

# Design and Implementation of an Intelligent System for Controlling a Robotic Hospital Bed for Patient Care Assistance

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**Abstract.** In this article we propose an intelligent system (IS) for automatic movements of a robotic-assisted hospital bed, it is based on posture classification and recognition using mattress pressure sensors. The proposed IS allows to program a sequence of movements of the robotic bed that are executed automatically through electric actuators in response to the pressure distribution of a patient on the bed. The experimental results show that programmed movements are useful in preventing bed-sores in patients who stay in bed for extended periods of time.

**Keywords.** Pattern classification, support vector machines, pressure sensors, intelligent systems, assistive robotics.

## 1 Introduction

In recent years, artificial intelligent systems (IS) have been used in several applications such as industrial control, robot control, traffic surveillance, remote sensing, and speech recognition, among others. In particular, IS applied to medical environments have been a challenging task due to high risk decisions in diagnosis, monitoring, and care of patients. However, in rehabilitation of patients with limited or restricted mobility, IS have been used to control the positioning of robotic hospital beds to prevent the appearance of bed-pressure ulcers, also in activity monitoring and bed-rails control [5, 1, 12, 13]. Most of the systems for automatic control of hospital bed positions are based in the detection of the posture of patients on the bed using presence sensors, digital cameras, thermal cameras, and mattress pressure sensors [6, 3, 10]. Those systems based on digital and thermal cameras have the disadvantages that they are affected

by the environment illumination, temperature conditions, and occlusions. On the other hand, mattress pressure sensors can be used to detect the posture of patients in any illumination and temperature conditions; this is done by performing an analysis of the pressure distribution obtained from the contact of the patient over the pressure sensor array.













**Fig. 1.** Rendering sketch of the developed robotic bed

In this research we propose an IS to control the positions of a robotic hospital bed. The purpose of the proposed system is to prevent accidents when the bed is moving and provide a mechanics to programming a sequence of movements of the robotic bed that are executed automatically. We recognize the posture of patients using a mattress pressure sensor and performing an analysis and classification of the pressure distributions. The proposed IS can be used to assist medical staff and also provides a mechanics for an automatic and non-assisted control of bed positioning.

## 2 Bed System Description

A robotic hospital bed is able to change its position depending on the needs of a patient. Figure 1 presents a diagram sketch of the developed hospital bed at the Hospital Juárez de México, and Table 1 shows all possible positions and transitions which it can adopt. The base position is the *home position*, to which all the others can transit, with exception of the *sit-to-stand position*. The transitions of the robotic bed are performed by means of electric actuators, and the time it takes to go from one position to another depends on the weight of the patient and the current position of the bed.

**Table 1.** Positions and transitions of the developed hospital bed that are most used by medical specialists

Number	Symbol	Name position	Transitions
0		Home	1-7
1		Trendelenburg	0, 2-6
2		Inverted Trendelenburg	0,1, 3-6
3		Fowler	0-2, 4-7
4		Lifting legs	0-3, 5-7
5		Orthopedic	0-4, 6,7
6		Cardiac	0-5, 7
7		Sitting	0, 3-6
8		Sit-to-stand	7
9		Lateral rotation	0

### 2.1 Pressure Sensor Array

The robotic bed uses a flexible pressure sensor array consisting of 512 units distributed in an area of  $1108 \times 544$  mm [11]. Figure 2 shows the pressure sensor system that is composed of two independent units of  $16 \times 16$  sensors. The pressure sensors are based on variable resistive devices with pressure levels ranging between 0 and 4096 and normal resistance from 1 to 4 kilohm. All pressure measurements were normalized to a range of



**Fig. 2.** Pressure sensor array of  $32 \times 16$  units in an area of  $1108 \times 554$  mm

values from 2500 to 4096 which correspond to the mean weight of an adult which ranges between 40 and 150 kg. A computer program was developed in order to synchronize the two independent pressure array units and obtain pressure maps of size  $32 \times 16$ .

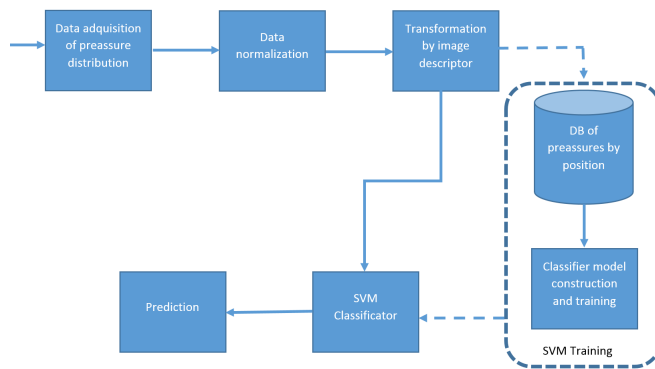
## 3 The Proposed Intelligent System

The proposed IS was designed to be part of a medical application, performing the classification of human postures. The recognition of human postures is an important task in the monitoring of patients and in the control of robotic hospital beds. The IS used in hospital environments must satisfy high quality norms and standards, only in such way an intelligent device is used to assist medical staff. However, there are applications in which low-risk decisions can be made by an IS. Examples of such applications are the IS used to prevent bed-sores in patients with restricted mobility and automatic positioning of robotic beds.

### 3.1 Technical Specifications

Figure 3 shows the main blocks of the proposed IS for posture recognition, based on a low-resolution pressure sensor array. The description of each stage is given as follows:

- a) *Data acquisition*: pressure maps are obtained from an array of  $31 \times 16$  pressure sensors. The measured pressure levels range between 0 and 4096, where 0 is the maximum pressure value and 4096 is the minimum pressure value.



**Fig. 3.** Main blocks of the IS for posture recognition

- b) *Data normalization*: in this block, raw data (matrices of size  $32 \times 16$ ) are normalized according to three basic considerations. The first consideration is based on the mean weight of a person, which ranges between 40 and 150 kg and corresponds to the pressure values from 2500 to 4096. Pressure values out of this range are omitted. The second consideration is normalization from the range 2500-4096 to the range 0-255 considered as gray-scale values. The last consideration is to apply an image interpolation algorithm to raw pressure maps. After this block, two kinds of pressure maps are obtained, raw- and interpolated pressure maps. A two factor scale was used for the interpolation algorithm, that is, the pressure maps are scaled to  $64 \times 32$  in size.
- c) *Image descriptors*: in this stage, image descriptors are computed. An image descriptor is a vector that represents the most relevant features in an image. HOG [4] and SIFT [9] descriptors were extracted from the interpolated pressure maps, which are considered as gray scale images.
- d) *SVM training*: in this block (delimited with dashed lines), a classification model is constructed using an SVM. A database of pressure maps is constructed with four different representations of the postures, that is, raw and interpolated pressure maps, HOG and SIFT vector descriptors. Then, for each set

of postures, a classification model is constructed.

- e) *SVM classification*: the classification is performed using the already constructed classification models. In this stage, we make a comparison of the performance of the classification results using each model.
- f) *Prediction*: we consider a majority voting scheme in order to output a prediction according to the classification results, for each classification model.

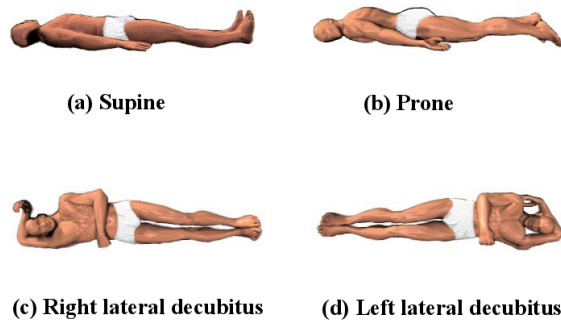
The output prediction can be used for another system in order to make a decision. In the following section, posture classification and recognition are described.

## 4 Posture Classification

The IS will be able to detect if the patient is in a correct position in order to perform the requested transition and will send a visible alert to prevent possible downfalls. In order to simplify posture recognition, we consider the sleeping positions according to the famous study by professor Chris Idzikowski [7], who classified the sleeping positions into six types: *foetus*, *log*, *yearner*, *soldier*, *freerfaller*, and *starfish*. A simplified set of positions was considered by grouping them into four basic classes: *left lateral decubitus* (foetus), *right lateral decubitus* (log and yearner), *supine* (soldier and starfish), and *prone* (freerfaller). In Figure 4 some examples of these classes can be seen.

Posture classification was performed using a *support vector machine* (SVM) [2], and a classification model was constructed for posture recognition. Four different databases were constructed for training; this was done in order to compare the performance of different representations of the pressure maps. The considered databases are the following ones:

1. Raw pressure maps
2. Interpolated pressure maps
3. HOG descriptors

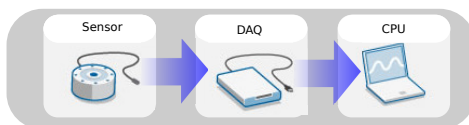


**Fig. 4.** The four basic sleeping positions (image source at [www.paramedicine.com/](http://www.paramedicine.com/))

#### 4. SIFT descriptors

Each considered database has characteristic vector features depending on the size of the pressure matrices. The raw pressure map database consists of the pressure matrices obtained from the sensor array. The interpolated pressure map database is an oversampling of the raw database. The HOG and SIFT databases consist of the extracted feature vectors in the interpolated pressure matrices. The motivation of considering four different databases is to find an efficient representation of pressure maps in the sense that vectors of features are small in size and representative.

### 5 Automatic Control of Robotic Bed Positions



**Fig. 5.** Principal elements of a DAQ system

Since robots interpret the real world through devices called sensors, it is important to ensure the communication status of these devices. These sensors are responsible for effectively getting all the information of the surrounding environment, and the data acquisition system is responsible for

collecting, conditioning, and transferring such information to the control unit. Figure 5 shows a general description of this system. These sensors contact pressure distribution in their applications; the sensor technology enables a two-dimensional array of pressure sensing elements in a thin, continuous sheet. By placing sensors on a flat surface, users measure and visualize pressure information in the interface using this simple but powerful resistive sensing approach.

Our development implies an IS which controls the robot in order to reduce the risks of operating a hospital bed with multiple positions. The main objective of our system is to prevent accidents when the bed is moving, this is done by detecting the posture of patients using a mattress pressure sensor and by performing an analysis and classification of pressure distributions using an initial training set of correct postures for all bed positions. The proposed IS can be used to assist medical staff and also provides a mechanics for an automatic and non-assisted control of bed positioning. Monitoring of leaning people is often used in a variety of hospital process such as geriatrics, rehabilitation, orthopedics, and is employed even in psychology and sleep studies [8]. Although patient monitoring is usually an activity of doctors and nurses, this can be automated to have better control of patients in any time with human intervention only to rate different positions through which the patient has passed, the time spent in each position, and incurred transitions. Given a high cost of fabrication of array pressure sensors, it is necessary to develop a method that uses few data to solve the classification issue.

We choose four basic positions according to the famous study by professor Chris Idzikowski [8], who classified the most common sleeping positions in six classes, that is, foetus, log, yearner, soldier, freefaller, and starfish. These positions can be grouped in four basic classes: the left lateral decubitus position or foetus, the right lateral decubitus position including the log and yearner positions, the supine position including the soldier and starfish positions, and the prone position or freefaller. We use a flexible array pressure sensor with 448 units distributed in an area of 1860x886 mm. We construct a database with pressure levels

(scaled to 0-255 range) and apply it in the HOG algorithm [4]. The database contains samples of four postures. With this database, we can construct a classification model using a support vector machine (SVM) classifier. This bed is able to adopt several positions depending on the needs of a particular patient; it can also be programmed to perform a series of movements within a period of time. The IS will be able to detect if the patient is in a correct position in order to perform the requested transition, and will send a visible alert to prevent possible downfalls. The main stages of the IS for the posture recognition are as follows: in the initial stage the pressure distributions are obtained from the pressure sensor array, in the second and third stages an analysis and pre-processing are performed, also a feature extraction using HOG and SHIFT descriptors is applied over the pressure distributions considered as gray scale images; in the fourth stage a database of features is constructed, and in the last two stages we construct a model for feature classification and prediction. Also, we compare the results of three classifiers such as Support Vector Machines, Decision Trees, and Naïve Bayes Networks. To apply posture recognition, we consider the basic postures; posture detection is achieved by an analysis of pressure distribution. Thus, a database of features is constructed such that it contains the sets of equal size of the basic positions and an appropriate number of their variants. Then, the model of the classifier is constructed in order to make predictions of pressure distributions that do not belong to the database.

Also, the IS can be used to control the actuators of the robotic hospital bed in a semi- or automatic way and to prevent accidents when the bed is moving slowly. Thus, when a bad posture is detected, the IS sends a signal to the actuators either to stop the transition movement or to return to the previous position. We use a HOG descriptor to characterize each pressure image. Then, for each pressure map, a vector of gradient directions is constructed. We consider that a histogram of gradient directions can be used for image classification since small changes in pressure images are easily detected as changes in gradient directions.

## 6 Experiments and Results

We must consider that the pressure sensor array consists of two independent modules with a resolution of  $16 \times 14$  units in an area of  $930 \times 886$  mm. Each pressure sensor has a response between 0 and  $25 \text{ kg/cm}^2$ . We develop an interface to synchronize the two modules at a frequency of 100 measurements per second.

### 6.1 Pressure Map Databases

Also, we have constructed four different pressure map data sets for classification: each data set consists of four classes, for every posture position. For each class, we generated 501 instances. Each data set has 2004 instances and is stored as an individual database.

The data sets are described as follows:

1. *Data set interpolated to  $640 \times 640$ :*
2. *Data set interpolated to  $320 \times 320$ :*
3. *Data set interpolated to  $100 \times 100$ :*
4. *Data set in raw format ( $32 \times 14$ ):*

Figure 7 shows some examples of interpolated pressure maps. We normalize the range of values of each attribute vector; this is done in order to improve the performance of the classifier.

Then, we construct four different databases for posture classification: raw data, interpolated raw data, HOG descriptors, and SIFT descriptors. The data sets are described as follows:

1. *Raw data:* consists of the  $32 \times 16$  pressure matrices, that are represented as vectors with 512 entries.
2. *Interpolated raw data:* consists of interpolated pressure data using bilinear interpolation. We use a factor of 2x for sub-sampling, generating pressure matrices of  $64 \times 32$  which are represented as vectors with 2048 entries.

3. *HOG descriptors*: we use the  $64 \times 32$  interpolated pressure matrices in order to compute the HOG descriptors using 9 bins and 3 windows per box. The descriptors are represented as vectors with 81 entries (see [4] for a detailed description of HOG descriptors).
4. *SIFT descriptors*: we use the  $64 \times 32$  interpolated pressure matrices in order to compute the SIFT descriptors. The size of the histogram of occurrences was 500. Thus, for each interpolated pressure matrix, we compute a sparse attribute vector with 500 entries (see [9] for a detailed description of SIFT descriptors).

The structure of each database consists in a table with  $n$  columns or the number of persons and four rows or the positions (see Figure 4), so that for each person and each position there are 501 vectors or variants of the considered position. The number of vectors for each position and for all persons is  $501 \cdot n$ , and the total number of vectors for each database is  $k = 501 \cdot 4 \cdot n$ . Table 2 shows a comparison of the size of each database with respect to the kind of descriptor vectors. It can be seen that the most efficient representation is through the HOG descriptors, while the interpolated representation is the most inefficient.

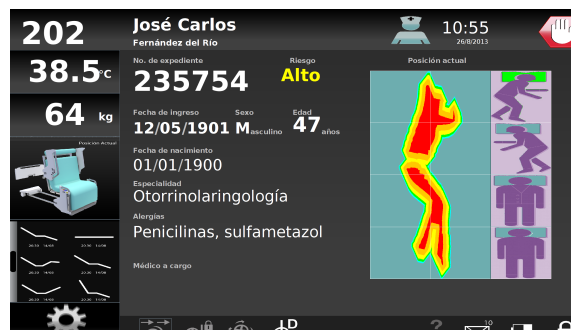
**Table 2.** Database size with respect to the vector descriptor and the number  $k$  of vectors in each database

Vectors	Total size database
Raw-data	$512 \cdot k$
Interpolated	$2048 \cdot k$
HOG	$81 \cdot k$
SIFT	$500 \cdot k$

## 6.2 Software System Interface

A software system interface was developed in order to interact with the IS and display information of each patient and the current state of the robotic bed (see Figure 6). This interface is able to show valuable information of the patient condition such as name, sex, age, temperature, weight, date of admission, specialty, allergies, patient risk, and the

name of the medical specialist. We have decided to show this information based on a survey applied to nurses, residents, and specialists at the Hospital Juárez of México. The interface also shows the current position of the robotic bed and provides a set of commands to manually operate the bed positions. Additionally, the patient position and pressure distribution are displayed.

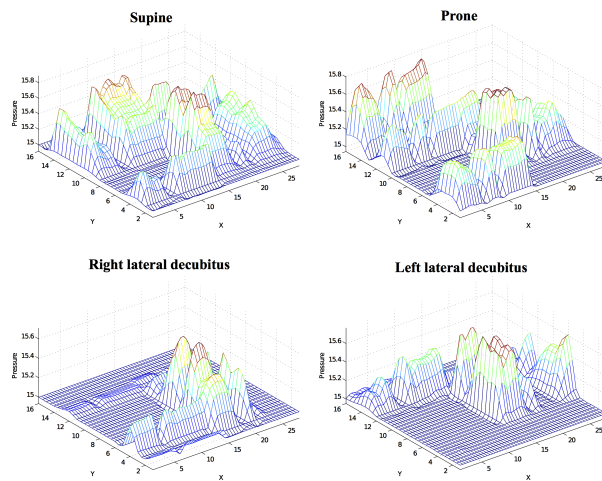


**Fig. 6.** Software system interface of the IS

## 6.3 Pressure Map Classification

We use the LibLINEAR toolbox to perform the posture classification, and we compare the results using the proposed databases. We found that the pressure maps for persons with the same height do not change significantly in their distribution. Therefore, the number of persons considered in order to perform our experiments was  $n = 1$ . Figure 7 shows an example of interpolated pressure maps for the four basic positions.

Table 3 shows the results of the classification using 10-fold cross-validation. As it can be seen, the raw and interpolated databases have the same performance, but with different time to build the classification model. This is a consequence of increasing the number of attributes in the interpolation. The HOG and SIFT databases have almost the same performance, but with a time noticeably different to build the models. It is important to note that the size of the HOG database is only about 0.158% of the raw database. This can be considered as a reduction of dimensionality in the attribute space. An important feature of using image descriptors is that the time to construct the



**Fig. 7.** Interpolated pressure maps corresponding to the four basic posture positions

model of the classifier is slower than when using raw and interpolated data.

**Table 3.** Percentage of correctly classified instances and the time to build the classification model

Database	LibLinear	Time to build model
Raw data	99.7005%	1.46 sec
Interpolated	99.7005%	4.3 sec
HOG	98.7026%	0.14 sec
SIFT	98.9521%	0.05 sec

Table 4 shows the confusion matrices for the classification results given in Table 3. It can be observed that the confusion matrices for the raw- and interpolated data are the same. This means that in terms of classifying pressure maps, the interpolation does not contribute to the description of the input data. The HOG and SIFT matrices have similar values and do not coincide in any entry. It can be seen that the Prone position was classified incorrectly as the Right position in most cases.

These experiments show that the classification of posture pressure maps can be done with a performance of 99.7% using a linear kernel for SVM. The use of image descriptors, so helpful in constructing and efficiently representing the pressure maps, reduces the time complexity to build the classification model.

**Table 4.** Confusion matrices for the raw- and interpolated data (top), HOG descriptor (middle), and SIFT descriptor (bottom)

	Supine	Prone	Right	Left
<i>Raw- and interpolated</i>				
Supine	501	0	0	0
Prone	0	498	3	0
Right	0	1	500	0
Left	0	0	0	501
<i>HOG-descriptor</i>				
Supine	495	0	6	0
Prone	8	484	7	2
Right	1	0	500	0
Left	1	0	1	499
<i>SIFT-descriptor</i>				
Supine	497	1	1	2
Prone	1	491	9	0
Right	3	3	495	0
Left	0	1	0	500

## 7 Conclusions

The intelligent system proposed in this paper represents a strategy to endow robotic assistant ability to detect risk scenarios for patients. In this case, when the robotic bed is moving, situations of risk can be generated if patients perform any bodily movement that is inappropriate to the robotic bed movement configuration. Our system represents an advance in medical care since through such kind of intelligent devices patients can be treated without participation of medical personnel who may run a risk of an injury when moving patients manually. In this case, the robotic bed can be programmed in such a way that the appropriate medical personnel could attend other patients while the bed automatically applies a certain movement therapy to patients with only supervised medical monitoring by hospital experts.

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