34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

A Robust Wheelchair Pressure Relief Monitoring System

Rui Dai, Sharon Eve Sonenblum, and Stephen Sprigle

Abstract— **It is essential to prevent pressure ulcers for people with spinal cord injuries (SCI). Pressure ulcer is likely to develop when there is excessive pressure on the body tissue for lengthy durations. Therefore, persons with SCI, who usually spend long time sitting in wheelchairs, are advised to perform regular pressure reliefs in their daily lives. This paper proposes a system for the monitoring of wheelchair users' pressure relief behaviors. The system utilizes piezo resistive sensors beneath a wheelchair cushion to monitor pressure, and employs supervised learning techniques to classify a wheelchair user's pressure relief status. Key features of the system include robustness and not interfering with cushion performance or the daily activities of wheelchair users. The system works well on different types of cushions, and achieves 91% sensitivity and 89% specificity based on tests on different wheelchair users.**

I. Introduction

Pressure ulcers (PU) are a major problem for people with spinal cord injuries (SCI). Statistics show that more than 50% of people with SCI experience pressure ulcers during their lifetimes [1, 2]. To reduce the cost of medical treatment and improve the quality of life for people with SCI, prevention of PU is of critical importance.

PUs are likely to develop when there is excessive pressure on the body tissue for lengthy durations. Persons with SCI, who sit in wheelchairs for many hours per day, are at high risk of developing PUs in their buttock areas. There are two primary strategies to prevent pressure ulcers for wheelchair users. One way is to design and select pressure-relieving cushions that can distribute the body weight evenly and over a large area [3]. Another is to require wheelchair users to perform pressure reliefs (PR) regularly. For example, one can push up from the chair, or lean forward or sideways to unload the buttock tissue. The frequency and duration of PR behaviors are contributing factors for the effectiveness of PU prevention.

It would be helpful to monitor the PR behaviors of wheelchair users during their daily activities. By analyzing the monitored behaviors in people with and without a history of recurrent PUs, we will determine if there is a relationship between PR behavior and PU development. Furthermore, real-time monitoring results can be used to remind wheelchair users when PR is necessary.

* This work was completed as part of the Mobility RERC, which is funded by the National Institute on Disability and Rehabilitation Research of the U.S. Department of Education under grant number H133E080003. The opinions contained in this paper are those of the grantee and do not necessarily reflect those of the U.S. Department of Education.

The authors are with the Rehabilitation Engineering and Applied Research Laboratory (REAR Lab), Georgia Institute of Technology, 490 10th St., NW, Atlanta, GA 30318, USA. (E-mails: rui.dai@gatech.edu, sharon.sonenblum@coa.gatech.edu, stephen.sprigle@coa.gatech.edu).

For pressure ulcer prevention, several wheelchair pressure monitoring systems have been designed based on commercially available interface pressure mats (IPMs), although none are used clinically for *long-term* remote monitoring. Bain *et al*. configured the Force Sensing Array (FSA, Vista Medical) IPM to achieve remote monitoring of sitting behavior of people of SCI [4]. However, the system is constrained by limited power supply and memory. Two studies created alert systems using the CONFORMat IPM (Tekscan Inc) [5, 6]. Both systems are designed to give alarm to users when the measured pressure exceeds a predefined cut-off threshold. Interface pressure sensing has also been used for sitting posture recognition in other applications such as home automation and human-computer interaction [7, 8]. These studies employed supervised learning techniques to recognize sitting postures.

Using commercial IPM systems placed on top of the wheelchair cushion for long-term monitoring, as in the studies previously described, has several practical limitations. IPMs are typically a little bit larger than the wheelchair cushion and have between 256 and 1024 individual sensors. The fine-grained IPMs can provide rich information, but the presence of an IPM on top of a wheelchair cushion impacts the performance of the wheelchair cushion [9]. The IPM may increase interface pressures and make the surface of the cushion slippery, resulting in sliding and a poor seated posture. Transfers and movement within the wheelchair can cause the IPM to shift and bunch up within the chair, affecting the accuracy of the data. Moreover, the amount of data for IPMs to be stored and processed is large, so the amount of power, processing and memory needed are not negligible.

The objective of this study was to develop a robust pressure relief monitoring system that enables long-term monitoring of wheelchair users' PR activities. Because of the above limitations of IPMs for long-term monitoring, we chose to place alternative sensors beneath the wheelchair cushion to perform the monitoring function. Our custom sensors were based on the piezo resistive technology of the FSA mat, with features suitable to real-world use. We employed a supervised learning technique to detect a user's PR status by processing the measurements from the custom sensors. In the training phase, 8 coarse-grained sensors are fixed beneath a wheelchair cushion. The fine-grained FSA IPM is placed on top of the cushion to measure interface pressure for data labeling. We let a user perform a series of activities on the chair, including normal upright sitting and various PR postures, and train a classifier based on the extracted features from the 8 sensors. Afterwards, we can monitor PR status using only the measurements of the 8 sensors. The system was evaluated by testing on different types of cushions and subjects.

978-1-4577-1787-1/12/$26.00 ©2012 IEEE

II. PRESSURE RELIEF MONITORING (PRM) SYSTEM

A. Equipment

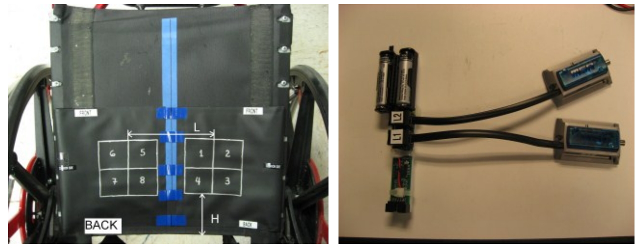
Pressure relief behavior is measured with 8 custom sensors placed beneath the wheelchair cushion. The sensors, made by Vista Medical, use the same piezo resistive technology as their FSA mats. The sensors were packaged in two mats, each containing 4 individual 2”x2” sensors and sealed within a robust polyethylene cover (Fig. 1(a)). By placing the sensors beneath the wheelchair cushion, they do not interfere with cushion performance.

For a long-term wheelchair user, the tissue near the person’s ischial tuberosities (IT) experiences the greatest loads during sitting, and therefore is at high risk of developing pressure ulcers. Therefore, we aimed to relate the pressures beneath the wheelchair cushion to the pressure around a person’s IT. Based on empirical studies on subjects with different body sizes, we have determined the best location to place the sensors. As shown in Fig. 1(a), the centers of sensing areas of the two mats are placed 15 cm apart (L=15cm), and the posterior sensing area is 7 cm to the back of the seat/cushion (H=7cm). This location is approximately beneath the pelvis, although differences in cushion design and wheelchair size might necessitate different positioning. The sensors were connected to an interfacing circuit board which measures the voltage passing through the sensors, and two data loggers (MSR Electronic GmbH) that store the sensed data (Fig. 1(b)). The voltage stored on the data logger is related to the conductance value of the circuit, which is proportional to the pressure on a sensor. The whole system can work at a sampling rate of 1Hz on two AA batteries for several weeks.

The two sensor mats can be placed either inside the cushion cover or on the seat pan of the wheelchair, while the interfacing circuit board, data loggers, and battery pack can be secured in the cushion cover or under the seat pan. This design enables long-term monitoring, and it does not introduce any interference on the wheelchair user’s activities or the pressure relieving function of the cushion. In the rest of the paper, the whole system is referred to as PRM.

B. Training Protocol

The goal of this project was to detect pressure reliefs from the measurements of the sensors beneath a wheelchair cushion. By definition, pressure relief is achieved when the pressure on the interface between the buttock area and the cushion is reduced to a certain extent. However, how the interface pressure is transmitted to the bottom of the cushion varies based on the specific materials and construction of the cushion, so determining pressure reliefs from the sensors beneath the cushion is not obvious. We propose a supervised learning technique to address this problem. For wheelchair users, the size, weight, and capability to perform pressure reliefs can be very diverse, and the materials of wheelchair cushions vary widely. Therefore, we propose to build an individualized classifier for each wheelchair user with a specific cushion.



(a) (b)

Figure 1. (a) PRM sensors (b) Interface circuit & data loggers

Before monitoring a subject for a long time, we introduce a short training phase, in which both the FSA IPM and the PRM are used. The FSA IPM is placed on top of the cushion to measure interface pressure, from which we can determine if a person is doing pressure relief (i.e., the truth data to label the corresponding PRM data). A classifier is then trained based on the labeled PRM data, and then the FSA IPM can be removed. Based on the classifier, pressure reliefs could be inferred from only the readings of the PRM sensors.

The training protocol is designed to capture different postures in a short period of time. With both the FSA IPM placed on top of the cushion and the PRM underneath the cushion, the subject performs a set of activities according to the protocol, which includes upright sitting (no pressure relief) and different pressure relief postures. The pressure relief postures include: front lean, side leans to both sides, and depression lifts. The postures are performed in a sequence like: Upright→full lean→medium lean→ small lean→upright→depression lift, with each position held for 20 seconds. The sequence is repeated for three times, once for each lean described. It takes around 10 minutes for a subject to finish this protocol.

III. DATA PROCESSING

A. Interface Pressure Measurement

Interface pressure, measured by the FSA pressure mat, is used to label the training data as pressure relief or upright sitting. We calculated the peak pressure index (PPI) in a FSA frame to determine if there is pressure relief or not. PPI is defined as the highest recorded pressure values within a 9-10 cm^2 area (approximately the contact area of an ischial tuberosity) under the ischial tuberosity [10]. The left and right IT regions were identified with manual palpation.

In this way, for each FSA frame, we can estimate the PPI on the left and right sides. To differentiate the PPI values for pressure relief and upright sitting, we studied the distribution of PPI under different postures. First, for each upright sitting (no pressure relief) segment in the training sequence, we find the average value of PPI for this segment, denoted by $PPI_{upright\_avg}$. This is used as a baseline value. Given the variance in PPI values across subjects, we calculate a normalized PPI in all frames by $PPI_{norm}=PPI/PPI_{upright\_avg}$. According to the distribution of normalized PPI for 6 subjects, 95% of the PPI_{norm} values for upright sitting are larger than 0.85, while 98% of the PPI_{norm} values for the subjects’ intended pressure reliefs are smaller than 0.85.

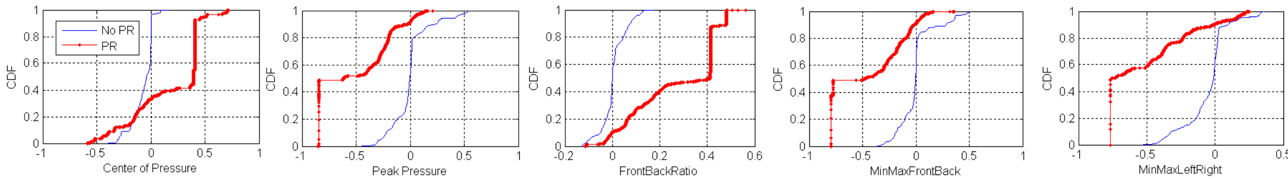


Figure 2. Feature distribution

Therefore, we set 0.85 as a cut-off threshold (T=0.85), and define that pressure relief happens when one side of the normalized PPI is smaller than the cut-off threshold, i.e., when $PPI_{norm\_left}<T$ or $PPI_{norm\_right}<T$.

B. *Pressure Relief Behavior Classification*

The labeled PRM training data is used to build a classifier. When a person sits on a wheelchair and changes his/her posture, the sensed pressure will show a sharp increase or decrease and later becomes stationary. We introduce a preprocessing step to divide a time series into stationary segments and non-stationary segments. Non-stationary segments can result from posture change or noise. In this paper, we focused on detecting the steady postures (doing pressure relief or not) as well as the duration of each posture. To guarantee the stability of classification results, only data in the stationary segments are considered for both training and testing of the classifier. We apply a moving window of 5 seconds on the signal from the PRM sensors. The signal inside a window is labeled as stationary if for each of the 8 sensors' measurements the standard deviation is within 10% of the average value.

Based on the statistics of stationary segments, we have extracted 5 features to detect pressure relief behaviors.

1) Center of pressure. It can be calculated from the pressure and location of each sensor.

2) Peak pressure: This is the largest pressure of the 8 sensors.

3) FrontBackRatio: Ratio of the sum of pressure in the front to that in the back.

4) MinMaxFrontBack: Calculate the maximum pressures of sensors placed in the back of the seat (sensors 3, 4, 7, 8 in Fig. 1(b)) and those placed in the front (sensors 1, 2, 5, 6), and find the minimum of the two.

5) MinMaxLeftRight: Calculate the maximum pressures of sensors placed in the left side (sensors 5, 6, 7, 8) and those placed in the right side (sensors 1, 2, 3, 4), and find the minimum of the two.

The features are all normalized with respect to baseline values corresponding to upright sitting. The baseline values for each feature are obtained with a moving window searching for segments of 3 minutes of stationary data while the subject was seated in the chair. This was based on the belief that a manual pressure relief is unlikely to last for more than 3 minutes. Thus, the features at every frame were normalized by the moving baseline value.

The first feature reflects the extent of change in posture, and the second feature captures if peak pressure is reduced or not. Features MinMaxFrontBack and FrontBackRatio are sensitive to pressure relief resulted from front leans, while MinMaxLeftRight is designed to capture pressure reliefs resulted from leaning sideways. The cumulative distribution functions of the normalized features are shown in Fig. 2. The distributions of each feature for pressure relief and no pressure relief are different. Based on these features, the k-nearest neighbor (knn) classifier (where k=1) is then used to determine the pressure relief status. All the data processing algorithms were implemented using Matlab, version 7.13.

IV. Performance Evaluation

We evaluated the performance of the classification algorithm in two tests. First, we tested the system in a laboratory setting on different types of wheelchair cushions, since they can transmit interface pressure differently to the underneath sensors. Four types of widely used cushions with diverse materials were selected (Table I). Each cushion was tested for around 1 hour. The same, able-bodied individual performed each test on a wheelchair. In the beginning, the subject performed the 10 minutes training protocol described in Section II. For the following 40 minutes, the subject sat freely on the wheelchair. In the end, the subject repeated the training protocol. The FSA IPM and PRM were in place in the entire test to provide truth data. We used the data in the first 10 minutes to train a classifier, and then tested it on the remaining 50 minutes. Table II presents the resulting sensitivity and specificity. It can be seen that the classification algorithm works well for cushions with different materials.

Our second test evaluated the classification algorithm on 3 different subjects who use wheelchairs as their primary mobility device. This protocol was approved by the local Institutional Review Boards and informed consent was received from all participants prior to the study. The three participants have SCIs. Their ages are 25, 24, and 54, and their weights are 160, 180, and 120 lbs. The subjects used their own cushions for the test, and the types of cushions include Roho, Jay, and Matrx. Each subject performed the training protocol in the beginning of the test, and repeated the protocol at a later time (two immediately following the training protocol, and one after one week of data collection). We tested the second data set using the classifier trained from the first data set. Results for this test are listed in Table III. For the three subjects, the average sensitivity is 91% and the average specificity is 89%.

Test result for one of the subjects is also visualized in Fig. 3. The data corresponds to the second training protocol. The normalized PPI values on both left and right sides (truth data) were used to identify the pressure reliefs. Predicted classes are also plotted, where 1 corresponds to PR and 0

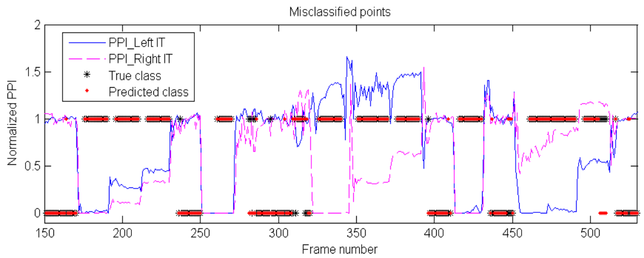


Figure 3. Test result on a subject

corresponds to no PR. Currently we focus on detecting pressure reliefs on stationary data, so data points during posture changes are not classified, which explains the small gaps in the predicted sequence. Despite a few misclassified points, the algorithm has successfully detected all the pressure reliefs in this sequence.

TABLE I. CUSION TYPES

Cushion name	Cushion construction
HR 45 Foam	Foam
Matrx	Memory foam
Jay 2 Deep Contour	Viscous fluid and polyurethane foam encased in vinyl atop nondeforming foam base
Roho Hi Profile	Single valve adjustable air cushion

TABLE II. INTER-CUSION TEST RESULTS

Accuracy (%)	Cushion Type			
	Foam	Matrx	Jay	Roho
Sensitivity	85.3	94.3	93.3	86.7
Specificity	97.9	82.1	92.1	89.9

TABLE III. INTER-SUBJECT TEST RESULTS

Accuracy (%)	Subject No.		
	1	2	3
Sensitivity	83.0	92.2	98.0
Specificity	95.3	85.7	84.9

We have summarized sources of errors after visualizing the results of all the above data sets. Misclassification usually occurs at small pressure reliefs and points where the normalized PPI values are near the cut-off threshold. Some errors are caused by the fact that placing sensors beneath the cushion is not as sensitive as the IPM. Sometimes, the PRM sensors need a few more seconds to respond to pressure change. In addition, the accuracy of the sensors' measurements is crucial to the performance of the detection algorithm. The FSA IPM mat for data labeling was calibrated to 0-240mmHg prior to each test. The PRM sensors' measurements were characterized by applying known pressure to them, and approximate linear relationship was found between the actual pressure and the sensors' measurements within the range of interest.

So far, the proposed classification algorithm achieves high accuracy in detecting PRs on stationary data. 75%-90% of the data in a sequence have been identified as stationary points. In the near future we will study the non-stationary data points which are related to posture changes, so that we can extract more activity information of the subjects. We will also try to detect the different magnitudes of PRs, and further classify PRs into full PRs and partial PRs.

V. CONCLUSION AND FUTURE WORK

In this paper we have proposed a robust pressure relief monitoring system for pressure ulcer prevention. The key design of our system is the use of 8 sensors placed beneath a wheelchair cushion that relates to sitting areas that are likely to develop pressure ulcers. Such design enables long-term and robust monitoring of a wheelchair user's pressure relief behavior without interfering the wheelchair cushion performance or the user's daily activity. We utilize a supervised learning technique to classify the pressure relief behaviors. Experimental results show that the system achieves good accuracy. In the future we will deploy the pressure relief monitoring system on various wheelchair user groups and monitor each user for two weeks. We will compare the pressure relief behaviors of persons with a history of recurrent pressure ulcers and those without, through which we will determine the relationship between pressure relief and pressure ulcer development.

ACKNOWLEDGMENT

The authors would like to thank Ricardo Lopez for hardware support, Ray Lin for data collection, and Chris Maurer and David Kreutz at Shepherd Center for collecting data on SCI subjects.

REFERENCES

[1] J. S. Krause and L. Broderick, "Patterns of recurrent pressure ulcers after spinal cord injury: identification of risk and protective factors 5 or more years after onset," *Archives of Physical Medicine and Rehabilitation* vol. 85, pp. 1257-1264, 2004.

[2] P. Raghavan, *et al.*, "Prevalence of pressure sores in a community sample of spinal injury patients," *Clinical Rehabilitation,* vol. 17, pp. 879-884, 2003.

[3] A. Gil-Agudo, *et al.*, "Comparative study of pressure distribution at the user-cushion interface with different cushions in a population with spinal cord injury," *Clinical Biomechanic,* vol. 24, Aug. 2009.

[4] D. S. Bain and M. Ferguson-Pell, "Remote monitoring of sitting behavior of people with spinal cord injury," *Journal of Rehabilitation Researcy & Development,* vol. 39, pp. 513-520, July/August 2002 2002.

[5] M. Eneling, *et al.*, "A pressure-controlled alarm and monitoring device for pressure ulcer prophylaxis in patients with traumatic spinal cord injury," presented at the World Congress on Medical Physics and Biomedical Engineering, Munich, Germany, 2009.

[6] B. S. Kozniewski and J. L. Cezeaux, "Wheelchair pressure monitoring alert system for the reduction of the occurrence of pressure sores," presented at the 2011 IEEE 37th Annual Northeast Bioengineering Conference (NEBEC) Troy, NY, USA, 2011.

[7] K. Kamiya, *et al.*, "Sitting posture analysis by pressure sensors," presented at the 19th International Conference on Pattern Recognition (ICPR) Tampa, FL, USA, 2008.

[8] H. Z. Tan, *et al.*, "A sensing chair using pressure distribution sensors," *IEEE/ASME Transactions on Mechatronics,* vol. 6, pp. 261-268, Sept. 2001 2001.

[9] L. Pipkin and S. Sprigle, "Effect of model design, cushion construction, and interface pressure mats on interface pressure and immersion," *J Rehabil Res Dev,* vol. 45, pp. 875-82, 2008.

[10] S. Sprigle, *et al.*, "Reliability of bench tests of interface pressure," *Assist Technol,* vol. 15, pp. 49-57, Summer 2003.