Chair Alarm for Patient Fall Prevention based on Gesture Recognition and Interactivity

Heather Knight, Jae-Kyu Lee, and Hongshen Ma

Abstract— **The Gesture Recognition Interactive Technology (GRiT) Chair Alarm aims to prevent patient falls from chairs and wheelchairs by recognizing the gesture of a patient attempting to stand. Patient falls are one of the greatest causes of injury in hospitals. Current chair and bed exit alarm systems are inadequate because of insufficient notification, high false-alarm rate, and long trigger delays. The GRiT chair alarm uses an array of capacitive proximity sensors and pressure sensors to create a map of the patient's sitting position, which is then processed using gesture recognition algorithms to determine when a patient is attempting to stand and to alarm the care providers. This system also uses a range of voice and light feedback to encourage the patient to remain seated and/or to make use of the system's integrated nurse-call function. This system can be seamlessly integrated into existing hospital WiFi networks to send notifications and approximate patient location through existing nurse call systems.**

I. Introduction

Patient falls are one of the leading causes of injury in hospitals among adults aged 65 or older. These falls currently cost the U.S. healthcare system an estimated 6-8 billion dollars per year [1]. In order to minimize patient fall incidents, hospital nurses are currently required to complete a fall risk assessment form for each admitted patient. This form evaluates a patient's risk of falling based on factors including history of falling, secondary diagnosis, ambulatory aid, intravenous therapy, gait analysis, and mental status [2]. The fall assessment score, commonly calculated on the Morse Fall Scale, dictates the required amount of nurse supervision [3]. Since it is impossible to have constant nurse supervision for every patient, many falls do occur in the current system. Recent changes to US medical insurance rules are providing additional incentive for hospitals to reduce the occurrence of these falls, as hospitals will no longer be reimbursed for costs associated with patient falls after the patient has been admitted. As a result, hospitals are quickly seeking more effective fall prevention strategies.

Based on discussions with clinicians at the Massachusetts General Hospital, one of the most common scenarios of falls in hospitals occurs when patients who are confined to a chair or bed, and are not strong enough to stand or walk, attempt to do so. These patients are often confused and overestimate their own mobility and can seriously injure themselves by standing in the absence of a care provider. Elderly patients are not the only ones subject to fall. Even an athletic young person disconcerted by being on an IV is at a very high risk of falling. Mechanical restraints, such as locking seat-belt devices, have been used in the past to prevent patients from standing. However, not only do these devices inhibit the basic freedom of patients, thus increasing the risk that they will try to escape, but when patient falls occur with these restraints in place, they tend result in more serious injuries [4].

Current commercial fall-prevention systems include weight-based bed alarms (*e.g.* Stryker Chaperone) and pressure-based chair alarms (*e.g.* Micro-Tech). These systems are typically binary alarms, which mean that they trigger on or off based on a parameter being above or below a threshold. In order to prevent false-triggers, many of these systems incorporate several seconds of delay before triggering the alarm, and thus further reducing the likelihood of preventing falls.

Academic research in fall detection/prevention system has predominantly focused on using patient-attached inertial sensors or computer vision-based techniques. These systems are currently not ready to be applied in hospital or nursing home settings as their reliability is thus-far inconsistent and their cost-factor is relatively high [5].

The GRiT chair alarm system is developed to prevent patient falls by adding sensor technologies to chairs and wheelchairs to recognize the cognitive state of a person. Then, based on a probabilistic model, this system assesses the likelihood of a patient attempting to stand, and alerts the nursing staff of the potential danger while providing local voice feedback to encourage the patient to remain seated. This system communicates wirelessly over existing WiFi networks that are now common in most hospitals and nursing homes. The key innovations of this system include:

- Multi-sensor hardware for measuring patient behavior
- Algorithms for converting sensor values to the patients cognitive state based on a probabilistic model
- Care provider alarms transmitted wirelessly over the existing WiFi networks
- Interactive audio and visual cues encouraging the patient to remain seated

The components of this system include the sensor system, signal processing and communications hardware, interactive user interface for both the patient and the care provider, and gestural recognition algorithms.

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II. BACKGROUND

Previous research in bed and chair occupant tracking demonstrates the utility of sensor pads in helping determine occupant behavior. For example, Harada et al used an array of force sensitive resistor (FSR) sensors to infer the patient's posture lying on the bed from the 2D pressure-image of the bed [6]. Other sensing chairs, intended for use in office environments, aim to improve user posture or to control peripheral devices. One project reported a classification accuracy rate of 96% for familiar users and 79% for new users [7]. A related implementation also explored optimal sensor placement [8]. In a different domain, Furugoi et al created a seat-based driver fatigue detection system [9]. These systems use pressure sensors exclusively, as opposed to the GRiT system, which also use capacitive sensing in the seat-back.

In the realm of furniture sensor arrays for elderly care and ubiquitous sensing, the SenseChair project at Carnegie Mellon University [10] has began to explore the relationship that the elderly often form with their favorite chair, which becomes their "activity hub." The project included vibratory and sound feedback but thus far is treated more as a research platform rather than for commercial use, and also does not discuss concepts for fall prevention. Other projects also modeled longer term human behaviors with a multiplicity of sensors. Aoki et al present framework for finding behavioral patterns by looking at sequences of sensor states [11]. Ubiquitous sensing systems also track human activity within a house using RFID tags and pressure-sensing floors [12]. Many of the sensor-fusion concepts from these projects can be applied the the GRiT chair alarm system.

III. SENSOR DESIGN AND IMPLEMENTATION

A. Sensor Pad Design

Sensors for the GRiT system include capacitance sensors located at the seat-back of the chair and pressure sensors located on the seat and the two armrests. Since the GRiT system is designed to be retrofitted onto existing chairs and wheelchairs, these sensors are incorporated into a 1/8" vinyl pad that can be draped or adhered to the seat and seat-back of any chair. The vinyl pad distributes the pressure applied to the sensors and can be sterilized using standard chemicals.

B. Capacitance Sensor

The capacitance sensors measure the distance between the seat-back and patient's back at various heights along the seat-back. The capacitance sensing hardware consists of seven horizontal conductive strips and a grounding pad installed in the seat. The patient, being a conductive object, greatly disturbs the electric field from the seat-back electrodes to the grounding pad, and thus produces a capacitance change inversely proportional to the distance between the electrode and the patient. Additionally, since capacitance sensors in this configuration have little sensitivity to nonconductive objects, personal effects such as books, pillows, and blankets will not falsely represent the patient body.

C. Pressure Sensor

Pressure sensors on the seat measure the patient's static and dynamic weight distribution. These measurements are made using a 3 x 4 array of force sensitive resistors (FSRs, Interlink), which lowers its resistance as a result of applied force. These sensors are sufficient to develop a qualitative map of patient contact position and pressure distribution. However, since the output from these sensors drift over long periods of time, these sensors they should be recalibrated regularly. Smaller FSRs are also installed in the armrests to measure the total arm pressure. These sensors are installed beneath the arm cushion to order to allow the cushion to evenly distribute the applied force.

IV. HARDWARE DESIGN

A. Microprocessor

The GRiT system is controlled using a MSP430 microprocessor (Texas Instruments). This device digitizes the voltages from the capacitance sensors and pressure sensors, and transmits this information via one of three possible communications links including WiFi, ZigBee, and USB. Multiple communications options were included to achieve maximum versatility for debugging purposes.

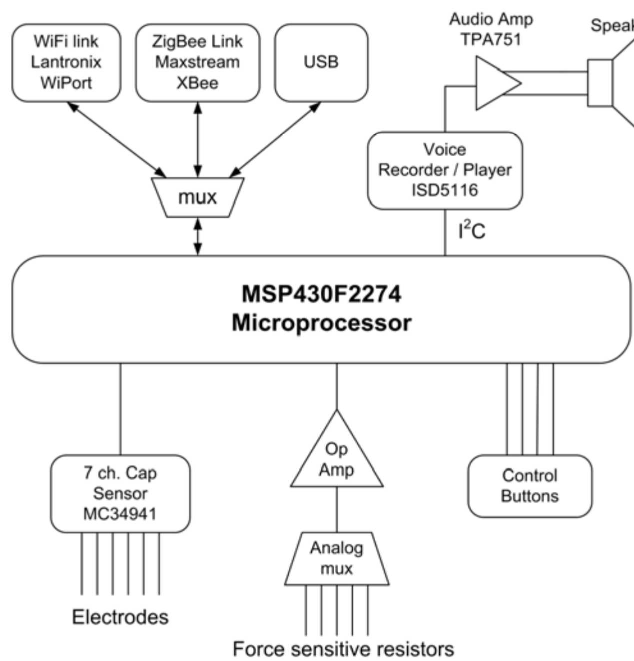

Fig. 1. System-level diagram of the GRiT system

B. Wireless Connectivity

Communications between the GRiT chair alarm and the care provider occur via standard WiFi networks that are now common in most hospitals and nursing homes. By taking advantage of existing hardware, this system does not require additional expenditures required of its own network. At the receiving end, one host PC receives messages from multiple GRiT alarms, and can eventually be configured to interface with the existing nurse call system so as to not introduce additional alarms that compete for nursing staff's attention.

C. Interactivity and User Interface

One of the GRiT chair's key fall-prevention strategies to act as a local interactive agent to remind patients when they are in danger of falling and encouraging them to remain seated. The GRiT system accomplishes this by providing patients with a voice-based feedback. The voice is digitally synthesized and loaded into an ISD5116 voice chip. The speech is programmed from the MSP430 and transmitted over I^2C.

V. Gesture Recognition

A. System Overview

As shown by the state diagram in Fig. 2, the GRiT gesture recognition algorithm deduces the likelihood that a patient will stand, and then uses a tiered response to address the problem address the problem and prevent patient falls.

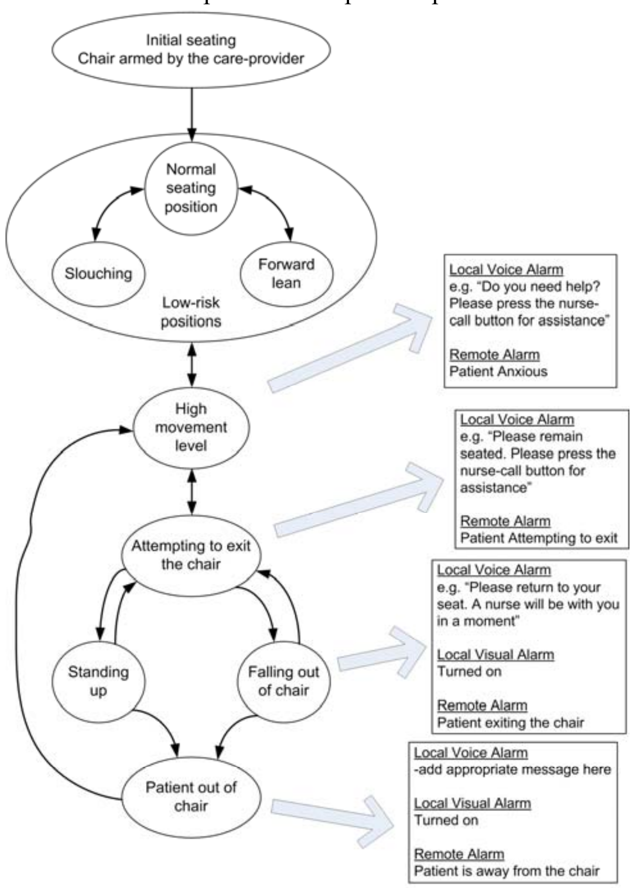

Fig. 2. Pattern recognition flowchart representing the GRiT patient behavior model and strategies for tiered response.

The gesture recognition algorithm is a three step process that involves: 1) Mapping sensor data to derive features about user state, 2) Probabilistically associating feature distribution with patient position or activity, 3) Using knowledge about flow of states to predict user behavior, specifically, the risk that the patient will soon slide off, fall out, or stand up from the chair.

B. Mapping Sensor to Features

The gesture state of the patient is evaluated from the sensor parameters via an intermediate abstraction layer of derived features. Features can combine any number of sensors and their variation as a function of time. In the GRiT model, sensors values are mapped to the following features: static back position, forward leaning angle, total bottom pressure, bottom pressure distribution (front-back or left-right), armrest pressure, total movement levels, as well as the time-derivatives of all of these features.

C. Using Features to Estimate User State

Gesture states are inferred using a probabilistic score obtained by adding values from the set of associated derived features. The base weighting can be determined empirically from usage data, and normalized and adjusted for the weight of each person. Gesture states transition when probabilistic scores for a new state rise above a preset threshold. These thresholds should also be calibrated to individual patients. As shown in Fig. 2, gesture states include sitting down, sitting, forward lean, slouching, high movement, attempting to exit, standing up, and falling out of chair.

VI. Results and Discussion

The experiments presented in this paper are aimed to evaluate the overall design effectiveness and qualitatively determine the relevance and accuracy of the gesture recognition software. One result from these experiments is the discovery that the arm data is not uniquely relevant and often offers no additional information. As shown in Fig. 3, the patient may or may not choose to use the arms as support while standing up, however the overall seat pressure will always serve as an independent indicator that the patient is getting out of the chair. If more pressure is applied to the armrests, then there is less on the seat. The information from the armrests is therefore redundant. However, armrest pressure can be an indication of other behaviors such as leaning one's chin or repositioning oneself in the chair.

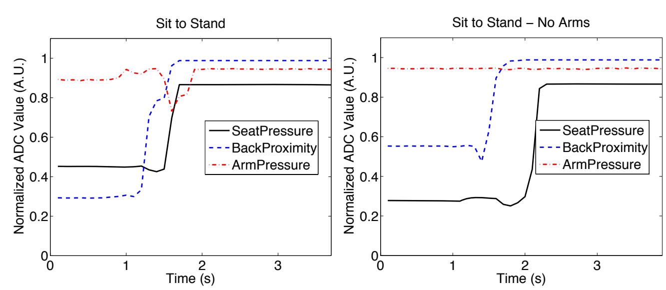

Fig. 3. Feature activation levels when patient stand with and without using wheelchair arms, including total seat pressure, average proximity to back of the chair, and total arm pressure plotted versus time.

The amplitude of sensor variation can be used to detect when a wheelchair is stationary and when it is in motion. As shown in Fig. 4, when the patient is moving forward and then backwards in the wheelchair, the amplitude of the electric field sensors is approximately 4% of full scale. However, the seat pressure can vary by as much as 35% of full scale. This measurement demonstrates why false triggering is such a huge problem in the traditional binary weight based alarms. However, the also graphs show that the combination of seat and back proximity data allows that the system can be used to infer actual patient behavior.

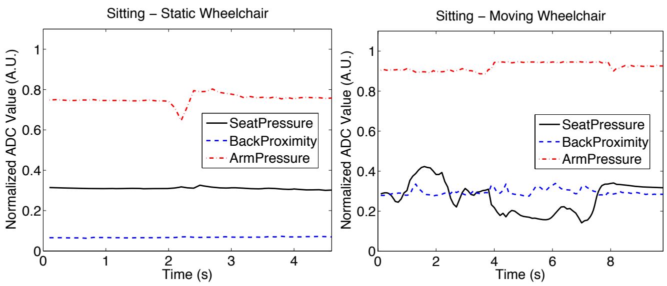

Fig. 4. Variability of average seat pressure sensor increases when wheelchair in motion, variability in average proximity to the back of the chair increases somewhat and arm pressure variability is little changed.

Fig. 5 (left) shows an interesting characteristic in the movement of a subject standing from the chair – there is an overall downward seat pressure increase before the person stands up from the chair. This is attributed to flexing leg muscles in preparation for pushing the occupant upwards. Perhaps this signal could be one of the key features for triggering the emergency patient exit alarm.

Looking at a graph of a user standing up and sitting down three times in Fig. 5 (right), it is clear that the forward lean angle from the back of the chair is the earliest indicator that the person is in the process of exiting the chair.

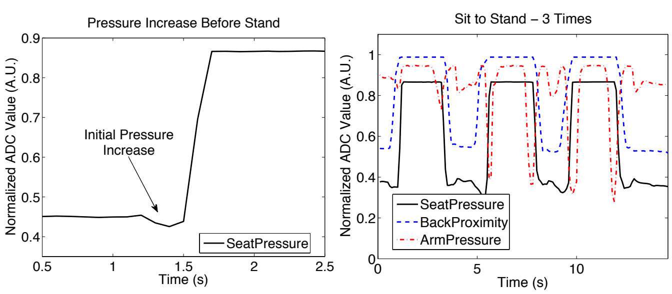

Fig. 5. The first graph highlights the presence of an initial increase of total seat pressure before a rapid decrease when a patient is exiting the chair. The second depicts a scenario when the patient is standing up and sitting down three times in sequence and in which the forward lean is the first parameter value to indicate the start of a stand.

However, note that the forward lean variable is activated in an almost identical fashion when the patient is just leaning forward to reach something as shown in Fig. 6. In order to distinguish between the two conditions, one can look at the total seat pressure variable in conjunction to separate the two gestures.

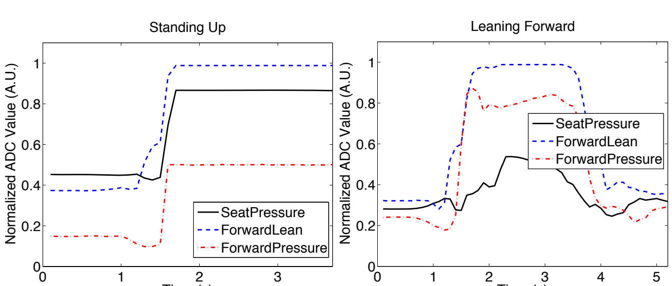

Fig. 6. Plots of patient standing (left) then leaning forward (right) and the respective feature variations in total seat pressure, forward lean angle and the forward pressure distribution on the seat of the chair.

Thus, one can use forward lean as an initial indicator that the patient might be soon be standing, but if the overall seat pressure levels do not change significantly, the system can reject this hypothesis.

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