Visualizing Effects of COVID-19 Social Isolation with Residential Activity Big Data Sensor Data

Anuradha Rajkumar
Systems and Computer Engineering,
Carleton University;
Ottawa, Canada
AnuradhaRajkumar@cmail.carleton.ca

Bruce Wallace
Systems and Computer Engineering,
Carleton University;
Bruyere Research Institute;
SAM^3 Innovation Hub; Ottawa, Canada
wally@sce.carleton.ca

Laura Ault
Bruyere Research Institute;
Ottawa, Canada
lault@bruyere.org

Julien Larivière-Chartier
Systems and Computer Engineering;
Carleton University;
Bruyere Research Institute;
Ottawa, Canada
JLariviereChartier@bruyere.org

Frank Knoefel
Bruyere Research Institute;
Faculty of Medicine, University of Ottawa;
Systems and Computer Engineering,
Carleton University;
Ottawa, Canada
fknoefel@bruyere.org

Rafik Goubran
Systems and Computer Engineering,
Carleton University;
Bruyere Research Institute;
Ottawa, Canada
goubran@sce.carleton.ca

Jeff Kaye
NIA-Layton Aging & Alzheimer's Disease Center;
Oregon Center for Aging & Technology (ORCATECH);
Portland, OR, USA
kaye@ohsu.edu

Neil Thomas
Bruyere Research Institute;
Faculty of Medicine, University of Ottawa;
Ottawa, Canada
nthomas@bruyere.org

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***Abstract*—The ability to understand and visualize big data sets is of increasing interest to caregivers and clinicians as ambient home sensing can provide massive amounts of data related to the activities of residents. However, this data is only useful if it can be effectively and simply visualized for review and analysis. This paper presents the visualization of longitudinal data sets from ambient well-being sensors deployed in 3 residences that have a spousal pair dyad where 1 resident has been diagnosed with Mild Cognitive Impairment or Dementia and the spousal partner is acting as a caregiver. The paper presents the differences in activity and behaviour that can be observed in the 3 residences by comparing two 30-day periods prior to and one 30-day period during COVID-19 social isolation precautions. The work shows the potential for this circle plot based visualization technique to summarize resident activity and also to convey external factors such as the variation in solar day that can itself influence behaviour.**

Keywords— big data visualization; ambient sensing; smart home technology; IoT; cloud processing.

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I. INTRODUCTION

Every year, as more members of the baby-boomer generation age, this leads to a concern of how the healthcare system can cope as care need increases. The fundamental challenge that older adults face as they age is changes in their health, resulting in decline in mobility, or cognitive impairment leading to conditions such as dementia. Many persons with dementia (PWD) and less severe cognitive decline, mild cognitive impairment (MCI), prefer to live in their own homes and receive care as needed from their family members. As the condition of a PWD advances it becomes more stressful for caregivers, as individuals may wander or even leave the house [1], [2]. In addition, the cognitively impaired aging population is also prone to falls [3] as they experience declines in mobility and balance over time. However, before these extreme or dangerous scenarios present themselves, they typically start with smaller behavioral changes. By recording and observing these changes, healthcare professionals and family members can take appropriate precautions.

It is very difficult to monitor these small behavioral changes during routine checkups or doctor's appointments, as patients visit annually or at best every few months. Patients may also forget to share information during their visits. Episodic clinical assessments and the patient's subjective reports may not fully capture aspects of day to day life that can impact health outcomes (e.g. true adherence to medications, physical activity levels) and could be enhanced with ambient sensing derived knowledge. A solution is to deploy pervasive sensing and computing systems [4]–[9] in homes of patients with cognitive disorders. By installing motion sensors in each room in the home, door contact sensors, and bed sensors, one can gain insights regarding behavioral patterns. Since these ambient monitoring sensors are not worn, they do not interfere with the daily living habits of the residents. The Collaborative Aging Research Using Technology (CART) initiative [10], which is the platform used in this work, allows for analysis work to be applied to a growing global set of homes leading to a common big data set for research.

Previous research has shown that PWD also commonly have sleep disorders and disturbed internal biological clocks which can lead to nighttime wandering, waking up at irregular times or having disturbed sleep [1], [11]. Not sleeping well overnight worsens the PWD's condition and this behavior can especially be taxing for caregivers as the need to constantly monitor the PWD [11]. By analyzing data from ambient sensors deployed around the home, changes in the sleep cycle of the PWD can be monitored. The sensors provide longitudinal data for the same individual so changes in behaviour can potentially be detected earlier than traditional methods. In addition, the caregiver can be alerted in case of any unusual or dangerous activity such as if the front door is opened overnight [1], [2].

By deploying sensors technology in multiple residences with individuals who have MCI, it is possible for researchers to compare daily behavioral patterns between groups of subjects living in similar smart home environments [12]. These comparisons can be between patients with cognitive impairments as well as comparisons to age-matched cognitively healthy persons. There are many benefits of collecting this behavioral knowledge, such as allowing clinicians to track any abnormalities in the activity of individuals as well as improving the overall health care database available to facilitate early diagnosis of other patients with similar symptoms.

In recent years, there has been a substantial amount of research related to in-home sensing. For instance, research using ambient sensors has been able to detect behaviour changes associated with MCI [13], allow self-management of early stage cognitive impairment [14], and use simple sensors to identify precursors to falls [15]. In-home sensing is an effective health assessment tool of functional status because the patient's inability to perform their routine tasks is associated with needing additional medical support and can provide indications for early detection of MCI [16], [17].

Over the past few years, there has been a rapid growth of the Internet of Things (IoT), and data acquisition and storage techniques [18]. Within a smart home, each of the sensors are now constantly relaying data which are being collected over months. Now, more than ever, it is crucial to extract valuable information to gain insights from these big data sets, especially data pertaining to medical information.

A major challenge with smart homes is finding an effective method of summarizing and visualizing the data. Extant visualizations of longitudinal data for ambient monitoring use a matrix model where multiple weeks of data are stacked on top of each other [19], [20]. It is evident that traditional visualization methods are unable to cope with the volume of data and advanced techniques are needed to view any trends or abnormalities present in these datasets, as they can provide key information that allows clinicians to make timely decisions. IoT is rapidly changing how we live, and at the same time generating massive amounts of data about our daily lives. It is important to have a robust visualization framework that can detect different events [21].

Researchers are required to find innovative ways to present data. For example, a recent study in bidirectional movement used charts with contour maps and multi-layer heat maps to efficiently analyze behaviors based on big movement data [16], [17], [22]. Furthermore, an additional layer of challenge is presented when visualizing many discrete events in a dataset over long timelines, as it is possible for the viewer to get overwhelmed with information or even miss critical data [23].

The primary goal of this paper is to present an effective visualization technique of big data pertaining to medical datasets using circle plots. This visualization technique is able to condense data from multiple weeks into a simple, yet powerful plot that allows the viewer to identify significant behavioral events or changes in patterns. This paper demonstrates the visualization of the residential activity for homes that have individuals with MCI, using big data sets of sensor information, to observe activity changes through multiple months including data from the months of the COVID-19 pandemic where social isolation orders were in effect.

The remainder of the paper is organized as follows. The next section presents methodology of data collection and analysis. Section III covers results obtained in this study and these findings will be discussed in Section IV. As a final point, this paper concludes with section V briefly summarizing the main findings and acknowledging future work of this research.

II. METHODS

A. Trial Design and Participants

This work reports on 3 dyads (6 participants) that are participating in the study from the Ottawa region. The study has ethics approval from the Bruyère Research Institute and Carleton University Research Ethics boards and all participants provided their informed consent. All 3 dyads joined the study prior to COVID-19 pandemic precautions causing a pause in the recruiting and installation of new systems within new residences. These participants continued to participate in the trial through the COVID-19 pandemic social isolation phases.

The 3 dyads are all male and female spousal pairs with all participants having a minimum of 12 years of formal education. Each dyad consists of an individual with cognitive impairment (MCI or early stage dementia) and their care partner. The average age of the caregivers is 62 and the person with cognitive impairment is 64. Two of the individuals with cognitive impairment are male and one is female.

B. Sensor System and Data Collection

The sensor system deployed in each of the houses is the CART platform [4]–[9] that includes a number of sensors placed throughout the participants home and in some cases wearable sensors. For this work, only the information from the room based motion sensors is used. These sensors are deployed within each of the living spaces of the home (kitchen, living room, bed rooms, dining room, bathrooms, etc.) using previously published protocols [9].

The motion sensor used is the NYCE Motion Sensor (part number NCZ-3041C4 from NYCE Sensors, Burnaby, BC, Canada). These sensors detect motion within a 90 degree cone from the sensor at a range of up to 5m. The sensors are connected to a Raspberry PI computer in the home using the ZigBee wireless protocol [9]. The computer captures events from the sensors and transmits the resulting events and associated time stamps to the project data center for post analysis over the Internet.

When a sensor detects motion, the message is sent to the Raspberry PI computer. Once the sensor detects no motion for 5 seconds, it will generate a no motion message to the computer. Should a sensor see continuous motion for an extended period of time, it does not issue subsequent motion events and similarly does not issue multiple no motion events.

Typical deployments within this trial will include up to 10 room level motion sensors and each of these sensors generates events on a continuous basis based on the activity in the residence. Within the trial, the system is deployed within the homes for a year resulting in an extensive big data set of asynchronous longitudinal time sample sequences.

C. Post Processing and Visualiztion

The longitudinal data captured from each of the homes is passed through post processing to develop a synchronous time sequence for each of the motion sensors. This work was performed on 5-minute intervals leading to each day being represented with 288 samples for each of the sensors. The algorithm for the conversion of the asynchronous sequence to a synchronous sequence is provided in algorithm in Figure 1.

```
for all 5 min intervals across study period
  if (motion reported in 5 min interval)
    set interval to motion occurred
  else if (no motion reported in 5 min interval)
    set interval to No motion
  else
    # case where there is no report in interval
    set interval to same a previous interval
  end
end
```

Fig. 1. Algorithm for processing asynchronous sensor data.

This algorithm reflects the behaviour of the sensors as they only report a change in state and hence an extended period of no reporting indicates that a motion/no motion state has not changed. This results in a 288 sample time sequence for each day in the study for each of the motion sensors deployed in their residence.

The data was further analyzed to see overall changes in behaviours that are indicated by changing levels of activity within the residence by counting the number of rooms with motion for each of the 5 minute periods.

In order to visualize this information, where there is a need to allow both the comparison of activity within the day and also between days, the data is presented in a radial presentation model where the first day is shown as the inner ring with each consecutive day on a larger ring with the last day as the outer ring. Each of the 5 minute periods is shown as a point on the ring with colours used to indicate the value or meaning.

Given that the overnight interval is of particular interest to allow focus on any circadian rhythm or night activity, the presentation uses a 24-hour clock starting from noon to noon the next day. The black vertical line on the plot indicates noon, which is at the bottom of the circle and midnight is at the top. The tool developed (Figure 2) includes the ability to adjust many visual parameters associated with the spacing between the rings, legend and size of the rings.

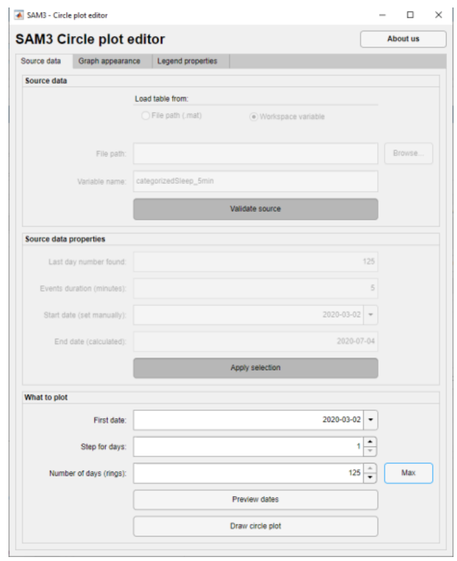

Fig. 2. User interface for the circle plot visualization tool created to allow for the visualization of longitudinal time series of data. The tool specifically allows for day to day patterns to be visualized.

Another key aspect that has been included in the tool is an overlay presentation of the solar day for the presented period. Our study, being located in Ottawa, Canada, has a significant variation in solar day between the summer and winter seasons. So a legend ring was added to show the day, night and sunrise/sunset times for the presented period with the sunset/sunrise times shown as the range that occurred across the presented days.

A MATLAB app was created for this work to allow the creation of the circle plot visualizations of the data and to allow user control of many aspects of the image. For instance, the user can select color scheme, circle properties, time zone, etc. The main user interface for the tool is shown in Figure 2. The visualization is based on polar coordinate scatter plots but the tool implements the needed conversions of the data including reversal, scaling and origin of the angle measure as positive angles in polar plots trace counter clockwise from the positive x axis.

III. Results

A. Techniques for data visualization

The access to daily activities of the residences is acquired using the motion sensors installed in three different residences from the study. The presented dataset selects sections of the data for comparison: during the late summer / early fall (before November 2019) for the initial period after the subject (or dyad) joined the trial, during late fall (after November 2019) and lastly during the COVID-19 social isolation period (after March 2020) in spring. This is done to observe whether the solar cycle, seasonal changes or external circumstances has an impact on the behavioral patterns of the residents.

The data for each sensor is processed according to Figure 1 and the number of rooms occupied are determined for a home by classifying the sensors activated during each of the events for a total of thirty consecutive days within each period. Once the number of rooms simultaneously used is classified, they are color coded and converted into circle plots.

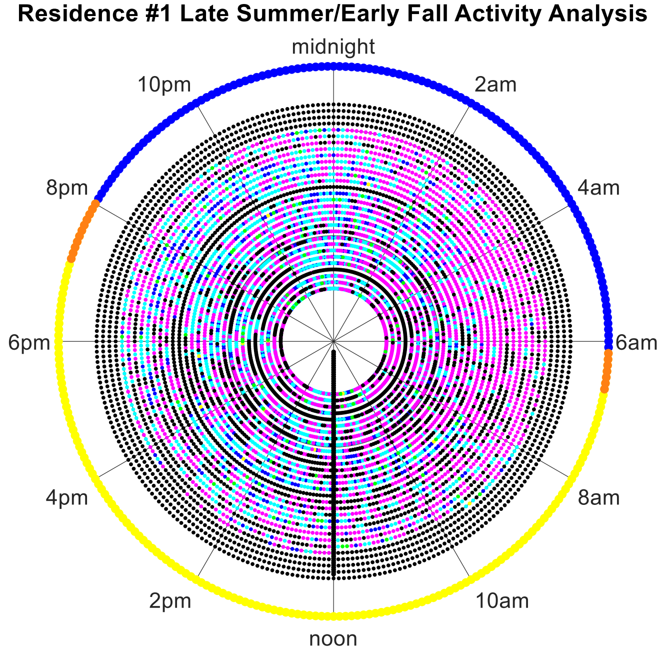

Fig. 3. Visualization of the residential activities for Residence #1 from 4 consecutive weeks during late summer / early fall 2019 showing the number of rooms with simulatenous activity. Legend: Black – 0/No motion; Magenta – 1; Cyan -2; Blue - 3; Green – 4; Yellow - 5; Orange – 6; Red – 7. Outer ring shows the solar cycle for the period with yellow showing day, blue indicates night and orange is sunrise/sunset range for the displayed days.

B. Data Analysis using Visualization tool

The circle plots presented in this section visualize of the daily activities of residents from the three different residences. The following circle plots depict home activity observed by the motion sensors showing number of rooms with simultaneous activity. For each residence, three different 30 day periods are visualized, firstly, the late summer / early fall where the sunrise and sunset times are around 6 am and 7 pm respectively, secondly, late fall where there are fewer hours of daylight and lastly, during COVID-19 social isolation where the day has extended again.

Figure 3 shows activity observed in the late summer / early fall period for Residence #1. There are a few unique features in this plot. Firstly, the black rings demonstrate that no motion sensors were activated meaning the residents were away for a few days towards the end of the period. Secondly, it can be seen that from 4 am to 8 am, only one sensor is activated on most days, suggesting that all residents are sharing the same space during that time. Secondly, the presence of only few yellow and green dots scattered around a ring, indicate multiple sensors are activated only when residents are moving from one room to another within the one event. Furthermore, this also provides an indication of the number of residents at a home during this time. During the overnight period the figure shows significant periods of time with zero or a single sensor trigger. This is expected at night when everyone is asleep. Small motions (roll-overs) or restlessness can result in the sensor being triggered.

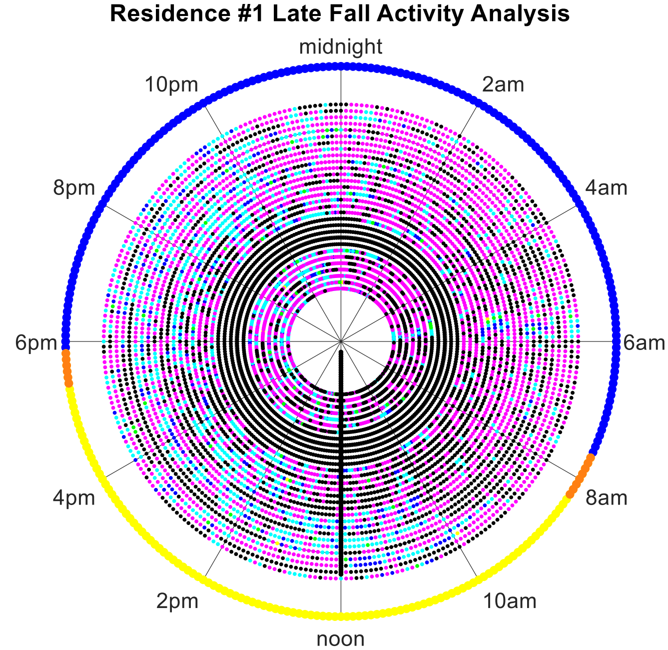

Fig. 4. Visualization of the residential activities for Residence #1 from 4 consecutive weeks during late fall 2019 showing the number of rooms with simlatenous activity. Refer to legend explained in Figure 3.

Figure 4 depicts the activities in late fall for Residence #1. The plot has more magenta overall as the number of rooms occupied seems to have decreased in comparison to Figure 3. From 10 pm to 10 am, the residents tend to stay in the same spaces as one another. Again, they were away for a few days within the period. It can also be assumed that the colder weather changes their activity levels.

Figure 5 shows data during COVID-19, there are larger amounts of activity during the day from 10 am to midnight and residents seem to be using multiple rooms simultaneously. There were 2 additional occupants during this period. There are more yellow dots than the previous plots, showing that even five different rooms were used simultaneously within a five-minute span. In addition, there are no black rings during this period, indicating the members did not leave their home for longer durations such as a day trip or overnight stays. During COVID-19, the residents tended to use many parts of their home frequently because outside activities were limited.

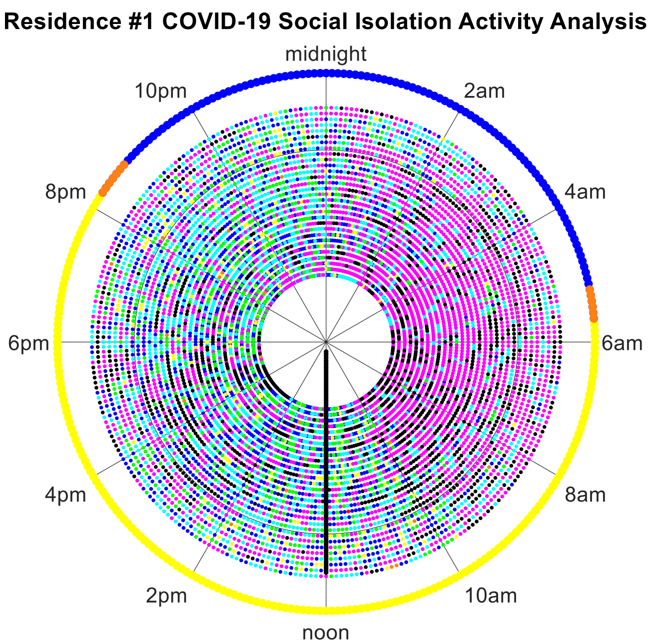

Fig. 5. Visualization of the residential activities for Residence #1 from 4 consecutive weeks during COVID-19 social isolation showing the number of rooms with simlatenous activity. Refer to legend explained in Figure 3.

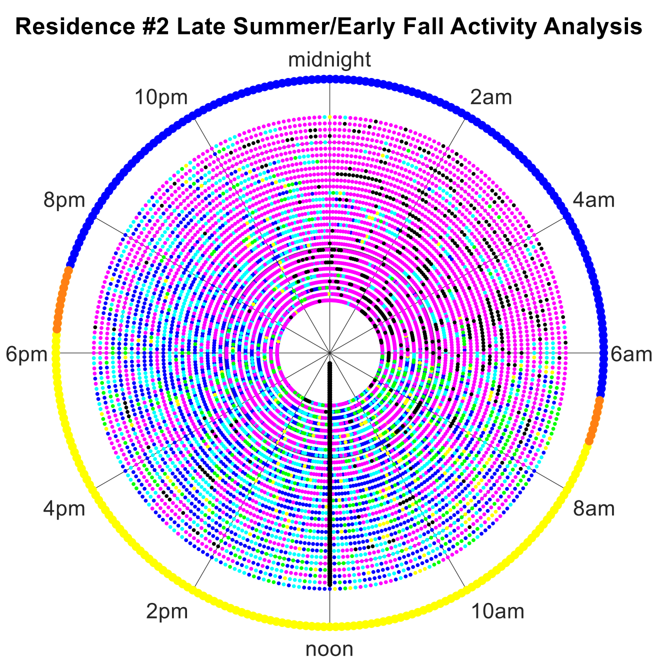

Fig. 6. Visualization of the residential activities for Residence #2 from 4 consecutive weeks during late summer / early fall 2019 showing the number of rooms with simlatenous activity. Refer to legend explained in Figure 3.

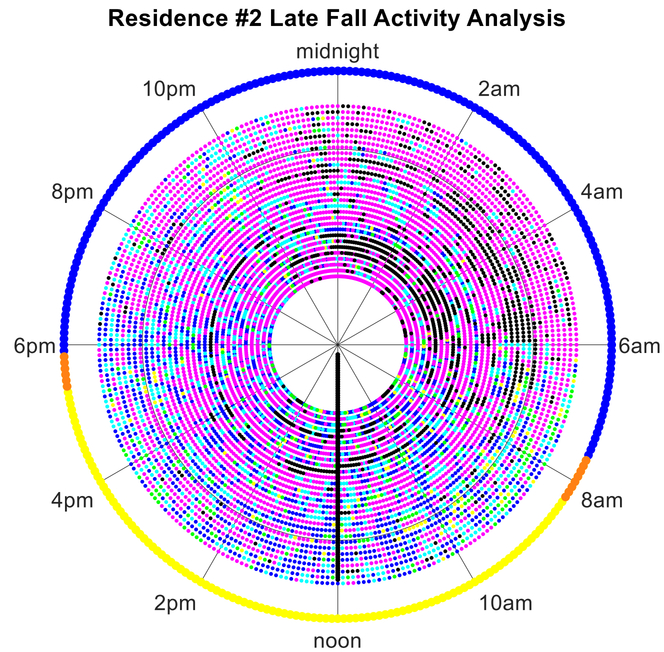

Fig. 7. Visualization of the residential activities for Residence #2 from 4 consecutive weeks during late fall 2019 showing the number of rooms with simlatenous activity. Refer to legend explained in Figure 3.

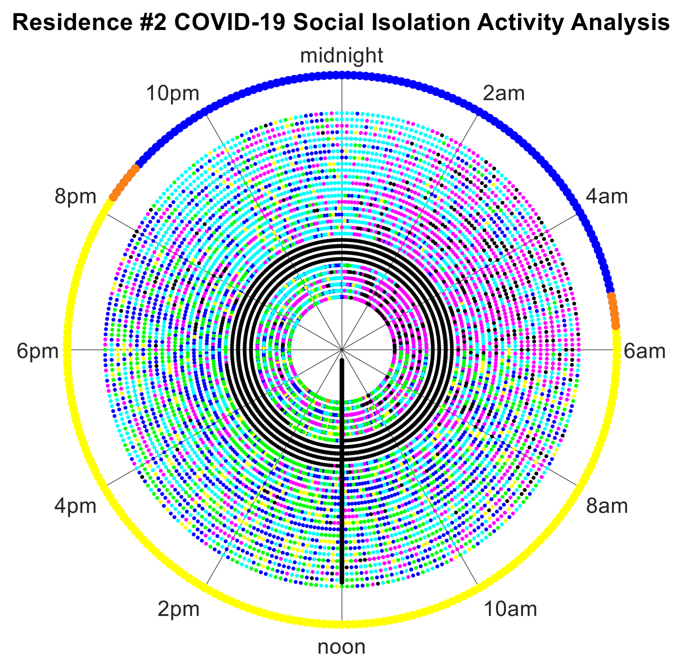

Fig. 8. Visualization of the residential activities for Residence #2 from 4 consecutive weeks during COVID-19 social isolation showing the number of rooms with simlatenous activity. Refer to legend explained in Figure 3.

Comparing all three plots of Residence #1, it can be seen that residents are generally active between 10 am to around midnight. There is a gradual change in habits observed when the weather transitions from the late summer / early fall to late fall. During COVID-19 social isolation, there was a higher amount of activity compared to Figures 3 and 4. Furthermore, black rings for absences in Figures 3 and 4 are not present in Figure 5 indicating the residents adopted their habits to conform with the travel restrictions imposed during the pandemic and instead they used all areas of their home more frequently than before.

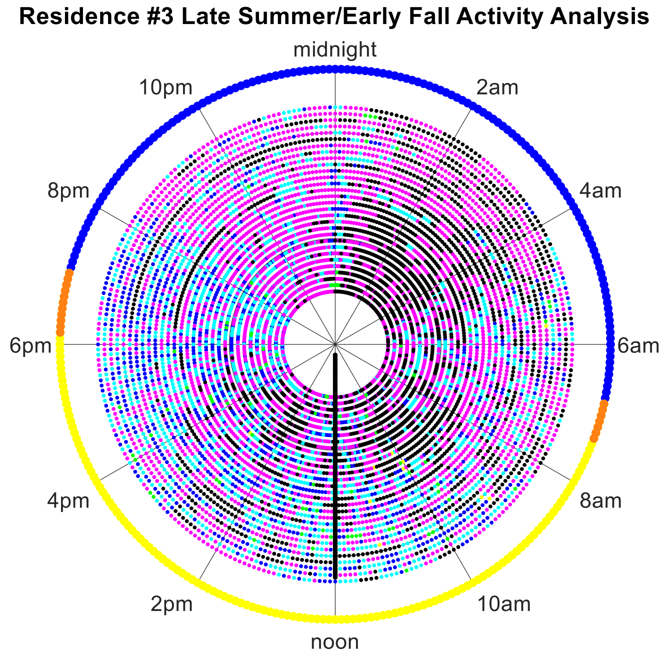

Fig. 9. Visualization of the residential activities for Residence #3 from 4 consecutive weeks during late summer / early fall 2019 showing the number of rooms with simlatenous activity. Refer to legend explained in Figure 3.

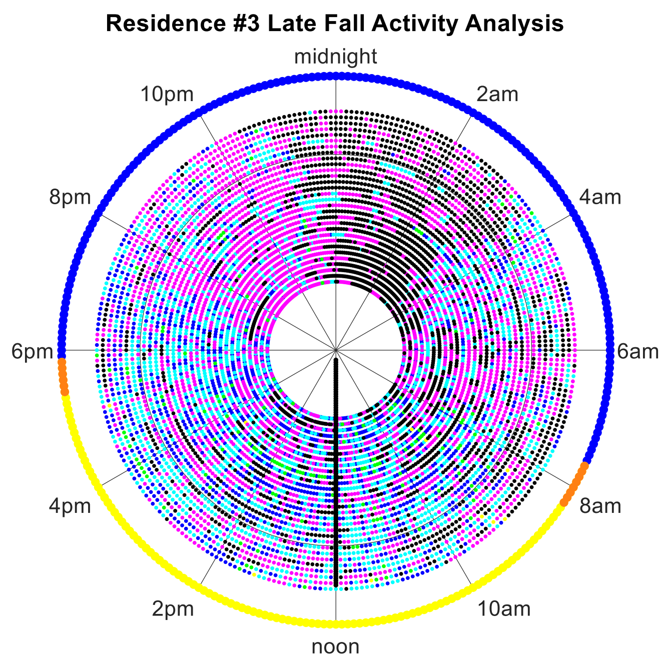

Fig. 10. Visualization of the residential activities for Residence #3 from 4 consecutive weeks during late fall 2019 showing the number of rooms with simlatenous activity. Refer to legend explained in Figure 3.

Figure 6 depicts activity observed in the late summer / early fall period for Residence #2. There are a few notable attributes in this plot. Firstly, the morning activity usually starts just after 6 am and the activities cease around 11 pm. From 6 am to noon, there are more prominent yellow dots, indicating that 5 different rooms are usually active during this time, so the residents must be active in different places of the home.

Figure 7 shows the activities in the late fall, and it can be seen that the activities of the home, have decreased in comparison to Figure 6. There is also more magenta in the plot overall indicating that the residents tend to share rooms, rather than using different areas of the home. Another interesting feature is the band of activity observed around 6pm, presumably the residents are cooking/eating supper consistently around that time.

Figure 8 is the data during COVID-19, this plot has the most amount of activity for Residence #2. There was 1 additional occupant at this residence during this period, which justifies the increase in activity levels observed. It can be seen that they are using multiple areas of the home simultaneously and are active throughout the day and night.

For Residence #2, it can be seen that Figure 8 has the most activity in comparison to Figures 6 and 7. During the COVID-19 period, this residence made use of many parts of their home consistently and also moved around their home throughout the day. Since they were unable to go out, they were more active indoors.

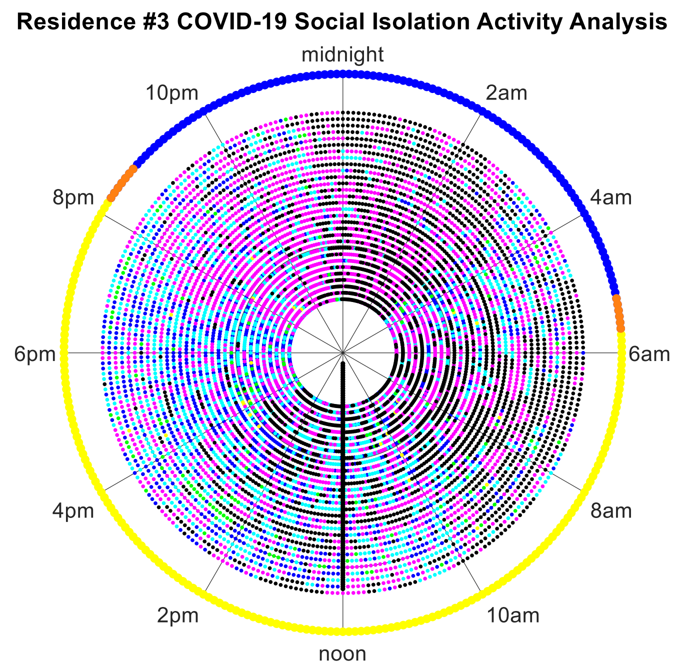

Fig. 11. Visualization of the residential activities for Residence #3 from 4 consecutive weeks during COVID-19 social isolation showing the number of rooms with simlatenous activity. Refer to legend explained in Figure 3.

Figure 9 is the activity plot for Residence #3 during September and October. The black dots between the midnight and 4 am period indicates there is little motion at that time, in other words, the residents are sleeping in bed. The activity in this residence decreases just after 8 pm. It suggests that these residents are early risers as there is activity through the day after

5 am. There are few yellow dots in the plot meaning they rarely use 5 rooms simultaneously. This home shows more times at night with no motion as the sensor is not detecting as much motion during the residents' sleep such as roll-overs or movements.

In Figure 10, one can observe that the residents begin their daily activity around 4 am in comparison to the later start (~5am) in Figure 9. The change from Daylight Savings Time occurred between these two periods. Similarly, there is a sharp contrast at 7 pm when all the activity seems to end. At night, they tend to stay in the same room (large sections of Magenta), while during the daytime, they are using many rooms simultaneously.

At Residence #3, there is a distinct amount of activity between 4 pm to 7 pm and in the early hours of the morning for all three plots. In Figure 11, although there is some activity in the early mornings, the next major activity can be observed after 10 am, while the other two plots have activities throughout the day.

These results indicate that there is a distinct activity pattern each residence adopted during May/June 2020 in response to the external circumstances that prevailed during COVID-19. Lastly, it is evident that each residence has a unique behavioral pattern, like a fingerprint, which can be used to distinguish the activities of the residents and differentiate them from others.

IV. Discussion

The visualization of longitudinal data sets of sensor data from an ambient smart home system has been presented in this work. The chosen format allows for the viewer to analyze behaviour patterns within days, but also allows for variations between days and between periods to be effectively visualized from a single image. The tool as presented allows a focus on the overnight periods by presenting each day as a noon to noon continuous circle (starting at the bottom of the circle). This can easily be adjusted to allow for the presentation of days on a midnight to midnight basis, based on the particular focus of analysis. The choice of noon to noon was made to allow for overnight periods to remain continuous to better assess nighttime and sleep behaviour.

The inclusion of the solar cycle within the image provides additional information to the viewer as the solar day can influence behaviors and it is especially useful when contrasting between periods with greatly differing solar days over the year such as more northern or southern locations. The tool also includes the ability to present information on a weekly or other basis as behaviour patterns for weekend days may differ from weekdays and the ability to quickly visualize these subsets can allow this analysis to occur.

Circle plots are more effective that the traditional matrix visualizations. Sprint et al. use density heat maps to show amount of time spent on a particular activity, where the x-axis represents one week, and y axis is the 24-hour clock [19]. There are a few different limitations to this visualization, namely large datasets cannot be represented easily, and one plot can only provide information about one particular activity.

Similarly, Robben et al. use a linear matrix representation, where x-axis indicates the hours of the day and the y-axis the days of the month [20]. The main shortcomings of this method is the lack of visual continuity at the two ends of the plot, and large data sets of data stacked will make it difficult to extract useful information easily. In contrast, circle plots can present multiple different activities for several weeks at once, they are more intuitive to understand as they are similar to clocks, and users can extract information readily while keeping track of the solar cycle.

By analyzing each event individually, researchers can gain in-depth information of activity patterns of the residents. For example, if multiple sensors in the hallway and the stairs are activated in a specific path, it can be said that a person is going from an area downstairs to upstairs. However, if there is activity in the kitchen downstairs and bedroom upstairs at the same time, one can conclude that two different members are simultaneously occupying different areas of the home.

The circle plots are a versatile tool that can be customized to support a wide variety of analyses. The data from the sensors can be sorted in many ways like day/time, sensor type or location, etc. This allows the researchers to specify days and rooms of interest. For example, one can visualize senior recovery before and after a surgery to observe improvements in mobility over several months. Furthermore, plots generated using the MATLAB app can be used for a specific sensor or group of sensors. In particular, one can visualize bedroom and bathroom activity of the individual with MCI over many consecutive weeks to gain insight about the individual's sleep activity, bathroom usage, time spent in bed, as well as motion within these rooms, etc. Furthermore, researchers can focus on certain times of day (ex. night-time) to monitor changes in sleep patterns over time.

Depending on the interest of the researcher, many comparisons can also be extracted from the circle plots. For instance, specific sensors can be selected in the algorithm to visualize those in detail. This is also beneficial for comparing data between residences. For example, the kitchen activity of all three residences can be analyzed to observe how change in seasons affects the daily routine of seniors. The circle plot is also effective in focusing on the time periods of interest, and certain changes in activity levels can easily be observed. In Figures 3 and 4, one can identify black rings, which indicates that the occupants were away from their home for consecutive days, so one can also observe effects such as desynchronises or jetlag after a trip.

Circle plots are a very effective and versatile tool to represent big data. One has the ability to investigate a single configurable interval (5-minutes for this work) as well as multiple days of data within the same plot. This plot comprehensively studies the activities of residents with which one can easily identify any changes in behavior and analyze whether any external circumstances (such as a pandemic) affect residents. In addition, these plots can be customized to limit or expand the activity observed from a single room (ex. Kitchen activity) to the entire residence. Using these circle plots, one can understand changes in behavioural patterns or sleep patterns over time, which can provide information on the health and wellbeing of the individuals in a residence.

Circle plots also helped understand the change in activity levels during COVID-19 social isolation. It was seen that as the circle extends outwards (weeks progressed), there was an increase in late night activity which extended past 1 am for Residences # 1 and # 2 as shown in Figures 5 and 8 respectively. Many inferences can be made from these observations. For example, the seniors were not as tired at night and this can help healthcare providers gain an understanding of the change in their circadian rhythm, physical activity levels and their mental health (in comparison to pre-COVID-19 time) as the activity outside their homes was minimal. Interestingly, Residence 2 shows the most drastic change before and during the pandemic as simultaneous activity can be observed all times of day except for between 2 am – 6 am. In contrast, for Residence # 3, activity levels before and during the pandemic stays relatively constant, proving that they were least affected by external changes in comparison to the other two residences. By observing how a pandemic affects seniors through circle plot visualization, health care professionals can better customize their care approaches.

The data presented for the three homes shows how the behaviours of residents differ between different seasons in the same home and between different homes. The differences in the activity levels for the each of the residences during the COVID-19 social isolation restrictions is qualitatively visible in Residence #1 and #2, while Residence #3 appears to have similar levels of activity.

V. Conclusion & Future Work

This work reports on a big data visualization technique and it allows for analysis of longitudinal data sets over extended periods of time so that they can be easily visualized and compared with important supporting information such as the solar day.

Visualization of data is a first step toward providing relevant summary information for clinicians and caregivers so that they can quickly understand behavioural changes that could be related to an illness or a decline in capability. Future work will explore the use of these visualization tools with analysis algorithms that identify specific activities of daily living such as food preparation, hygiene, night-time wandering as well as percentage of time spent in different locations of the home. Longer periods of time like consecutive months can also be visualized. A clear visualization of these behaviours will support care teams to be able to adjust and adapt care plans to better support the aging adult.

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