Objective Pressure Injury Risk Assessment Using A Wearable Pressure Sensor

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***Abstract*—The healthcare industry has placed significant effort on reducing pressure injuries as they often occur while patients are seeking treatment for an unrelated condition, lengthen the stay of the patient, impact treatment options, are extremely painful, and can result in death. Current work has shown that an increase in nursing care can reduce pressure injury occurrence, but increased nursing care is not sustainable. The Braden Scale is the current method of stratifying patients by risk of forming a pressure injury, but previous work has shown that the Braden Scale is not an accurate predictor of pressure injury formation. We present an objective mobility measure of pressure injury risk that can be used in addition to the Braden Scale using a wearable pressure-sensing device. By assessing the current pressure readings in real-time we can determine when a patient is mobile and present this data to the clinic. In future we aim to use this mobility measurement in a Cloud-based system that can compare the mobility measurements to similar patients to assess risk with increased accuracy.**

***Index Terms*—pressure injury prevention, connected health, pressure sensing, objective health**

I. Introduction

Pressure injuries are a current unsolved burden in healthcare. More than 90% of pressure injuries occur while patients seek treatment for other conditions [1] and in the U.S. every year there are over 2.5 million patients affected at a cost of $11 billion [2]. In addition pressure injuries are "never events", meaning they should never occur in healthcare, and have a big impact on quality of life as they cause severe pain, treatments are painful and uncomfortable, and they impact the social life of the patient [3] [4].

The current standard of care is to assess the patient's risk of forming a pressure injury using the Braden Scale [5] and set a periodic schedule to rotate high-risk patients [6]. The Braden Scale as well as other proposed risk assessment scales, e.g. Norton [7], Waterlow [8], and Cubbin and Jackson [9], have been shown to be ineffective at predicting pressure injury occurrence [10]. It has also been shown that rotating a patient does not always relieve pressure [11] [12], meaning additional tools may be needed to assess whether a turn is effective.

A popular, proposed many times over, solution are beds that can adjust to or control the patient, defined as Support Surfaces by the National Pressure Ulcer Advisory Panel (NPUAP) [13]. Support Surfaces are heavily studied and are more effective at reducing pressure injuries when compared to a hospital mattress, which is not well-defined, but a sheepskin overlay is also more effective at reducing pressure injuries when compared to a hospital mattress and at a much lower cost than a Support Surface [14].

Studies have shown that if you increase care pressure injury incidence can be reduced [15] [16]. But, this method of reducing pressure injuries does not seem sustainable in the U.S. as it does not scale with an increase in patients as the Baby Boomer generation ages and a nursing shortage is predicted because of the reduction in nursing graduates [17].

A viable alternative to focus nursing attention is to use sensing strategies to objectively measure pressure injury risk. Such a method can both stratify patients into risk groups and also present information to the healthcare staff that inform future actions, such as an objective mobility measurement or tracking the posture of the patient. We use the word posture as in the literature as a way to classify positions in bed. Some of the more common postures can be seen in Figure 1.

In this paper we generate objective analytics from a novel wearable pressure-sensing device that can be calculated and displayed to healthcare staff in real-time. The proposed system can be used to determine pressure injury risk of a patient. We will compare and contrast this work with other related work in Section II. We will discuss the design of the wearable pressure-sensing device and the experiment design in Section III. In Section IV we will discuss how we analyzed the data to construct a best-fit plane. In Section V we discuss how we used the best-fit plane to assess the mobility of a patient. In

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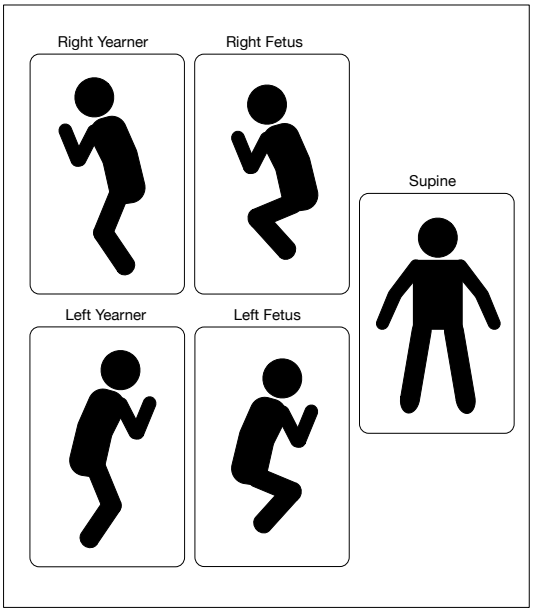


Fig. 1: Common postures used in pressure injury and sleeping analysis

Section VI we discuss how we used the best-fit plane to assess the posture of the patient. In Section VII we discuss how to apply the analysis to a real-time system. We discuss future work in Section VIII and we conclude in Section IX.

II. Related Work

New technologies are being developed to prevent pressure injuries. Some of these technologies could be used in conjunction with our sensing and others offer different trade offs. The are two current commercialized sensing strategies: Continuous Bedside Pressure Mapping (CBPM) and Inertial Measurement Unit (IMU) monitoring. Two other very promising strategies are limb-identification algorithms that can track the amount of pressure per limb as the patient rotates and skin integrity monitoring.

CBPM uses a pressure sensing mattress overlay to monitor the real-time interface pressure of a patient on a mattress. In this way healthcare staff can use the real-time visual to assess the repositioning of the patient. Two controlled trials have been performed using CBPM and a lower incidence of pressure injuries was reported [18] [19], but a Randomized Controlled Trial showed no reduction in pressure injuries using CBPM [20]. This system may help with repositioning, but the current software does not assess the risk of the patient meaning healthcare staff would still spend the same amount of time per patient making it not sustainable. These systems can also be expensive because of the number of sensors required to make the pressure sensing mattress overlays.

IMU monitoring uses accelerometers, gyroscopes, and sometimes magnetometers to track the movement and orientation of a patient. IMU monitoring was clinically tested in a Randomized Controlled Trial and found that turning compliance, the reliability that healthcare staff turn a patient at a designated periodic time, increased [21]. This sensing strategy is inexpensive and could possibly be used to stratify patients based on risk using the level of mobility of a patient. The advantage of using a wearable pressure sensor is the same mobility can also be tracked and in addition pressure accumulation can also be tracked as it is established that it is pressure over time that correlates to pressure injuries [22].

A software-based approach using the same pressure sensing mattress overlay as in CBPM can be used to identify the limbs of a patient making it possible to track the amount of pressure per body part over time [23] [24] [25] [26] [27]. This solution offers the highest granularity of risk as each individual limb can be assessed, but the pressure overlay is expensive and how this data would be used in a clinical setting has not yet been evaluated. A wearable pressure sensor offers a subset of the abilities as pressure limb-tracking as individual areas of the body can be tracked where a wearable is placed at a much lower cost.

Skin integrity monitoring aims to determine the health of the skin, which can be used to detect the formation of a pressure injury or track the healing progress of a pressure injury. A hand-held scanner was developed and tested [28] as well as two bandages [29] [30]. This type of monitoring offers the benefit of assessing skin health, but it is limited to the area being monitored and currently does not offer a way to stratify patients based on the risk of forming a pressure injury. A wearable pressure sensor can offer stratification of patients and in addition monitor the pressure at a location.

There are also many other types of monitoring that can be used assess pressure inury such as temperature and humidity, blood flow, biomarker, electrocardiography, camera, ultrasound, and others [31]. But, these works currently are too preliminary to compare and contrast with a wearable pressure sensor.

III. Wearable Pressure-Sensing Device Design And Data Collection

Interface pressure was measured using a wearable pressure sensing array placed between a Mepilex Border Sacrum (Mölnlycke Health Care, Gothenburg, Sweden) adhesive wound dressing and Tegaderm (3M, Maplewood, USA) transparent film dressing. The sensing array consisted of circular (1cm diameter) flexible piezoresistive pressure sensors (Micro Deformable Piezoresistive “Uneo” sensors; Uneo Inc., New Taipei City, Taiwan) placed in a 4x4 array with 1 cm spacing between each cell. These 16 cells were connected using 8 traces (4 vertical, 4 horizontal), which were routed through a 30 cm flexible cable to a printed circuit board. The PCB (Printed Circuit Board) consisted of a voltage divider circuit with fixed 10k ohm resistors in series with the variable pressure sensor resistors. The change in pressure sensors' resistance was measured using a microcontroller and Bluetooth transmitter/receiver chip (BLE 112 module; Silicon Labs, Austin, USA), which scanned and transmitted (frequency = 1 Hertz) the measurements to an iPad mini 2 (Apple Inc.,

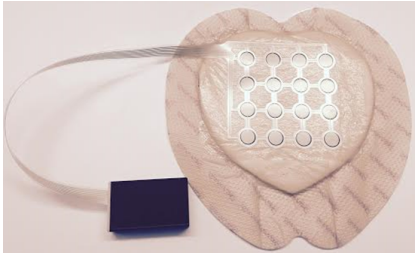
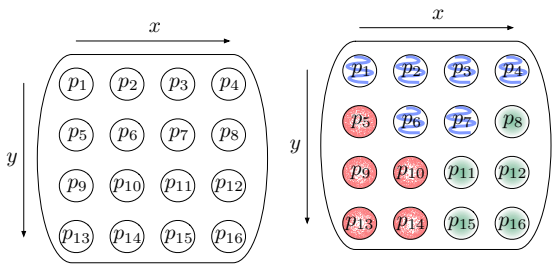


Fig. 2: Wearable pressure sensor



(a) Layout

(b) Layout with color-coded coordinates

Fig. 3: Pressure sensor layout

Cupertino, USA) running an application written for this study. Figure 2 shows the actual wearable pressure sensor used in the study.

There were a total of five patients enrolled in the study. The patient's skin was observed for lesions, baseline documentation was performed, and the pressure sensitive wound dressing was placed on the sacrum of the patient following standard Mepilex application procedures. The end of the flexible flat cable was plugged into the electronics box and a coin cell battery was placed into the electronics box. The study application was selected on the iPad and the patient's study number was entered into the application. Once the patient's number was entered into the application, the iPad connected to the BLE112 and commenced data collection. Data was collected until the dressing was changed (during which data was not collected, but after which data collection resumed), the patient left the ICU (Intensive Care Unit), or the patient was disenrolled from the study.

IV. Fitting A Pressure Plane

At every reading of the sensor we obtain one pressure reading from each pressure location for a total of sixteen pressure readings, where the relative position of each pressure location is known as depicted in Figure 3. Our goal is to interpret this data to infer the mobility and posture of the patient. We form a best-fit linear plane to the sensors pressure readings and then use the planar characteristics to infer movement and posture.

For the purpose of discussion we will define a *cell* as a triple with the three values x, y, p, where x is the horizontal location, y is the vertical location, and p is the pressure reading at that x, y location.

We assign an x, y location at each cell and normalize the three values x, y, p. x and y are normalized on assignment such that the highest value of x and y is 1. The pressure values are normalized such that the maximum possible pressure value is 1. When we use the variables x, y, p in this paper we are using the normalized values. As an example the four corner cells have values of:

$$cell_1 = (0, 0, p_1), cell_4 = (1, 0, p_4),$$
$$cell_{13} = (0, 1, p_{13}), cell_{16} = (1, 1, p_{16})$$

Given any three points we can form a plane. We formed three new points by averaging x, y, p values in the following manner:

$$threecell_1 = average(cell_1, cell_2, cell_3, cell_4, cell_6, cell_7)$$
$$threecell_2 = average(cell_5, cell_9, cell_{10}, cell_{13}, cell_{14})$$
$$threecell_3 = average(cell_8, cell_{11}, cell_{12}, cell_{15}, cell_{16})$$

The cells chosen for each $threecell$ is based on their spatial locality. The averaging of the cells helps to form a best-fit plane, but in addition it helps to eliminate some of the noise captured by the pressure sensors. Figure 3 depicts a pictorial presentation of the grouping.

From $threecell$ we can form a plane by finding the normal to the plane by performing the cross product of two vectors in the plane. Using the normal and a point on the plane we can then solve for the final value in the planar equation. The following is the general planar equation and how the normal relates to the general planar equation.

$$ax + by + cz = d$$
$$n = (a, b, c)$$

A calculation to find the complete planar equation using $threecell$ is as follows:

$$\vec{v}_{12} = threecell_2 - threecell_1$$
$$\vec{v}_{13} = threecell_3 - threecell_1$$
$$n = \vec{v}_{12} \times \vec{v}_{13}$$
$$d = threecell_1 n^T$$

From the plane we are interested in two characteristics, the x_{slope} and y_{slope}. Although we could use the x and y slope directly for our mobility and posture analysis in the later sections we instead use a new metric related to the x and y slope we call the x_{angle} and y_{angle}, which are related to the slope as follows:

$$x_{slope} = -a/c$$
$$y_{slope} = -b/c$$
$$x_{angle} = \frac{360}{2\pi} \arctan(x_{slope}) \quad (1)$$
$$y_{angle} = \frac{360}{2\pi} \arctan(y_{slope}) \quad (2)$$

The x_{angle} and y_{angle} give us a more intuitive way to think about the rotation of the patient, although it is important to keep in mind that we do not relate the degree of these metrics to an actual degree of rotation the patient is experiencing, but instead use it as a relative metric.

We verify our best-fit plane by calculating the Root Mean Squared Error. Our results can be seen in Figure 4. Each experiment lasted for a different amount of time and therefore the graph time scales are not equivalent. Also a gap in data means the sensor was disconnected for that period of time.

We see our best-fit plane is close to the actual values, but we also do not expect the Root Mean Squared Error to be zero as we are approximating the sensor information as a linear plane, which may not always be accurate as current pressure values may be better modelled as a quadratic, exponential, logarithmic, etc. plane. In addition the process of forming the best-fit linear plane we eliminate noise, which also contributes to why our Root Mean Squared Error is not exactly zero. But, overall the Root Mean Squared Error is mostly below 0.2, which we believe is acceptable.

V. Mobility Analysis

We are able to provide an objective mobility metric based on the sensor readings. We will describe why mobility is an important metric to monitor, the relation to the Braden Scale, and our methods for calculating the metric.

We use the term mobility as defined in the Braden Scale [5], the patient's ability to change body position. The mobility score can have one of four values. A one, "completely immobile", indicates the patient cannot change body position without assistance. A two, "very limited", indicates the patient can make slight changes that are not frequent or significant. A three, "slightly limited", indicates the patient can make frequent small movements. A four, "no limitations", indicates the patient can make significant changes frequently and independently. We do not use the same scores in our results, but we reproduce the mobility scale as a reference and for future comparison.

Garcia-Fernandez et al conducted a study to determine the top risk dimensions that cause pressure injuries from an expert panel. The expert panel determined that mobility is in the top five risk dimensions that lead to pressure injuries [32]. In addition Alderden et al. surveyed the literature and also identified mobility as one of the top five risk factors for pressure injuries [33].

We developed two metrics to assess mobility: movements per minute, $Movements/min$, and movement strength, $Movement\ Strength$. Both metrics are based on our definition of a movement. A movement is calculated by setting a threshold on both the x and y angle gradients. We calculate the gradient at location i, where i is the ith sample. In our case the data is sampled at every second and therefore i corresponds to the number of seconds. The gradient is calculated based on the x and y angles as seen in Equations 3 and 4.

The x and y gradients are then combined into a singular $xy_{gradient}$ metric that does not differentiate between positive and negative angle and the threshold of movement was defined as $xy_{gradient}(i) > 2$ from visual inspection of the data.

$$xy_{gradient}(i) = max(|x_{gradient}(i)|, |y_{gradient}(i)|) \tag{5}$$

In Figure 5 we show graphs of mobility based on actual patient data. The y-axis is the calculated $xy_{gradient}$, but we also label it as "Mobility" as the $xy_{gradient}$ when graphed is visually showing the change and strength of movements over time. Below the legend of each graph we show the calculated metrics $Movements/min$ and $Movement\ Strength$. The metric $Movements/min$ is the number of entries in $xy_{gradient}$ that have a value larger than 2 divided by the number of minutes that have elapsed. $Movement\ Strength$ is the average of the $xy_{gradient}$ values that are greater than 2.

$$movement = \begin{cases} True & \text{if } xy_{gradient} > 2 \\ False & \text{otherwise} \end{cases} \tag{6}$$

The data in Figure 5 shows the mobility of five patients. The length of each experiment varied, but for comparison we display the first 24 hours of each experiment. For certain segments of time no data is displayed, e.g. patient 2, patient 3, patient 4. This is either because the experiment was shorter than 24 hours or the pressure-sensing device was disconnected for a certain amount of time.

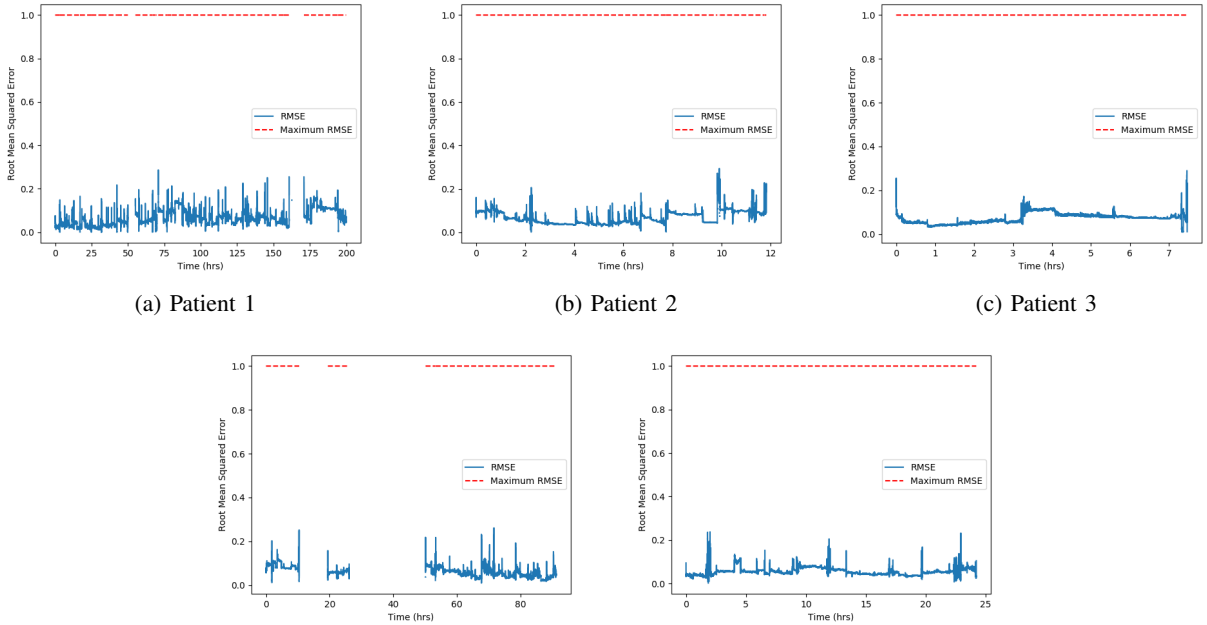
On each mobility graph we also mark with a red asterisk where the patient was repositioned by healthcare staff to give the reader a sense of which movements were made by the patient and which were assisted. It is easy to see visually how a higher $Movements/min$ corresponds to more frequent movements by the patient. Although we use the same length of time to display the graphs for comparison the objective metrics $Movements/min$ and $Movement\ Strength$ are calculated based on the entire length of the experiment and only when the device is connected.

VI. Posture Analysis

We attempt to track the posture of the patient using the x_{angle} and y_{angle} from Equations 1 and 2. We use the data from a short experiment of a healthy volunteer that includes reliable labels of posture. We first filter out movement based on our definition from Equation 6. We then plot the x_{angle} and y_{angle} against the labels.

The x_{angle} and y_{angle} will have a value of 0 when there is an equal of amount of pressure across the sensor device. This means in theory regardless of posture the x_{angle} and y_{angle} can be 0. From our data we find often that there is a gradient across the sensor and we attempt to use this to infer the posture of the patient.

The intuitive expectation based on the orientation of the sensor we would expect that when the x_{angle} is negative the patient is on their left side and when the x_{angle} is positive the patient is on their right side. When the patient is supine we would expect an x_{angle} close to 0. Likewise the y_{angle} should



(a) Patient 1 (b) Patient 2 (c) Patient 3

(d) Patient 4 (e) Patient 5

Fig. 4: Root Mean Squared Error of patient data.

$$x_{gradient}(i) = \begin{cases} x_{angle}(i+1) - x_{angle}(i) & \text{if } i = 0 \\ x_{angle}(i) - x_{angle}(i-1) & \text{if } i = \text{last value} \\ (x_{angle}(i+1) - x_{angle}(i-1))/2 & \text{otherwise} \end{cases} \tag{3}$$

$$y_{gradient}(i) = \begin{cases} y_{angle}(i+1) - y_{angle}(i) & \text{if } i = 0 \\ y_{angle}(i) - y_{angle}(i-1) & \text{if } i = \text{last value} \\ (y_{angle}(i+1) - y_{angle}(i-1))/2 & \text{otherwise} \end{cases} \tag{4}$$

correspond to the amount of elevation the patient's head is above the patient's back.

In Figure 6 we present our results using a healthy volunteer experiment. We do not have enough data to evaluate the simple intuitive analysis based on the sign of the x_{angle}. With more data if this approach does not work a Machine Learning approach would be a natural analysis choice.

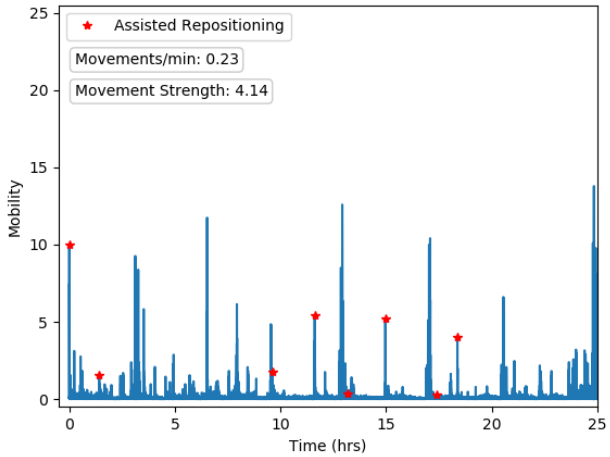
VII. Application To A Real-Time System

In the previous sections we present our analysis based on collected data. Because we are using collected data we can perform analysis, such as finding the max pressure of an experiment, that is not possible in real-time. In this section we will outline the types of analysis we used and how we can adjust our technique to apply the same analysis in real-time. We believe it is very important to use this analysis in real-time in order to present data in the clinic. We are also currently working on such a system entitled PIMAP (Pressure Injury Monitoring And Prevention) that is designed specifically to monitor objective health measurements in the clinic.

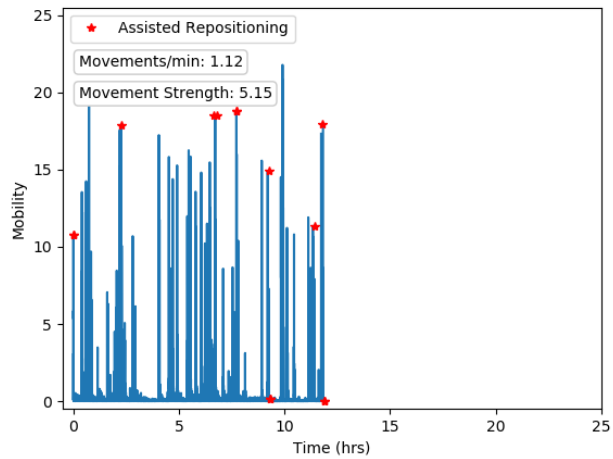
The prominent technique we use in this paper is creating a best-fit plane. From the best-fit plane we calculate the x_{angle} and y_{angle}, which we use for posture analysis, and the $xy_{gradient}$, which we use for mobility analysis.

Calculating the best-fit plane relies on normalization, i.e. giving equal weight between the position of the sensors and recorded pressures. In our case we examine pressure, which when calibrated gives a fixed range of values. Pressure is defined as a force divided by an area. The sensor we use to collect data is a fixed area and force is a mass times an acceleration. The majority of the time acceleration for this application is gravity, which is fixed. This boils down to the pressure we measure is proportional to the mass of the patient. In a real-time system we can normalize the pressure based on a minimum pressure (a mass of 0) and a maximum pressure (close to maximum mass of a patient).

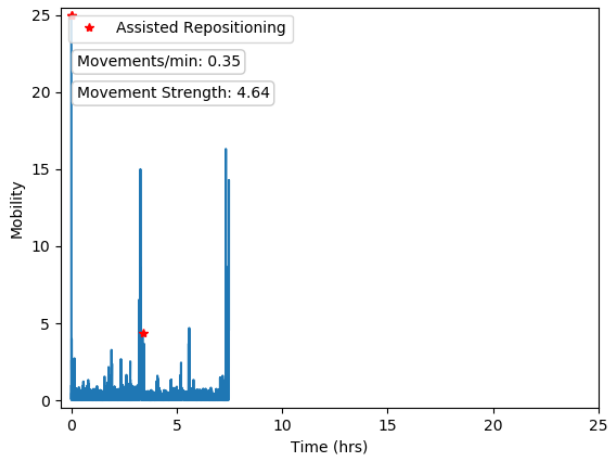
We do not need the actual maximum mass of the patient. An approximation will work fine because having a patient that exceeds the maximum mass will cause anomalous results, but the patient is anomalous and therefore the system should react accordingly.



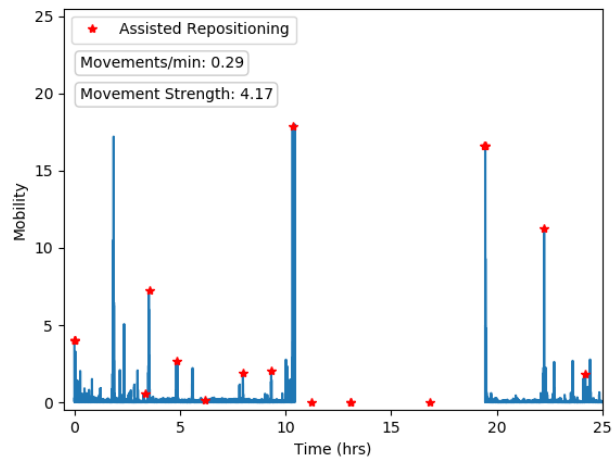
(a) Patient 1



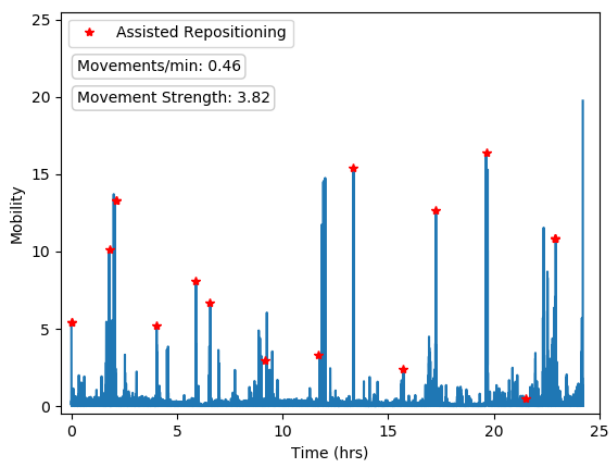
(b) Patient 2



(c) Patient 3



(d) Patient 4



(e) Patient 5

Fig. 5: Mobility metrics and graphs of patient data. Mobility is the equivalent of the $xy_{gradient}$.

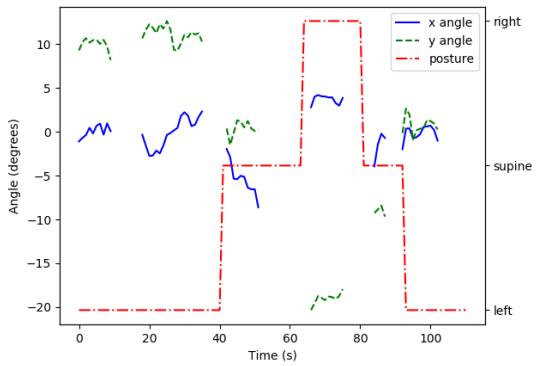


Fig. 6: Posture compared to x and y angle.

After normalization we can calculate the best-fit plane on a per sample basis. There will be a maximum sampling rate based on the time to calculate the best-fit plane, but this maximum sampling rate should be much below the typical rates of one sample a second unless running on a bizarre system, in which case there are bigger problems than the maximum sampling rate.

The x_{angle} and y_{angle} can be calculated directly from the best-fit plane and add little to the calculation overhead. The $xy_{gradient}$ relies on time and therefore needs in the worst case three samples (if i is the current location of the gradient calculation we need $i-1$ and $i+1$ to calculate the gradient at i) to calculate the previous gradient value, meaning there is a delay of one sample. At typical rates of one sample a second this is a one second delay, which is not significant for this application.

Although all analysis techniques were presented based on collected data the techniques can easily be used in a real-time system.

VIII. Future Work

With more well-labeled data we can most likely provide an accurate prediction of posture. If using only the x_{angle} as the predictor is not enough it would be a very natural fit to use Machine Learning techniques to predict the current posture by stochastically predicting the current posture based on the x_{angle}, y_{angle}, and maybe the current average pressure.

This work is a proof of concept of how to use a wearable pressure-sensing device to objectively measure mobility. Another goal we have is to provide a real-time system that can be used in the clinic to present this data directly to healthcare staff. We entitle this system PIMAP (Pressure Injury Monitoring And Prevention). In addition to being a real-time system to monitor pressure injuries we also view this system as a research tool to study pressure injury formation as there is currently no system dedicated to this task. In future work we will present the PIMAP system design and philosophy.

IX. Conclusion

In this work we present an objective way to assess the pressure injury risk of a patient in real-time using a novel wearable pressure-sensing device. We discussed our methods on how to analyze the data to assess the mobility of the patient. We also discussed analysis on how to track the posture of the patient, but admittedly more well-labelled data is needed before we can confirm this method.

Our analysis methods were performed on collected data, but we also discuss how and why we can apply these same techniques to a real-time system and in future work we aim to continue investigation on providing accurate posture measurements as well as providing a proof of concept of a real-time system to deliver the objective measurements directly to the clinic.

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