A Low-Cost Mattress Sensor for Automated Body Position Classification

Lowne, Duncan; Tarler, Matthew

Cleveland Medical Devices Inc., Cleveland, OH 44103 United States

Abstract

Determination of body position on a mattress in a clinical setting is important for both diagnosis of sleep disorders and management and prevention of pressure sores. At present, patient body position is measured by visual inspection or by post analysis of either a video monitoring system or expensive, high-resolution arrays of pressure sensors. Due to the high cost and time consumption involved with these methods, a set of accelerometers tethered to the patient is often used instead. However, these accelerometers only provide directional orientation of the patient torso, and yield little information regarding the total body position. We present here a design for a low-cost sensor mat that combines a minimum number of sensors with a feed-forward neural net for autonomous detection and distinction of body position into a set of discrete patterns.

Introduction

Each year, over 1.6 million people in the United States suffer from pressure ulcers, and 60,000 people die annually due to pressure ulcer complications[1]. Each incidence of a pressure ulcer incurs an average cost greater than US$29,000[2]. Although pressure ulcers can be averted by regular repositioning of the patient, current automated approaches have been expensive and inefficient, focusing primarily on shifting the body at pre-set intervals, and have not adequately addressed the problem of prolonged, localized surface pressure. In addition, current methods of body position classification are expensive and inadequate, usually requiring human intervention in the way of visual inspection or post-analysis and/or expensive hardware in the way of video monitoring systems or high-resolution arrays of pressure sensors.

Methods

Data was collected from an FSA mattress sensor array, containing 1,024 pressure sensors, each 1.9cm wide by 5.1cm tall, arranged in a 32 by 32 rectangular grid layout. Data collected at this resolution was dithered down to 17 equal or lesser sensor resolutions ranging from 32 to 1,024 sensors, outlined in Table 1.

Ten subjects ranging in height from 160cm to 188cm were recruited for data collection. In addition to their varying heights, these subjects represented a diverse cross section of body statures. Each subject was recorded in each of ten body positions, holding each position for at least five seconds. In general, the body positions are grouped into four categories: front, back, left and right whereby the front and back are further broken down into right, left and straight categories, and left and right into straight and tucked subcategories.

Sensors in the X Direction	Sensors in the Y Direction [Total Sensor Count]
32	32 [1024]
	16 [512]
	8 [256]
	4 [128]
	2 [64]
	1 [32]
16	32 [512]
	16 [256]
	8 [128]
	4 [64]
	2 [32]
8	32 [256]
	16 [128]
	8 [64]
	4 [32]
4	32 [128]
	16 [64]
	8 [32]
2	32 [64]
	16 [32]
1	32 [32]

Table 1 – *Sensor Array Layouts. Gray boxes indicate tested sensor configurations.*

After recentering and normalizing the data, we emulated resistive sensors and capacitive sensors by using peak-pressure and average-pressure. When simulating lower-resolution sensor arrays (resolution of *I* by *J*), the resistive array points were simulated by taking the peak value (***M***) over an area of input from the original sample matrix **X**, whereas capacitive sensor arrays were simulated by taking the mean value over an area of input:

$$Y_{i,j} = \underset{m}{M}\,\underset{n}{M}\, X_{m,n}$$

Eqn. 1: *Algorithm for simulating resistive sensors*

$$Y_{i,j} = \sum_{m}\sum_{n} \frac{X_{m,n}}{m*n}$$

Eqn. 2: *Algorithm for simulating capacitive sensors*

In both instances, the cells of each simulated lower-resolution sensor $Y_{i,j}$ include the elements $X_{m,n}$ of the original sample matrix where:

$$m = i*\alpha \rightarrow (i+1)*\alpha - 1$$

$$n = j*\beta \rightarrow (j+1)*\beta - 1$$

such that α = 32/I and β = 32/J.

Between the two experimental sets, four separate classification system architectures were examined. For the guided-clustering algorithm, 10 cluster centers corresponding to the body-position classifications were initialized on a set of input vectors[5]. For each of the three neural-net architectures, a κ-hidden-layer feed-forward neural net (2 < κ < 4) was trained on the input vectors[4]. Each system was observed with a distinct test set of 20 input vectors.

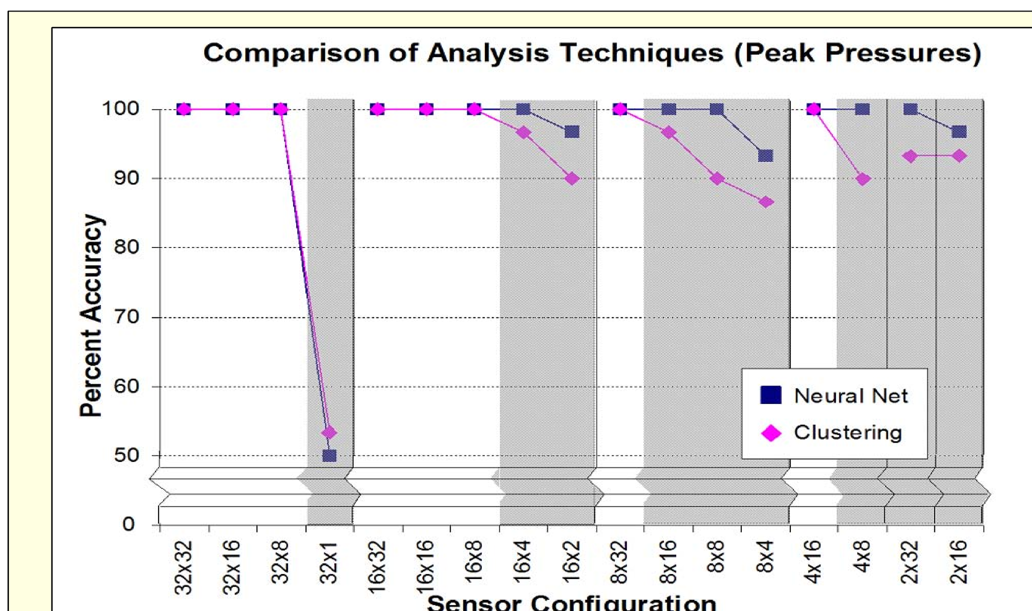

Fig. 1 – *Accuracy comparison between clustering and neural net classifiers simulating resistive (peak pressure) sensor arrays.*

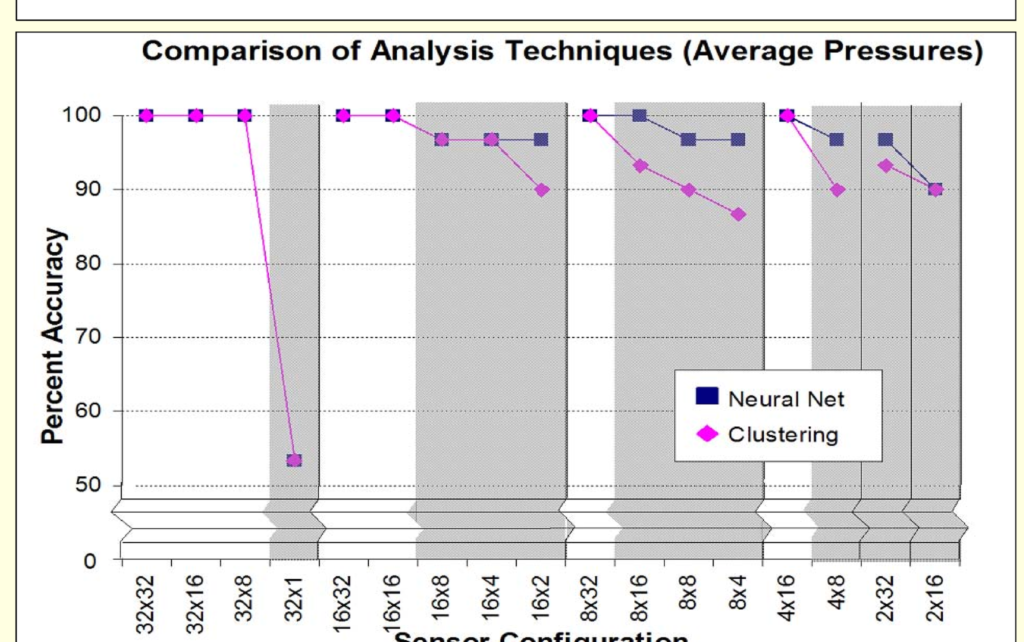

Fig. 2 – *Accuracy comparison between clustering and neural net classifiers simulating capacitive (average pressure) sensor arrays.*

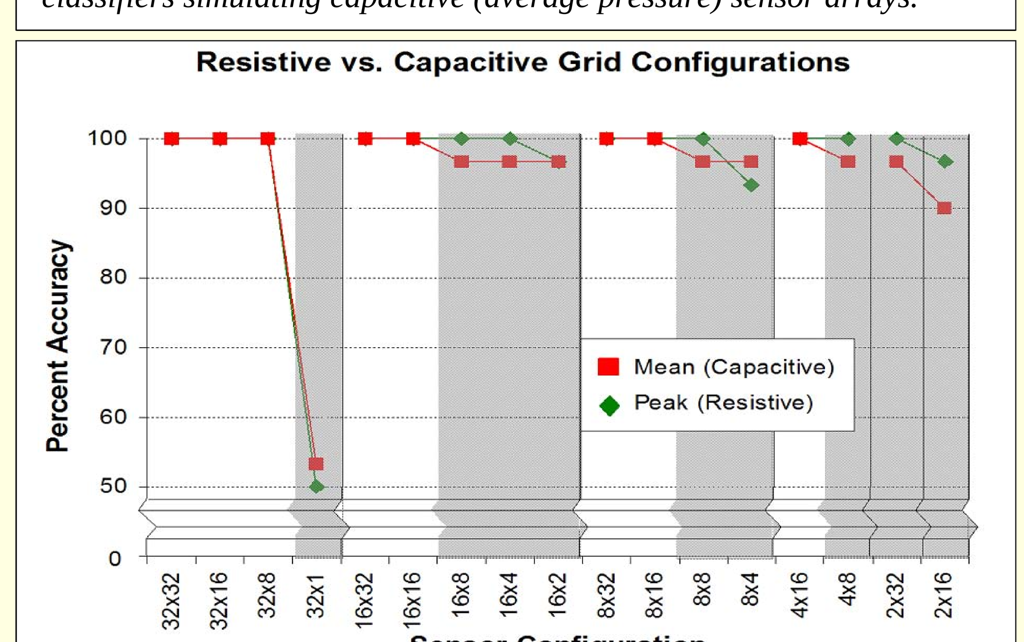

Fig. 3 – *Accuracy comparison between capacitive and resistive sensor arrays using a 4-HL neural network classifier.*

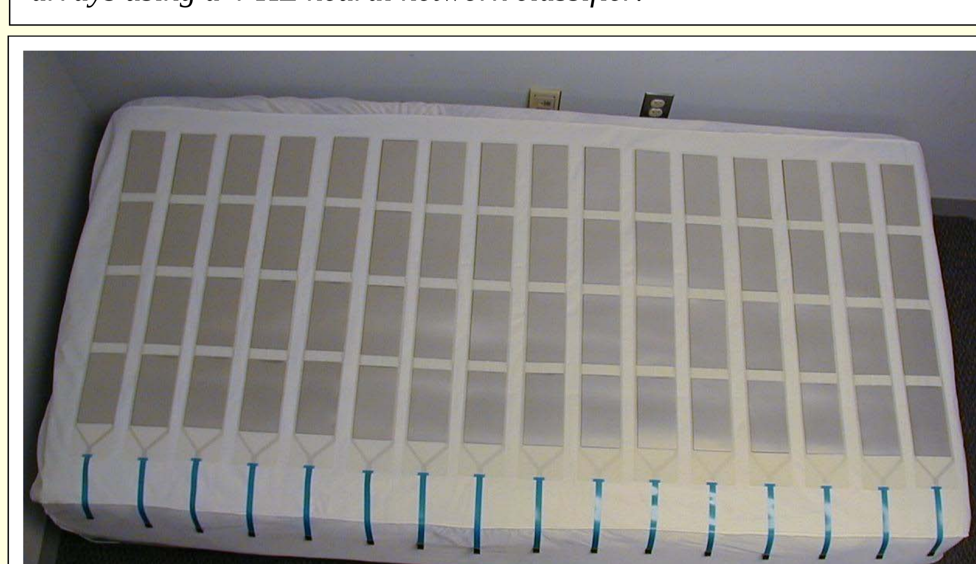

Fig. 4 – *Prototype low-cost sensor array installed on a standard twin-size bed.*

Results

Of the 288 data sets collected from test subjects, 142 were used for system training, 20 were used for system tests and 126 were discarded. Redundancy was the primary cause of data set rejection.

In the first set of tests, we compared accuracies of three sensor architectures (guided clustering and neural networks with two and three hidden-layer nodes) for 17 sensor layouts using both peak and average pressure values. This was followed by a second round of testing using two architectures (one guided clustering system and one four-HL neural network). The results of this round of testing are depicted in Fig. 1 and 2. Each graph depicts the percentage of correctly identified body positions by each system on the indicated sensor layout. Sensor layouts with less than 100% accuracy for either classifier are grayed out in each figure, highlighting the most promising system architectures.

For the purposes of this study, the optimal configuration for a prototype mattress sensor configuration was defined as the lowest resolution (hence the fewest sensors) for which both resistive and capacitive sensor arrays would achieve 100% classification accuracy working within the constraints of this series of experiments. By this definition, the optimal sensor configuration was determined to be an array of 64 sensors in a 4 by 16 grid.

The work performed in this study enabled us to develop a prototype sensor mat conforming to the derived specifications. The 4 by 16 grid of flexible pressure sensors can easily be installed on any standard twin-size mattress, and is depicted in Fig. 4. Prototype interface software is also shown in Fig. 5.

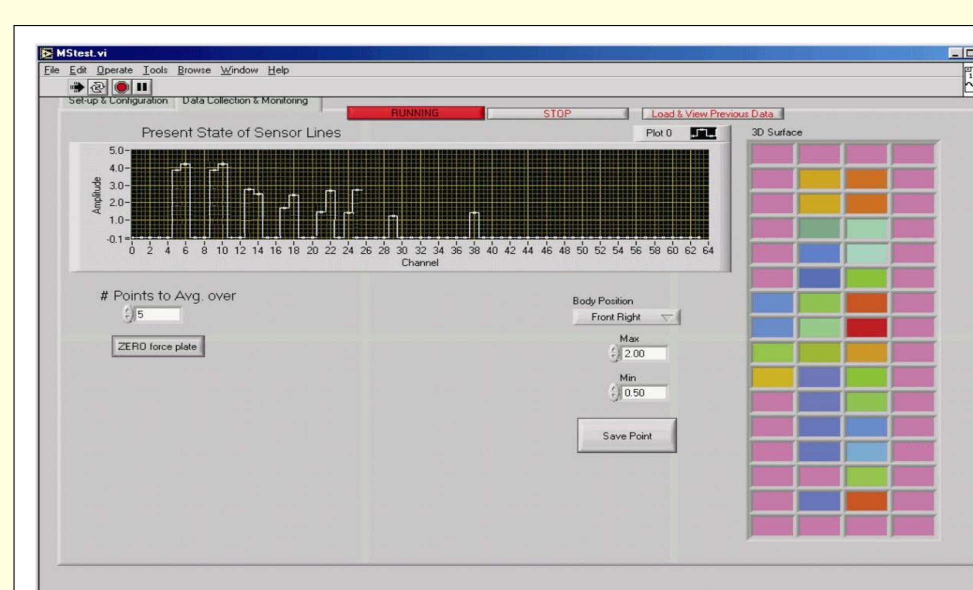

Fig. 5 – *Interface software for prototype device*

Conclusions and Future Work

The results of this study have shown that a low-cost, reliable utility to aid in the prevention of pressure sores among bed-ridden patients is an achievable goal. We have shown that this can be done with a relatively low sensor grid resolution using existing inexpensive sensor technology. Future work shall include testing of the prototype device using a significantly larger sample size. Challenges to address with further experiments include enabling system functionality while taking into account a wider range of physical attributes such as missing limbs. Finally, further investigation should be performed into incorporating a dynamically re-trainable system for further adaptability to individual patients' needs.

Literature cited

1. Russel, J.A. and S.L. Lichtenstein, *Randomized Controlled Trial to Determine the Safety and Efficacy of a Multi-Cell Pulsating Dynamic Mattress System in the Prevention of Pressure Ulcers in Patients Undergoing Cardiovascular Surgery.* Ostomy Wound Management, 2000. **46**(2): p. 46-55.
2. Service, U.S.D.o.H.a.H.H., *Treatment of Pressure Ulcers.* Vol. 15. 1994, Rockville, MD: Agency for Health Care Policy and Research.
3. Rees, R.S. and J.A. Hirshberg, *Wound Care Centers: Costs, Care, and Strategies.* Advances in Wound Care, 1999. **12**(2): p. 4-7.
4. Rumelhart, David E. *et al.*, *Learning Representations by Back-Propagating Errors.* Nature, 323(9): 533—536, Oct 1986.
5. Hartigan, J.A. *Clustering Algorithms.* John Wiley and Sons, 1975.

Acknowledgments

This work was supported in part by the National Institutes of Health under Grant No. 1R43HD042368-01.

Further Information

More information can be obtained by contacting D. Lowne at dlowne@clevemed.com or M. Tarler at mtarler@clevemed.com