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Multi-scale graph modeling and analysis of locomotion dynamics towards sensor-based dementia assessment

Changqing Cheng[a] and Hui Yang[b]

[a]Department of Systems Science and Industrial Engineering, State University of New York, Binghamton, NY, USA; [b]Complex Systems Monitoring, Modeling and Control Laboratory, The Pennsylvania State University, University Park, PA, USA

ABSTRACT

Dementia is a general neurodegenerative disorder beyond normal aging, which is not only overwhelming for the patients, but also negatively affects their caregivers and families. In the state of the art, paper-based survey methods such as the Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA) are widely used for the assessment of dementia conditions. However, these methods require lab visits or administration from nurses, physicians and examiners, and are limited in the ability to track temporal degradation (or daily variations) of dementia conditions. With rapid advances in sensing technology, there is growing interest in the development of new, sensor-based methods that provide more flexibility in dementia monitoring and require minimal interventions from practitioners. In this article, we propose a new, sensor-based method that estimates dementia conditions with daily locomotion data. The proposed methodology is evaluated and validated with both simulation and real-world case studies. Experimental results show the compelling predictive accuracy, with both true positive and true negative rates above 85%. This article shows that sensor-based methods have great potential for real-time monitoring of temporal variations of dementia conditions from daily gait locomotion dynamics.

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Dementia; graph model; locomotion dynamics; Mini-Mental State Examination; multi-scale analysis; paper-based survey; wireless sensing

1. Introduction

Dementia is a general term of brain dysfunction that embodies deterioration in cognitive function beyond the normal phenomena of aging (Montero-Odasso *et al.*, 2012). This progressive neurodegenerative disorder is overwhelming not only for the patients, but also negatively affects their caregivers, families and society. Globally, there are currently 47.5 million people suffering from dementia. The incidence is steadily escalating, and 7.7 million new cases are reported annually (World Health Organization, 2012). Dementia care is critical to improving the quality of life for patients and supporting their family members. The optimal delivery of dementia healthcare hinges on the detection of dementia conditions and monitoring of temporal degradation before the devastating symptoms unfold.

In the clinical practice, physicians need to go through the subjects' medical history, physical examination, laboratory tests, and brain imaging for the diagnosis of dementia. This process is time-consuming. Also, such expensive tests and sophisticated equipment are not always readily available to track the variations of dementia conditions in a finer time scale (e.g., daily). Thus, paper-based survey methods such as the Mini-Mental State Examination (MMSE) (Ismail *et al.*, 2010) and the recently developed Montreal Cognitive Assessment (MoCA) (Hollis *et al.*, 2015) are designed and developed for the assessment of dementia conditions. Nonetheless, both MMSE and MoCA methods also require lab visits or administration from nurses, physicians and examiners, and are limited in the ability to track temporal degradation (or daily variations) of dementia conditions.

Advanced sensing technologies such as wireless and wearable sensors provide an unprecedented opportunity to develop a new generation of sensor-based methods that provide more flexibility in dementia monitoring and require minimal intervention from practitioners. Note that there is a shortage of skilled neuropsychologists and behavioral neurologists for dementia care in rural areas. Also, human experts generally require medical appointments to see a patient, and are not available for daily tracking of the variations of dementia patients. Sensor-based automatic data collection and analysis is conducive to optimal health management and treatment of dementia subjects. Real-time monitoring is critical for the screening and detection of dementia in a timely fashion. As such, sensor-based methods are urgently needed to improve the quality of care for dementia-afflicted patients—a population that is anticipated to swell as Baby Boomers age and life expectancy edges up.

Non-invasive sensing in a home environment or assisted living facilities has shown promising potential for continuous monitoring of dementia conditions and cognitive changes. A smart home system was tailored to provide real-time

CONTACT Hui Yang huy25@psu.edu Complex Systems Monitoring, Modeling and Control Laboratory, The Pennsylvania State University, 310 Leonhard Building, University Park, 16802 PA, USA.

monitoring of dementia subjects (Amiribesheli and Bouchachia, 2017), aimed at improving the home care and life quality for human subjects with cognitive ailments. A computer game system was also designed by Campo *et al.* (2016) to evaluate cognitive performance on tasks involving significant brain resources. Carr *et al.* (2008) utilized eye tracking and pupil dilation for real-time monitoring and diagnosis for dementia illness, and further helped measure the effectiveness of behavioral interventions. In contrast to existing works, we investigated a novel, sensor-based approach that leverages daily locomotion data for continuous monitoring and prediction of dementia conditions. Note that the proposed approach of sensor-based locomotion analysis does not require significant investment, as in smart home systems, or higher-level expert interventions, as in computer gaming and eye-track systems, but can perform real-time monitoring of daily locomotion dynamics with cheaper accelerometer sensors.

Increasing clinical evidence (Verghese *et al.*, 2002; Karakostas *et al.*, 2012; Beauchet *et al.*, 2008) has shown that degradation of cognitive functions is often accompanied by gait and balance disorders. Consequently, a variety of gait- sensing technologies have been used to systematically characterize walking behaviors, as wireless sensors and wearable devices are increasingly available to monitor health conditions (Le *et al.*, 2013; Cheng *et al.*, 2016). Erratic walking patterns (e.g., repetitive, back-and-forth, and aimless walking) are shown to have strong correlations with declines in executive cognitive function (Borson *et al.*, 2013). Gait disorders help identify problems beyond normal aging. Compared to existing survey methods and other screening tools for dementia, including positron emission tomography (Harper *et al.*, 2014) and structural neuroimaging (Golrokh *et al.*, 2016), a gait sensing approach is much easier to implement at a lower cost, and is sensitive to cognitive decline (Karakostas *et al.*, 2012; Verghese *et al.*, 2007).

Therefore, we propose a new, sensor-based method for the estimation of dementia conditions with daily locomotion data in this article. Our contributions are as follows:

1. Wireless sensing enables automatic data collection and makes non-intrusive monitoring of dementia subjects much easier. We deploy a wireless sensing system to track locomotion dynamics of subjects in an assisted living facility (ALF) while they were performing daily routine tasks.
2. We develop a new, multi-scale graph method to characterize the gait patterns across different spatial scales extracted from an in-door locomotion tracking system, and further extract biomarkers (transition entropy, Laplacian eigen-energy, and eigen-entropy) sensitive to differentiate the normal and dementia-altered locomotion trajectories.

In the proposed approach, minimal interventions or lab visits are required (i.e., important for long-term study). Although this study is the first step to develop new, sensor-based methods and validate them with data from dementia patients, it is indispensable to achieving the final goal of sensor-based monitoring of temporal degradation of dementia conditions. The proposed methodology is evaluated and validated with both simulation and real-world case studies.

2. Research background

Gait is a complex motor behavior with a multitude of features, including gait speed, stride length and variability (Montero-Odasso *et al.*, 2012; Ghoussayni *et al.*, 2004). These features are often derived from video or wearable sensors, encompassing accelerometers, gyrosensors, and force/strain gauges, among others, attached to the subjects' body (e.g., foot and wrist). A number of researchers have endeavored to exploit such features for dementia detection. In those studies, video camera systems were first adopted for gait analysis in rehabilitation and medical treatment (Jahn *et al.*, 2010). In such settings, a multi-view motion capturing system in conjunction with a force measurement platform (e.g., ground-reaction) were adopted to characterize gait. However, this system often entails specialized locomotion labs, expensive and sophisticated video equipment, and lengthy setup process. This has defied the widespread application of video-based gait study. Alternatively, gait analysis using wearable sensors/devices has become a promising option.

Ambulatory subjects are often required to traverse a prescribed path with constraints imposed, such as walking speed, stride length, path complexity and dual tasking. In the dual tasking paradigm, the subjects are required to perform a secondary attention-demanding task while walking in a designated fashion (Hausdorff, 2005). As two simultaneously performed tasks compete for cortical brain resources, slower gait, elevated gait variability and instability are shown to be indicative of cognitive disorders (Beauchet *et al.*, 2008). Sheridan *et al.* (2003) showed that high gait variability is a sensitive marker of dysfunction in the frontal cortical control of walking for subjects with dementia, while low variability reflects efficient and fluent gait patterns. Hausdorff (2005) suggested that normal variability in stride time is usually below 3% among healthy adults, and confirmed the interplay between gait variability and cognitive dysfunction. Specifically, the degree of stride time variability is negatively correlated to the efficiency of executive function. Although statistical features can represent the gait variations, they often fail to disclose subtle and insidious alterations. To this end, fractal dynamics, or self-similarity structure of gait (Goldberger et al., 2002), has received considerable attention of late. For example, it is shown that the time fluctuation from stride to stride is not simply random noise. The long-range correlation of stride times has been utilized to identify abnormal gait (Hausdorff *et al.*, 1996, 2001; Kearns *et al.*, 2010).

Nonetheless, the subjects are required to perform walking tasks according to preset rules in most existing studies. This typically requires a lab visit or a significant amount of intervention from the investigators in the dual tasking paradigm. For some time, multiple visits to research labs have been required due to poor data acquisition. Recently, walkways

with embedded sensors have been adopted by several research groups to simplify the data collection process. For instance, Verghese and co-workers (2002, 2007) studied gait patterns collected from sensor-equipped walking mats and investigated neurologic abnormality of gait (e.g., unsteady, frontal and hemiparetic gait) to predict the likelihood for the subjects to develop non-Alzheimer's dementia. Similarly, Karakostas *et al.* (2012) deployed an instrumented walkway in the subjects' residences to maintain familiarity with the surroundings. Although no lab visit is needed, the guided gait study still requires necessary intervention from the investigators.

In contrast, recent advances in movement tracking technologies have offered a great opportunity to characterize unconstrained movements, both indoors and outdoors (Terrier and Schutz, 2003; Kearns *et al.*, 2016). Those gait sensors are usually inexpensive and applicable in non-laboratory scenarios. However, very little has been done to develop new, sensor-based methods that estimate dementia conditions with daily locomotion data and help track temporal degradation (or daily variations) of dementia conditions. In this article, we propose a sensor-based assessment system to record the subjects' locomotion in unconstrained voluntary movements to detect abnormal gait patterns. Compared to previous studies, the proposed approach has the advantage of obtaining data while the subjects are performing their daily routine tasks, and no lab visit or on-site intervention is required.

3. Research methodology

This article leverages wireless sensors to collect locomotion dynamics of dementia patients during their daily life in assisted living facilities (ALF). Then, we develop a multi-scale graph model of daily locomotion data at different spatial resolutions. Three biomarkers are extracted to represent the pattern variations in locomotion dynamics, which are then used to differentiate normal and dementia-altered locomotion trajectories.

3.1. Wireless sensing

This study utilizes a Ubisense ultra wideband radio system for locomotion tracking, which consists of waist-worn transponders and four wall-mounted receivers installed at each corner of the living space. Figure 1 shows the floor plan of an approximately rectangular area, with the dimension of 25.6 m $\times$ 9.3 m. The monitored area depicted here represents the common space for dining and daily activities in the ALF. When the subject is in motion, the transponders transmit the location (x, y, z) relative to the origin at the lower left receiver every 0.43 seconds to four Ubisense receivers (i.e., large blue/dark dots in Fig. 1). The footstep trajectory of a subject on a certain day is also shown in Fig. 1.

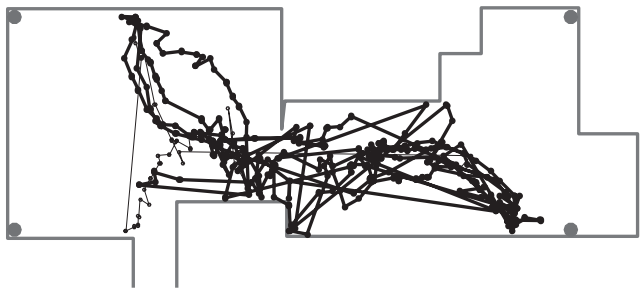

Figure 1. Floor plan of the common place in the ALF and a typical subject's footstep trajectory on a certain day. The black-line trajectory represents the locomotion path of a subject. The large blue dots are four Ubisense receivers.

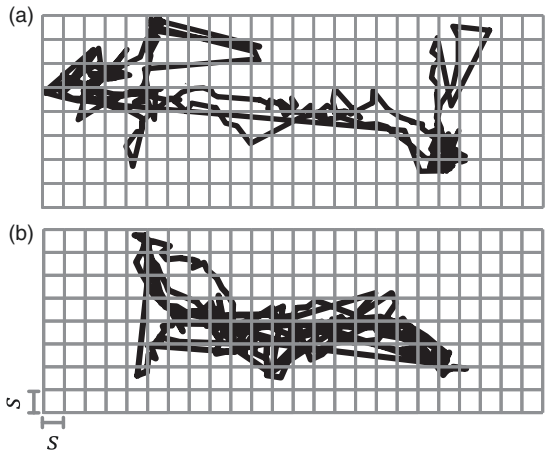

Figure 2. Schematic diagram of the locomotion trajectory for (a) normal and (b) dementia-afflicted subjects from one-day data collection: the blocks represent the spatial neighborhood. s is the block size.

3.2. Graph modeling

As shown in Fig. 2, we propose to divide the common space into an array of blocks of equal size s for studying how the subject moves in the space. In this way, the footstep trajectories can be modeled as a random walk on a graph, where each vertex characterizes a small neighborhood of the physical location; i.e., the block shown. The graph modeling approach helps investigate the stochastic transitions from one block to other blocks, and further characterizes the variations in gait locomotion dynamics. Figures 2 (a) and (b) show the daily locomotion data of a normal subject and one identified with dementia, respectively.

As the subject moves in the common space, a weighted and directed graph $G = (V, E, W)$ is constructed (see Fig. 3), where $V = \{v_1, v_2, \ldots, v_m\}$ is the set of vertices, the cardinality $V = m$, $E = V \times V$ is the edge set of ordered pairs of nodes, and (v_i, v_j) indicates the directed motion from vertex i to j. The weight W_{ij} is defined as the number of traverses from vertex i to j. As shown in Fig. 3, constructed from Fig. 2, the magenta/light dot represents the vertex, and the arrow indicates the direction of the motion. As only a subset of the blocks will be visited by one subject (see Fig. 2), those never-occupied blocks become isolated (inactive) vertices in the graph. Therefore, only those active vertices are represented in Fig. 3. Further, we utilize a self-organizing network approach (Liu and Yang, 2017; Yang and Liu, 2013) to optimize the layout of the vertices. The

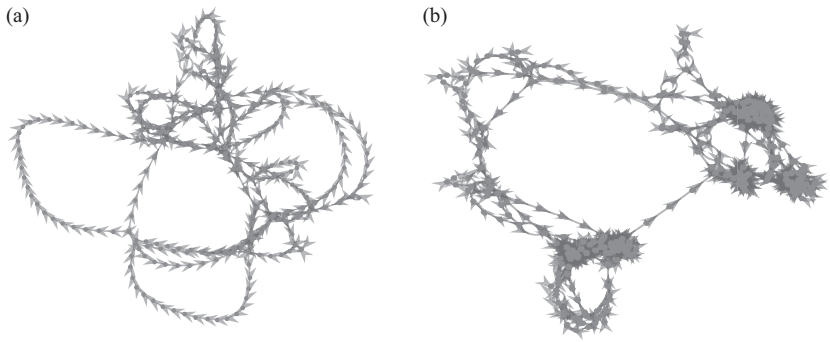

Figure 3. Self-organized graph representation of locomotion trajectory for the (a) normal and (b) dementia-afflicted subjects from one-day data collection (i.e., corresponding to the subjects in Fig. 2 (a) and (b)): the magenta/light dot represents the graph vertex, and the traverse direction is indicated by the blue/dark arrow.

block size is defined in such a way that the problems of spurious vertex visit and long-time trap in a vertex are mitigated. The multi-scale effects (i.e., different block sizes) are further investigated in details in Section 5.

As shown in Figs. 3 (a) and (b), graph representations of one-day gait for normal and dementia-afflicted subjects show distinct patterns. The dementia subject tends to revisit some vertices more frequently. As a result, the paths (traverse along the vertices) are more intertwined. This is consistent with wandering behaviors, the most pronounced syndrome of dementia that typically encompasses repetitive and disoriented locomotion patterns, such as revisiting certain locations more frequently and back-and-forth movement between several physical locations (Hausdorff *et al.*, 2001). In contrast, the normal subject tends to have more independent (e.g., paths are not heavily intertwined) and aimed paths. Such variations of path patterns are helpful for the estimation of dementia conditions.

3.3. Feature extraction

We extracted three biomarkers from each locomotive graph to quantify the underlying patterns.

Transition entropy H_T characterizes the spread out of a graph along the edges. According to the formulation of Shannon entropy, the transition entropy is defined as

$$H_T = -\sum_{j=1}^{m} p_j \log p_j. \tag{1}$$

where $p_j = \frac{W_j}{\sum_{j\in V} W_j}$ is the relative frequency of traverses to vertex j, $m = V$ is the total number of active vertices, and $W_j = \sum_{(i,j)\in E} W_{ij}$ represents the total frequency of directed edges to vertex j in graph G. Thus, H_T delineates how the movement is concentrated or clustered on a few vertices. That said, small H_T indicates repetitive movements visiting several spatial locations more frequently. In contrast, normal subjects tend to have an aimed locomotion path, resulting in approximately equal probability in spatial transitions and large H_T. Note that it is important to avoid sparse transitions with large number of vertices (i.e., blocks with small s) and the issues of artificially suppressed transitions with scant vertices (i.e., blocks with large s). In this investigation, we conducted a series of experiments on different block sizes $s \in [0.5,\ 2]$ to choose the optimal spatial resolution for H_T.

On the other hand, disordered and disoriented locomotion patterns (back-and-forth movement) are more concerned with small block size. Therefore, we studied the weighted and directed graph $G = (V,\ E,\ W)$ in a much finer spatial scale $s \in [0.2,\ 0.5]$, and the degree matrix is given as

$$D = \text{diag}\ (W_1,\ W_2,\ W_3, \ldots,\ W_m) \tag{2}$$

Similar to the undirected graph, we define the Laplacian matrix for G as $L = D - W$. The graph *Laplacian eigen-energy* is then defined as

$$E_L = \sum_{i=1}^{m} \lambda_i^2 / m \tag{3}$$

where λ_i's are the eigenvalues of the Laplacian matrix L. We further denote the normalized eigenvalues as $\rho_i = \lambda_i^2 / \sum_{i=1}^{m} \lambda_i^2$, so that the *Laplacian eigen-entropy* is depicted as

$$H_E = -\sum_{j=1}^{m} \rho_j \log \rho_j \tag{4}$$

Intuitively, the back-and-forth movement renders certain blocks more frequently revisited, resulting in a few vertices in graph G with high importance or centrality, corresponding to large Laplacian eigenvalues (Qi et al., 2012). Furthermore, the uneven distribution of those eigenvalues tends to suppress the Laplacian eigen-entropy H_E. Notably, the transition entropy H_T has a larger variance at a small block size, because there are too many vertices and only a sparse set of edges connecting them for the estimation of transition probability. That is also the reason why we studied those features at different scales, and hence the multi-scale graph model.

3.4. Support vector machine

Finally, a support vector machine (SVM) model with radial basis function kernel is developed to predict the dementia conditions using these extracted graph features. Let $x = (H_T, E_L, H_E)^T$ denote the features and y is the dementia status, respectively. The decision function is $f(x) = \sum_{i=1}^{n} \beta_i y_i K(x_i, x) + \beta_0$, where $K(x_i, x) = \exp(-\gamma x_i - x^2)$ is the radial basis kernel function and makes SVM flexible to model complex decision boundaries, $\beta_i > 0,\ i = 1, \ldots, n$ are the weights, and β_0 is the bias term. The β_i's are obtained through an optimization process to maximize the margin between the two classes, subject to the constraints

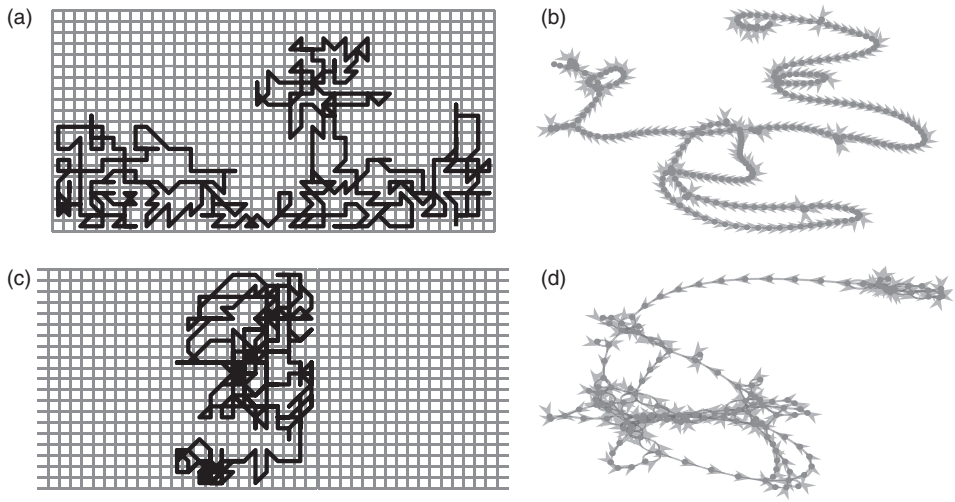

Figure 4. Locomotion trajectory and graph representation for a large $\tau = 0.9$ ((a) and (b)) and a small $\tau = 0.5$ ((c) and (d)).

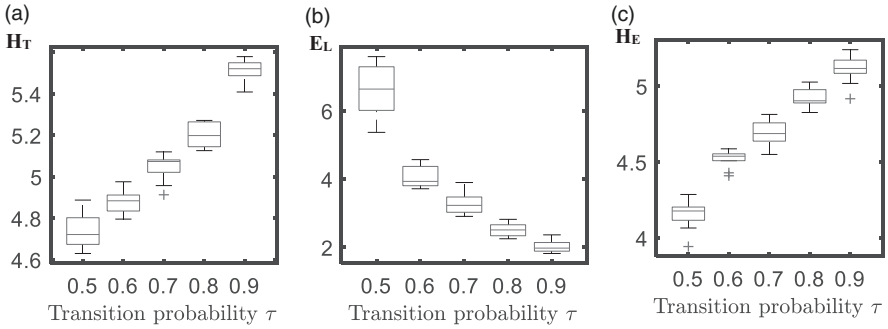

Figure 5. The variations of H_T, E_L and H_E extracted from graph representation of locomotion trajectories for different transition probability τ.

$$\begin{aligned} \textstyle\sum_{i=1}^{N} \beta_i y_i &= 0 \\ 0 \le \beta_i &\le C, \ \ \forall i \in [1, n] \end{aligned} \tag{5}$$

The parameters $(\gamma,\ C)$ are obtained via five-fold cross-validation. Specifically, the dataset is randomly divided into five parts of equal size and SVM is trained on any four of them; then, the classification accuracy is evaluated on the rest one-fold based on the trained SVM to select the optimum $(\gamma,\ C)$ from a grid search. SVM provides a good generalization performance, as it simultaneously minimizes the empirical risks $\frac{1}{N}\sum_{i=1}^{N} \ell(y_i, f(x_i))$ on the training dataset and diminishes the complexity of the fitting function via the constraints in Eq. (5).

4. Simulation study

We design a simulation study to evaluate and validate the proposed graph methodology and graph theoretical features. Here, we use the random walk to simulate the locomotion trajectory. At any time and any block, the subject transits to one of eight neighboring blocks according to the following rules: to a new block with probability $\frac{\tau}{8-N_{AV}}$ and to an already-visited block with probability $\frac{1-\tau}{N_{AV}}$, where N_{AV} is the number of already-visited neighboring blocks. In the extreme case when $N_{AV} = 0$ or 8, one of eight neighboring blocks will be selected with equal probability. Note that a large τ will lead to more aimed behaviors and pathways (see Figs. 4 (a) and (b)). This corresponds to the real-world situation that normal subjects may have well-planned activities but occasionally exhibit random locomotion. In contrast, a small τ tends to generate more randomness in daily locomotion trajectory, leading to back-and-forth movement among frequently visited blocks, as shown in Figs. 4 (c) and (d).

Next, we extracted data-driven biomarker H_T, E_L and H_E from the graph representation for multiple realizations as we vary τ. Figure 5 shows that H_T and H_E increase steadily when τ gets bigger, as the blocks are more equally likely to be visited. In addition, the pathways are more concentrated at several dense blocks for small τ, giving rise to highly unevenly distributed eigenvalues, with several extremely large ones, hence the elevated eigen-energy E_L.

The simulation study demonstrates the effectiveness of graph representation and data-driven biomarkers for the characterization of stochastic transitions in the space. However, locomotion data from the real-world case study tend to be contaminated with noises, artifacts, and missing recordings. Therefore, we will further evaluate the performance of sensor-based graph modeling at different spatial scales of locomotion data from human subjects in a real-world case study, as detailed in the following section.

5. Real-world case study

In this real-world case study, we performed long-term monitoring for 14 human subjects with approved IRB protocols.

Each subject was monitored for 30 days in an ALF in Tampa, FL. Locomotion data were collected from 30-day monitoring of each subject. The network model was then constructed using the daily data. The total sample size is $14 \times 30 = 420$; i.e., 180 from dementia subjects and 240 from normal subjects. The dementia conditions for each subject were determined based upon lab tests and neuroimaging, and were confirmed by human experts in aging studies. Note that the sample of 420 daily locomotion trajectories is from the subjects with a variety of dementia conditions, from normal to severe dementia. In addition, the MMSE test was conducted separately by independent examiners, blind to the dementia statuses of the subjects.

As shown in Fig. 1, we utilized the Ubisense ultra wideband radio system with small-size tags (i.e., 38mm $\times$39mm $\times$16.5mm) and four wall-mounted sensors for automatic collection of locomotion data from each subject in a duration of 8 to 10 hours per day for 30 days. Although normal subjects may occasionally exhibit random behaviors (e.g., searching for keys), it is very unlikely that they will show a high level of abrupt behaviors during an interval of 8–10 hours. Although the cognitive status of a subject does not change dramatically within this 30-day period, locomotion data show significant daily variations for each subject. Therefore, we focus on the estimation of dementia conditions with daily locomotion data, which corresponds to 420 daily locomotion trajectories to be classified as normal and dementia conditions.

6. Experimental results

In this section, we present the experimental results and investigate the effects of spatial resolution on the performance of multi-scale graph models; i.e., at large-scale s_1 and small-scale s_2. The dataset is randomly divided into training (80%) and testing sets (20%) for the assessment and validation of model performance.

6.1. Large-scale block size

First, we varied the large-scale block size $s = s_1$ in the range $s_1 \in [0.5,\ 2]$, and then derived the graph representation and computed the transition entropy H_T among the vertices for the training dataset. We performed the statistical t test to compare the distribution of H_T between normal and dementia subjects. Table 1 shows the variations of p value for different block sizes. The smaller the p-value is, the more significant the differences between the two groups.

Note that the block size of 1 m yields the lowest p value of 1×10^{-7}. Figure 6 shows the comparison of H_T distributions with $s_1 = 0.5\,m$ (panel (a)) and $s_1 = 1\,m$ (panel (b)). Clearly, the contrast between the groups of "N" (normal) and "Y" (dementia) is much better at $s_1 = 1\,m$. Further, if we slightly increase the block size from 1 m, the p value only marginally increases. In order to get a reliable estimation of transition entropy (H_T), we use the block size $s_1 = 1\,m$ rather than $s_1 = 1.25\,m$ in the graph model. Note that, at this stage, the two classes still have considerable overlap.

Table 1. The variation of p values with a different block size s_1.

s_1 (m)	p value
0.5	7×10^{-7}
0.75	2×10^{-7}
1	1×10^{-7}
1.25	1.1×10^{-7}
1.5	1.2×10^{-7}
1.75	1.4×10^{-7}
2	4×10^{-7}

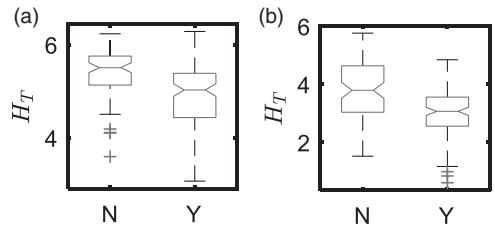

Figure 6. Box plots of transition entropy H_T for dementia ("Y") and normal subjects ("N") based on the graph representation with the block size (a) $s_1 = 0.5\,m$ and (b) $s_1 = 1\,m$.

Table 2. Performance comparison of the predictive modeling for different block sizes s_2 in terms of accuracy (ACC), true positive rate (TPR) and true negative rate (TNR).

s_2 (m)	ACC	TPR	TNR
0.2	0.75/0.12	0.73/0.05	0.79/0.10
0.3	0.74/0.13	0.76/0.09	0.69/0.05
0.4	0.80/0.06	0.79/0.05	0.81/0.06
0.5	**0.86/0.06**	**0.85/0.07**	**0.87/0.05**
0.6	0.76/0.09	0.82/0.04	0.74/0.13
0.8	0.73/0.07	0.70/0.12	0.79/0.06
1.0	0.72/0.12	0.64/0.16	0.76/0.09

6.2. Small-scale block size

Furthermore, we varied the small-scale block size $s = s_2$ in the range of $s_2 \in [0.2,\ 0.5]\ m$ and then derived the graph representation to compute Laplacian eigen-energy E_L and eigen-entropy H_E for the characterization of locomotion patterns. Table 2 summarizes the comparison of model performance metrics of prediction accuracy (ACC), true positive rate (TPR) and true negative rate (TNR), along with the standard deviations using SVM with the feature vector $[H_T, E_L,\ H_E]^T$ extracted from both scales. The standard deviation here is derived from 10-fold cross-validation.

As shown in Table 2, the block size $s_2 = 0.5\,m$ yields the best performance for the testing dataset (i.e., ACC 86%, TPR 85%, and TNR 87%). As $0.5\,m$ is on the boundary of interval of interest, we further extend the original interval to $s_2 \in [0.2,\ 1.0]\,m$. It is not uncommon that the locomotion data collected in real-world settings are corrupted by noises and artifacts. However, the sensor noises and errors are typically in the range of $<0.10\ m$, which are negligible considering modeling scales i.e., the smallest block scale is $0.50\ m$.

Note that a comprehensive statistical analysis on the usable data from 48 studies—42 from the community setting and 6 from the primary care setting—showed that the MMSE performance is dependent on the cut point (or decision boundary) (Creavin *et al.*, 2016). If the cut point is selected to be 25 for MMSE, then the sensitivity will be 0.87 and the specificity will be 0.82. If the cut point is selected to

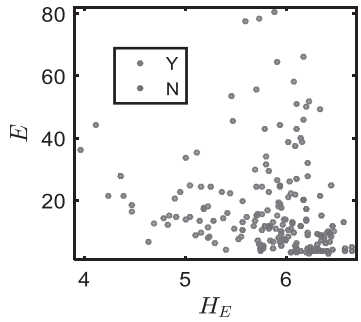

Figure 7. The scatter plot of Laplacian eigen-entropy H_E and eigen-energy E for dementia ("Y") and normal subjects ("N") based on the graph representation with the block size $s_2 = 0.5\ m$.

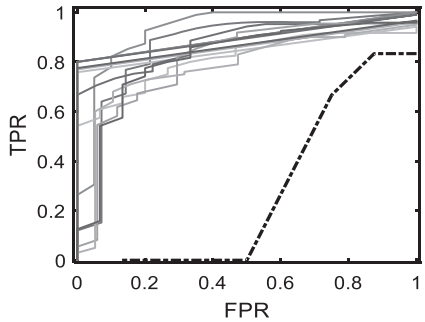

Figure 8. Ensemble of the ROC curve (true positive rate vs. false positive rate): the black/dark dashed line represents the ROC curve for MMSE screening, and the light solid lines are for the multi-scale graph model.

be 24, then the sensitivity will be 0.85 and the specificity will be 0.90. In particular, the specificity drops dramatically to 0.70 when the level of education is taken into consideration. Also, Cruz-Orduna *et al.* (2012) achieved sensitivity of 0.80, but the confidence interval was as wide as [0.52, 0.96]. More recently, Breder *et al.* (2017) showed the low sensitivity of MMSE for specific subject groups. Our experimental results show that sensor-based graph models yield a compelling predictive performance, with both true positive and true negative rates above 85%, and can be used as an effective tool for dementia assessment (i.e., they provide more flexibility in dementia monitoring and require minimal interventions from practitioners).

Figure 7 shows the distribution of eigen-energy E and eigen-entropy H_E for dementia ("Y") and normal subjects ("N"). Locomotion for normal subjects tends to generate graphs with lower eigen-energy E_L and higher eigen-entropy H_E. In other words, eigenvalues λ_i for erratic gait locomotion are concentrated on a few larger numbers, while those for normal locomotion are rather evenly distributed. The normalized Laplacian eigen-energy E_L is related to the centrality (importance) of vertices. Indeed, the Laplacian energy drops when the centrality of vertices is smaller in the graph. Intuitively, abnormal locomotion dynamics with back-and-forth movements will render certain vertices more important than others in the graph. Further, the random nature of walk dynamics leads to uneven centrality of the vertices. Normal locomotion with well-directed walk patterns results in almost uniformly distributed Laplacian eigenvalues, and hence a large Laplacian eigen-entropy E_H.

The selection of s_1 and s_2 reflects locomotion patterns at the large scale ($\sim$1 m) or the small scale ($\sim$0.5 m). It does not really depend on the floor plan, but rather the resolution in which we are interested at the locomotion dynamics. The entire home space or floor plan tends to be much bigger than movement steps of human subjects and thus only affects the locomotion in the extra-large scale; e.g., the long-range direction due to the limit of the floor plan. Movement directions in the extra-large scale tend to be not significant in the modeling and analysis of dementia subjects. Hence, this investigation focuses on multi-scale graph modeling of stochastic transitions in spatial scales from $0.5\,m$ to $2\,m$, which is also robust to sensor noises. As shown in Tables 1 and 2, we have extensively studied the influences of different block sizes of s_1 and s_2 and investigated the optimal spatial resolution for the analysis of locomotion dynamics for the detection of dementia conditions. Figure 8 shows the receiver operating characteristic (ROC) curves from multiple runs of the predictive model on randomly generated testing datasets, as well as that for the MMSE. The average area under the ROC curves of 0.85 is obtained for the multi-scale graph model, which shows the effectiveness of the proposed sensor-based method.

7. Conclusions

Smart health is poised to reduce the cost and improve care efficiency with smart sensors, wearable devices, and information technology, ushering in a paradigm shift from reactive to preventive and proactive care for chronic diseases. The complexity of dementia poses significant challenges in terms of detection and screening. As such, the Alzheimer's Foundation of America and the Alzheimer's Drug Discovery Foundation have called for regular screening of dementia (Borson *et al.*, 2013). In the current practice, paper-based survey methods such as MMSE and MoCA are widely used for the assessment of dementia conditions. However, these methods require lab visits or administration from nurses, physicians and examiners, and are limited in their ability to track temporal degradation (or daily variations) of dementia conditions. There is an urgent need to develop sensor-based automatic data collection and analysis for optimal health management and treatment of dementia subjects.

This article presents a wireless sensing system for automatic locomotion data collection and a new, multi-scale graph model for gait locomotion analysis, which are indispensable to the next step for real-time monitoring of temporal degradation of dementia conditions. The proposed approach automates the locomotion data collection process and only requires minimal intervention from investigators. As a result, locomotion data can be collected while the subjects are performing their daily routine tasks. Experimental results show that biomarkers extracted from the multi-scale graph representation of locomotion data achieve the performance of both TPR and TNR above 0.85. The proposed sensor-based approach has great potential for real-time monitoring of temporal variations of dementia conditions from daily gait locomotion dynamics. In future work, we will extend this study to collect more locomotion data and conduct a longitudinal study to characterize and model how

the locomotion patterns change over time with the degradation of dementia conditions.

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