s}} (0.7724 * i) - (0.554 * i) - (0.309 * i) + (0.008 * i), \tag{2}$$

being i the index for rows.

B. Classification Algorithm Performance

We tested the k-NN algorithm with all training matrix generated within the proposed methodology ($\boldsymbol{Y}$, $\boldsymbol{X}$, $\boldsymbol{Z}$, and $\boldsymbol{U}$). The corresponding classification accuracy reached in a cross validation (10 iterations) fashion are shown in Table IV.

It is worth noticing the significance reduction reached in the classification (also, prediction) power of label D with respect to the other labels. This is tentatively assigned to the lack of information of the ultrasound sensors corresponding to such a posture. After applying the proposed methodology (the electronic device, and data analysis), an overall average performance of 76.05% is observed. Upon setup on the wheelchair and real time classification, a value of 75.2% prediction accuracy in posture detection was obtained for the the embedded system as is summarized in Table V.

As notable remarks about the Table V, it is important to mention the subsequent ones: The embedded system cannot storage the matrix $\boldsymbol{Y}$, since its size is bigger than flash memory available capacity. The matrix $\boldsymbol{X}$ consumes a lot of memory resources causing that the system some times does not response. With matrix $\mathbf{Z}$, the system works at a comparable performance than the one reached with the complete database. Even better with matrix $\boldsymbol{U}$ as the battery consumption is significantly lower. The battery consumption was made at the detection of 10 postures.

By reducing the memory consumption, the program-counter-records reading cycles become significantly limited, while the embedded systems' lifetime is increased. Another advantage, given the computational-cost lowering, system can be switched to sleep mode more properly, as their records are not focused any longer on reading a large amount of data and may couple better with these programming platforms. Finally, Table V shows the execution times of the simulation and the real implementation of the system. It must be considered that the value of the simulated time can be affected by the characteristics of the higher-performance computer where such a program is running. When working in real conditions, the execution time increases considerably. This is because the system to function better has an internal reset that deletes (re-initializes) the program counters -which keep so until new data is provided by the sensors. This process, on the one hand, helps to get a better reading and comparison among new information. And on the other hand, it generates a response delay of the system due to the process itself execution. With the matrix $\boldsymbol{X}$, the reset process is affected considerably and causes the system to have a longer reaction time to the smaller matrices. In this sense, it must be considered that regarding the user perception (vision) the system does not have a significant response time between one data set and another. Nonetheless, at a device level, accordingly to the internal clock of 16 MHz, it can mean that there are thousands of lines of work in such a small-time interval.

An essential goal for this work is reducing as much as possible the magnitude necessary of resources for carrying out the embedded system tasks. Then, in order to set a reference point, a comparison -in terms of computational performance- with a higher performance system (in this case, a standard PC) is performed. To that purpose, we use a mathematical formula able to quantify the functionality embedded system behavior. Let f be a real or complex valued function and g a real valued function, both defined on some unbounded subset of the real positive numbers, such that $g(x)$ is strictly positive for all large enough values of x, then it is satisfied that:

$$f(x) = O(g(x)), \tag{3}$$

$$O(g(x)) = \sum_{m=1}^{M} \sum_{k=1}^{K} \frac{1}{\alpha_m} \log \frac{x}{k\beta_k}, \tag{4}$$

where $O(\cdot)$ is a complexity operator, $x \longrightarrow \infty$, $\{\alpha_1, ..., \alpha_M\}$ is the set of weighting factors. To make selection of weighting factors intuitive, we use probability values so that $0 <= \alpha_m <= 1$. Likewise, $\{\beta_1, \ldots, \beta_K\}$ are performance variables, therefore they are used for normalization purposes, so that the importance is presented in a decreasing order regarding their values. A detailed explanation of this measure is presented in [27].

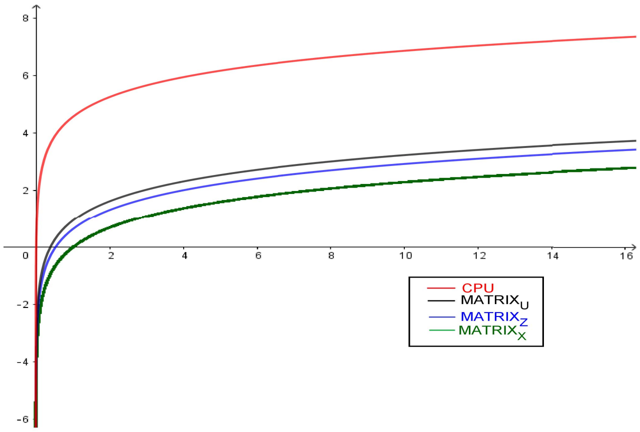

Fig. 6. Funcionality performance comparison between a standard PC (CPU) and the proposed embedded system tested over different representation matrices.

In terms of the measure $f(x)$, our system is compared against a standard computer (processor core I7, RAM 10Gb, 1 Tb of memory). The tests are carried out with matrices $\boldsymbol{X}$, $\boldsymbol{Z}$ and $\boldsymbol{U}$. Matrix $\boldsymbol{Y}$ is discarded since it cannot be directly used to feed our system. Nonetheless, by taking advantage of its computational capabilities, over the standard PC the classification procedure is performed with the matrix $\boldsymbol{Y}$. The Fig. 6 shows the resulting plotting of $f(x)$ for each considered matrix. The axis x means time execution of the system and y axis means the performance in scale 1 to 10.

As naturally expected, the standard PC outperforms the proposed system outcomes when testing the reduced matrices, however, the standard PC battery is very consumed for this algorithm and others task the system makes. Notwithstanding, it can clearly observed how the systems when run over matrix $\boldsymbol{U}$ not only resembles the shape of the functionality curve of the reference PC but overcomes the rest of system runnings (using either $\boldsymbol{Z}$ or $\boldsymbol{X}$). This fact further justifies the benefit of the use of techniques for reducing the needed training set size.

IV. Conclusions

In this work, we have proposed the design of an embedded system incorporating a k-NN classification algorithm inside the RAM memory, which, along with proper training-set resizing stages, is able to detect sitting posture defects on a wheelchair reaching an average accuracy of over 75%. Additionally, our system achieves a significant reduction in dimensionality, as well as reduces the amount of required training-data by 88%. Particularly, this is reached by applying CNN as a prototype selection algorithm, a KS data balance algorithm, and PCA. Thus, this minimal data representation enables our system to both storage and classify some sitting postures in real time by means of any simple classification algorithm (for instance, k-NN algorithm as done in this study).

The performance of the system was considered acceptable given its computational resources and context conditions. An important characteristic to be highlighted is that the system responds to poor posture in approximately 1 second, which enables the generation of an adequate warning to the user when seated in a bad posture.

Our experimental results demonstrate that the wheelchair users' quality of life can be notably enhanced through implementing cost-effective embedded-systems-based solutions powered by machine learning.

V. Future Works

As a future work, on one hand, the data collection stage is to be improved so that the classification accuracy is increased. Another issue to explore is the battery consumption, along with the sensors location, in order to accomplish a system flexible to user's movements as well as optimal in terms of a proper trade-off between resources usage and accuracy.

On the other hand, additional comparisons are to be performed with other low-computational-cost, representative approaches for both data representation (prototype selection, data balance, dimensionality reduction, vector quantization, and/or feature extraction/selection) and supervised classification, namely: distance-based (linear discriminant classifier), model-based (support vector machines), heuristic (artificial neural networks), density-based (Bayesian classifier), dendogram-based (decision tree) classifiers, and among others.

A remarkable aspect to be considered for further research is the use of CSV format files for readings within the electronic system. Such a format is easy to read and demands low resource consumption being suitable for intelligent systems aimed at making decisions rapidly (i.e. real time applications). As well, the incorporation of an extra sensor to improve the system performance is considered, especially regarding location D to minimize errors at identifying postures B and C.

Acknowledgment

The authors are in debt to J. C. Moreno for a critical reading of the manuscript. The authors also thank the Universidad Técnica del Norte and the Instituto Tecnológico 17 de Julio-Yachay for kindly providing access to their electronics laboratories to perform the system tests. As well, the authors especially thank to SDAS Research Group (www.sdas-group.com) for its valuable support.

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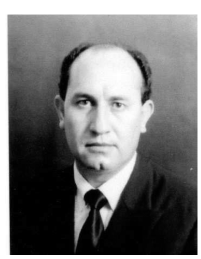

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