Detecting Agitation Onset in Individuals with Dementia Using Smart Phone Sensors

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***Abstract*—Individuals living with dementia (ILWD) often experience problematic agitated behaviors, this occurs in up to 80% of ILWD. These behaviors lead to stress for caregivers and increased frequency of institutionalization. There are many proven methods to intervene during agitated behavior outburst and the earlier these methods are used the better the results. Technology has been used successfully to monitor many aspects of health monitoring for older adults. Technology is now being investigated to evaluate the effectiveness of predicting the onset of problem behaviors, especially escalating agitation in ILWD. Off the shelf technology, smart watches and android phones, are being tested to measure limb movements, vocalizations, heart rate and location in facility, to evaluate their ability to provide data that is helpful in predicting agitated behaviors about to occur. This project is a collaboration between nursing and computer science in a major university setting. Currently, work has been completed on volunteers acting as patients to evaluate the ability of this technology to measure the desired parameters. Positive results have been obtained; the goal is to trial this technology on ILWD that have documented history of agitation in an assisted living environment.**

Keywords- dementia; behavior problems; wearable technology; bio measures

I. INTRODUCTION

Dementia affects over 5 million in the U.S and the numbers are projected to climb to over 7 million by 2025 [1]. Additionally, it is estimated that over 46 million people worldwide are living with dementia with the fastest growing population of older adults occurring in China, India, South Asia and the Western Pacific [2]. Those with Alzheimer's and other forms of dementia often go through a period of significant behavioral symptoms of dementia (BSD). It is estimated that between 60 and 80% of these individuals will suffer from BSD during the time they are dealing with this disease [3]. BSD's are generally divided into several categories; physical and non-physical agitation or aggression and verbal agitation. Non-physical behaviors include, disrobing, hording, hiding things, and exit seeking behavior. Physically aggressive behaviors include biting, hitting, kicking, pushing, scratching, and unwanted sexual advances. There can also be verbal concerns such as cursing, yelling and repeated calling out attention seeking behavior [4]. These behaviors are very difficult for caregivers to manage and are positively correlated with caregiver distress [5]. They also contribute to increased cost of care for persons with dementia and are a primary reason for institutionalization [6] [7] [8]. Behavioral problems are a safety concern for family members and professional caregivers as well as other older adults living in communal environments.

There are well-validated non-pharmacologic methods to deal with BSD. These methods include redirection, music therapy, one-on-one socialization, art therapy and animal assisted therapy [9]. A pressing issue concerning BSD is the recognition of triggers – those events that can precede an unwanted behavior [10] [11]. In an attempt to identify these antecedents, various technologies have been used to augment or enhance the input from staff in a facility or caregivers at home. These technologies include video monitoring to capture the event and review the events surrounding the behavioral incident [12]. Another technology that is less intrusive to the communal living or home environment involves using actigraphy sensor technology to monitor disruptive behaviors [13] [14]. One group of researchers used this technology by placing a wearable device that measured movement at the wrist, waist and ankle on individuals identified as having dementia and behavioral issues [14]. The wearable technology demonstrated usefulness by measuring the severity of agitation and showing it compared well to a more established observer measures, such as the Cohen-Mansfield Agitation Inventory (CAMI) [14] although accuracy depended on the time of the day measurements were taken.

There is currently very little known about the ability to use technology to *predict* agitation in persons with dementia in real time. Over the years, use of smart devices and wearables has increased dramatically in the field of healthcare. These wearables are used for a variety of applications ranging from safety to monitoring health measures such as sleep quality and quantity [15]. Pansiot et al discussed how ambient and wearable sensors could be used in health monitoring of patients by recognizing the human activity [16]. Sudden agitated behaviors can be harmful to these individuals and the caregivers or others around them, often leading to aggressive behaviors that are more difficult to ameliorate when they occur.

 ISBN: 978-1-61208-597-5

In this paper we discuss the various tools and methods used for data collection followed by a description of the experiment. Finally we discuss the results and state our conclusions for this study.

II. METHODS

Our hypothesis is that we will be able to first detect agitated behavior and second recognize the onset of agitated behavior in dementia patients using regular, off-the-shelf sensors that can be found in smart watches and/or smart phones. We report in this paper on the development of a feasibility study that is planned to ascertain whether or not we can recognize agitated behavior in actors that simulate such behavior using the fusion of three sensors: a tri-axial accelerometer, an optical heart rate monitor, and a microphone.

The preliminary data was obtained from a series of experiments consisting of five volunteers acting in the role of a patient. Each person was instructed to wear an android Moto 360, which sends the accelerometer and the heart rate values to a server. The volunteers were asked to show agitation or aggressive behaviors that includes random arm movements, such as punching in the air for 2 minutes and then they were instructed to be stable (sitting, sleeping, walking, eating) which involves hand movements but not at a pace as before. Each volunteer performed these actions 10 times wearing the wearable on both the right and left hands. There was a time gap between the actions while training to allow us to label the data with the specific activity performed.

Standard machine learning algorithms used for classification cannot be directly used to predict the mood of a person from the raw data obtained from the wearable. As the device's sensor readings contribute to a lot of noise in the data due to its hardware sensitivity, there is a need of filtering to attenuate the spikes in the data. We used 3rd order low-pass Butterworth filter with a cutoff frequency of 25Hz which removed the outliers in the data. We then used a low pass filter to smooth the remaining spikes in the data, experimenting with different threshold values. We set the threshold to 0.3 by comparing filtered data to well-known data.

According to our experiments, any agitated human activity takes 1-2 seconds to get completed, so we divided the entire data into continuous windows of 2 seconds and all the relevant activities were then captured. Each sample has a length of 2 seconds with 50% overlap so that we do not lose the data in between the samples as we are considering real time data.

The architecture shown in Fig. 1 consists of wearable sensors attached to patients where the sensors send a stream of data over a Wi-Fi to a processing module at a backend server. Heart rate is measured through a smart watch which also measures limb movement through its accelerometer.

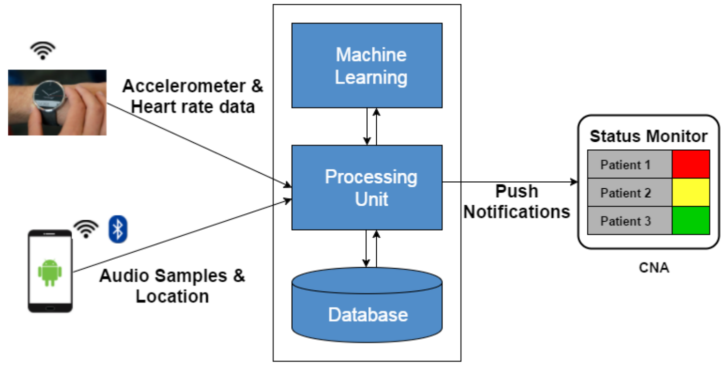

Figure 1. Architecture of the Monitoring System

Audio is sensed by a smart phone and also transmitted to the processing module. Bluetooth beacons are installed in the lab at the University; the smart phone will be able to sense how far it is from what beacon and transmit a stream of location data to the processing unit. The processing unit stores the raw data in a data base for later report analysis and it also produces output data sent to an observer's smart phone. That observer can then display the status of any patient being monitored.

III. EXPERIMENT

The experiment collected data on several measurement parameters. The limb movements of the dominant arm, the emotions and decibel level of the voice, the heart rate and specific location.

A. *Limb movement*

We attached to an actor a wearable and send the sensor values to the backend server in 5 second intervals. The range of values is [0.0 - 6.0] measured in g. (1g =9.8m/s2); 0 m/s2 is the lowest value recorded when the wearable device is kept on the table without movement; 6.0 m/s2 is the highest value recorded when a normal person wearing device punches into a wall with extreme force. At the server, we pre-process the raw values obtained from the sensor using the box filter and Butterworth filter of 3rd order to remove outliers from the data, after which the values are normalized. We next invoke a machine learning module for further processing. We have used three different models: Support Vector Machine (SVM), Random forests and K Nearest Neighbors (KNN). Among the three algorithms, SVM gave us the results with highest accuracy of 87% and hence we are using this model for all our studies. The features we select include the mean of four seconds of accelerometer values, standard deviation, relative differences between the vectors, angle between them, interquartile values, correlation between values obtained from different axes, so that we can increase the accuracy of prediction.

B. *Emotions*

Using a smart phone that was located at a fixed position on the actor's waist, we recorded the audio on the phone and send it to a server for analysis. For the analysis of emotion, we used the default natural language processing techniques provided by the Vokaturi software. The training set of the Vokaturi software consist of speech databases like Emo_DB and Savee. The contents of these databases store annotated speech recordings to predict the patient's emotional state. During the training phase, we verified the accuracy of the model by correlating the results with the observations recorded by human observers who are visually observing the patient and making notes on the emotional state of the patient. On the backend, Vokaturi extracts the acoustic features of a user's voice including: pitch, intensity, spectral scope, which is the energy difference between the frequency bands and computes the relative emotion probabilities for fear, anger, sadness, happiness and no emotion. This is computed with a neural network with three levels of linear connections (2 hidden layers). Once the analysis on the audio is done, the raw audio data is deleted to ensure patient privacy. We focused on predicting aggression, and only considered the probabilities of anger and fear. For both of these emotions the software produces values in the range [0 - 1]; ranging from 0 meaning not being angry/fearful at all through 0.2 meaning somewhat angry/fearful, to,…, 1 meaning extremely angry/fearful.

C. *Heart rate*

We collected heart rate readings of the patients and also pitch of the audio from sensors in the wearable devices. The sensor produces values in the range [40-130] heartbeats per second; 40 hbps corresponds to a very low resting rate of an extremely athletic person; 130 hbps is the maximum heart rate for a 60-year-old person. So far, our experiments have not shown any significant correlation between aggression and changes in heart rate. The same is also true with the pitch of the voice. We are currently sending the data collected from the wearable instantly to the server, analyzing it and storing the data. We have a website to view the current status of each patient and we present the readings from the wearable in the form of graphs.

D. *Decibel level*

We also have the emotion software produce a loudness measure. The values range in the interval [20 – 80] decibel (dB); 20dB corresponds to whisper or rustling of leaves; 80dB corresponds to the sound the typical garbage disposal makes.

E. *Bluetooth*

We use Bluetooth beacons to track the patient's location and this information can be provided to the caregiver making it easier to locate the patient exhibiting changes. We plan to place the Rad beacons at pre-determined locations in the facility. We then use the signal from the Bluetooth of the android phone to identify the position of the patient in the facility. We make use of the push notifications to update the caregiver on the patient's location and the status of a patient.

IV. RESULTS

We have obtained useful results from our initial volunteer patient trials. The wearable devices are able to measure changes in movements and voice pitch and then relay this change to a volunteer caregiver. In Fig. 2 we show the output of the system for a patient that has been identified by the system as behaving aggressive. The figure shows a red threshold line that is being crossed by the accelerometer reading. At this time the red line is simply one deviation from the average. In the future we want to use machine learning techniques that will analyze the five measurements streams and produce a classification of agitated or not. We will use various algorithms such as simply summing the values of the streams to more complicated ways of defining agitation such as a weighted sum of the streams. We will use the observations of trained nurses that have categorized patients as being agitated at various points as the gold standard for the machine learning algorithm to decide which the best predictor of agitation is.

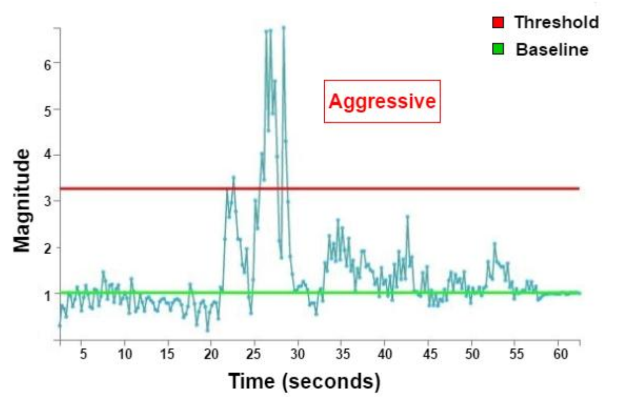

Figure 2. Alert by system

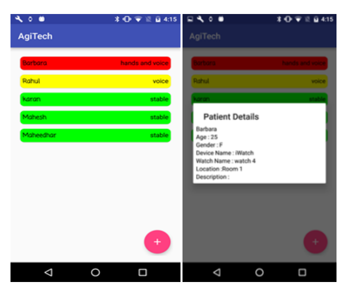

Figure 3. Caregiver monitoring

The details of our volunteer patients' wearable's and their status, whether they are aggressive or stable, are presented in a mobile application. Fig. 3 displays the list of users wearing the wearable. Each cell in the view represents a user with their name on the left and action by which we are recognizing the user is agitated. The background color of each user cell represents the status of the user where red means the person is agitated, yellow means the person is slightly agitated and green means the person is stable.

V. CONCLUSION

We will perform a study with patients in an assisted living facility specializing in dementia care. This study will evaluate how accurate the various algorithms of our system detect agitation and whether or not we will be able to identify the onset so that caregivers can be alerted and deliver remedial actions. This next phase of our work will involve 6-10 individuals with documented BSD such as, unsafe wandering, resisting care, striking out at staff and other individuals, throwing objects, yelling, screaming or likely a combination of these behaviors. Individual residents displaying these behaviors will be selected and their medical power of attorney will be approached for consent to have their loved one participate. These patients will wear the devices for 4-hour blocks of time over several days, totaling 24 hours of monitoring. Each patient will be followed by a trained person (student nurses) that will record any behavior as identified on the CAMI scale. We have already developed a convenient interface that will automate the recording and send the data to the database on the backend server. The major emphasis of this next study will be to ensure that the data streams from the sensors on the patients agree with observations the trained persons have recorded. The IRB of a major research university has approved this research plan.

Once this next phase is complete and all of our data is evaluated, if the systems provides helpful for these individuals with dementia and their caregivers, we plan to perform a larger study. The larger study would involve individuals in various settings, those living in other institutions as well as at home. This system could also be considered for other populations that also have potential adverse behavior issues such as those with traumatic brain injury (TBI) or special needs children for example. Finding methods to intervene earlier when behavior problems occur can reduce caregiver stress, overall cost of care and likely reduce the amount of medications provided to individuals with BSD. The emotions experienced by people with BSD are real, and developing tools to predict outbursts will improve their overall wellbeing as well.

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 ISBN: 978-1-61208-597-5