

GPS-Based Outdoor Activity Pattern Recording and Analysis System

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Abstract—In this paper, a recording and analysis system is designed and developed for outdoor activity patterns characterization. Some mental problems of aging, especially the occurrence of dementia, are not easily noticed in early stage. In this study, the proposed system is employed for outdoor activity patterns analysis. From the pattern analysis, the abnormal activity which is different from the usual patterns may be differentiated and warned. The proposed system integrates the tablet PC and GPS to track and to detect the occurrence of abnormal condition off-line. In the beginning, the sequence of GPS data is segmented in time frame, and represented in vector form for data reduction. Some filtering technique is also applied for noise reduction.

I. INTRODUCTION

With the rapid advance of technological and medical development, the problem of population aging continues to deteriorate. According to the statistics of Taiwan's population till June 2012, the number of the elderly people takes up 10.98% of the whole population, with an aging index 73.91%. Issues of the long-term health care of the elderly become important. Many initial symptoms of aging and disease are now taken seriously and constantly brought into discussion. Dementia is a typical disease of elderly degradation.

Dementia is a brain-disease-syndrome that occurs primarily in old people. It is not a normal part of aging. Usually of a chronic or progressive nature, in which there is disturbance of multiple higher cortical functions. The symptoms of dementia may include the degradation of memory, thinking, orientation, comprehension, calculation, learning capacity, language, and judgment. But the most important is that the impairments of cognitive function are commonly accompanied, and occasionally preceded, by deterioration in emotional control, social behavior, or motivation. According to World Health Organization (WHO), dementia is a public health priority. There are 35.6 million people living with dementia, and a new case of dementia is diagnosed every 4 seconds. Since the caregivers of dementia patients often experience high strain, early diagnosis will help improve the quality of life of people with dementia and their families. In Taiwan, the number of elderly people with dementia accounts for 4.8% of the elderly population, and it grows at a breakneck speed. It is estimated

that in 2050, four out of a hundred people may suffer from dementia.

Currently, the clinical dementia rating (CDR) [1] is usually used to divide dementia into mild (early), moderate (medium), and severe (late) cognitive impairment. It is also found that some of the symptoms of mild-scale dementia is very easy to be ignored and confused with general forgetfulness (Table 1) [1].

Table 1: Clinical dementia rating

	Questionable	Mild
Memory	Consistent slight forgetfulness; partial recollection of events; "benign" forgetfulness	Moderate memory loss; more marked for recent events; defect interferes with everyday activities
Orientation	Fully oriented except for slight difficulty with time relationship	Moderate difficulty with time relationship; oriented to place of examination; may have geographic disorientation elsewhere
Judgment & Problem Solving	Slight impairment in solving problems, similarities and difference	Moderate difficulty in handling problem, similarities and differences; social judgment usually maintained

As mentioned above, mild cognitive impairment in patients with mild symptoms are often ignored. However, on the one hand, if these patients who suffer from early dementia go out, their safety problems may not be ensured, or become disoriented, etc. On the other hand, wandering is described as one of the most commonly occurring and potentially risky behavior in PWD (persons with dementia).

Therefore, in this paper a GPS[2] based recording and analysis system for outdoor activity patterns characterization is proposed and developed to detect the abnormal patterns. It is a two-stage detection: the first part is to detect the abnormal pattern (wandering behavior), and the other part is to dynamically compare the similarity of everyday path. Thus, the problem of case dependent may be alleviated.

II. METHODS

A. Wandering Behavior

Over the years, the term wandering has been used to describe a multitude of behaviors exhibited by individuals with cognitive impairment. Wandering is frequently defined as aimless movement [3], either manifested by wandering or by wheelchair motion. Although Hussian (1987) defined wander as apparent non-goal-directed ambulation or locomotion.

But one of the most classic patterns was proposed by Martino-Saltzman, et al [4]. They explored spatial

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movements in elderly nursing home residents with dementia and identified four patterns of independent traveling pattern.

- (1) Direct: a single straightforward path from one location to another,
- (2) Random: a continuous path with multiple points in no particular order,
- (3) Pacing: a repeating path back and forth between two points, and
- (4) Lapping: a repeating circular path involving at least three points.

The four patterns proposed by Martino-Saltzman are adopted in this study. Accordingly to the report of Chiu [5], the lapping and pacing are two commonly occurred patterns. Therefore, the following rules are applied to characterize the lapping and pacing.

- (a) A pacing pattern would include more than 2 (at least 3) consecutive to-and-fro movement; and
- (b) A lapping pattern would contain at least two circular routes involving at least 3 points.

B. Pattern similarity

To detect the wandering behavior, the normal behavior of activities should be reliable. In general, the normal activity patterns might be affected by some irresistible obstacles, and lead to the similar wandering patterns. Therefore, a similarity comparison algorithm is used to differentiate two patterns.

In 2004, Miskelly [6] only monitored elders whether left safe areas or not, but did not record their mobility behavior. Therefore, Miskelly [7] introduced a new method to track the mobility of elder using global position system (GPS) in 2005. However, he only recorded walked distances and times for elders, there were no records about place where elders went to.

In 2008, Shoval et al. [8] not only used GPS to recorded walked distances and time of elders but also recorded places where elders went to. Furthermore, in 2010, Shoval et al. [9] overcome weaknesses of time-space diary and analysis regarding mobility of people in general and elderly people. But due to small sample they cannot detect differences in mobility behavior.

1. Association rules -Apriori

This algorithm is based on the association rules proposed by Hsu (2012) [10]. The classic association rules [11], and Apriori algorithm [12] are modified and used to get the strength of the correlation of the two patterns. This algorithm is described in the following.

Step 1:

For each user, a starting point is selected, and the path coordinates including the latitude and longitude is then computed using the following equations:

$$\begin{aligned} Dx_i &= R * \cos^{-1}(\sin y_0 \sin y_i + \cos y_0 \cos y_i \cos(x_i - x_0)) \quad (1) \\ Dy_i &= R * \cos^{-1}(\sin x_0 \sin x_i + \cos x_0 \cos x_i \cos(y_0 - y_i)) \quad (2) \end{aligned}$$

Let the origin and position p_i ($i=1, 2, \dots, k$) are (x_0, y_0) and (x_i, y_i) , where x is longitude value and y is latitude value. Besides, the radius R of the earth is set to be 6371 km.

Step 2:

In this step, the relative coordinates with respect to the default starting point (i.e., the origin) may be obtained. Then, all coordinates are divided into several segments for later analysis. Firstly, let Dx_i and Dy_i rounding up, and the movement trip is shown as the path formed by the trace of cells $(CS_1, CS_2, \dots, CS_n)$ which a user is traversing while using his GPS. In this study, 120 seconds or 100 points is set to be the cutting threshold.

Step 3:

This step is to extract mobility from the segmented trajectory data. Mining approach starts by using Cell Sequences (CSs) to abstract personal trajectory data. Two consecutive CSs are combined to be Cell-Cell Sequence (CCS) in the form $\{(CS_0, CS_1) \dots (CS_{K-1}, CS_K)\}$, where $(i = 0, 1, \dots, k)$. For all CCSs, if there are two duplicated consecutive CCSs, then, the first one is eliminated [13].

Step 4:

If all the trajectories are originated from the same CCSs passing through the same and ending at the same CCSs, then all such trajectories are said to frequent pattern. But in reality, it is not so. The frequent CCSs of the trajectories is defined as the one met the user defined support threshold value as:

$$\text{sup}(CCS_j) = \frac{\text{Number of CCS}_j}{\text{Number of trip segments}} \quad (3)$$

Step 5:

In this step, the confidence of all mobility patterns is computed. Confidence is defined as the probability of seeing the CCS_j ($j = 1, 2, \dots, k$) under the condition that CS_i also contain the CS_{i+1} ($i = 0, 1, \dots, k$) as:

$$\text{con}(CCS_j) = \frac{\text{sup}(CCS_j)}{\text{sup}(CS_i)} = \frac{P(CCS_j)}{P(CS_i)} = P(CCS_j | CS_i) \quad (4)$$

Step 6:

In this step, the method proposed by Abraham et al. is used and the $SimR(n_j, d_j)$ (n : normal patterns; d : detect (anomaly)) is defined as:

$$SimR(n_j, d_j) = \frac{\text{No. of CCSs common to } n_i \& d_j}{\text{Total no. of CCSs in } n_i \& d_j} \quad (5)$$

From the spatial similarity measure, the common CCSs from two patterns may be found. The confidence of CCSs is set as x -coordinate and the support as y -coordinate.

Step 7:

The similarity of distance $SimD(nc_i, dc_j)$ is computed in this step using the equation as follows.

$$SimD(nc_i, dc_j) = SimR(n_j, d_j) \times \frac{\sum_{k=1}^1 |\text{Distance}_n[k] - \text{Distance}_d[k]|}{k} \quad (6)$$

where x denotes the value of confidence and y the value of support.

Step 8:

In this step, $SimS(nc_i, dc_j)$ representing the similarity of slope between n CCSs and d CCSs is obtained as:

$$SimS(nc_i, dc_j) = SimR(n_j, d_j) \times \left(1 - \frac{\left(\frac{\sum_{l=1}^k |Slope_n[l] - Slope_d[l]|}{180} \right)}{k} \right) \quad (7)$$

Step 9:

These $SimD(nc_i, dc_j)$ and $SimS(nc_i, dc_j)$ is combined using equation (8). In which, α is the smoothing factor, and $0 < \alpha < 1$.

$$SimT(nc_i, dc_j) = \alpha \times SimD(nc_i, dc_j) + (1 - \alpha) \times SimS(nc_i, dc_j) \quad (8)$$

Finally, if $SimT(nc_i, dc_j) < \text{threshold } \lambda_T$, then it is detected as an anomaly behavior.

Step 10:

After similarity analysis of patterns, the average of 3-5 days activity is obtained as the new normal reference pattern. Here, the threshold λ_T is set as 0.8.

2. Virtual vector

The algorithm basing on chain code for curve comparison used by Chen is employed in this study. A pattern is divided into a multi-set of vectors, and the degree of similarity between two patterns' vectors is then compared. This algorithm is described in the following:

Step 1:

In order to correct the errors of GPS recording data, the averaged error is first obtained. A circle with its radius denotes the error range. The centroid of the intersection of the two circles is found to be the accurate path. The corrected results are shown in Figs.1 and 2.

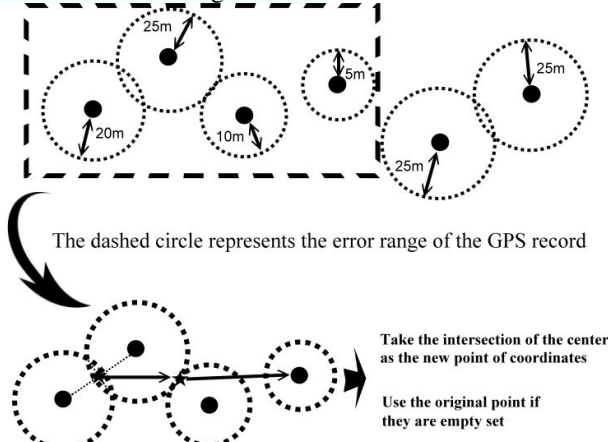


Figure 1: Smoothing function

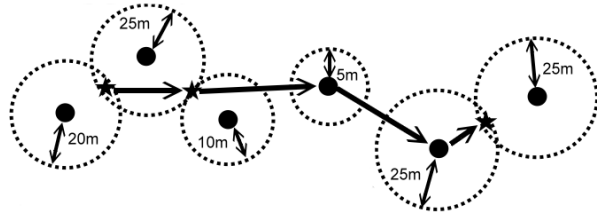


Figure 2: Smoothing results

Step 2

After Smoothing, the pattern's vector becomes clear to be distinguished. The pattern in accordance is represented as the vector and the slope. The formula is shown as follows:

- (1) Choose every three points $P_i(x_1, y_1)$, $P_{i+1}(x_2, y_2)$, $P_{i+2}(x_3, y_3)$ to get two vectors.

$$\vec{A} = \overrightarrow{P_i P_{i+1}} = ((x_i - x_{i+1}), (y_i - y_{i+1})) \quad (9)$$

$$\vec{B} = \overrightarrow{P_{i+1} P_{i+2}} = ((x_{i+1} - x_{i+2}), (y_{i+1} - y_{i+2})) \quad (10)$$

- (2) Take the dot product of two vectors to calculate the angle between the two vectors as:

$$\theta = \cos^{-1} \left(\frac{\vec{A} \cdot \vec{B}}{|\vec{A}| \times |\vec{B}|} \right) \quad (11)$$

Then, it is projected on a two-dimensional coordinate basing the degree occurrence. Every 30 degrees is divided and labeled as code as shown in Fig.2.

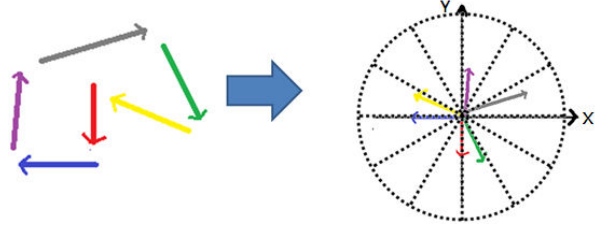


Figure 2: Vector projecting on the two-dimensional coordinate

From Fig.2, an example pattern is represented as a 12-dimensional virtual vector as (1,0,1,0,0,1,1,0,0,2,0,0).

Step 3:

In this step, the Euclidean distance is used to find two virtual vector's distance.

Thus, the average of these 30 patterns' virtual vector is then obtained for later error analysis. This average virtual vector is considered as the center point for pattern similarity measure. By this, the distances can help us to define to threshold between normal and abnormal.

III. EXPERIMENTAL RESULTS

Two algorithms mentioned above (A and B) are combined to develop the off-line pattern analysis system. Firstly, a GPS tracking System is implemented as shown in Fig. 3 to allow recording the data in a format as we need to do and to remove the noises.



Figure 3: GPS tracking System

This system is built on Motorola XOOM Tablet PC with Android operating system. The GPS in tablet is Broadcom BCM4750. The results of the accuracy test show an average of 7.06 m (stop) and 9.37m (walk). It is within an acceptable range in this study.

Secondly, the accuracy between two algorithms is compared. 2 sets of pattern with 30 patterns are the same patterns from my home to office. The same pattern is analyzed to the accuracy. The result of the comparison as Table 3:

Table 3: Results of methods comparison

	Apriori	Virtual Vector
Pattern1	100%	96%
Pattern2	100%	56%

According to this results, Apriori is better for comparing two patterns' similarity.

Therefore, the dynamic detection is applied to detect whether the behavioral patterns of the past few days are the same as those of today. The criteria for warning level are presented as following (Table 4):

Table 4: Warning Levels

	Pacing or Lapping	No Wandering
Not Similar	1	2
Similar	3	4

Alert level from high to low arrangement for 1→2→3→4.

For example, if we detect, first, a certain level of difference between a person's pattern and his past learning pattern, and then, his wandering behaviors such as pacing and lapping, by following the rule of Table 3, we can judge that he/she falls in the first level of alert (most needed to be paid attention to the warning), because this person has not only some unusual activity but also wandering behaviors.

IV. CONCLUSION

In this paper, a GPS based recording and analysis system is developed and applied to outdoor activity patterns characterization. This proposed system is suitable for people with different ages but having mental problems, especially the elderly with dementia. After outdoor activity pattern analysis, some early warning and rescuing procedures may then be activated. In addition, some symptoms of mental problems may also be revealed and recorded for later diagnosis by physician. The timely treatment will be very helpful in healthcare system.

Nonetheless, the detection accuracy of wandering behavior still needs further investigation. It may be due to the fact that the cases of wandering pattern acquired in this study are all simulated in a specific indoor environment. In practice, there are many unavoidable factors that may affect us when walking outdoors. In the future, we will work on the wandering behavior analysis using artificial intelligence such that a self-learning mechanism for individual activity pattern may be modeled.

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