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Intelligent System for the Prevention of Pressure Ulcers by Monitoring Postural Changes with Wearable Inertial Sensors †

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Abstract: Pressure ulcers affect the quality of life and health level of patients while causing a cost increase for the health system. Despite all of this, there is no monitoring system for this disease, even though it is very common in hospitalized patients. To resolve this issue, in this work, we present a prototype for monitoring and caring of pressure ulcers, through an intelligent system based on wearable inertial devices. The system detects the position of patients with reduced mobility while in bed, walking, or standing; providing, to medical staff and caregivers, useful information by means of mobile devices, in particular: (i) A historical record of body activity and (ii) notifications when a single position persists for a prolonged period of time. The following contributions are presented in this paper. Firstly, a technological survey of healthcare systems applied to pressure ulcers is presented. Secondly, an architecture and a methodology for modelling wearable inertial sensors for classifying body position are proposed. Finally, experimental tests with real cases were conducted to evaluate machine learning approaches and to validate the position estimation of the case study developed with four participants.

Keywords: body monitoring; elder care; wearables; sensor; pressure ulcers

1. Introduction

Pressure Ulcers (PUs) as a medical condition are defined as localized lesions on the skin or underlying dermic tissue, usually over a bone prominence, as a result of pressure [1]. PUs affect the health level and life quality of patients, reducing their independence for self-care, causing low self-esteem, affecting negatively upon their families and caregivers, and even causing death in extreme cases [1]. Body position and postural changes are the main preventive mechanism [2], and it has been shown that "preventive care is necessary and sufficient to prevent the onset of pressure ulcers" [3]. Therefore, the conventional way of preventing and controlling PUs nowadays is to avoid maintaining a sole body position for a long period of time. Generally, persistence in the same position must not exceed two hours [3]. Patients, where possible, need to change the position by themselves or with the support of an assistant. Handling these changes of postures; however, could result in excessive physical and emotional stress for the caregivers [4].

In this work, an intelligent system to monitor body position of patients using wearable inertial sensors is presented as a tool to support this assistance. Inertial wearable devices are located on a

patient's shoulder and ankle to monitor their posture in an automatic way. Acceleration data from these inertial sensors are then aggregated and evaluated by machine learning approaches to determine the patients posture behavior in real-time.

1.1. Motivation

The problem of PUs has increased over the years and has been described as a "living and alarming epidemic that lives under the sheets of patients at different levels of care". Consequently, it has been identified as a critical shortcoming in patients' care [5]. Table 1 shows the prevalence of PU patients around the world. For adults over 60 years, there is a higher prevalence of PUs (51%) [6]. PUs also can appear in patients with limited movement, such as amyotrophic lateral sclerosis and paraplegias cases. For PUs, care treatments need to be customized and planned individually for each patient [7]. For PU lesion treatment, the intervention methods involve electrical or ultrasounds applied directly to the lesions, making the process painful for patients and expensive for the health system. Studies on the cost analysis of PUs were conducted by Palfreyman and Stone [7]. This systematic review was carried out on the economic impact of this intervention for PUs, concluding that: (i) The cost of treatment increases with the severity of the ulcer because of the longer healing/recovery time; and (ii) this cost is composed by expenses in materials inputs, nursing time, and hospitalization charges for the health system, resulting in a significant impact of PUs into the national care system and governmental budget; therefore, prevention is the best strategy to address this public health problem.

Table 1. Prevalence of pressure ulcers (PUs) in patients in the world.

Country	Prevalence of Pus	Source
United States	10.6%	[8]
Canada	26%	[9]
México	1.5%	[10]
Brazil	23.1%	[11]
Germany	10.2%	[12]
Belgium, Portugal, Italy, United Kingdom, and Sweden	18.1%	[12]
The Netherlands	23.1%	[13]
Spain	7.2%	[14]
Colombia (Bogotá, Bucaramanga, Cartagena)	18%, 5.27%, 24%, respectively	[15]

Currently, despite the seriousness of the problem, there is a lack of technology-based work to improve the care and monitor postural changes to prevent PUs. Some of most relevant advancements in this sense, for example, have been developed in Spain [16] as an ad-hoc computer application for PU management. This system allows for risk assessment of patient's suffering from PUs and to make a screening of the nutritional status of the patient, favoring the exchange of data between professionals and levels of care to support decision making. Additionally, a wider range of solutions have been looking for a patent in this regard. The first developments were in 1995 when the authors of [17] generated a primitive idea based on remote databases. In [18], the design of a device was presented without specifying neither the type of sensors, nor the control mechanism. Instead the approach simply aimed at measuring the "pressure", rather than the time lapse or body orientation. In [19], a recent patent has been submitted that assesses whether "the movement of a patient is correct", but without providing an alert system based on the time spent in the same position. Taking into account all related work described, this research is targeting the development of technology, coupled with intelligent systems, with the perspective of ensuring improved treatment for the population that presents this pathology.

1.2. Related Works about Technologies for Pressure Ulcers (PUs)

In recent years, academic and industrial research initiatives have been developed on smart systems for healthcare, with the scope of supporting future healthcare demands for the elderly population, improving the quality of life, reducing healthcare costs, and complementing specific medical delivery services [20].

Table 2 shows four kinds of technologies proposed between 2012 and 2018, which have been published in international journals, and presents support tools for the monitoring and treatment of PUs.

Firstly, it shows information systems for monitoring patients who are in bed and hospitalized. Secondly, the usual support tools for the treatment of PUs are surfaces such as mattresses, cushions, heel pads, mittens, and others. Mobile applications in relation to prevention, management, risk, and PU monitoring are also described. Finally, there is an overview about applications and tools used for training of medical personnel.

Table 2. Summary of the technological projects for the follow-up and treatment of PUs.

	Title	Authors	Type and Number of Sensors	The Data Processing Techniques	Population and Sample
Systems Information for Monitoring PUs	Electronic-assisted system for the rehabilitation of pressure ulcers [21].	Hugo Daniel Aguagüiña Pilataxi—Cesar Granizo	Pressure sensors and accelerometer, piezoelectric sensor, optical sensor (camera) video graphics array pixel complementary metal oxide Semiconductor	Main processing card, a webcam, 7″ liquid cristal display digital image processing, artificial vision.	Population and sample will not be required.
	Measurement of the area of venous ulcers by means of two types of software [22].	Thaís Dresch Eberhardt2 Suzinara Beatriz Soares de Lima3 Luis Felipe Dias Lopes4 Eline de Lima Borges5	Does not use sensors.	To use software Autocad e Image Tool.	The data were collected from 21 patients with venous ulcers.
	Systems information for management PUs [23].	Olga Bueno Yáñeza, Jimena Rodríguez Arrietab, Miren I. Bagüés Bafaluyb y Juan José Calvo Aguirrec	Does not use sensors.	Computer application.	The sample is made up of people over 65 with a total of 69 people.
Support Tools for PU Treatment	Clock as position tool: revolving clock for help in the prevention of ulcers [24].	Ortopedia Moverte	Bed sensor, chair sensor.	At the moment the patient gets up from the bed or chair, the monitor emits a signal that reaches the wireless receiver to notify the assistant/caregiver, allowing him to manage the situation.	Does not specify.
	The special surfaces of pressure management in the prevention and treatment of pressure ulcers. Literature review [25].	Laura Herrero Boil	Bed sensor.	Clinical instruments for monitoring pressure ulcers	Eight systematic reviews, published between 2005 and 2012.

Mobile A Applications	Application: "wound analysis" [26].	Care and Wound	Does not use sensors.	Application—email monitored data for the doctor.	Does not specify.
	Guía PU mobile (at the foot of the bed) [26].	Pérez-Barreno David, Arantón-Areosa Luis	Does not use sensors	Application	Does not specify
	Smart PU integrated system for the prevention of pressure ulcers [27].	Society for the regional development of Cantabria, government of Cantabria.	Does not specify.	Application	Does not specify.
	Application "Integrated system for wound management (HELCOS) [28]	Grupo Nacional para el Estudio y Asesoramiento en Úlceras por Presión y Heridas Crónicas GNEAUPP—Foundation Sergio Juan Jordán	Does not use sensors.	Application	Does not specify.
Training Application	Caring for the skin through a weblog—Universidad Javeriana de Colombia. [29]	Renata Virginia González-Consuegra, María Alejandra Chauta Salguero, Lady Catalina Cruz Peña	Does not use sensors.	Weblog.	Does not specify.
	Consultation of tele ulcers in a complex wound unit in the treatment of ulcers [30].	Casals Zorita, Marta	Does not use sensors.	Telemedicine system for remote monitoring of UPP.	Does not specify.
	Use of information and communication technologies (ICTs) in Teaching about chronic wounds in nursing [31].	Cristina Castanedo Pfeiffer y J.M. Zamanillo Sainz de la Maza, Member,	Does not use sensors.	Information system.	Does not specify.

According to the design carried about by Aguagüiña and Granizo [21], the objective of this technology is contributing to patients' care during rehabilitation. The system detects body movements and positions using video acquired through a Raspberry PI 3 card, receiving image data through a webcam located in front of the patient's bed at a predetermined distance. Some limitations were observed, since the camera must have a proper/suitable position, avoiding vibrations and poor illumination, or else it can trigger false alarms for caregivers. In the study carried out by Dresch, the purpose was to compare the measurement level of venous ulcers' area through the software Autocad and the software Image Tool. The data were collected from 21 patients with ulcers. These data were collected by nurses who took pictures of the wounds. In another study conducted by [16], a computer application was presented aimed at standardizing the criteria for prevention, treatment, and follow-up of PU during the patient's hospitalization. The system consists of an application used by nurses to collect information in real-time, with software capable of interpreting through decision algorithms, evaluating the type of control performed on the patient.

On the other hand, the company ortopedia moverte [24] has a product described as a rotating wall clock to prevent ulcer formation, allowing for the creation of a personalized protocol of postural changes for each patient at risk, by using graphic illustrations of patient positions within a timeframe to be interpreted easily and intuitively. It is composed of six rotating analogic wheels to select between the three resting positions of a patient in bed according to a time moment, serving as a reminder to the caregiver for compliance with the care protocol. The authors Herrero and Sanjuan present a literary review of special surfaces for pressure management in the prevention and treatment of PUs, such as cushions, beds, mattress covers, mattresses foam, static, alternating air pressure, and devices called Special pressure handling surfaces, which allows the redistribution of pressure and; therefore, a relief of it in patients' bodies who have PUs, or are at risk of developing them, comparing the effectiveness between low pressure alternating air mattresses and mattresses of overlap. The product wound analysis application is a system with the following characteristics: It generates photographs and records of the patients, authorized by patients in a written consent to carry out the treatment. This application defines an objective curve about the evolution of the wounds, and also aids consultations between professionals sharing cases through this application. The version patient application has the option of empowering patients with self-registration of their wounds and gives notifications to their device to identify anomalies in their treatment.

Another product named integrated system for the prevention of pressure ulcers (smart PUs) uses artificial intelligence as disruptive technologies for those patients at risk of suffering PU [27]. The application collects information from the patient and applies risk scales to elaborate a personalized guide of preventive actions. The application named "integrated system for the management of wounds" (HELCOS) [28] is a tool that targets both professionals and patients for the management of wounds. The application allows for tele-consultation with experts from other disciplines, through a chat function in the application for a specific case. The application "pressure ulcer guide" provides information and prevention strategies on pressure ulcers, eschars, or wounds. It uses a tool called Braden's Scale to evaluate the risk of pressure ulcers or decubitus eschar. The Mobile PU guide (at the foot of the bed) [26].

Addresses all the problems related to deterioration of the cutaneous and tissue integrity and risk of suffering it, as well as assessment modalities, approach, and treatment options. The contents of this application are developed in six large blocks: Classification, epidemiology, etiopathogeny, risk factors, PU classification, location, and characteristics of the PUs.

2. Architecture and Implementation

This section details a proposed methodology followed for the development of an intelligent system for PU prevention, by monitoring postural changes using wearable inertial sensors.

2.1. The Components Involved in the Intelligent System

- Wearable inertial devices. They collect accelerometer data from an inertial sensor, sending them in real-time by Bluetooth low energy (BLE) to a gateway. In this work, we propose the use of android wear devices, located on the shoulder and ankle of patients, in order to describe the orientation of patients in a non-invasive way.
- Smart board. A low-cost mini board, such as Raspberry PI 3 (RP3), is configured as a gateway to receive data from wearable devices under BLE protocol. These data are stored in a local database where the time and three-axis of the accelerometer are collected in raw format. Then, data processing is computed with the smart board to extract the features from accelerometer data of signals. Finally, features are evaluated by a classifier, determining the orientation/position of the patient. In case the orientation exceeds a predefined time threshold, an alert is sent to the mobile device of caregivers.
- Mobile application. Caregivers can access detailed information on the orientation and postures estimated by the classifier, in the form of a visual timeline. Finally, a notification service allows to be informed by the intelligent system in case of persisting postures exceeding recommended time limits.

Figure 1 shows the architecture along with the described components, the steps of data processing, and feature extraction for classifying the body position of patients, which will all be described in the next section.

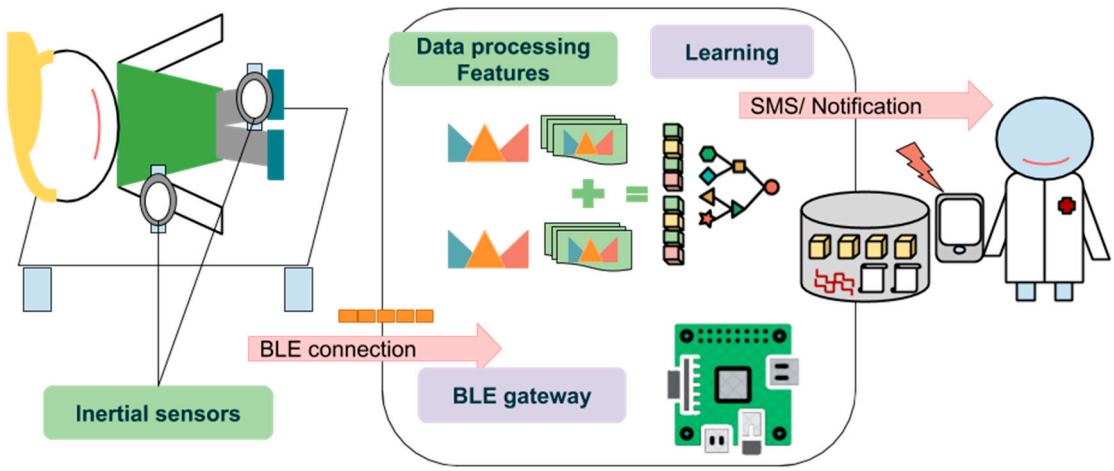

Figure 1. Architecture of components for the prevention of pressure ulcers by monitoring postural changes with wearable inertial sensor.

2.2. Data Processing, Feature Extraction, and Intelligent Systems Classifiers

In formal definition, a sensor D collects data in real-time in the form of a pair $\bar{s}_i = \{s_i, t_i\}$, where s_i represents a given value/measure of the sensor and t_i is the time-stamp. Thus, the sensor data stream of the device is defined by $S_D = \{\bar{s}_0, \dots, \bar{s}_i, \dots, \bar{s}_n\}$. In this work, three-axial acceleration (x,y,z), providing three data streams S_x, S_y, S_z for each for each inertial sensor and wearable device.

Collected data are then filtered for removing noise by means of an exponential smoothing filter, which generates an equivalent prediction to a Kallman filter with faster performance [32].

$$s'_i = w \cdot s_i + (1 - w) \cdot s_{i-1}'. \quad (1)\ (2)$$

Then, temporal segmentation defined by a window size L to select the relevant and recent measures $\bar{\boldsymbol{s}}_{\boldsymbol{i}}$ is applied [33,34]. Relevant and smoothing measures $\boldsymbol{s'}_{\boldsymbol{i}}$ are aggregated by a given function $\mathbf{T}_{\boldsymbol{k}}\ (\boldsymbol{S_D}, \boldsymbol{t}_*\ )$ whose value defines a feature $\mathbf{T}_{\boldsymbol{k}}$ of the inertial sensors $\boldsymbol{S_D}$ in current time $\boldsymbol{t}_*$.

$$\mathrm{T}_k\ (S_D, t_*) = \cup_{s_i}^{\bar{s}_i} s'_i\,, t_* - t_i < \mathrm{L}, t_* \geq t_i. \quad (3)\ (4)$$

Therefore, starting from a set of sensors $S = \{S_1, \dots, S_N\}$ and a set of aggregation functions $T = \{T_1, \dots, T_M\}$, we define a total number of features NxM to describe the sensor for each given point of time t_*.

Since our model is based on a data-driven supervised approach, the features describing the wearable sensors are related to a label $L(t_*)$ for each given time t_*:

$$T_1(S_1, t_*), \dots, T_j(S_i, t_*), \dots, T_M(S_N, t_*) \rightarrow L(t_*), \quad (5)\ (6)$$

where $L(t_*)$ defines a discrete value $L = \{L_1, \dots, L_l\}$, and L_l identifies a posture. Here, we focus on classifying the next postures of the patient: Supine, inclined, left lateral, right lateral, sitting, partially incorporated (stretched legs and elevated torso), and walking (for those patients who has partial mobility).

Finally, the features and labels previously defined are used to train a classifier. In this work, we evaluated some classifiers, such as K-nearest neighbors (KNN), naïve Bayes (NB) support vector machine (SVM), or decision trees (C4.5), whose implementation in Java and C++ [33-34] enable embedding/deployment in miniature boards or mobile devices.

3. Experimental Setup

In this section, we describe the experimental setup and results of a case study developed in the Smart Lab of the Center for Advanced Studies in Information and Communication Technologies-CEATIC University of Jaen (Spain), in order to evaluate the proposed methodology. In the case study, four participants were included for data collection, using two wearable inertial sensors to detect eight given target classes: Supine, inclined, left lateral, right lateral, sitting, partially incorporated (stretched legs and elevated torso), walking, and idle (changes between positions).

Two Polar M600 devices, located on the shoulder and ankle of participants, were used. Each participant repeated the experiment twice, thus obtaining two cases for each user. An external observer labeled the posture in real-time during data acquisition. A total of 100.422 samples were collected.

On the preprocessing of data, the following parameters were used: The exponential filter 'w' was set to 0.01 to smooth and remove noise, and the window size L was defined as L = 2.5 s, since this has been demonstrated as a suitable configuration for evaluating inertial data in activity recognition [35]. The features set extracted from inertial sensors included Max–min values, averages, and standard deviation, which have been proven to be efficient and suitable features to describe inertial sensors in Activity Recognition (AR), and allow for the identification and recognition of the actions or goals of the habitant. AR is usually used in monitoring the activities of elderly residents to support management and prevention of diseases [36]. This feature set, with two wearable three-axial inertial sensors, corresponds to a total of 24 features.

4. Results

In this section we present the results of the case study. We evaluated the performance (precision, recall, and F1 score) using leave-one-participant-out cross-validation in two configurations: (A) The test is determined by inertial data and labels from a given participant and the training model is composed only by inertial data and labels not including the target subject (strict leave-one-out) table 3 and table 4; and (B) half of the inertial data from the participant is included in the training set to implement the model's adaptation/personalization (adapted model), table 5 and table 6.

4.1. Training Using Leave-One-Out

In this section, we present the results of the experimental setup without including personalization of the user in learning. That is, using, as training, the data from other users and evaluating the data for the unseen data of the test user (any data for the case scenes of this user is included in learning).

In addition, we present the results aggregating two classes—walking and idle—which are not key to monitoring PUs, as the time spent in these classes does not require position changes within prevention protocols.

4.2. Training-Adapted Model.

In this section we detail the results from the experimental setup, including one of the two cases repeated by the participant in training. Thus, learning includes personalization of inertial data and postures for the test user prior to evaluation. First, in Table 3, we show the results for classifying the seven proposed postures.

Moreover, we report results aggregating the two classes–walking and idle, in Table 4.

Table 3. Results without personalization for the seven postures including walking and idle. Grouped in four classifications: SVM (Support Vector Machines), NB (Naive Bayes), C4.5 (Decision tree), KNN (K-nearest neighbor's algorithm).

	SVM			NB			C4.5			KNN		
Class	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**
Idle	0.653	0.345	0.451	0.711	0.420	0.528	0.695	0.224	0.339	0.654	0.507	0.571
Supine	0.507	0.657	0.572	0.697	0.724	0.710	0.366	0.351	0.358	0.547	0.485	0.514
Reclined	0.514	0.581	0.545	0.658	0.657	0.657	0.264	0.434	0.328	0.720	0.656	0.687
Left side	0.608	0.932	0.736	0.644	0.959	0.771	0.183	0.850	0.302	0.652	0.934	0.768
Right side	0.959	0.956	0.958	0.779	0.959	0.860	0.769	0.949	0.849	0.891	0.955	0.922
Standing	0.727	0.883	0.797	0.969	0.945	0.957	0.382	0.602	0.467	0.662	0.864	0.750
Walking	0.896	0.740	0.810	0.977	0.953	0.965	0.927	0.861	0.893	0.852	0.731	0.787
AVG	0.702	0.791	0.736	0.787	0.866	0.820	0.482	0.675	0.533	0.721	0.771	0.738

Table 4. Results without personalization aggregating idle and walking.

	SVM			NB			C4.5			KNN		
Class	**Pre**	**Recal l**	**F1**	**Pre**	**Recal l**	**F1**	**Pre**	**Recal l**	**F1**	**Pre**	**Recal l**	**F1**
Supine	0. 847	0.557	0.672	0.883	0.664	0.758	0.873	0.437	0.583	0.456	0.407	0.430
Reclined	0.507	0.657	0.572	0.697	0.724	0.710	0.366	0.351	0.358	0.471	0.467	0.469
Left side	0.514	0.581	0.545	0.658	0.657	0.657	0.264	0.434	0.328	0.709	0.635	0.670
Right side	0.608	0.932	0.736	0.644	0.959	0.771	0.183	0.850	0.302	0.643	0.876	0.741
Standing	0.959	0.956	0.958	0.779	0.959	0.860	0.769	0.949	0.849	0.803	0.913	0.855
Movement	0.727	0.883	0.797	0.969	0.945	0.957	0.382	0.602	0.467	0.495	0.760	0.600
AVG	0.694	0.761	0.713	0.772	0.818	0.786	0.473	0.604	0.481	0.596	0.676	0.627

Besides in the Table 5 and 6, data from the participant is included in the training model's. In the same way as in the previous tables, we will show the results in Table 5 without personalization, while in Table 7 we will show the participant data with personalization.

Using patient data, in the following table we aggregating add two classes walking and indl with personalization of participant.

Finally, in Table 7, below are the best final results according to each position within the four classifiers used.

Table 5. Results with personalization for the seven postures including walking and idle.

	SVM			NB			C4.5			KNN		
	Pre	**Recall**	**F1**	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**
Idle	0.447	0.495	0.470	0.762	0.417	0.539	0.856	0.238	0.372	0.757	0.761	0.759
Supine	0.976	0.903	0.938	0.000	0.000	0.000	0.000	0.000	0.000	0.796	0.961	0.871
Reclined	1.000	0.883	0.938	0.999	0.945	0.971	0.115	1.000	0.206	1.000	0.946	0.972
Left side	1.000	0.819	0.900	1.000	0.940	0.969	0.000	0.000	0.000	0.999	0.979	0.989
Right side	1.000	0.888	0.940	1.000	0.964	0.982	0.057	0.877	0.107	1.000	0.944	0.971
Standing	0.973	0.916	0.944	1.000	0.964	0.981	0.000	0.000	0.000	0.982	0.976	0.979
Walking	0.447	0.495	0.470	0.977	0.955	0.966	0.934	0.969	0.951	0.964	0.886	0.923
AVG	0.899	0.817	0.855	0.829	0.795	0.812	0.184	0.474	0.211	0.957	0.949	0.951

Table 6. Results with personalization aggregating idle and walking.

	SVM			NB			C4.5			KNN		
Class	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**
Supine	0.808	0.980	0.886	0.872	0.576	0.694	0.924	0.359	0.517	0.888	0.862	0.875
Reclined	0.988	0.949	0.968	0.000	0.000	0.000	0.000	0.000	0.000	0.796	0.961	0.871
Left side	1.000	0.938	0.968	0.999	0.945	0.971	0.115	1.000	0.206	1.000	0.946	0.972
Right side	1.000	0.900	0.948	1.000	0.940	0.969	0.000	0.000	0.000	0.999	0.979	0.989
Standing	1.000	0.940	0.969	1.000	0.964	0.982	0.057	0.877	0.107	1.000	0.944	0.971
Movement	0.986	0.956	0.971	1.000	0.964	0.981	0.000	0.000	0.000	0.982	0.976	0.979
AVG	0.964	0.944	0.952	0.812	0.731	0.766	0.183	0.373	0.138	0.944	0.945	0.943

Table 7. Final results with personalization.

	SVM			NB			C4.5			KNN		
Class	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**	**Pre**	**Recall**	**F1**
Idle	0.447	0.495	0.470	0.762	0.417	0.539	0.856	0.238	0.372	0.757	0.761	0.759
Supine	0.808	0.980	0.886	0.872	0.576	0.694	0.924	0.359	0.517	0.888	0.862	0.875
Reclined	1.000	0.883	0.938	0.999	0.945	0.971	0.115	1.000	0.206	1.000	0.946	0.972
Left side	1.000	0.938	0.968	0.999	0.945	0.971	0.115	1.000	0.206	1.000	0.946	0.972
Right side	0.959	0.956	0.958	0.779	0.959	0.860	0.769	0.949	0.849	0.891	0.955	0.922
Standing	0.959	0.956	0.958	0.779	0.959	0.860	0.769	0.949	0.849	0.803	0.913	0.855
Walking	0.986	0.956	0.971	1.000	0.964	0.981	0.000	0.000	0.000	0.982	0.976	0.979
AVG	0.447	0.495	0.470	0.977	0.955	0.966	0.934	0.969	0.951	0.964	0.886	0.923

In Figure 2 we can observe the frequency guideline of each posture. additionally, that in Figure 3 we present the confusion matrix of best configuration for SVM including personalization.

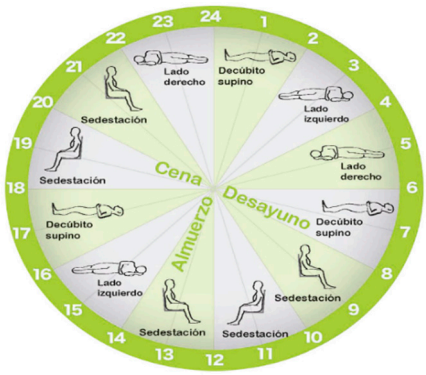

Figure 2. Frequency guideline tool on posture change [2].

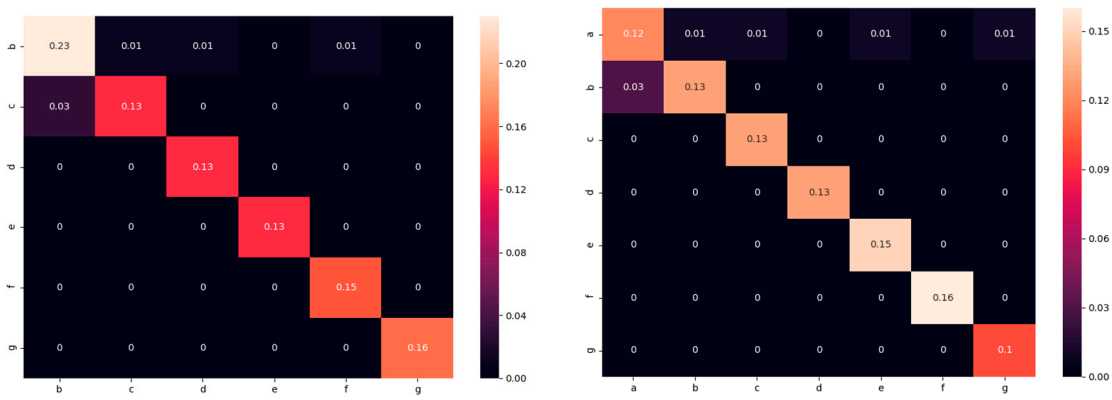

Figure 3. Confusion matrices for SVM with personalization. (**Left**), defines the seven classes (a) idle, (b) supine, (c) reclined, (d) left, (e) right, (f) standing, and (g) walking. (**Right**), (a) includes walking and idle.

5. Discussion

Based on the results of table 7, we identified SVM and KNN as suitable classifiers for inferring the body position of user with a F1 closer to 0.95. In addition, we observe that the best classification is developed using personalization, meaning it is key to include some training data of the target subject to enhance accuracy performances. Decision trees were excluded in the comparison since they may not be the best approach using inertial sensors, due to their limitation to handle non-discrete attributes [37]. Finally, the discrimination between idle and walking slightly decreases the performance. This distinction; however, is not relevant for the case of preventing ulcer pressures; therefore, an optimal set of target activities is the reduced set.

Results suggest that a care plan should be established for each type of patient according to the wound level. This care plan needs to be developed in collaboration with the caregivers once the initial assessment is completed, and it will be updated whenever there is a change in the patient's medical situation or when the wound does not progress towards healing. Pressure injury management strategies should also be customized considering attitudes, beliefs, culture, daily needs, and the personal preferences of the patient. In addition, it is essential that the control passes from the interprofessional team to the person to empower them to help themselves to adhere to their care plan.

6. Limitations

The causality of the formation of PUs is associated to types of forces: pressure, friction, and shearing; PUs Type 2 are associated with friction, and Types 3 and 4 to shear and pressure forces. In this work, we focus on PUs Type 4.

7. Conclusions and Future Work

In this work we presented a prototype intelligent system for the prevention of PUs. A solution based on two wearable inertial sensors on the ankle and shoulder was proposed to provide an accurate estimation of a patient's body orientation. Changes in posture are considered as the main prevention mechanism and it has been shown that it "is necessary and sufficient to avoid the appearance of pressure ulcers". This work aimed to provide the caregivers with real-time continuous body position monitoring, thus reducing the required effort thanks to automatic control.

The evaluation of different classification approaches showed that SVM and KNN provide better results in determining the position of the patient according to the data collected, the high competence, and the inherent design to work with numerical attributes. Personalization was implemented including some data of the target patient. This increased the precision and recall performance notably.

In future work we will address the use of the integrated inertial sensor in an Internet of Things device to present a less invasive approach that could be used in case studies with patients to avoid pressure ulcers. In addition, we will include linguistic rules and configuration of the alerts according to the frequency that each patient needs and the position; the intelligent system is able to prevent the ulcer by evaluating the risk and the mobility of the patient. This intelligent system would help hospitals to be more efficient and would optimize nurses' time.

We note the novelty of this work is that it proposes the use of wearable inertial sensors to monitor patients through an intelligent system which determines the position in real-time in an automatic fashion.

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