Trend Analysis in the Trajectory of the Dementia Patients

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***Abstract*—Studies of the navigational patterns of assisted living facility residents with dementia have resulted in many insights into the progression of dementia e.g. more tortuous navigation has been associated with declining mental capability. In this pilot investigation, we found minute changes in navigational features such as speed, path-efficiency, angle-turn and, ambulation-fraction were predictive of cognitive function. In this study, navigational data of 10 subjects living in an assisted living facility were collected daily over a period of one year using an Ultra-wideband real-time location system with an accuracy of 20cm at 1Hz, and compared with their cognitive status as measured by the Mini Mental State Exam. Two patients evidenced significant linear trends in angle-turn and path-efficiency with the maximum variability captured by angle-turn (14.7% and 11.7%). Both subjects were later found to have very low MMSE value (6 and 9 respectively).**

I. Introduction

The application of technology is not new in the health care industry [1]. But, with the increasing capability of the ubiquitous devices in terms of processing speed, better power management and ability to perform a complex computational task, it has generated keen interest in the usability of these devices. The increase has also been marked by the readiness of healthcare professional to adopt these devices for general and specific use [2]. Gone are the days when patients were reluctant to use such devices. Now more and more people are adopting these devices. Health devices such as activity tracker: Fitbit [3], smart-watch, etc. are becoming an integral part of one's life. Increasing use of these health devices has also transformed many aspects of clinical practices. Doctors can rely on the data provided by the patients. The data generated in this regards can be very crucial to come with personalized health care services which are considered as the holy grail in the medical care.

With the increasing proportion of elderly population and myriad of complication faced by them at the later stage [4], healthcare facilities are burdened with providing quality support and service. One of the major challenge faced by elderly population today is dementia. Dementia is the symptoms associated with the loss of the cognitive function of a person which results in various behavioural and psychological changes [5]. The symptoms common to dementia are behavioural, such as agitation and restlessness; searching or scanning behaviour, hovering or other stationary behaviour and pacing as in the back and forth motion if a person is under pressure, anxious or irritated.

Wandering is one of the very significant problem faced by dementia patients. It is a serious concern for family and professional care providers as well as for scientists, clinicians, and policy makers, because the behavior is associated with some of the gravest adverse outcomes in dementia care (e.g., accidents, falls, getting lost, and even death). A growing number of studies [6] reflect this concern focusing on the various aspects of this pervasive and intriguing behavior that include: (1) the nature of wanderingits descriptors, measurement, and natural history; (2) the outcomes of wandering such as getting lost and elopement; (3) wandering-related behaviors such as intrusion, shadowing, or exit seeking; and (4) techniques for wandering management and intervention.

Location-acquisition system provides a convenient way for tracking a persons' trajectory. The tracking device records trajectory as sequence of points where each data point represents location and time stamp information[7]. Wide varsities of tracking devices such as Global Positioning System (GPS) for the outdoor and Received Signal Strength (RSS) of the wireless devices, Radio-frequency identification (RFID) reader and Ultra Wide-Band (UWB) sensor in indoor scenarios are now available. With these tracking sensors becoming very inexpensive and integrated into most ubiquitous devices such as mobile phones and smart watches, a large amount of navigational data are now available for analysis. Our aim is to realize the full potential of these data to identify and extract the features of significance in the trajectory of the dementia patients.

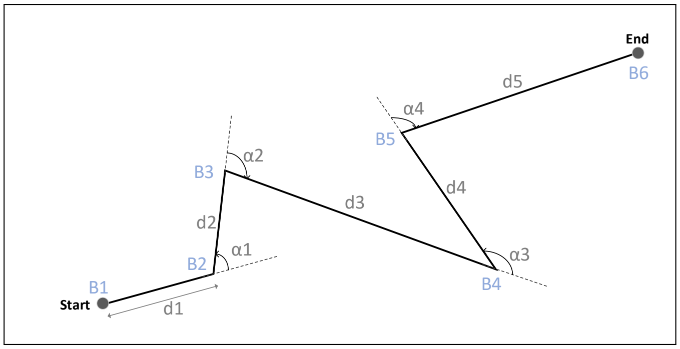

Fig. 1: A sample trajectory path

II. Motivation

In the course of dementia progression, a patient goes through a series of medical and clinical test. The doctor recommends some medication and is mostly interested in monitoring the effectiveness of the medication, which can decide on the future course of action and suggestive change in dosage or completely changing the medication style. It is very difficult to track observable changes and often it is reflected over a long-time duration, so it creates a challenge for a timely action plan. The statistical methods are more precise over observatory procedure. The development of such system will also allow the researcher to create day to day chart of parameters of wandering. It can also be used to identify a deviation in these parameters from normal trend and prescribe a test for the measure of cognitive impairment such as Mini Mental State Examination (MMSE) or Revised Algase Wandering Scale for Community Version (RAWS-CV) in the case of deviation. This will also harness the possibility of timely intervention and decision making by clinician and caretakers.

Visual inspection method has a limitation in calculating the descriptive parameters such as randomness, average speed, path-length etc. for the navigational. A computational method using the mathematical representation of the path is best suited to identify and quantify these features. We aim to calculate such features from navigation data and identify their importance from the analytic view. We will inspect such features in this paper and identify their strength and importance in distinguishing between two diagnostic groups. Along with above mentioned features we also find linear trends in the afore-mentioned features over a lengthy period which provides useful information concerning dementia progression.

III. Preliminary

A. Navigation in the Physical Layout

We define the navigational pattern as the spatio-temporal sequence in a geographical spaces, represented by a series of chronologically ordered points called burst of location as B_i, for example, $B_1 \rightarrow B_2 \rightarrow \ldots \rightarrow B_n$. Where each point represents spatial coordinates and time stamp of the point as $B = (x, y, t)$. Fig. 1 represents one such episode of navigation consisting of six burst of relocation from $B_1 \rightarrow B_6$.

Path-tortuosity is defined in terms of Fractal Dimension (Fractal D) is one of the descriptive parameter, which varies from 1 representing a straight path to a value of 2 for a completely random path. Fractal D captures the spatial variability in terms of the geometry of the path and is employed to study the change in the path direction. It has been identified as the significant indicator of the cognitive ability of a patient [11]. Fractal D has augmented earlier research findings by elucidating the severity and trajectory of cognitive deficit [10].

The categories of features that can be extracted from these sequential data are:

- Spatial
- Temporal
- Spatio-temporal
- Contextual

Examples of spatial features are path-tortuosity, angle turn per unit distance, mean episode-length, etc. Temporal features can be defined as: time of navigation for each day, the fractional distribution of time for wandering pattern. Spatio-temporal features such as: heat-map of the wandering pattern in the layout at different time of the day and contextual features can be identified as the intensity of different wandering pattern in context of external or internal stimuli. Spatio-temporal data contain the state information of the navigation, an event, or a position in space over a period of time. It poses many challenges in representing, processing, analysis and mining of such dataset due to the complex structure of spatio-temporal objects and the relationships among them in both spatial and temporal dimensions.

B. Descriptive Parameters in the Patients' Trajectory

Fig. 1 represents a sample episode. A subject transverses the path from start to end location and takes many turns on its way before reaching to it's destination. The parameters which can be used to uniquely characterize the patients' trajectory is *Burst*, it contains the spatio-temporal information about the path. All the features of the trajectory can be derived from this information. The sample path consists of six burst B_1 to B_6, d_1 to d_5 is the distance in meter between each pair of bursts and α_1 to α_5 are absolute angle in degree $[0, 180]$ irrespective of clockwise or anti-clockwise direction.

For the computational purpose we define:

$$\textit{Path-length} = \sum_{i=1}^{5} \mathbf{d_i}$$

$$\textit{Angle-turn} = \sum_{i=1}^{5} \alpha_\mathbf{i}$$

$$\textit{Time-taken} = \sum_{i=1}^{5} \mathbf{t_i}$$

The descriptive features are calculated for each subject using the formula as defined below:

$$\text{Path Efficiency } (\textit{path-eff}) = \frac{||\mathbf{B_1} - \mathbf{B_6}||}{\textit{Path-length}}$$

TABLE I: The Subject Demographics

		MMSE	
	No of Subjects	**Mean**	**SD**
Clinical Diagnosis of Dementia	6	13.33	7.6
No Dementia	5	19	9

$$\text{Angle turn per unit Distance } (\textit{angle-turn}) = \frac{\textit{Angle-turn}}{\textit{Path-length}}$$

$$\text{Average Speed of Ambulation } (\textit{speed-amb}) = \frac{\textit{Path- length}}{\textit{Time-taken}}$$

$$\text{Ambulation Fraction } (\textit{amb-frac}) = \frac{\textit{Total time in ambulation}}{\textit{Total time of recording}}$$

Along with above mentioned features we also calculate the fraction of time spent and distance traversed during wandering episode.

IV. Experiment

A. Subject and Layout

An archived indoor position-tracking data set recorded from 10 volunteers in an Assisted Living Facilities (ALF-s) in Tampa, Florida, provided the source of the archival information, which has been described in detail elsewhere [8]. Six subjects had received clinical diagnoses of dementia with MMSE scores averaging 13.33 (SD=7.6) while the four control subjects MMSE averaged 19 (SD=9), as shown in Table I. All were capable of independent movement with or without assistive devices. All participants wore a Ubisense [9] compact tag during daytime for approximately one year which transmitted data only when in motion. The tag was worn on wrist, which transmitted x, y, z-coordinate location information in meters with respect to a fixed origin in the corner of the room, coincident with a timestamp at 0.43 second intervals. The monitored space was approximately rectangular with dimension: (25.6m x 9.3m). Approximately 7.7 million observations were generated during this period.

B. The Proposed Algorithm

Fig. 2, shows the complete steps in the processing. It consists of three phases. In the *pre-processing* phase, data collected from UWB sensor contains sensor noise. We clean the data before starting a mining task. The data collected from sensor devices is passed through outlier detector. Heuristic-based outlier detection method has been used. One type of outliers removed are the points which lie outside the physical layout of the facility. The other type of outliers was identified based on the mean speed of navigation for the predecessor points for the fixed window length. If the speed is greater than the threshold value it is considered as a potential outlier. For the next *segmentation* phase, we partition the navigation into ambulation and sedentary (no movement by subject) episodes. One of the challenges associated with the identification of sedentary point is the sensor noise, which can have the false representation of movement. From the analysis of these data it has been found that usually, the noisy data vary significantly from its neighbour point in terms of speed and sharp turns made by adjacent points. These considerations have helped us in the removal of noise substantially. Sedentary episodes are

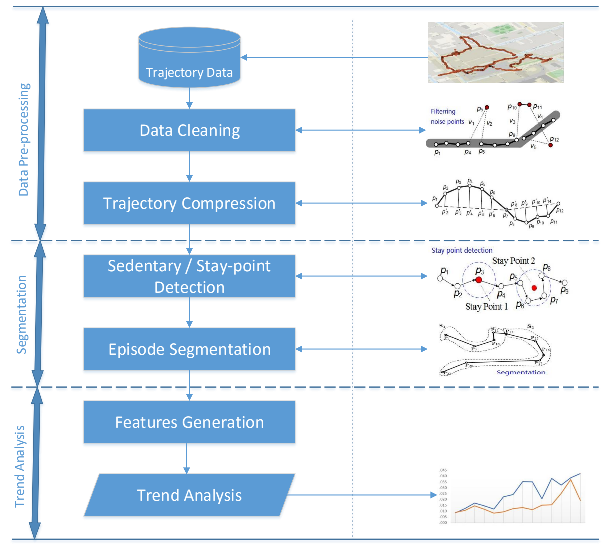

Fig. 2: The Complete Framework

important to identify *Point of Interest (POI)* in the physical layout. In the final phase of processing an episode is represented as burst (B_i) of relocation from *start* to the *end* of navigation period. Each episode represents the one complete trajectory path of a subject. Two episodes are separated by sedentary phase where subjects halts for substantial amount of time to perform some specific life event. All the features, which was discussed in the earlier section are calculated for the ambulation episodes and finally *trend-analysis* is done on these features using linear contrast analysis to find trend on the means of these parameters, grouped in months in order.

C. Ethical Considerations

The Institutional Review Board (IRB) of the University of South Florida approved the study protocol #106249 'Locomotor Variability in ALF Residents with A/D MCI, after determining it qualified for expedited review and constituted no more than minimal risk to human subjects.

V. Results and Discussion

We hypothesized that linear trends in the aforementioned features over a lengthy period might provide useful information concerning dementias progression. We employed linear contrast analysis to identify increasing and decreasing trends in the features and evaluated the change using one-way ANOVA to compare the trends within the two diagnostic groups. Two patients evidenced significant linear trends in *angle-turn* $(p < 0.001, F = 45.06, 34.68)$ and *path-eff* $(p < 0.001, F = 13.99, 12.98)$ with the maximum variability captured by *angle-turn* (14.7 and 11.7). The trend for both the subjects is shown in Fig. 3. Both subjects were later found to have very low MMSE value (6 and 9 respectively). The plot depicts the trend observed in two subjects (Subject-1 and Subject-2) over period of one year. A decreasing trend was observed in path efficiency *(path-eff)* for both the subjects and increasing trend was observed for angle turn per unit distance *(angle-turn)* parameter. Trend observed for ambulation fraction *(amb-fract)* and average speed *(speed-amb)* was not significant. In four

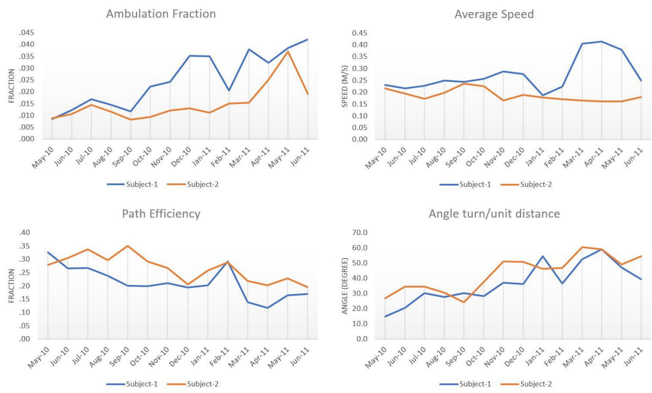

Fig. 3: Trend in features over a long period of time

other residents *angle-turn* consistently increased over the 1-year monitoring interval suggesting that their cognitive abilities may have correspondingly deteriorated over this interval.

The method discussed here is able to identify features that may reliably differentiate between older adults with diagnoses of dementia and those without. We have also devised the method for the quantification of movement variability from real-time data acquisition methods and how this information may be used to study cognitive decline. For example, those whose dementia worsens over time will likely evidence increasing *angle-turn* and decreasing *path-eff* over long durations.

Statistical and data analysis methods can also be applied to identify the hidden correlation and quantitative dependence between features of navigation and clinical measures of dementia such as MMSE and RAWS-CV. These methods can be reliably used in Assisted Living facility (ALF) and clinical setting to quantize the nature of wandering and can be used to monitor dementia progression. The initial study done of the 10 subjects real world data set shows the potential of such analysis. It will lead to more research into wandering because it is easier to analyse the data of dementia patients and thus will give us a complete picture.

VI. Conclusion

In this paper, we derived some simple features such as speed of navigation, efficiency in path traversed, amount of randomness in path measured as absolute deviation from the straight path and, fraction of ambulation episode in the navigation of the dementia patients. The framework consists of complete processing stage from data cleaning to features extraction to trend analysis. We were able to reliably identify trends in the data which were later confirmed with a low MMSE score of the subject. For the future study, we will look into the larger group of subjects with many more features for a comprehensive analysis on the strength and weakness of the method. We will also be analysing the trend observed in these features during different time of day.

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