

# Designing a Low-Cost Mattress Sensor for Automated Body Position Classification

Duncan R. Lowne, *Member, IEEE*, Matthew Tarler

**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, often the alternative, a set of accelerometers tethered to the patient is used. However, these accelerometers only provide directional orientation of the patient torso, and yield little information regarding the total body position. We present in this paper 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.

## I. INTRODUCTION

EACH year, millions of individuals are affected by pressure ulcers, injuries which are extremely susceptible to infection. In recent months, due to several high-profile fatalities associated with pressure ulcers, the epidemic scale of this problem has been brought into the foreground of international attention. These afflictions are treatable by simple repositioning of the patient at regular intervals. Unfortunately, automated approaches to solving this problem of repositioning have been expensive and ineffective, and have been geared more toward simply shifting the body at certain pre-set intervals, an approach which does not necessarily redistribute pressure in an effective manner.

Over 1.6 million people in the United States suffer from pressure ulcers each year [1]. This population comes from the 12-66% of the hospitalized surgical patients [1], 3-30% of acute care facility patients [2], and 2-23% of the skilled care and nursing home patients [2, 3] that develop new pressure ulcers each year. Due to a healed wound having poor structural and functional characteristic as compared to normal tissue, approximately 70% of all pressure ulcers recur [4]. The occurrence of a single pressure ulcer has been attributed to a 3.5 to 5 fold increase in the length of a patient's stay. In 1992 the estimated hospital and physician charge for a patient with a pressure ulcer was \$24,575 [2], in 1998 pressure ulcer treatment cost were \$29,000 at the University of Michigan Medical Center. Wound care for pressure ulcers has been reported by the Agency for Health Care Policy and Research

(AHCPR) to be a \$200 billion/year industry [5]. In some cases a musculocutaneous flap is used to repair a pressure ulcer and can cost approximately \$40,000 [5]. In addition to the direct costs due to pressure ulcers, indirect costs include the expense of disability payments, prostheses, rehabilitation, loss of income and lost jobs. Ultimately, there are approximately 60,000 people each year whose deaths are due to complications of pressure ulcers [1].

Attempts at understanding the causes of pressure sores have been made for more than a century, but Kosiak performed the initial work to measure the effect of time and pressure on dogs [6], and then later Reswick and Rogers produced the classic pressure vs. time curve, shown in Figure 1. This pressure vs. time curve illustrates the inverse relationship between the allowable time for a given pressure [7].

The goal of this work was to produce a cost effective means to monitor how long someone has been laying in the same position and therefore when they are at risk of ulcer breakdown.

### Sleep Monitoring

Nearly one in seven Americans suffer from some type of chronic sleep disorder. Only 50% of the people in this country are estimated to get the required 7 to 8 hours of sleep every night. It is estimated that sleep deprivation and its associated medical and social costs (loss of productivity, industrial accidents, etc.) exceed \$60 billion.

Nocturnal polysomnogram (PSG) is the standard method of diagnosing sleep disorders. Polysomnography involves the evaluation of physiological functions during sleep and therefore

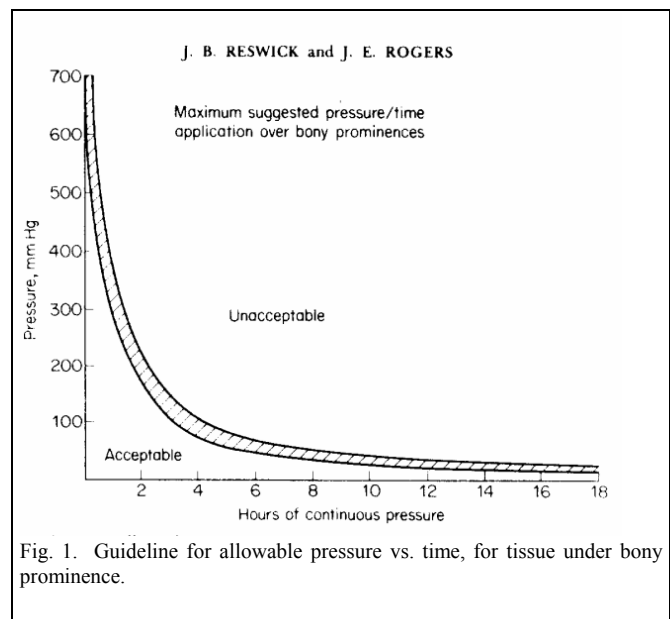


Fig. 1. Guideline for allowable pressure vs. time, for tissue under bony prominence.

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D. R. Lowne is with Cleveland Medical Devices Inc., 4415 Euclid Ave. Suite 400, Cleveland, OH 44103 USA (phone: 216-791-6720; fax: 216-791-6739; e-mail: dlowne@clevemed.com).

M. Tarler, Ph.D., is with Cleveland Medical Devices Inc., Cleveland, OH 44103 USA (e-mail: mtarler@clevemed.com).

should be performed under conditions conducive to natural sleep. Electrodes such as EEG, EOG, EMG, and ECG are placed over the scalp, face, chin and the chest of the patient. Sensors placed near the nose/mouth and over the chest and abdomen measure airflow and respiratory effort. The position of the patient is also tracked for correlation with the data recordings. This body position monitoring plays an essential role in diagnosis with many sleep disorders including Positional Apnea, Periodic Limb Movement Disorder, Restless Legs Syndrome, Nocturnal Seizures, and episodes of Parasomnias including Night Terrors and Sleep Walking. This subset of sleep disorder includes a significant percent of all of the sleep disorder patients. About 56% of all Obstructive Sleep Apnea patients were found to suffer from Positional Apnea [8] and studies estimate that up to 15% of the population [9] have Periodic Limb Movement Disorder.

## II. METHODS

### A. Data Collection

#### 1) Hardware Set-Up

Data for this investigation was collected using an FSA mattress sensor array. The mattress contained 1,024 pressure sensors arranged in a 32 x 32 rectangular grid format. Each sensor was 0.75" wide by 2.0" tall. This detailed resolution was then dithered down to reflect 17 equal or lesser sensor resolutions. Tested resolutions ranged from 1024 to 32 sensors using the uniformly distributed sensor configurations highlighted in Table 1. Non-highlighted cells represent mattress architectures that were observed but not rigorously tested.

Given that one of the objectives of this research was to create a prototype of a lower-resolution array of sensors, tests needed to be performed on the acquired data that would simulate capacitive and resistive sensors, both of which were candidates for the new sensor design. As such, preprocessing on the acquired data yielded sets reflective of peak pressure (simulating resistive sensors) and average pressure (simulating capacitive sensors).

Common to each subset of data was a re-sampling of the original sensors into a simulated architecture of  $x$  sensors by  $y$  sensors, yielding  $(x*y)$  total sensors. Each simulated sensor consisted of  $32/x$  by  $32/y$  actual sensors. The combination of the real sensor values into a single simulated sensor is what specifically differed between the resistive and capacitive subsets of data. A peak value was used to simulate a resistive sensor while an average value was used to simulate a capacitive sensor.

Two rounds of processing were performed on the acquired data. The first round of processing incorporated three separate processing methods (two neural net architectures and one clustering algorithm). From the results of these initial trials, we performed a second set of analyses using refined system architectures (one neural net and one clustering algorithm).

### 2) Experiment

Subjects were recruited for the study and given a description of the experiment. The description of the experiment included instructions on the 10 different body positions through figures, physical demonstration and a verbal explanation. The definition for each position was left general enough to allow and encourage each subject to lay in their own unique position that is comfortable for him or her. 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, straight and left subcategories and the left and right are further broken down into straight or tucked subcategories. Different subjects, however, being free to interpret and perform each position to their own comfort, might perform a position like right side tucked as both legs tucked up, only their right leg tucked up, only their left leg tucked up, arm(s) up, arm(s) down, or any of many variations that would still meet the general description of that position. Each subject was then asked to perform a series of these positions, holding each position for about 5 seconds before the next position was requested.

### B. Data Analysis

Using the 1,024 pressure sensor array, 34 sensor configurations were simulated using 17 sensor layouts, described in Table 1, and were applied to both capacitive and resistive sensor algorithms. When simulating lower-resolution sensor arrays (resolution of I by J), the capacitive array points were simulated by taking the peak value over an area of input from the original sample matrix  $\mathbf{X}$ :

$$Y_{i,j} = \prod_m \prod_n X_{m,n}$$

Resistive sensor arrays were simulated by taking the mean value over an area of input:

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

In both instances, the area of each simulated lower-resolution sensor  $Y_{i,j}$  was defined with the constraints:

$$\begin{aligned} m &= i * \alpha \rightarrow (i+1) * \alpha - 1 \\ n &= j * \beta \rightarrow (j+1) * \beta - 1 \end{aligned}$$

where  $\alpha = 32 / I$  and  $\beta = 32 / J$ . The resulting array of size  $I * J$  constitutes the classification engine's input vector  $\mathbf{S}$ :

$$\mathbf{S} = [X_{i,j}, X_{i+1,j}, \dots, X_{I,j}, \dots, X_{I,J}]^T$$

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. For each of the three neural-net architectures, a  $\kappa$ -hidden-layer feed-forward neural net ( $\kappa : 2 \rightarrow 4$ ) [10] was trained on the input vectors. Each system was observed with a test set of 20 input vectors (not included in the input vectors used for training).

### III. RESULTS

#### A. Experiments

A total of 10 subjects were recruited for data collection. For each subject, the experiment was described and an informed consent form was thoroughly explained and signed. Variations in height, weight and body stature among the subjects were adequate to reflect a reasonable cross-section of patients ranging in height from 5'3" to 6'2". All subjects were classified as "normal," meaning each had full autonomic motor control with no muscular or neurological disabilities affecting movement, and none had significant corporeal anomalies such as missing, abnormal or prosthetic limbs.

Although 10 subjects were recruited and put through the full series of positions, data from 2 of the subjects was lost due to technical error. Careful documentation was performed to record the time for each position so that the data file could be parsed and each body position could be identified. The video served as a backup, in case serious doubts or questioning of the recorded position and actual position arose.

#### B. Analysis

For this phase of the project only static analysis was performed. Therefore, the data from the 8 subjects provided a total of 288 potential data sets, each representing an individual position performed by a subject.

Of the 288 collected data sets, 142 were used for system

Sensors in the X Direction	Sensors in the Y Direction [Total # of Sensors]
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 I. Sensor Array Layouts. Gray boxes indicate tested sensor configurations.

training, 20 were used for system tests, and 126 were discarded. Redundancy was the primary cause of data set rejection. The preprocessing phase of the pattern classification scheme (centering, normalizing and aggregating) led to a significant number of identical or essentially identical data files, which were excluded from the training data, to prevent the results from being skewed or biased toward any single position or body stature, and excluded from the test set, since the output of using data identical to the training data would automatically result in the "correct" output by definition and hence artificially boost the results [11]. While it may be advantageous in the second phase of the research to weigh training data based upon statistical probability of positions, such an analysis was beyond the scope of this exploratory phase.

A limited number of data sets were not included in training or analysis sets due to patient location. When part of the patient was off the mattress, the corresponding data was not used for training. Under these conditions, this data does not resolve to a known body position, but the paucity of activated sensors indicates the patient is over the edge of the sensor array and will be useful for presenting a fall-prevention alarm. For the purposes of this study, however, the actual sensor values acquired in such trials will not be meaningful.

In order to determine the actual data frame that was used, certain criteria were applied. For each position many data sets, each representing a single scan of the sensor array, were captured since the subject was instructed to hold the position for about 5 seconds. Within the appropriate section of data, a section with at least one second of stable data was found from which simply the middle data frame was extracted and incorporated into either the data training set or data testing set.

#### C. Result Statistics

Due to the stochastic nature of training neural networks and initializing cluster centers, each system was tested on identical data sets three times in an effort to achieve consistent results. The smallest sensor array resolution that consistently attained 100% accuracy for all 10 body positions was four sensors wide by 16 sensors long.

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. All pattern classification systems in this set were developed and tested in Matlab. 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 Figures 2 and 3. The revised architectures consisted of custom software developed in C++. Using information gleaned from the first round of testing, we were able to develop a more robust pair of classification systems with less overhead and faster training times. These systems are also better equipped to detect and handle input errors such as broken sensors. 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, thus highlighting the most promising system architectures.

As shown in Figs. 2 and 3, the four-layer hidden neural-network showed distinctly better results for lower sensor resolutions. Thus, we present in Fig. 4 a side-by-side comparison of results for resistive vs. capacitive sensor grid configurations, both using a four-HL neural network.

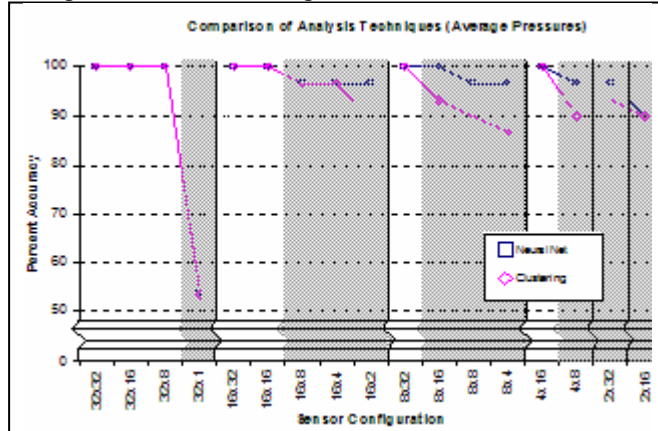


Figure 2. Accuracy comparison between clustering and neural net classifiers using capacitive (average pressure) sensor arrays.

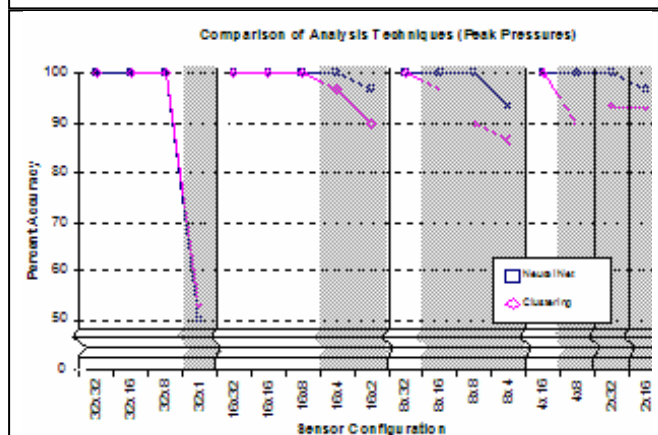


Figure 3. Accuracy comparison between clustering and neural net classifiers using resistive (peak pressure) sensor arrays.

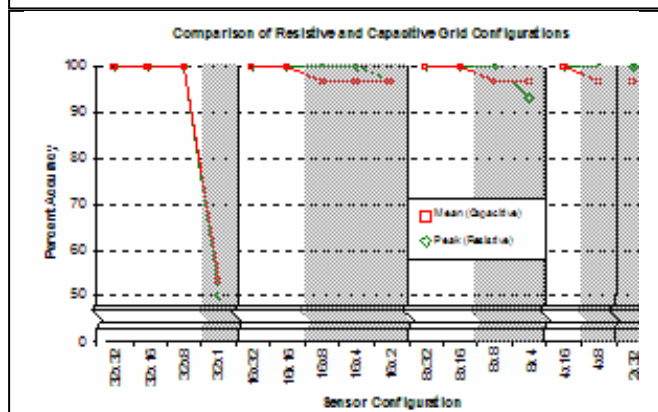


Figure 4. Accuracy comparison between capacitive and resistive sensor arrays using a 4-HL neural network classifier.

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 will be an array of 64 sensors in a four by 16 grid.

#### IV. 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. Moreover, we have shown that a relatively low sensor grid resolution using inexpensive, existing sensor technology can be used for such a system. Future work shall include building and testing such a sensor prototype and performing further tests with a significantly larger sample size. Challenges to address with further experiments include enabling system functionality with a wider range of physical attributes including anomalies such as missing limbs. Finally, further investigation should be performed into incorporating a dynamically re-trainable system for further adaptability to individual patients' needs.

#### REFERENCES

- [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] Meehan, M., L. O'Hara, and Y.M. Morrison, *Report on the Prevalence of Skin Ulcers in a Home Health Agency Population*. *Advances in Wound Care*, 1999. **12**(9): p. 459-467.
- [4] Maklebust, J. and M. Sieggreen, *Pressure Ulcers Guidelines for Prevention and Nursing Management*, ed. S.M. Glover. 1991, West Dundee, IL: S-N Publications.
- [5] Rees, R.S. and J.A. Hirshberg, *Wound Care Centers: Costs, Care, and Strategies*. *Advances in Wound Care*, 1999. **12**(2): p. 4-7.
- [6] Kosiak, M., *Etiology and Pathology of Ischemic Ulcers*. *Archives of Physical Medicine and Rehabilitation*, 1959. **40**(2): p. 62-9.
- [7] Reswick, J.B. and J. Rogers, *Experience at Ranchos Los Amigos Hospital with Devices and Techniques to Prevent Pressure Sores*, in *Bedsore Biomechanics*, R.M. Kenedi, J.M. Cowden, and J.T. Scales, Editors. 1976, Macmillan Press: London. p. 301-10.
- [8] Oksenberg, A. et al., *Positional vs Nonpositional Obstructive Sleep Apnea Patients*. *CHEST*. 1997. **112**(3): 629-39.
- [9] National Center on Sleep Disorders Research; National Heart, Lung, and Blood Institute; National Institutes of Health. *Restless Legs Syndrome: Detection and Management in Primary Care*. NIH Publication No. 00-3788. March 2000.
- [10] Rumelhart, David E. et al., *Learning Representations by Back-Propagating Errors*. *Nature*, 323(9): 533-536, Oct 1986.
- [11] Hartigan, J.A. *Clustering Algorithms*. John Wiley and Sons, 1975.