A Unified Grid-based Wandering Pattern Detection Algorithm

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Abstract— **The aim of this study was to develop and validate a robust algorithm for indoor and outdoor wandering pattern detection and to analyse the relationship of these patterns to other clinical measures. Much of the previous work in this area addressed the measurement of wandering indoors or outdoors and to the best of our knowledge, there has not been a unified algorithm proposed which can deal with both scenarios. We present a novel grid-based layout representation strategy to identify the patterns, which is applicable to both indoor and outdoor scenarios. The algorithm is sufficiently robust to identify interleaving and hybrid patterns and performed with identification accuracy of 90% on a real-world sample.**

I. INTRODUCTION

Wandering is one of the first and foremost indicators of progressive dementia and it presents a serious concern for family members and caretakers. Wandering behaviour is associated with some of the gravest and adverse outcomes in dementia care [1], including falling, getting lost and elopement. Many attempts have been made to understand the nature of dementia wandering; one prevailing strategy has been the classification of navigation patterns based on the geographical region by Martino-Saltzman [2]. The author categorised the pattern into four basic types: Direct, Random, Lapping and Pacing. Out of these four patterns, Direct is considered the most efficient means of navigation and is not considered as wandering, while other three types are considered inefficient wandering patterns. Our study of wandering patterns is based on Martino-Saltzmans classification.

Wandering behaviour can occur both indoors and outdoors. When it occurs outdoors, dire consequences such as getting lost, falling or elopement may result. Attempts have been made to identify these patterns taking into consideration indoor or outdoor behavior [3], [5] but not both. This poses a serious problem in system design for the practical application of wandering detection. We propose a grid-based approach for detecting wandering which can efficiently handle both domains and facilitates data analysis of these patterns.

The major intellectual contributions of this work include the following:

First, we propose a hybrid algorithm for wandering detection in indoor and outdoor environments. We also illustrate the modeling of paths using grid based layout representation. We then apply our algorithm to a real-world dataset and report the performance of the algorithm in terms of precision, recall and accuracy. In our case of multi-class classification, precision is defined as the number of instances correctly predicted by algorithm out of all the predicted labels (e.g. for a given class X), and recall is defined as number of instances correctly captured for all instances that should have a label X. Accuracy measures total instances that were correctly predicted over all the class labels.

The rest of the paper is organized as follows: Section 2 of this paper presents some of the work done in wandering pattern detection and their shortcomings. Section 3 discusses our proposed approach and methodology. Section 4 evaluates the performance of proposed method and reports the results and finally Section 5 concludes the paper.

II. RELATED WORK

With the proliferation of new sensing, computing and communication devices, inexpensive technological solution have been developed to tackle the problems associated with wandering. iWander [4], is an Android based application which predicts wandering from the contextual information collected from mobile sensor and sends notification to the caretakers.

Focusing on outdoor wandering, Lin et al. [5] have proposed a data driven model for the detection of lapping and pacing based on the user's GPS traces, where the angular sum of the turning points has been used to identify lapping and pacing motions. N.K. Vuong et al. [6] developed a mobile phone application that used Wi-Fi and inertial sensors to identify wandering in an indoor environment. Although the Wi-Fi positioning was not very precise or reliable, it was very cost effective since the only hardware used was a mobile phone and Wi-Fi router. In a later paper N.K. Vuong et al. [3] carried out a systematic study of the automatic classification of wandering patterns. A set of machine learning and deterministic algorithms were used to compare the accuracy of the methods used. It was found that tree-based deterministic method was most suitable for real-time application.

The majority of the literature has focused on distinguishing wandering from the Direct pattern. However, some researchers have explored the characteristics of wandering based on the geographical pattern of the behavior. In a series of studies Kearns and colleagues [7], used Ultra-wideband positioning to study random characteristics in the paths of wandering PWD, ignoring Martino-Saltzman's distinctions among Direct, Lapping, Pacing and Random patterns and focusing instead on the amount of tortuosity

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in each path generated by each subject over time as they moved about conducting normal daily activities in their home assisted living facility (ALF) environment. A subjects path was defined by a period of at least 60 seconds of no movement followed by a movement phase that was followed by another 60 seconds of no movement. Path tortuosity was scaled from 1.0 (perfectly straight path) to 2.0 (Brownian motion) and daily means computed for each subject. Approximately 70% of the ALF residents had been clinically diagnosed with dementia. The investigators found path tortuosity was negatively (Pearsons r = -0.47) and significantly correlated with scores on a key clinical cognitive measure used to evaluate dementia, the Mini Mental State Exam (MMSE). These results support the notion that the amount of randomness in walking paths can be a useful tool for studying the relationships of movement variability and cognition in older adults. One of the drawbacks of Kearns et al.'s work is that their analytical framework was one-dimensional, and collapsed across all of the Martino-Saltzman categories believed by Algase and others to hold significance for the study of dementia. To date there has been very little work examining the fine-grained structure of these patterns.

III. WANDERING DETECTION ALGORITHM

In this section, we describe our grid-based wandering pattern detection algorithm. First, we discuss the key concepts which have been considered while designing the algorithm.

A. Grid Layout representation of World

With respect to our problem statement, grid layout provides the optimal way for physical landscape representation for indoor as well as outdoor navigation. It has high representation power since an obstacle can be easily represented as shaded region as shown in Fig. 1., path planning and path-length computation is also very fast. Noise reduction and path smoothing are inherently possible using this kind of representation. The size of the grid has to be carefully chosen as larger grid size may smooth out the fine patterns whereas smaller one may diminish the noise reduction property. Grid has also been traditionally used in a number of cases for path planning in robot navigation [8]. To the best of our knowledge, this is the first time it has been used in wandering pattern representation.

B. Wandering typology in a grid map representation

In this section, we define the typology with respect to grid layout representation. Traditionally the typology has been verbally defined [2] for ease of understanding, as usually human perception was the only means for labeling the observed typologies. However, with the torrent of navigation data arising from tracking PWD it has virtually become impossible to do this manually, and the process has been prone to human error. This has necessitated the requirement to redefine the typology such that mathematical modeling can be utilized to automatically label patterns and preserve the original definition statement.

A navigation pattern can be represented as shown in Fig. 1. Here, the Direct pattern can be defined as non-intersecting grid path from source to destination up to a certain level of optimality. The Random path can be non-intersecting as well as intersecting with a very low level of optimality. Lapping and Pacing are looping patterns with at least two consecutive loops, roughly overlapping each loop. The distinction between Lapping and Pacing can be made according to the area enclosed by the loop. Even if a pattern has a loop but does not conform to the requirement of the number of loops or overlapping conditions, it will be considered as a random pattern.

In our grid layout representation, navigation from one grid to the adjacent grid is allowed only through edge movement, no diagonal movement is permitted which minimizes much of the representational and computational overhead.

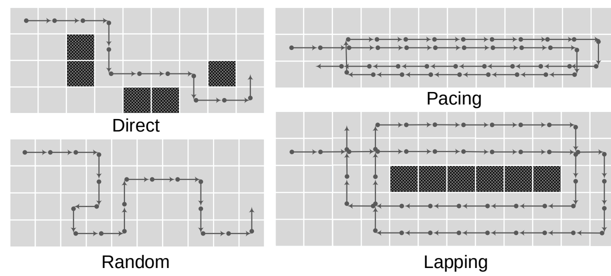


Fig. 1. Navigation pattern classification based on Martino-Saltzman

C. Episode Segmentation and representation

The navigation path consists of an alternating locomotion and non-locomotion phases as shown in Fig. 2.a. If there is no motion for more than 60 seconds it is considered as a non-locomotion phase. Each locomotion phase constitutes an episode in navigation as shown in Fig. 2.b. It consists of a burst of relocations which contain spatial and temporal information of an episode. Bursts are generally non-uniformly distributed in spatial and temporal co-ordinates. To simplify the navigation path we compute distance and angle between two consecutive bursts as shown in 2.c. and divide them into equal step-lengths as shown in Fig. 2.d. A *step-length* of 0.4m was found to give the best approximation of actual step-length for casual walking motion. In one step, navigation is only allowed to only one adjacent grid. This simplifies the statistical and features calculation step. An episode can be represented as:

$$E_i = \{B_1, B_2, ..., B_n\}$$

where, $i \in \{1, 2, ..., N\}$,
N: No. of episodes, and n: No. of bursts in an episode.
A burst can be represented as:

$$B_i = [x, y, timestamp]$$

B_i: i^{th} burst for the navigation path.

After discretization, an episode is divided into steps that can be represented as a vector of length *step-length*:

$$\mathbf{S_j} = step\text{-}length \cdot \hat{d}$$

where, $j \in \{1, 2, ..., m\}$, m is total steps and $\hat{d}$ is a unit vector in step direction. In the grid layout we can represent an episode as:

$$\mathbf{V_i} = \left[\mathbf{S_1}, \mathbf{S_2}, \ldots, \mathbf{S_m}\right]; \mathbf{Time_i} = \left[t_1, t_2, \ldots, t_m\right]$$

So, a uniquely episode in the grid layout system is represented by:

$$E_i = [\mathbf{Stcord_i}, \mathbf{V_i}, \mathbf{Time_i}]$$

where, $\mathbf{Stcord_i}$ is the start co-ordinate for an episode.

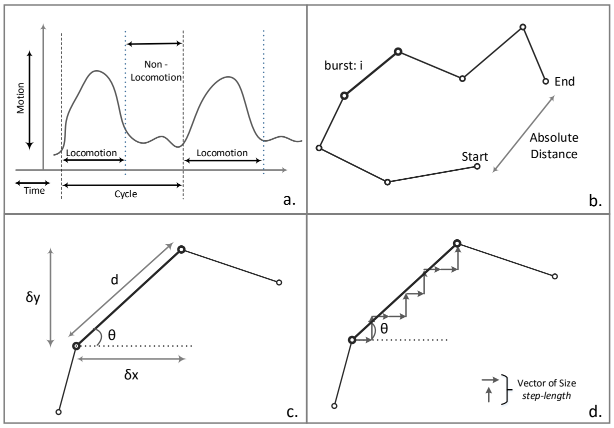


Fig. 2. Step Discretization method in episode plotting: a. Phases in navigation, b. A sample locomotion phase, c. Parameters for step discrization and d. Final disctretized steps

D. Pattern identification

From the analysis of an actual episode, it has been found that each episode can be very complex, and can be split into simpler looping/non-looping segment. Here a looping segment is defined as the largest continuous segment which intersect with itself whereas, a non-looping segment does not intersect. Algorithm 1 splits the episode into looping and non-looping segments.

Data: Sequence of step: **V**, Total number of step: m;
Result: Returns a linked-list which stores the index of looping path;
Initialize a matrix M of dimension $m \times m$ with zeros;
for i = *1 : m - 1* **do**
  for j = *i + 1 : m* **do**
    $M_{i,j} = |\sum_{k=i}^{j} \mathbf{S}_k|$;
    if $M_{i,j} == 0$ **then**
      There is loop between step i and j, store the index in a linked-list;
    else
      There is no loop, do nothing;
    end
  end
end

Algorithm 1: Finding loop-index in an episode

First, we process non-looping segment, which can be either random or direct. To find the optimal path from source to destination we use A* algorithm given by (1). Here, $layout$ represents the physical layout in grid world representation. Actual path length is scalar sum of steps as calculated from (2) and, Path efficiency η is calculated from (3). This is an important parameter that is used to arrive at the optimal labeling of the segment. It has been found in our case that $\eta_0 = 0.6$ gives the most logical and accurate result for the segment.

$$\text{Optimal Path Length} = A^{\star}(\mathbf{Stcord_i}, \mathbf{V_i}, layout) \quad (1)$$

$$\text{Actual Path Length} = \sum_{i=1}^{m} |\mathbf{S_i}| \quad (2)$$

$$\text{Path Efficiency} : \eta = \frac{\text{Optimal Path Length}}{\text{Actual Path Length}} \quad (3)$$

Next, Algorithm 1 detects any loop in an episode. Each loop is processed separately to find wandering patterns i.e. lapping, pacing or random. Lapping and pacing are repetitive in nature with at-least two loops. Distinction between lapping and pacing is done by finding the area enclosed within the loop. If the area is less than minimum area possible with the given segment length, it is considered as pacing, or else it is classed as lapping.

IV. EXPERIMENTAL EVALUATION

A. Data collection model

The indoor navigation data was gathered by a Ubisense, Inc. Ultra-wideband (UWB) radio research pack with wrist-worn transponders and 4 wall-mounted sensors. The layout used for data collection is approximately rectangular ($25.6m \times 9.3m$) living room in the ALF's located between subjects' private rooms and the dining area. Participants were 25 volunteers (19 females) from two ALF sites with mean age of 81 (SD = 9.5) years and MMSE score of 17.7 (SD = 8). Fourteen subjects were diagnosed with dementia and all were capable of independent movement with or without assistance devices. Subjects wore a tag during the daytime for 30 days. When in motion, tags transmitted x, y, and z coordinates in centimeters at 0.43 second intervals with a time-stamp. Approximately 1.4 million observations were generated for analysis. The source of the data has been described elsewhere [9]. 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.

The outdoor data collection method used HTC One M7 internal GPS receiver set to maximum accuracy and sampling rate of 1Hz. The GPS trace from the mobile device was recorded from one subject who was instructed to simulate various walking pattern in a pre-defined order, and then in a random order. The subject was instructed to delay by 60 seconds for consecutive patterns and later to execute the patterns in random order without a delay. Approximately 12,000 readings were recorded over 5 hours. The subject in this experiment had no symptoms of dementia.

The data collected from both scenarios was conditioned using the same set of processing steps with grid-size equal to 0.5m, so the application was blind to the data source; the same algorithm was applied to both the indoor and outdoor data.

B. Data preprocessing and reduction

Data preprocessing removed outliers and inconsistent data from the readings exceptionally high speeds identified as outliers were removed as noisy data. The noise may have been caused by reflected signals from buildings or metal structures in the ALF (for UWB).

Due to the high sampling rates of the devices and subject inactivity (e.g. halting or rarely moving), data collected, especially from UWB, were found to be very crowded. Not all points were required to plot an episode and processing speed was adversely affected by the large number of points. We used a mean shift clustering algorithm to reduce the number of points.

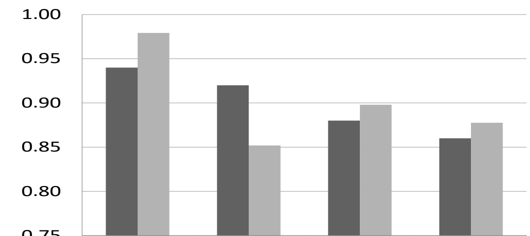
Episode segmentation based on the stopping criteria of 60 seconds performed very poorly in the real-life situation since even when there was no physical movement, sensors transmitted new trace information due to noise. We employed smoothing followed by filtration based on speed to segment navigation from non-navigation. This resulted in very good segmentation accuracy in both indoor and outdoor scenarios.

C. Evaluation and Result

A total of 823 episodes were extracted from the indoor navigation data, but most of these episodes were either direct or random and very few were identified as lapping or pacing. To tackle the class imbalance problem we selected equally sized classes of 25 episodes per class from the UWB data. This was matched with equal number of cases per class from the outdoor navigation data. So, we used 200 distinct episodes for testing of our proposed algorithm, 100 each from indoor and outdoor navigation. To ascertain the accuracy of identification, ground truth for the pattern was established through manual plotting and labeling of these episodes. All the episodes were processed in the same manner irrespective of originating in an indoor or outdoor environment.

Fig. 3. shows the recall and precision of our proposed algorithm. For the direct pattern, recall and precision was found to be very good and the algorithm was able to identify almost all the instances with very few misses. The random pattern also has a very high recall value, but the precision was lower because the other three patterns were occasionally misclassified as a random pattern. Lapping and pacing also performed well, but precision and recall was a bit lower, particularly because of the complex nature of these patterns. Some of lapping patterns were misclassified as pacing and vice-versa. Overall the algorithm was successful in identifying most of the patterns and had an accuracy of 90%. Noise from the sensors can adversely affect the identification accuracy, where direct, lapping and pacing episode may be misclassified as a random pattern.

It is difficult to do a fair comparison with other similar methods, the closest being an algorithm proposed by N. K. Vuong et al. [3], where they compared sensitivity, specificity, precision, recall and F1-measure for different deterministic and machine learning algorithms. But their dataset used room-to-room movement information of subjects, whereas we used coordinates of the physical layout, which is most generic form of data collected from sensors in indoor localization.



	Direct	Random	Lapping	Pacing
Recall	0.94	0.92	0.88	0.86
Precision	0.98	0.85	0.90	0.88

Fig. 3. Precision and recall of the proposed algorithm

V. CONCLUSIONS

In this paper, we have presented a novel approach for indoor/outdoor wandering pattern detection for dementia patients. Performance of the algorithms have been tested on a real world dataset, and it was found to be very accurate, efficient and reliable. The approach followed is also automatic and can be easily integrated into a ubiquitous device. Since it has high processing speed, all the steps are possible in real time. Automatic labeling of an episode is also possible with good accuracy.

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