Automated Patient Handling Activity Recognition for At-Risk Caregivers Using an Unobtrusive Wearable Sensor

Feng Lin[1], Xiaowei Xu[1], Aosen Wang[1], Lora Cavuoto[2], and Wenyao Xu[1]

***Abstract*— Patient handling activities with awkward postures expose healthcare providers to a high risk of overexertion injury. The recognition of patient handling activities (PHA) is the first step to reduce injury risk for caregivers. In this paper, we propose a system to solve the problem, which comprises an unobtrusive wearable device and a novel spatio-temporal warping (STW) pattern recognition framework. The wearable device, named Smart Insole 2.0, is equipped with a rich set of sensors and can capture the information of patient handling activities. The STW pattern recognition framework fully exploits the spatial and temporal characteristics of plantar pressure, to quantify the similarity for the purpose of activity recognition. we perform a pilot study with eight subjects, including eight common activities in a nursing room. The experimental results show the overall classification accuracy achieves 91.7%. Meanwhile, the qualitative profile and load level can also be classified with accuracies of 98.3% and 92.5%, respectively.**

I. INTRODUCTION

Nurses and nursing assistants are among the top five occupations with the highest injury rates and U.S. hospitals report 6.8 work-related injuries per 100 full-time employees, higher than construction and manufacturing workers [1]. These rates likely under-represent the true injury incidence as 24% of nurses and nursing assistants have reported using sick leave to recover from their work [2] and 8 of 10 nurses report frequent pain during work [3].

The recognition of workplace conditions, particularly physical exposures experienced by the worker, is the first step to reduce injury risk of healthcare providers. Traditional approaches to exposure assessment often rely on visual inspection performed by an observer. Because of limitations of an individual observer, sampling methods are applied such that only a few workers are typically observed and only for a relatively short duration [4]. Wearable sensors, such as inertial measurement units (IMUs), have been investigated for overcoming the limitations of observational approaches. Most of the current workplace sensor applications have focused on posture analysis, task classification, basic physiological monitoring, or a computerized application of traditional observational tools. In nursing, wearable sensors have been used to recognize activities important for staffing decisions and documentation of nursing workload, tracking hygiene, and monitoring patient care activities such as blood draws and medication distribution. However, to monitor complex patient handling activities, multiple IMU sensors on different body locations are often needed [5], which is inconvenient for long-term use and may even disrupt the normal work flow in the nursing room. Furthermore, from the patient's perspective, it is critical to consider privacy, and ordinary sensing tools, such as a camera, cannot be adopted in this application scenario.

In this paper, we propose a solution for automated patient handling activity (PHA) recognition. The solution comprises a Smart Insole 2.0 and a spatio-temporal warping (STW) pattern recognition framework. Smart Insole 2.0 utilizes an advanced electronic textile (eTextile) fabric sensor technique providing accurate plantar pressure measurement in both ambulatory and static status. Furthermore, it is cost-effective and unobtrusive in use. The STW pattern recognition framework is proposed to quantify the similarity among different PHAs by exploiting the plantar pressure attributes in spatial and temporal domains. We perform a pilot study with *eight* subjects to examine *eight* common activities in nursing room. The experimental results show our method succeeds in qualitative profile recognition, PHA recognition, and load estimation with the overall classification accuracy of 98.3%, 91.7% and 92.5%, respectively.

II. RELATED WORK AND SYSTEM OVERVIEW

To date, there are several commercial-off-the-shelf (COTS) in-shoe devices available in the market. Pedar in-shoe system [6] embeds single or multiple piezoelectric sensors into the shoe for real-time monitoring. F-Scan from Tekscan [7] is also able to provide plantar pressure assessment. In academic society, "GaitShoe" [8] and "Hermes" [9] are developed to measure foot pressure as well.

Our proposed system for PHA recognition consists of two modules including Smart Insole 2.0 and the STW framework. The diagram of this system design is shown in Fig. 1. In this design, Smart Insole 2.0 is developed acting as a sensor to collect plantar pressure during various PHAs unobtrusively. The STW framework contains an STW signal processing part and an STW-based kNN classifier, which together contribute to the similarity measurement for disparate PHAs classification. The computing of the STW framework is implemented in the smartphone.

III. UNOBTRUSIVE WEARABLE SENSOR: SMART INSOLE 2.0

In this section, we will introduce a novel wearable sensor for activity monitoring: Smart Insole 2.0. This smart device

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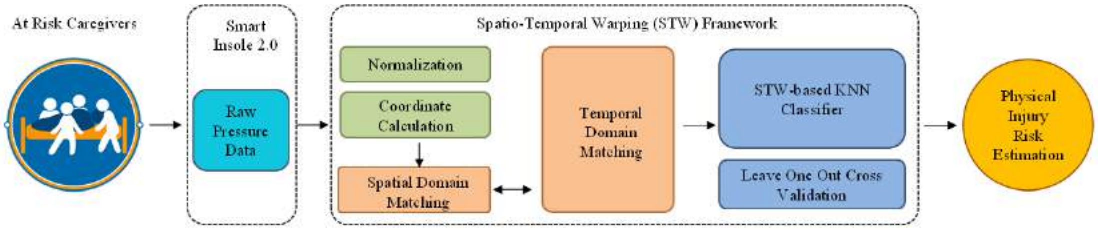


Fig. 1. The diagram of overall system design including Smart Insole 2.0 and the spatio-temporal warping pattern recognition framework. Caregivers activities and injury risk estimation are the input and output of the system.

is upgraded from an early version of Smart Insole [10]. In Smart Insole 2.0, the functionality and usability have been enhanced by the design of longer battery life [11] and smaller form factor.

A. Hardware

The printed circuit board (PCB) design of Smart Insole 2.0 control system is shown in Fig. 2(a), in which each component is covered by a rectangle with different colors. The integrated modules are (1) the MCU and BLE module, (2) the 9-axis inertial motion sensor, (3) the micro-USB connector, (4) the battery module, and (5) the 48 to 1 channel MUX.

1) Textile Pressure Array: The textile pressure sensor array is used to obtain the high-solution pressure map under feet. It is based on advanced conductive textile fabric sensor technique [12] and can be efficiently integrated in Smart Insole 2.0 system.

2) Inertial Motion Sensor: The accelerometer and gyroscope are inertial sensors which measure the movement information of the subject. The magnetometer is used as the baseline when the inertial sensors (accelerometer and gyroscope) are being calibrated.

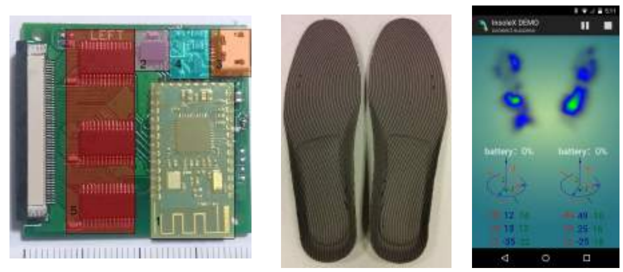
3) Micro Control Unit and Bluetooth: The MCU and Bluetooth are implemented by a single device CC2541 from Texas Instruments. The CC2541 combines a radio frequency (RF) transceiver with an enhanced 8051 MCU. The sampling rate can be adaptive for specific applications, up to 100 samples per second (Hz).

4) Battery and Micro-USB Connector: The battery is the power supply of the system. The micro-USB connector is used for charging battery, programming CC2541, and online debugging.

5) Package and Ergonomic Design: Smart Insole 2.0 is lightweight (<2 oz.), thin, and convenient to use. It does not need calibration and only requires minimal setup procedures. The package of Smart Insole 2.0 is shown in Fig. 2(b). Smart Insole 2.0 is similar to a normal insole without any extra cable, antenna, or adhesive equipment.

B. Software and Visualization

A GUI application (App) on smartphone has been developed to record, visualize, and analyze the data from Smart Insole 2.0. The data are transmitted to the smartphone from Smart Insole 2.0 via Bluetooth, and stored in the memory of the smartphone. The visualization of plantar pressure from the GUI App is shown in Fig. 2(c).



(a) The PCB design. (b) The prototype. (c) The GUI App.

Fig. 2. The control system, prototype and GUI App of Smart Insole 2.0.

IV. SPATIO-TEMPORAL WARPING FRAMEWORK

Different body postures of patient handling have distinct foot pressure distributions, as shown in Fig. 3. In the temporal domain, the plantar pressure can be modeled as a bunch of time series along the period of patient handling. In the spatial domain, the plantar pressure is distributed in different locations including toe, metatarsal, and heel area. Based on the spatio-temporal characteristic of plantar pressure, we propose the STW for similarity measurement.

A. Spatio-Temporal Warping Distance

In spatial domain, suppose there are N_{pr} training samples, each with a value of pressure p_j^m. And N_{pr} testing samples, each with a value of pressure $\widetilde{p_k^n}$. The $cost = [c_{jk}]$ of matching normalized pressure is defined as the Euclidean distance between each training-testing pair. Our task is to find a flow, $F = [f_{jk}]$, that matches the normalized pressure from the testing samples to the training samples with the least cost:

$$\min \sum_{j=1}^{N_{pr}} \sum_{k=1}^{N_{pr}} c_{jk} f_{jk}, \tag{1}$$

subject to

$$\sum_{j=1}^{N_{pr}} p_j^m = \sum_{k=1}^{N_{pr}} \widetilde{p_k^n}, f_{jk} \geq 0, 1 \leq j \leq N_{pr}, 1 \leq k \leq N_{pr}, \tag{2}$$

$$\sum_{k=1}^{N_{pr}} f_{jk} \leq p_j^m, 1 \leq j \leq N_{pr}, \sum_{j=1}^{N_{pr}} f_{jk} \leq \widetilde{p_k^n}, 1 \leq k \leq N_{pr}. \tag{3}$$

Then, the spatial distance is obtained as:

$$\mathrm{D} = \frac{\sum_{j=1}^{N_{pr}} \sum_{k=1}^{N_{pr}} c_{jk} f_{jk}}{\sum_{j=1}^{N_{pr}} \sum_{k=1}^{N_{pr}} f_{jk}}. \tag{4}$$

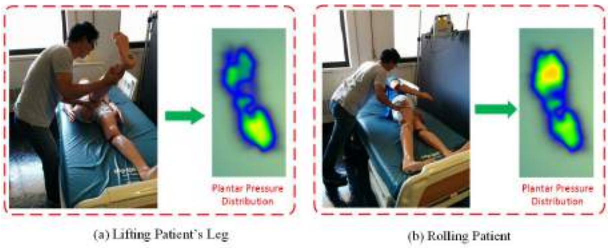


Fig. 3. Two patient handling activities and corresponding peak plantar pressure distributions.

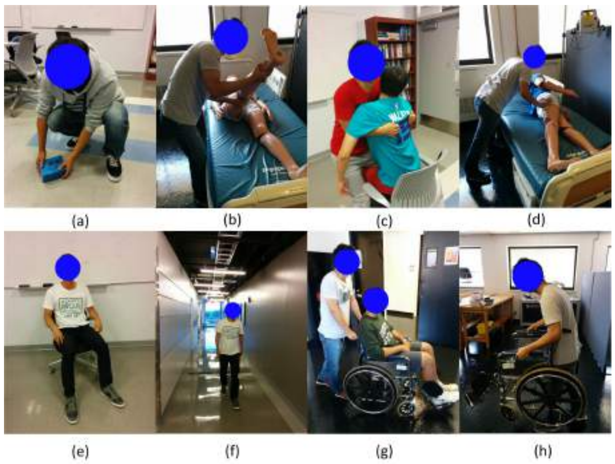


Fig. 4. *Eight* different PHAs performed in experiments including: (a) Bend to lift an item from floor level; (b) Stand while lifting patients leg; Stand while rolling patient; (c) Stand while lifting patient from wheelchair; (d) Stand while rolling patient; (e) Sit normally; (f) Walk normally; (g) Walk while pushing wheelchair forward; h) Walk with both hands carrying a chair.

In temporal domain, we align the time series data, which are similar but locally out of phase, in a non-linear manner by warping the time axis iteratively until an optimal match between the two sequences is found, formulated as:

$$cd(n,m) = \mathrm{D}\,(n,m) + \min \begin{cases} cd(n,m-1) \\ cd(n-1,m) \\ cd(n-1,m-1) \end{cases}, \quad 1 \le n \le N, 1 \le m \le M. \tag{5}$$

where $cd(n,m)$ is the current minimum cumulative distance for $\mathrm{D}(n,m)$ descripted in Eq. (4), and the initial setting is $cd(0,0) = 0, cd(0,m) = cd(n,0) = \infty$. After that, the STW distance can be found as:

$$T = \sqrt{cd\,(N,M)}. \tag{6}$$

Note that k nearest neighbors embedding with the STW distance T forms the PHA classifier.

V. Evaluation

A. Experimental Setup

We ran a series of experiments to evaluate the performance of our proposed STW framework for PHA recognition. The dataset is collected by Smart Insole 2.0 from *eight* subjects including seven male and one female. The weights of all participants are from $58 - 85$ kg and heights from $160 - 185$ cm. Each subject performed *eight* different PHAs, as described in Fig. 4.

TABLE II
Confusion Table of Recognition on Categorized Activities

	Stand (a, b, c, d)	Sit (e)	Walk (f, g, h)	Total	Recall
Stand (a, b, c, d)	319	0	1	320	99.7%
Sit (e)	0	80	0	80	100%
Walk (f, g, h)	10	0	230	240	95.8%
Total	329	80	231		
Precision	97.0%	100%	99.6%		

TABLE III
Confusion Table of Recognition on Categorized Load Levels

	Heavy (c, d, h)	Light (a, b, g)	No (e, f)	Total	Recall
Heavy (c, d, h)	213	22	5	240	88.8%
Light (a, b, g)	11	223	6	240	92.9%
No (e, f)	0	4	156	160	97.5%
Total	224	249	167		
Precision	95.1%	89.6%	93.4%		

B. Quantitative Evaluation in a Controlled Study

In this quantitative evaluation, each subject is required to perform 10 trials on each activity. Therefore, the sample size equals to 640 in our case.

1) Accuracy Evaluation: The quantitative evaluation performance is measured by classification accuracy. The accuracy (ACC) is defined as:

$$ACC\ (\%) = \frac{TP + TN}{P + N} \times 100\%, \tag{7}$$

where TP represents the true positive, TN represents the true negative, P represents the positive, and N represents the negative. In injury risk estimation, qualitative profile recognition, PHA recognition, and load estimation are three key parameters [13]. PHA recognition is used for estimating injury probability for each PHA. Qualitative profile recognition and load estimation are used in estimating workload and load in performing PHA, respectively.

a) Qualitative Profile Recognition: In qualitative profile recognition, all the aforementioned *eight* PHAs are categorized into three qualitative profiles, as described in Table II, which facilitates the workload estimation. Based on the percentages of all-body activities (i.e., walk related), upper-body activities (i.e., standing related), and break (i.e., sitting) in a working period, we can infer the intensity level of the workload. Both recall and precision achieve more than 95.8% as shown in Table II. The overall accuracy is 98.3%, which shows high performance of qualitative profile recognition.

b) PHA Recognition: The goal of PHA recognition is to accurately classify each PHA defined in Fig. 4. Table I shows the confusion table with respect to PHA classification using 48 pressure sensors. The overall accuracy is 91.7%. We notice the activity *walk with both hands carrying a chair* has the lowest recall rate 81.3%, which is often confused

TABLE I
CONFUSION TABLE OF RECOGNITION ON EIGHT PHAS USING 48 PRESSURE SENSORS

	a	b	c	d	e	f	g	h	Total	Recall
a	80	0	0	0	0	0	0	0	80	100%
b	0	72	6	2	0	0	0	0	80	90%
c	7	2	70	0	0	1	0	0	80	87.5%
d	0	5	2	73	0	0	0	0	80	91.3%
e	0	0	0	0	80	0	0	0	80	100%
f	3	0	0	0	0	76	1	0	80	95%
g	0	0	3	0	0	6	71	0	80	88.8%
h	1	0	3	0	0	4	7	65	80	81.3%
Total	91	79	84	75	80	87	79	65		
Precision	87.9%	91.1%	83.3%	97.3%	100%	87.4%	89.9%	100%		

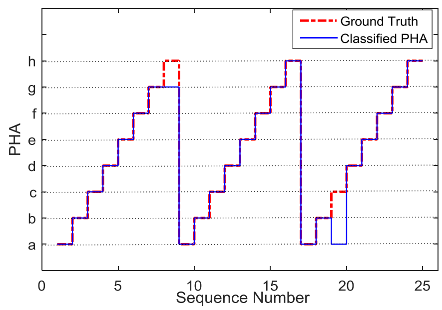


Fig. 5. A set of eight PHAs performed sequentially against ground truth.

with *walk normally* and *walk while pushing wheelchair forward*. The reason of this is that all the three activities are performed in walking status, in which the pressure obtained from them all shows similar pseudo-periodic nature. The remaining seven recall rates are above 87.5%. Specifically, *sit* reaches 100% recall and 100% precision because of the minimal fluctuation it exposed that differentiates it from other activities. In terms of precision, *stand while lifting patient from wheelchair* shows the lowest rate of 83.3% because the data from other activities show similarity to the data of *stand while lifting patient from wheelchair* leading to mis-classification.

c) Load Estimation: The load estimation is to estimate the load imposed on caregivers when they perform certain PHA. The grouping criterion depends on the specific ongoing activity. Note that we decide *bend to lift an item from floor level* as *light load* because that item the subject picked up indicates the specific weight of the object in our experiment. Likewise, the confusion table with respect to load levels is shown in Table III. The overall accuracy is 92.5%. *Heavy load* has the lowest recall of 88.8%, in which 22 activities are mis-classified as *light load*. Since these two load level both involve forceful exertion, they may be confused with each other.

C. Evaluation of a Longitudinal Pilot Study

We carried out a longitudinal study of continuous monitoring through a number of aforementioned PHAs. More specifically, each of the *eight* activities was performed sequentially to test whether the proposed framework can classify them correctly. Fig. 5 shows the evaluation result, where the red dash line indicates the ground truth, and the blue line indicates the actual classification outcome. We observed that only two out of 24 activities are mis-classified.

VI. CONCLUSION

To accurately recognize the PHA, we first developed Smart Insole 2.0 to capture the plantar pressure change information caused by the PHA. An STW framework is proposed to analyze the pressure data for classification. The experimental results showed that our framework can achieve 98.3%, 91.7%, and 92.5% recognition accuracy with qualitative profile, PHA recognition, and load estimation, respectively.

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