DAAD: A Framework for Detecting Agitation and Aggression in People Living with Dementia using a Novel Multi-Modal Sensor Network

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***Abstract*—With an increase in the population of older adults, the number of cases with dementia also increases. People living with dementia (PLwD) exhibit various behavioral and psychological experiences; agitation and aggression being the most common. Aggressive patients with dementia can harm themselves, other patients and the staff. In the past, researchers have used actigraphy to detect incidences of agitation and aggression in persons with dementia. However, actigraphy based solutions only consider body movement based parameters. In this paper, we present a novel multi-modal sensing framework currently being installed and tested at Toronto Rehabilitation Institute, Canada. This framework uses video cameras, wearable device (for both movement and physiological data), motion and door sensors, and pressure mats to collect various types of data that may be used to Detect and predict incidences of Agitation and Aggression in people with Dementia (DAAD). In this paper, we discuss the data collection, data processing and data fusion aspects using each of the sensors. Using the DAAD sensing platform, we present two pilot studies to demonstrate its effective functioning. We also discuss the challenges experienced with respect to ethics, hardware installation, software issues and data management.**

***Keywords*—Dementia, Sensors, Actigraphy, Agitation, Machine Learning**

I. Introduction

Providing care for a rapidly aging population constitutes one of the most challenging global health care issues. The fact that many older adults have dementia (approximately $564,000$ in Canada [1]), further exacerbates this problem. Older adults with advanced dementia living in institutionalized settings often have behavioural and psychological experiences of dementia (BPSD), with agitation and aggressive behaviours among the most common experiences [2]. BPSD refer to the constellation of experiences encompassing disturbances in "perception, thought content, mood, and behavior" [3]. The most prevalent BPSD are apathy, depression, irritability, agitation, and anxiety [2][4]. Agitation is defined as "inappropriate verbal, vocal, or motor activity that is not judged by an outside observer to result directly from the needs or confusion of the agitated person," whereas aggression is defined as "destructive actions directed toward persons, objects or self" [5], [6]. As documented increasingly in the literature and popular media (e.g. [1], [7], [8], [9], [10]), these behaviours can lead to resident-on-resident and workplace physical responsiveness towards staff in long-term care facilities. At least 25% of persons with dementia experience agitation and aggressive episodes during the course of the disease [11]. While statistics are difficult to find on resulting injuries and deaths, in British Columbia, 16 patients have died in a period from 2012-2016 in nursing homes after physical confrontations that involved aggressive persons with dementia [9]. Traditionally agitation is measured using behavioral scales such as Positive and Negative Syndrome Scale, Neuropsychiatric Inventory (NPI) and CohenMansfield Agitation Inventory (CMAI) [12]. Since these measurements require manual observations from doctors and caregivers, they involve human labor and are time consuming. Another down side of these measurements is possible errors due to biases of the observers. Different observers might focus on different behavior patterns, which could may effect the consistency and accuracy of results [13].

Due to the above-mentioned limitations, we want to be able to detect incidences of agitation and aggression in PLwD automatically. Machine Learning algorithms can help to identify patterns of such behavior automatically with little manual effort involved. Previous studies suggest that actigraphy (accelerometer) based devices are useful to measure incidences of agitation and aggression[14]. However, actigraphy can only measure body motion related information, which may not be sufficient to predict the occurrences of agitation. For example, if a person did not have a good night sleep or had changes in heart rate, would it lead to agitation? Does the degree of motor activity of PLwD correlate with agitation? An actigraphy based solution cannot tackle these scenarios. Therefore, we need a multi-modal sensing platform that can sense and measure different modalities that are relevant to detecting agitation. In this paper, we present, DAAD, a novel multi-modal sensing framework that consists of cameras, wearable devices, pressure mat, motion and door sensors.

II. Literature Review

In this section, we provide a brief overview of techniques that use either actigraphy or multiple sensors for detecting agitation in PLwD.

A. Actigraphy

Several researchers have conducted studies to evaluate the use of actigraphy in identifying agitation and aggression behaviors in PLwD [15][16][17][18]. These studies verify the correlation between actigraphic measurements with traditional questionnaire based clinical assessment tools such as CMAI/NPI. In these studies, actigraphy devices were worn on patients' wrist, waist, opposite leg, chest or ankle for time range from 30 minutes to 14 days with the subject quantity varying from 20 to 183. The results from these studies showed that the motor activity, which was measured by actigraphy, was greatly correlated to standard questionnaire based methods. these results also verified the correlation between actigraphic measures and CMAI/NPI. These studies also identified the advantages of using actigraphy in agitation identification over other traditional assessing methods as it did not require observing during recording, and could record patients' behavior in a continuous and uninterrupted manner. These studies provide evidence that actigraphy can be a useful and effective tool of detection agitated behaviors in PLwD. However, further studies are needed to understand how actigraphy can be better used to measure and identify agitation in the dementia population and how it varies for different individuals.

B. Multi-Modal Sensing

Previous studies have shown the use of multi-modal sensing framework in behavioral detecting for PLwD. Rose et al. [19] presented a multi-modal sensor framework to collect data on sleep pattern, night agitation behavior and urinary incontinence in PLwD. The sensors they used included wrist actigraphy to collect movement data, a commercially available wetness sensor to collect urinary incontinence data, Intel WISPs tags to monitor body positions and movements during sleep. They conducted the study with 50 PLwD for a period of 5-7 weeks and the collected data was being processed. Belay et al. [20] presented a study aiming to provide cost effective technology to reduce or prevent agitation in dementia. They analyzed data collected from body-worn sensors, environmental acoustic sensors, light and temperature sensors and motion sensors, including parameters such as body gestures, activity and task sequences, ambient light, sound and temperature. However, their study used simulated data. Fook et al. [13] presented a fusion architecture for multi-modal sensors that monitored agitation behavior in PLwD. They used sensors such as ultrasound sensors, optical fiber grating pressure sensors, acoustic sensors, infrared sensors and video cameras. This study was not conducted with PLwD. Teipel et al. [21] presented the use of multi-modal sensor to assess challenging behaviors such as agitation and aggression in PLwD. They placed three sensor bracelets on each patient to collect activity data, ambient loudness level, ambient light intensity and air pressure data. They also used video recording for accurate behavior annotation. They conducted the study for 4 weeks with 17 residents with moderate to very severe dementia in two nursing care units. The data collected was used to train their machine learning algorithms. They found the suitability of multi-modal sensing framework to assess challenging behaviors in PLwD.

These above mentioned studies point out challenges such as mis-labelling of reported incidences of agitation and aggression, mismatch of detection results, incomplete capture of patients' movement or location data, interference between sensors, internet connection problems, inconsistency between collected data and the incidence report. To maximize the sensing coverage and minimize the problems mentioned above, we present a novel multi-modal sensing framework (DAAD) that incorporates new sensing devices such as pressure mat and motion/door sensors to monitor important parameters such as sleep quality and physiological data and motion of the PLwD in the care facility. The DAAD framework eliminates using too many sensors to avoid data cluttering and sensor communication issues. In the next section, we will present the framework, DAAD, for the **D**etection of **A**gitation and **A**ggression in PLw**D** using a novel multi-modal sensor network.

III. DAAD – Multi-Modal Sensor Framework

The DAAD framework consists of the following devices:

1) Video Cameras
2) Wearable Device
3) Pressure Mats
4) Motion and Door Sensors

The video cameras were installed in the hallways of the Geriatric Psychiatry ward at Toronto Rehab Institute-University Health Network (TRI-UHN), Toronto. These video streams are to be used to collect the ground truth for identifying agitation behavior of the PLwD. A wearable device is to be worn on a patient's dominant hand that will collect the patient's physiological and movement data. Two motion sensors are to be placed in two corners of each washroom and one door sensor is installed on each of the washroom door in the ward. Pressure mats are to be placed under the mattress on the patient's bed to monitor the patient's bed exit status, position change, sleep quality, respiration and heart rate. Documentation of the patient's responsive behaviors will also be collected from the nursing staff clinical documentations (patient's charts) that consist of the time, nature of the patient's behaviour and its location on the unit. These documentations will help in finding the corresponding camera and sensor data, and to locate the exact timelines of occurrences of agitation. Therefore, the agitation and aggression documented in the patient's chart by the nurses are used as the gold standard for annotation of video and sensor data. This step will help in improving the quality of the labelled data and is essential in building accurate machine learning classifiers to automatically identify and predict incidences of agitation and aggression.

The use of multiple sensors to capture different modalities will lower uncertainty due to sensing devices and will increase the coverage of subject's movement and physiology pattern to better determine patient's agitation status. These different modalities present unique opportunities to either analyze the sensor data separately or in conjunction with each other. For example, we may want to observe the correlation of agitation with sleeping patterns of a person (using only pressure mats). We can also combine and harmonize the data from the wearable device and motion/door sensors in conjunction with pressure mats to get a global idea about the other vital signs of a patient that correlates to aggressive behaviours. In case a modality does not capture an incident, the other modality can act as a place holder. For example, if the cameras cannot capture an incident in the bedroom due to non-placement or out of coverage, the wearable device, pressure mat or the motion/door sensor can still capture other parameters. This multi-modal sensing capability also ensures correct annotation of data to train accurate classifiers and build generalizable predictive models. Together, these sensors will illustrate the daily routine of the patient's activity with corresponding physiological, movement and other vital information that will be used to develop the predictive models for identifying agitation behavior in PLwD.

We will now discuss each of the sensing modality in detail in the subsequent sections.

A. Video Cameras

A certified electrician installed 15 cameras in the hallways and common areas of the Geriatric Psychiatry ward at TRI-UHN. Ethics and security approvals were taken for installing these cameras. Six of these video cameras are wireless and nine of them are wired. The cameras were not installed in patient's room to protect their privacy. All the cameras send the data to a Digital Video Recorder (DVR) that is placed at a secure location in the nursing station (refer to Figure 1). The video recordings for each of the cameras can be scheduled using the in-built DVR software that is installed on UHN encrypted computer. The software also provides the capability to remotely monitor these videos. Testing results of camera recordings show that 15 cameras' one day recording from $7:00$ to $23:00$ stores around 70 GB of data. The internal storage of the DVR is only 500 GB; therefore, we needed a better way of transferring and storing the video data. To deal with this, we used FTP setup which can backup selected time of recording to the destination network folder in the form of 5-minute videos in assembler source (.s) format. To view the video, we used a software called McdPlayer that is provided by the DVR. Compared to other method of transferring the videos, FTP backup has the benefit of minimized human labor and time spent, and be able to transfer the data in real time. All the videos will be stored on the TRI-UHN encrypted network (as per the ethics guidelines).

B. Wearable Device

A few wearable devices were evaluated for the use of gathering a patient's motion and physiological data. We evaluated these devices based on the following features:

- Battery Lifetime,
- Device Size,
- Charging Time,
- Accessibility and Usability,
- Size of Data Recorded in the Device,
- Type of Data Collected,
- Data Recording Indicator on the Device,
- Button Size to Start/Stop Recording, and
- Real-Time Monitoring through Mobile Application.

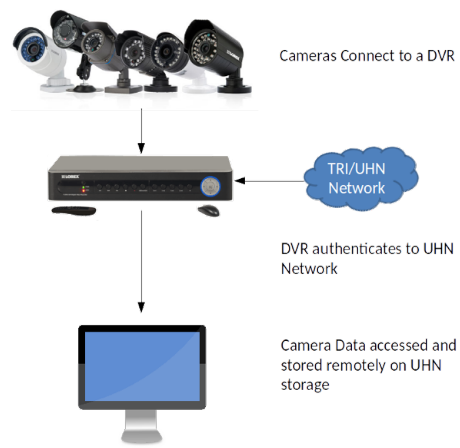

Fig. 1. Data collection from cameras

Based on the above evaluation, two wristbands were initially chosen as the more suitable options for this study. We collected test data from one of them, which is discussed in this paper in Section IV. This wristband is worn on the dominant hand of a patient to collect physiological and movement data. It stores raw sensor data, such as photoplethysmogram (PPG) and 8 sets of accelerometer (ACC, sample frequency of 16 Hz) in text files. It also provides pre-computed features such as average heart rate, energy expenditure, respiration rate and activity count. Nurse training video is made to give them better understanding of the device with specific instructions on wearing/removing the device and using the buttons to start/stop the data collection. In this study, we will primarily use the raw data (ACC and PPG) to improve the accuracy of behavior monitoring. The access to raw data will give researchers the flexibility to extract engineered features or learn generic features (using deep learning methods) to build generalizable predictive models. The wearable device stores the data on its internal storage and does not need internet during the recording. To measure patient's physiological data, the sensor at the back of the wristband needs to touch the skin all the time. We achieve this by tightening the wristband to a state that does not make the patients feel uncomfortable. Patients might try to take the wristband off deliberately, a way of securing it is needed. Nagel et al. [22] added a plastic strap to prevent patient from removing the device but no detail of the strap is mentioned in the paper. We will use medium silicone O-Rings to secure the wristband [23] in our study as shown in Figure 2. The wristband shown in Figure 2 is currently under investigation; the results shown in the pilot study 1 (see Section IV-A) are from the other device. Patient will wear it on the dominant hand the whole-time (full day and night except for shower time) during the course of the study. Battery life of the fully charged wristband is around 48 hours that also corresponds to the maximum internal storage. Due to this limitation of the device, the researchers need to take it off from the PLwD every two days to offload the data, reset and recharge the wristband for the next round of recording. This process takes around two hours; therefore, any agitation behavior during this time may not be recorded by this device.

Data Processing: We term one continuous data collection cycle in a given time frame by the wearable device as a 'trial'.

Fig. 2. O-Ring Used to Secure Wristband

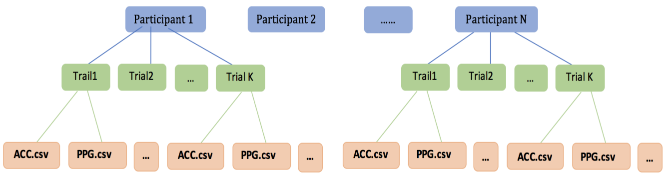

Fig. 3. Wristband Data Storage

There will be multiple trials per patient during the course of the study. All the data will be stored on the encrypted TRI-UHN network without outside access. The data for different trials of the wearable device need to be organized for easy access and retrieval. Figure 3 shows the nested file organization used for this study. One trial of ACC data contains different parameters of date, time, 8 set of ACC data (each has x,y,z direction). These ACC files are too large to be imported into MATLAB directly for feature extraction due to the computer memory limit. Therefore, a new approach was developed to overcome this challenge. Mapreduce and Datastore are MATLAB functions developed to analyze big data. The Datastore function allows users to access and process a collection of data in a chunk-based manner [24]. The DataStore function creates a repository to hold collections of data, divides and loads the data in equal chunk from which features can be extracted. A MATLAB script was written to automatically find and read all ACC files in the storage framework. To improve the efficiency of the program, it is designed to only process the files that have not yet been processed before. The feature extraction program then extracts standard time and frequency domain features from this data [25]

Challenges: A major challenge is to label all the records in ACC files to be either 'agitated' or 'non-agitated' based on the documentations by the nurses. Since the number of records is huge, we will use MS-Access to write SQL queries to precisely annotate a given time frame as 'agitation' or not. One pilot trial data on a healthy adult and the corresponding results are presented in Section IV-A.

C. Ambient Sensing Framework

1) Sensors Setup: The motion detection sensors and door sensors are used to record patient's daily motion related activities in a specific area of the care facility. In this study, we focus on the washrooms as they are attached to their bedrooms. For a given time slot, if the sensors detect abnormally high frequency of motion or open/close door alert, it can be an indicator of a patient's agitated behaviour.

Fig. 4. Motion Sensors

Fig. 5. Door Sensor

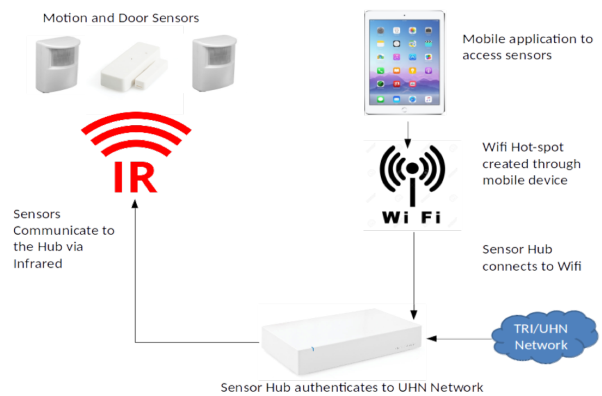

Fig. 6. Data collection from motion and door sensors

Two motion sensors (M) and one door sensor (D) (both Insteon Wireless Sensors [26]) are installed in each washroom in the wards at TRI-UHN as shown in Figures 4 and 5. These sensors authenticate with the UHN network and communicate to a hub that is placed at a secure location in the nursing station that receives signals from these sensors (as shown in Figure 6). The hub, then sends notifications to a mobile application and to a preset email address. During the setup, because of the range limitation between sensors and the hub, an extra range extender is further placed to enhance the signal. The range extender is also kept at a secure location where patients have no access. The hub will send email alerts to destination email address once it detects any motion and door sensors will send email alert when it is open. The notifications on the mobile application are also useful to provide real-time movements of PLwD; however, in this study we focused on the email alerts because they can be processed and a holistic view of the PLwD can be maintained over a longer duration. The detecting area of the motion sensors can be adjusted by changing the direction they point to. There are also switches on the motion sensor that allow modification of sensitivity of the device, in this study we used the default settings.

Data Processing: A Microsoft (MS) Outlook email account was created for receiving email alerts from these ambient sensors. These alert emails are configured to be stored by using MS Outlook 2010 on a local disk. We then used MS Access to import all the received emails and used SQL queries to select and generate needed data. Alerts from all the sensors are sent to the same email address with different titles such as 'M1 motion detected' and 'D2 opened'. By using the SQL queries, we can extract data that contains only alerts from desired sensor(s) for further processing. MS Access Forms are also created to enable automatic generation of tables for a given sensor's data.

Challenges: Sometimes, there are delays in receiving motion/door alerts due to network glitches (usually by a few minutes) depending on the internet condition. The washrooms in the hospital rooms may be shared by more than one PLwD, these sensors are not designed to detect motion activity of a specific person, which may result in noisy data.

A pilot study is presented in Section IV-B to show the function of these ambient sensors.

D. Pressure Mat

To better monitor a patient's physiological data and sleep quality, we use pressure mats developed by BAM Labs [27]. The pressure mats are placed under the patient's bed mattress and connected to an adapter that is plugged into a power source as shown in Figure 7. It collects data such as bed exits, heart rate and respiration rate in a continuous, real-time fashion and send it to a mobile device. They also provide access to the raw data in a text file format. This data can be used to validate incidences of agitation and aggression and compare with other sensors data to get a better idea of a patient's activity. A nurse training session is designed to better prepare the nurses to be familiar with this device.

Challenges: Patients are directed to sleep in their own beds at night and monitored regularly, so we are confident in the reliability of the overnight data. However, it is common for patients to wander into other rooms and nap in each others beds during the day. This lends some uncertainty and unreliability to the daytime data, as we have no way of confirming the identity of the napper.

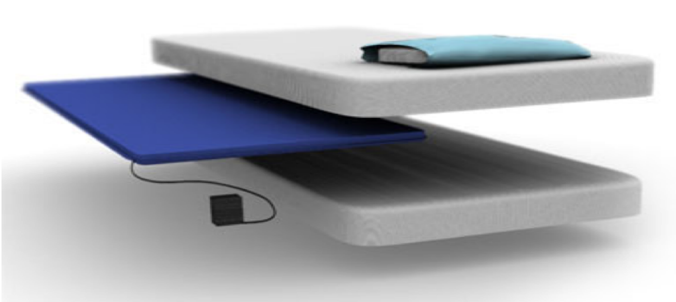

Fig. 7. Data collection from Pressure Mat

E. Data Fusion

To build generalizable predictive models to identify incidences of agitation and aggression, the data from different sensing devices may need to be combined. However, different sensing devices are synchronized to different time zones; therefore, time synchronization is the primary step before these data can be combined. To achieve this, before each trial, we synchronize all devices with either EST or UTC time zone based on each device's setting. After data collection, all the data will be stored in one database where we can convert all time to EST (Toronto local time) and proceed to the next stage of the study. The process of combing data from all sensors (except for camera recording) is shown in Figure 8

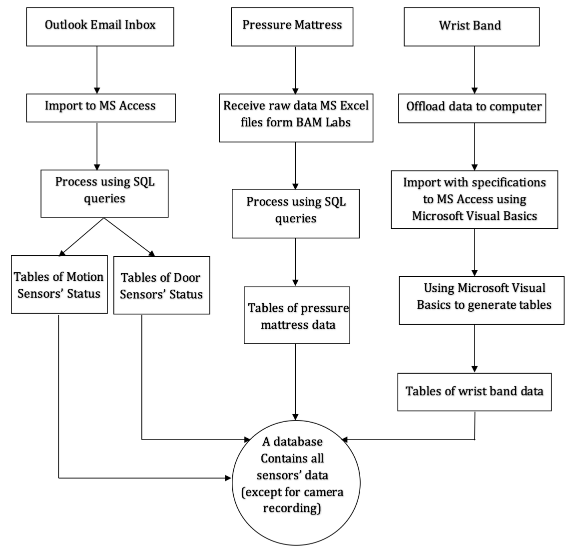

Fig. 8. Database Setup Procedure

IV. Pilot Studies

To demonstrate the actual functioning of sensors deployed within the DAAD framework, we present two pilot study trials in this section. In both pilot studies, the data was collected from young and healthy volunteers in the research team. The data collected from these pilot studies will provide a first-hand experience of the challenges associated with data collection, processing and storage, understand the technical glitches and to gain insights in interpreting the data that will be useful in developing predictive models.

A. Pilot Study 1

The wearable device was worn by Researcher#1 (R1) for a period of 54 hours and was only taken off during shower time. R1 was used to wear a watch. Therefore it did not cause any discomfort. We calculated the magnitude of one accelerometer (a) using the formula below:

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

where a_x, a_y and a_z are the raw acceleration values in the x,y and z direction. PPG data was also collected during this time. Figure 10, shows the heart rate data derived from the raw PPG data in a 24-hour period.

Data Interpretation

Figure 9 shows the plot of a w.r.t. 24-hour period. It shows that the magnitude of accelerometer is high between $8:00$ and $22:30$ and much lower between $22:30$ and $7:00$. This greatly corresponds to the participant's record of that day, where R1 wakes up at around $7:00$, work from $9:00$ to $19:00$, and go to sleep at around $22:30$. Figure 10 shows the heart rate for the 24-hour time period corresponding to ACC data. During the day time between $8:00$ and $22:30$, R1 has higher heart rate than during sleep between $22:30$ and $7:00$. This greatly corresponds to the ACC data. Between $7:00$ and $8:00$ in the morning, R1 did not wear the device; therefore, there is constant ACC data (showing no motion) and abnormally high heart rate data (showing noise).

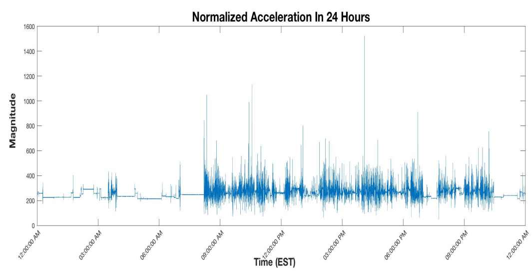

Fig. 9. Magnitude of Accelerometer in 24 Hours from R1

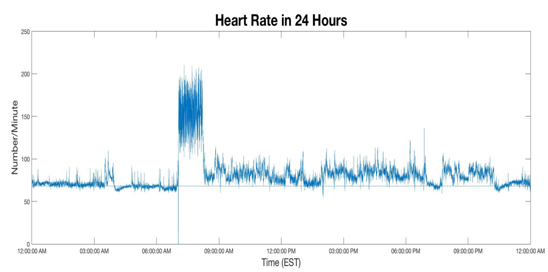

Fig. 10. Heart Rate in 24 Hours from R1

B. Pilot Study 2

To test the functionality of the motion and door sensors, we installed them in Researcher#2's (R2) apartment. One pressure mat is placed on R2's bed and only collects physiological data and in bed status from R2. The three motion sensors labeled as M1, M2, M3 (in orange color shown in Figure 11) are installed in R2's bedroom, living room/kitchen and washroom. One door sensor labeled as D1 (in green color shown in Figure 11) is installed on the washroom door. D1 will be in 'closed' status only when the door is closed (e.g. when someone is using the washroom, but not necessarily). R2 lives with a roommate (RM), whose agreement is taken for this pilot. Living room, kitchen and washroom are shared space between R2 and RM, so M2 and M3 detects movements from both R2 and RM whereas M1 only detects R2's movements.

Data Interpretation

As shown in Figure 12, R2 was in bed between time $23:30$ to $7:30$ on a work day. This corresponds to the data from M1 in the bedroom in Figure 13, where most motion are detected before time around $00:00$ and after $7:30$. M1 also shows that R2 come back home at around $18:00$ after work. The motion detected by M1 at time around $3:00$ and $6:00$ could be due to movement of R2 in sleep. M2 detects movements in the kitchen and living room as shown in Figure 14. M3 and D1 detect washroom status, as shown in Figure 15. The result of this pilot study shows that by using DAAD sensory framework, a general profile of persons' behaviour can be constructed over a duration. In future, a real study will be carried out with PLwD and activity profile will be obtained. Based on the activity profile, abnormal behaviours may be deduced without continuous observing and will greatly reduce caregivers' workload.

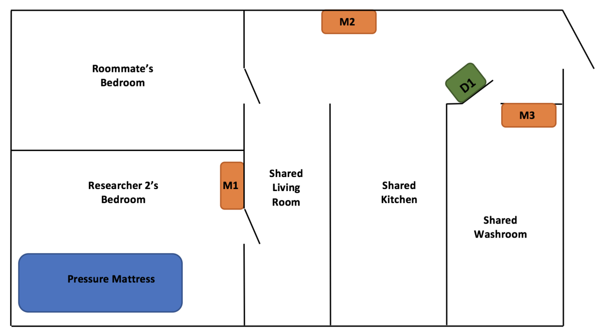

Fig. 11. Sensors' setup in R2's apartment

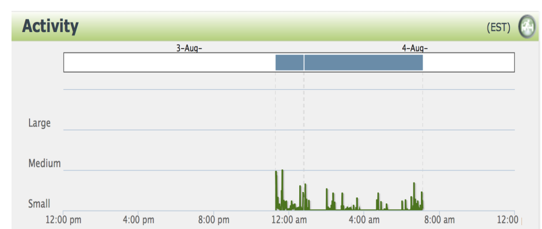

Fig. 12. Pressure Mat Status on a Workday

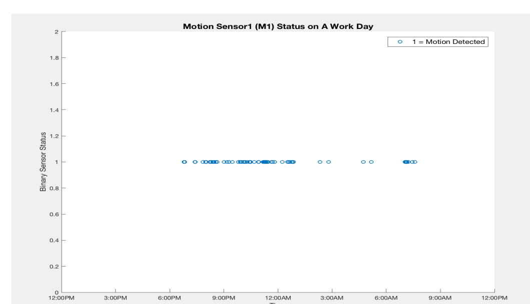

Fig. 13. M1 Status on A Work Day

V. Key Challenges

In this section, we discuss some of the key challenges encountered during the setup of DAAD. We group them as technical and clinical challenges, which are described below:

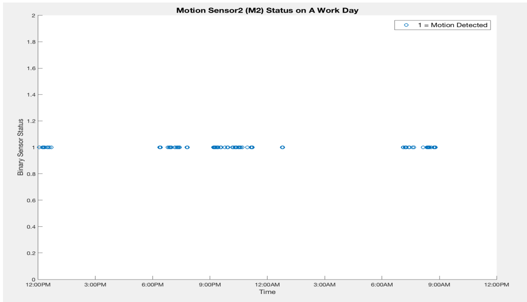

Fig. 14. M2 Status on A Work Day

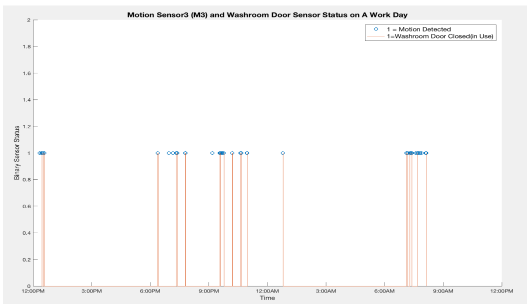

Fig. 15. Washroom Sensors' Status (M3 and D1) on A Work Day

Technical Challenges

- A multi-modal sensing environment should not take a lot of time for installation and should be easily deployable in different settings. A major challenge is to remotely monitor the malfunctioning or consistency of sensors that can severely affect the performance of the predictive models. There must be provisions to handle software and device crashes, Internet connectivity, power outages, sensors tampered (thrown or turned off) by patients.
- There can be several differences in studies conducted in home-care and long term facilities environment for agitation and aggression detection for PLwD. If a video camera is used in a home-care setting, most likely the subject being tracked is the target subject. However, in a long-term care, there may be multiple people in one scene that is hard to handle. In a home-care setting, one set of wearable or ambient sensors can be used easily. However, in a long-term care, different sets of wearable devices may be needed for tracking different subjects that should be identified uniquely. This also brings challenges associated with simultaneous transfer of data to a base station and synchronizing multiple devices at the same time. Therefore, we need separate studies and technologies for both types of care facilities. A multi-sensory model trained and tested in one facility may not work properly in another. A major research focus should be on automatically transferring the learned knowledge from one environment to another without losing the accuracy of the predictive models.
- Data captured through sensor networks will potentially be very large. Therefore, best practices in storing and accessing big data must be employed. A major challenge is to securely store the private health information of patients. Researchers must verify from their respective ethics boards that whether such data can be stored on cloud services; if not, then alternative secure storage devices must be deployed (with backup). Another challenge is the real time analysis of the data in deployment phase. If there are lags in the predictive modeling phase, it can introduce unnecessary processing delays that may compromise the utility of the underlying technology.
- Research must also be directed towards new non-invasive sensing modalities that do not compromise the privacy of the patient or caregiver. Some of the sensing modalities that can be useful are - thermal camera, electromyography, radar sensing, galvanic skin response, blood volume pressure, heart beat/rate, respiration, EEG and ECG.
- Based on the current progress in the field of machine learning, we recommend using the emerging predictive modeling techniques that use ideas from ensemble methods and deep learning. There are other challenges that need to be addressed from the machine learning perspective. The incidences of agitation/aggression may be not as frequent in comparison to the normal activities, which can create a skewed data. Having a good balance between false alarms and missed alarms is critical for any predictive algorithms and the models should be tuned after their careful considerations in a real world setting.
- The sensors' data is prone to noisy observations and missing values. The data processing techniques must automatically handle such data abnormalities without affecting the accuracy of the predictive models.

Clinical Challenges

- Apart from delays caused by ethics board's approval, there may be unnecessary delays due to patient recruitment, collecting consents from patients and caregivers, training staff to use the system and protocols to record incidences of agitation, participant withdrawal from the study, change in technology, refusal to use/wear sensors, cost over runs and hardware failures.
- Informed consent is a fundamental ethical concern for both research and clinical application in translational research [28]. The PLwD may not give informed consent but their caregivers can give such consent and provide feedback. However, many PLwD have no family to grant such consents [29]. Hospital staff members and caregiver's consent and their acceptability of these systems are also important to deploy such systems. For example, a staff member might object to the use of cameras due to privacy reasons. Therefore, studies need to incorporate sensing modalities that can be useful but also protect privacy to handle this problem.
- An individual's BPSD may be very different from others based on the severity of dementia, gender and other factors. A first step would be to provide personalized assistive tools that can be trained and adapted on a person's behaviour over time.

VI. Conclusion and Future Work

In this paper we presented a multi-modal sensor network to identify incidence of agitation and aggression in PLwD. We discussed the installation of various sensing devices in the DAAD's framework, data collection mechanism, data preprocessing and storage issues. We also identified key challenges in the installation of different sensors, data management and data synchronization. We presented two pilot studies; one that used a wearable device and the other which motion/door sensors and presented their results to test the effective functioning of the multi-modal sensor network. In the pilot studies, sensor data are collected and analyzed separately for different individuals; however, in test trials, all the sensors in the DAAD framework will work together to provide a holistic view of a person's vital parameters and activities. Currently, the ambient sensors cannot be tagged to an individual and the data collected by them give a globalized view. In order to develop personalized predictive solution, we plan to introduce tags to uniquely identify particular users so that personalized data can be collected and processed. At this stage, we are awaiting ethics approval and we hope to continue our study on PLwD. We plan to recruit at least 10 PLwD in the study for a period of 2 months. This will provide a great opportunity to collect large amount of data and develop accurate predictive models for identifying agitation in PLwD.

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