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Research paper

Human Activity Monitoring and Recognition of Elderly People with Mild Cognitive Decline

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Abstract

Elderly people suffering from Dementia and Alzheimer meet with a progressive cognitive decline. This make them experience hardship in performing their everyday conventional activities especially in their outdoor navigation as they tend to forget landmarks even in familiar environments due to gradual decline in their memory and thinking abilities. Hence, disorientation and wandering become common issue. Providing assistive guidance to the elderly people in their outdoor mobility has become a challenging task for caretakers and family members as most of the elders prefer to live independently. Thus, there arises a need for efficient solutions that can monitor the elderly people movements and notify the caretakers in the event of disorientation or wandering being detected. The main objective of this paper is to propose one such solution which can support the provision of the best monitoring care in the outdoor navigation by mining through the elder's historical movement trajectories and detecting outliers if any, in the elder's current on-going trajectory. Further, the system tries to identify the underlying wandering pattern such as lapping, pacing or random in the outlier that could possibly help in analyzing the effect of medication in the treatment of dementia.

Keywords: *Alzheimer, Cognitive Decline, Dementia, Disorientation, Historical movement trajectories, Lapping, Pacing, Random wandering.*

1. Introduction

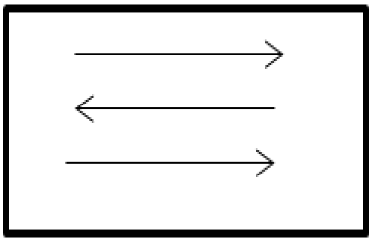
Dementia is a syndrome commonly associated with a gradual decline in thinking, perception, reasoning, communication and memory. Elderly people are the major victims of dementia which can become severe enough to reduce their ability to perform everyday routine activities. Dementia causes confusion and disruptions in elderly people's thinking and behaviour including attention and perception which could possibly result in disorientation and wandering in their mobility thereby forcing the elders to restrict their voluntary movements.

The most common form of dementia is Alzheimer's disease accounting 60 to 80 percent of all dementia cases. Similar to dementia, Alzheimer also imparts several problems such as forgetfulness of events, getting lost in unfamiliar and even in familiar environments, misplacing things and so on. [1].

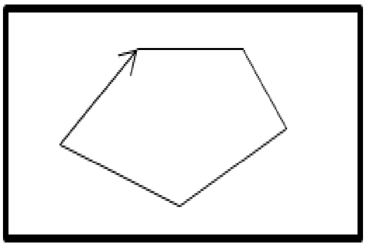
Disorientation is often termed as the condition of having lost of one's sense of direction. In daily life situations, it is quite possible for elderly people to perform their routine outdoor navigation by their own without any assistive guidance from their family members as most of the elders prefer to live their lives independently. This render a major concern for care takers as older adults with mild dementia face the risk of getting lost in unfamiliar locations and even in familiar locations for those with moderate cognitive decline.

Wandering may be coined as a complex behavior prevailing among dementia sufferers characterized with purposeless and repetitive navigation arising due to confusion and memory decline.

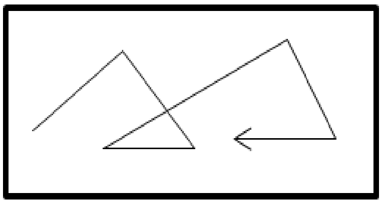
Older people with dementia may exhibit different types of wandering such as lapping, pacing and random wandering. According to Martino-Saltzman, Pacing may be explained as a repetitive back and forth movement between two locations (Figure 1.1). Lapping may be characterized as a repetitive travel circling a large area (Figure 1.2). Random wandering may be explained as visiting of places randomly with no pattern involved (Figure 1.3).



1) Pacing Pattern



2) Lapping Pattern



3) Random Wandering
Fig. 1: Wandering Patterns

Disorientation and wandering together provides a serious issue of concern for beloved persons as these behaviors are associated with adverse effects such as fall, injuries, elopement and sometimes death.
Hence, there arises a need for an assistive technology for constant monitoring and recognizing the presence of unusual behavioral patterns in the current outdoor mobility of the older people based on their past historical movement trajectories. The system shall then alert the caretakers as well as family members in case of emergency situation being recognized [14].
Further, an analysis on the type of wandering pattern [3] [11] [15] observed may help in better treatment of cognitive decline as researchers suggest that pacing is an indicator of agitation and anxiety while random pattern may indicate worsening of cognitive decline stating the necessity for immediate attention by the care takers.
Assistive technology is any aid that can provide people with practical solutions to everyday life activities such as monitoring, assisting mobility, communication etc., thereby improving the autonomy and independency of the vulnerable people of our society. The most common example for assistive devices in outdoor mobility is GPS (Global Positioning System) [12].
This paper aims in proposing an efficient solution that can be implemented in real-time to monitor and recognize the deviation if any, in the elder's on-going outdoor mobility based on the information received from GPS embedded in mobile phones of the elder. Further, the algorithm tries to identify the underlying wandering pattern and intimates the care taker.
The rest of the paper is organized as follows: Section II describes the literature survey on several wandering and disorientation detection algorithm. Section III gives the proposed detection method. The Experimental results are given in Section IV. Section V presents conclusion and future work.

2. Literature Review

Qiang Lin and Daqing Zhang et al. [14] proposed a novel approach of using historical GPS trajectories along with the current on-going trajectory of the elderly people suffering from mild cognitive to automatically detect disorientation or wandering pattern if present. They gave the idea of directly comparing the current movement with the history and alerting the caretaker as well as family members in the event of emergency being recognized. The authors suggested that the minimum threshold for categorizing a trajectory as deviating should be kept 3 since there is a possibility for the elder to visit back a place for the reason that he/she had forgotten things or interested in visiting again due to personal reasons.
Qiang Lin, Daqing Zhang and Xiaodi Huang et al. [9] proposed the idea of using sharp changes found in the on-going trajectory in detecting wandering patterns. Sharp changes were identified based on the vector angle computation of the current and previous points in the on-going trajectory. If the angle computed is 180° between the points, then the identified sharp change corresponds to Pacing. If the vector angle is between 90° and 180°, then the sharp change is categorized into lapping.

Lin Liao, Dieter Fox, and Henry Kautz et al. [2] proposed a method of simultaneously solving the task of identifying the significant locations and labelling the places from raw GPS data. For this, the authors used conditionally trained relational markov network and dynamically adding the graph during the interface. This model creates the complete interpretation of the logs of the user data which includes transportation as well as activities performed.
Jesse Hoey, Xiao Yang, Marek Grzes et al. [6] proposed using decision theoretic model to monitor the beliefs about the system states. By adopting POMDP (Partially Observable Markov Decision Process) interactions can be made independently with the environment. LaCasa (Location and Context-Aware Safety Assistant) is encoded based on the variable describing whether the person is at-home and another variable describing whether the elder is close to a known location. Known locations refer to the places where the elders are already familiar with landmarks in those places. Thus this model takes into account of all the information related to the context of the situation and models to detect the risky wandering of the elders and report to the care takers accordingly.

3. System Design

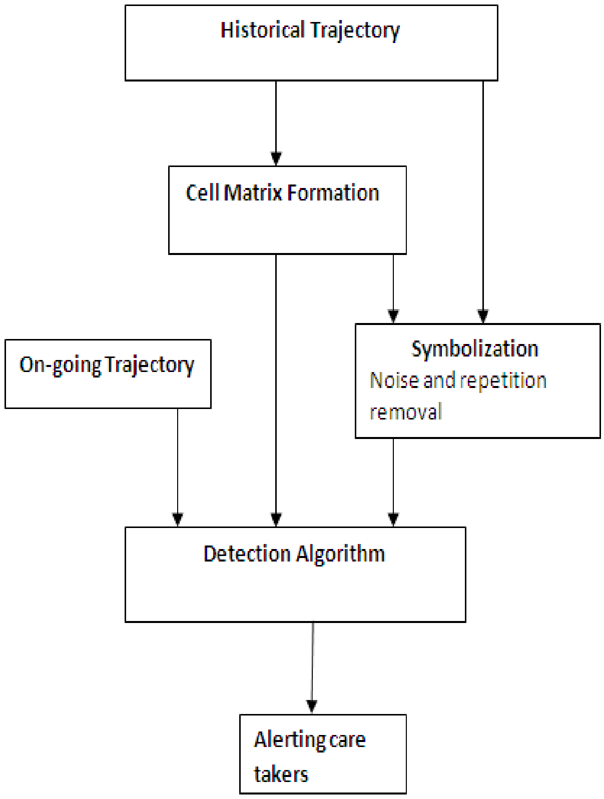


Fig. 2: Block diagram of the proposed system

3.1. Overview

GPS is a locating device that uses transmitter to send location information to the mobile phones via a network of telecommunication satellites. Now-a-days almost all mobile phones have a built-in GPS thereby reducing the burden of carrying additional device for surveillance [13]. Therefore, the proposed method uses GPS (Global Positioning System) for recording the trajectory path traversed by the individuals and storing the information obtained as historical movement trajectory.
Historical movement trajectory is a set consisting of

$T_{set} = \{t_1, t_2 \dots t_n\}$, where n is the total number of trajectories stored in the trajectory set and t_i corresponds to a particular trajectory i. Each trajectory consists of latitude and longitude points obtained from GPS corresponding to a particular location. Each trajectory contains a starting, ending and several intermediate locations.

The proposed method comprises of three main steps. Firstly, traverse the entire historical trajectory set to identify minimum, maximum latitude longitude coordinates to form a cell matrix with rows as latitude and columns as longitude. Secondly, form a symbolization set to transform the historical trajectory set into a sequence of traversed cells. Finally, the formed symbolization set and cell matrix along with the on-going trajectory points are given to the algorithm to detect any outliers in the on-going trajectory. The overall process is represented as block diagram in Figure 2.

3.2. Cell Matrix Formation

Given a historical trajectory set of an elder, the minimum, maximum latitude and longitude value in the entire set is identified to decompose this large area into a series of cells of equal size. This forms a cell matrix (Figure 2) with latitude and longitude as rows and columns respectively. Each cell size in the matrix is chosen to be 150 meters so that all the latitude longitude coordinates within the mentioned range falls onto the same cell thereby avoiding the illusion of considering two nearby latitude and longitude values as different locations.

$$\begin{pmatrix} C_{11} & \dots & \dots & \dots & \dots C_{1n} \\ \vdots & \vdots & \vdots & \vdots & \\ C_{m1} \dots & \dots & \dots & \dots & C_{mn} \end{pmatrix}$$

Fig. 3: Cell Matrix

Algorithm for Cell Matrix Formation

Input: Historical trajectory set, $T_{set} = \{t_1, t_2 \dots t_n\}$

Result: A Cell Matrix, $C_{[m][n]}$ where m is number of rows and n is the number of columns, where m represents the number of latitude points and n represent the number of longitude points and the cell matrix covers the entire region within min max latitude and longitude values.

Algorithm

1. Determine the minimum, maximum latitude longitude values from the entire history;
2. Calculate the number of rows and columns needed. //with each cell size refers to a fixed range;
3. Form a matrix named Cell Matrix, $C_{[m][n]}$ and initialize the cells in the matrix with value 0;
4. For each latitude and longitude value in the history
5. Determine corresponding i and j values in the Cell Matrix // i^{th} row and j^{th} column corresponds to a particular range of latitude and longitude value respectively
6. Set the C_{ij} to 1 //value 1 denotes the visited cells
7. End For

3.3. Symbolization Process

This process transforms the historical trajectory set into a sequence of traversed cells by mapping each GPS point in the trajectory set into the matching cell by searching cell matrix. Since GPS points are subject to high sampling rate, the historical trajectory set may contain repetitive and noisy points. Noise may arise due to surrounding conditions such as bad weather and tall buildings. Therefore, this process should detect and remove the repetitive and noisy points. For this purpose, the process compares the current GPS point to the previous point. If the current point lies in the same cell as previous, repetitive cell situation is identified and the corresponding point is discarded. If the point is not a repetitive one, then the distance between the current and previous point is computed to determine whether it is a noisy point. If the distance exceeds a threshold, the point is regarded as noisy and is it removed.

As human mobility is highly random and different people visit locations in different frequencies, it is necessary to store the frequency information along with the traversed sequence of locations. Thus there arises a need of a suitable data structure which efficiently stores and retrieves the traversed information. Therefore, the process uses hash table.

Algorithm for Symbolization Process

Input: Historical trajectory set, $T_{set} = \{t_1, t_2 \dots t_n\}$; formed Cell Matrix, $C_{[m][n]}$

Result: A Hash Table, $\text{Hash}_{[Key,Values]}$ with “Key” as visited locations obtained from Cell Matrix and “Values” representing the next location traversed from the current key location. Also, frequency on visiting the next location from the current key location is maintained.

Values = [{frequency, next location}, {frequency, next location}, {frequency, next location} ...]

Algorithm

1. For each latitude and longitude value in the history Do
2. Determine the validity of the value //check for noise and repetition
3. If invalid then discard the value End If
4. Else
5. Search $C_{[m][n]}$ to find i, j values
6. Insert into hash table, with “key” as (i*n)+j //”value” to this key is the next location traversed from the current key location with frequency as 1; each time the frequency is incremented by 1 while encountering same “value” for the key
7. End Else
8. End For

3.4. Deviation Detection Algorithm

This algorithm detects whether the on-going trajectory of the elder has any outlier and returns 1 on the account of outlier being detected. This algorithm has states for each counters representing disorientation, lapping, pacing and random wandering which are initially initialized to zeros. If any of the counter value reaches the threshold value, then the algorithm returns a non-zero value indicating the presence of outlier.

Threshold is kept as 3, because revisiting a place for the first time may possibly denote that the elder changes her mind, revisiting second time may have the reason that she forgot something. Similarly, the threshold for disorientation is set as 3 in order to have larger deviation from normality before declaring as disorientation i.e., allowing a deviation of about 300 m for the cell size of 150 m before being flagged as disorientation.

Algorithm for Detection Process

Inputs: Cell Matrix - $C_{[m][n]}$;

Symbolized set - Hash $_{[Key,Values]}$;

Elder's on-going trajectory, CurrTrajectory = {p_1, p_2 . . . p_n} where

p_i = {latitude, longitude} of the GPS co-ordinates

Result: Returns state of the label *l*, *l* can take any values among 0,1,2,3,4 where each value corresponds to normal, disorientation, pacing, lapping, and random pattern respectively

Algorithm

1. **Initialize** label *l* to value 0;

WorkingSetHash $_{[Key,Values]}$ to Hash $_{[Key,Values]}$;

Initialize L_D (disorientation label), L_L (Lapping label), L_P (Pacing label), L_R (random label) to 0 and VisitedList is set to null //an empty list

2. **For** each p_i in CurrTrajectory **do**
3. **Determine** the validity of the value
4. **If** invalid **then** discard the value **End If**
5. **Else**
6. **Search** $C_{[m][n]}$ to **find** i and j values for the corresponding p_i
7. VisitedList = VisitedList $\bigcup C_{ij}$
8. **If** C_{ij} == 0 **then** increment L_D by 1 and **set** VisitedList is set to null **End If**
9. **Else**
10. **Insert** into tempHash $_{[Key,Values]}$ with "key" as i*n+j value //"value" to this key is the is the next location traversed from the current key location with frequency as 1; each time the frequency is incremented by 1
11. **If** the key is found in WorkingSetHash $_{[Key,Values]}$ and **If** the frequency of [Key, Value] pair is less than or equals as that of frequency value in WorkingSetHash $_{[Key,Values]}$ **then**
12. **Obtain** all the values from the current key and Obtain their [Key, Value] pair from WorkingSetHash$_{[Key,Value]}$ and then **Set** WorkingSetHash $_{[Key,Values]}$ to newly obtained Key, Value pairs
13. **End If**
14. **Else**

//Case 1: Pacing

If VisitedList (end) == VisitedList (end-2), **then** increment L_P by 1; **End If**

Else If //Case 2: Lapping

Set flag=false

15. **Repeat Until** the flag == true or all values are processed in VisitedList

Find if VisitedList (end) == VisitedList (end-i) //where initially i= total length of VisitedList and each time decrement i by 1**, Set** flag = true and L_L by 1

16. **End Else If**
17. **Else //Case 3:** Random Wandering

Increment L_R by 1 **End Else**

18. **Set** VisitedList **= [**VisitedList **(**end-1), VisitedList (end)]
19. **Set** WorkingSetHash$_{[Key, Values]}$ to Hash $_{[Key, Values]}$
20. **End Else**
21. **If** either L_D, L_L, L_P, L_R equals to 3
22. **Update** *l* with 1 or 2 or 3 or 4 depending on the variable that got exceeded, **Return** *l*
23. **End For**
24. **Return** *l*

4. Results and Discussion

4.1. Evaluation Metrics and result

In the evaluation, an open dataset with more than 160 individuals' GPS traces released by Microsoft Research Asia [4] [5] is used. 10 individual's GPS traces each consisting of 30,000 records with attributes as latitude, longitude, time stamp, trajectory number collected at the rate of 2-5 second per meter is chosen as test datasets. The detection accuracy of the proposed algorithm is obtained by manually labeling the on-going trajectory. Confusion matrix is used as evaluation metrics and precision, recall and accuracy values are shown in Figure. 4 and Table 1.

Precision

Precision is a ratio of true positive tuples and all positive tuples in a dataset. Precision is given by,

Precision = TP / TP + FP (1)

a. Recall

Recall is a ratio of true positive tuples against positive and negative tuples. Recall is given by,

Recall = TP / TP + FN (2)

b. F-Measure

F –Measure is a mean of precision and recall.
It is given by,
F – Measure = 2 * ((precision * Recall) /

(Precision + Recall)) (3)

c. Accuracy

It is a ratio of positive tuples and negative tuples against all the tuples. It is given by,

Accuracy = TP + TN / TP + TN + FP + FN (4)

True Positive, **TP:** Correctly labels an outlier as an outlier
True Negative, **TN:** Correctly identifies normal trajectory as normal
False Positive, **FP**: Incorrectly identifies a normal trajectory as an outlier
False Negative, **FN**: Incorrectly identifies an outlier as normal

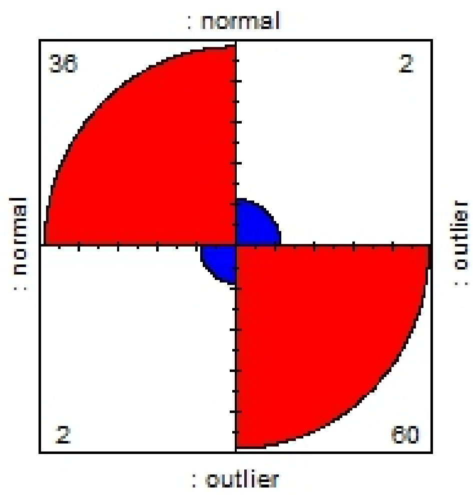


Fig. 4: Representation of Confusion Matrix

Table 1: Evaluation Metrics

	Precision	Recall	F measure	Accuracy
Normal	0.947	0.947	0.947	94
Outlier	0.967	0.967	0.967	96

5. Conclusion and Future Research

In this paper, an efficient algorithm which automatically detects outliers in the elderly people outdoor mobility with the help of their historical movement trajectory records has been proposed. Further, the algorithm tries to identify the underlying pattern in wandering which could serve as an indicator of effectiveness in clinical treatment of the elderly people suffering from dementia.

In future, providing navigational assistance can be combined with the detection algorithm which can improve and safeguard the quality of life of the elderly people preferring to live independently without any manual assistance.

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