A Fast and Low-Cost Repetitive Movement Pattern Indicator for Massive Dementia Screening

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***Abstract*— Because of the worldwide aging population, more and more elders suffer from dementia problem. Nowadays, it is an inconvenient and time-consuming process for medical doctors to diagnose elders who live independently with possible dementia because the process imposes a large quantity of diagnostic questions from a checklist that needs to be answered by elders themselves or their caregivers either directly or after a long-term observation. In order to help doctors to make this diagnostic process easier, this article proposes a supporting system that can quickly estimate the likelihood for an elder of having dementia based on 2 to 4 hours monitoring of a behavioral test done by the elder. During the test, the elder only needs to perform certain activities selected from the so-called instrumental activities of daily living (IADL) in a smart home environment, and their movement trajectories will be extracted from motion sensors deployed in the smart home environment and be analyzed to find a potential correlation with the indoor wandering patterns. A machine learning algorithm is selected to carry out the classification task, namely, into dementia and nondementia groups, based on our proposed features of the aforementioned wandering patterns. Two data sets are employed for performance evaluation, where the first one is 232 elders including seven dementia, whereas the second one is collected by ourselves from a senior center, which is 30 elders including nine dementia. It turns out that the average precision and recall for the first data set are both up to 98.3% with area under the ROC curve (AUC-ROC) being 0.846, and those for the second data set are 89.9% and 90.0% with AUC-ROC being 0.921.**

***Note to Practitioners*—We proposed a supporting system which can classify the elders as either dementia or nondementia with high accuracy. The trajectories of the elders will be extracted from motion sensors that deployed in the smart home environment. The indoor wandering patterns according to repetitive movements are analyzed and classified using the machine learning technique. The proposed system used ambient sensors instead of wearable sensors or cameras to let the elders feel more comfortable when they are being monitored. In addition, the proposed system only required a short period of time to screen the elders and easier for medical doctors to diagnose the elders without wasting time for asking the large quantity of diagnostic questions from a checklist that needs to be answered by the elders themselves or their caregivers.**

***Index Terms*— Dementia, indoor wandering pattern, machine learning, motion sensors, quickly monitor, smart home.**

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I. Introduction

NOWADAYS, various advanced technological developments in medicine lead to rapidly increasing aged population worldwide, which in turn cause a major issue in our society, namely, a growing number of dementia subjects. According to the statistics in [3], there are 50 million people with dementia in 2018, and the numbers will more than triple to 152 million by 2050. For elders aged over 60 years old, about 4.6%–8.7% of them suffer from dementia, who may have symptoms including wandering, sleep disturbances, repetitive vocalizations, anxiousness, restlessness, overactivity, resisting, or refusing care [4], [5]. As these symptoms deteriorate, it becomes harder to take care of them. Thus, it is important to discover dementia in the early stage so that the chance for their symptoms to get worse is reduced by a proper intervention.

About 72% of elders with mild behavioral impairment (MBI) or mild cognitive impairment (MCI), and 97% of elders with Alzheimer's disease (AD) or other dementia have difficulty completing instrumental activities of daily living (IADL) [6]–[9], which means that behaviors of the cognitively healthy (CH) elders may be different from those of dementia subjects. Thus, it implies that if a CH elder evolves into one with MBI or MCI, then his/her behavior will experience some changes. However, it is difficult to identify the behavior changes because many elders live independently, and there is hardly a ready mechanism for observing those changes in such a situation. Even if we resort to doctors for diagnosis, a similar long-term observation record taken by the elders' families or caregivers apparently will be needed, which suggests that some kinds of behavioral monitoring over a duration will be imperative to understand the possible deterioration of an elder's cognitive ability.

Fortunately, advanced technologies nowadays can fulfill the need to solve this problem. The elders' behavioral information of performing various daily activities can actually be perceived by ambient sensors installed in their homes for long-term monitoring [10]–[12], and those activities at homes can also be recognized with the help from both ambient and wearable sensing under the setting of a supervised machine learning system [13]. Such technologies deployed in the smart home systems can, in fact, save enormous human's efforts while monitoring elders all day, whereby the medical doctors can also diagnose elders more precisely.

Following [14], we further examine the supporting system in a smart home environment that can quickly estimate whether an elder is dementia or not after he/she has performed eight activities from IADL by using a machine learning classification technique. In order to identify the reliability of the proposed system, we collect our own data set from Zhishan (ZS) Senior Home, Taipei, Taiwan, under an institutional review board (IRB) approval. Some of the eight activities are also redesigned to adapt to our different cultural and environmental backgrounds of Taiwan as compared with the public data set used in our previous study. The trajectory of the elder will be extracted from motion sensors, which are deployed in the smart home environment based on 2 to 4 hours behavioral test done by the elder. Then, we analyze the pattern of trajectory and the potential correlation with the indoor wandering patterns. Furthermore, we also compare our proposed system by using both data sets and discuss their results based on the ZS data set.

The main contributions of this article can be summarized as follows.

1) We implemented our proposed dementia screening system in a real home setting, which is ZS Senior Home.
2) We redesigned some activities in public data set to adapt to our different cultural and environmental backgrounds of Taiwan as compared with the public data set used in our previous study.
3) We demonstrated the feasibility of the proposed system that only required 2 to 4 hours to screen the elders and easier for medical doctors to diagnose the elders.
4) We carried out an experiment to evaluate the performance of the proposed system and discussed our proposed system in details.

The remainder of this article is organized as follows. Section II summarizes the related works and presents the contributions. Section III describes the problem setup. Section IV describes the proposed supporting system. Section V describes the experimental data and explains how features can be extracted from the movement trajectories generated by the combined motion data. Section VI presents and discusses the results. Finally, the conclusion and future work are provided in Section VII.

II. Related Work

A smart home is a smart environment built with intelligent sensor networks and artificial intelligence technologies which can control the physical home and monitor the daily activities [15]. As a result, we can collect information about inhabitants' daily living via such a smart home environment rather than through long-term camera watching, whereby the privacy issue will be much more alleviated. Moreover, smart homes can also serve as an aid for health assessment and can send alerts to inhabitants' clinician if necessary [12].

Akl *et al.* [10], [11] have analyzed the information of 68 elders' daily living collected from their apartments over an average period of three years in order to detect whether elders became MCI from CH. Specifically, the work in [10] extracted the amount of activity changes by motion sensors in each room, whereas the work in [11] obtained appealing results by extracting walking speed, age, and gender as features. However, it is worth noting that the walking speed may be affected by many factors such as shin injury, arthritis, or other diseases. Urwyler *et al.* [16] used an ambient sensor to collect data which consists of ten healthy controls and ten dementia patients for 20 consecutive days. They proposed circadian activity rhythm (CAR) [17] to recognized differences activities of daily living (ADL) between dementia and healthy control. The drawback of these works is a long-term observation that is needed to detect MCI or dementia.

Concerning "wandering" which is one kind of behavior of elders with dementia, Kearns *et al.* [18] hypothesized that path tortuosity (an index of casual locomotor variability) would be different between elders with dementia and those without dementia and, thus, proposed a monitoring system to detect dementia. There were 25 elders including 19 females and 14 with dementia monitored for 30 days, and they were classified correctly with fractal dimension (fractal D) as the input feature. Fractal D is originally used to measure path tortuosity in movement ecology studies in order to characterize exploratory behavior in numerous species [19]. Another works by Vuong *et al.* [20], [21] proposed automated systems to detect the indoor wandering patterns. Wi-Fi was used to record elders' movement locations and directions in [20]. The elder needed to carry a mobile phone and executed 40 predefined walking paths. Active RFID system was used to record elders' movement locations in [21]. There were totally five elders who were included for the experiment, and the recording is for 24 h. Antennas were set up on the ceilings of each room, and individual tags were worn by the elders. These works mentioned so far all require elders carry mobile phones or tags which might make the elderly feel uncomfortable [22], [23].

In order to shorten the monitoring time duration needed for collecting the sensor data in a smart home, Dawadi *et al.* [24] proposed a system to assess cognitive health condition by monitoring "day out task" (DOT), which is a naturalistic task for all participants who only need to complete the interweaving subtasks within a few hours. Participants involved in this work include two elders with dementia, 32 elders with MCI, and 145 elders with CH. It turned out that the classification among participants with CH and MCI as well as that among participants with CH and dementia were not very satisfactory. Later, a better classification result was demonstrated after 14 more participants with dementia who did not complete all of the DOTs were added as the additional inputs. However, this better result might because of most of the participants with dementia failed to complete all of the DOTs, whereas participants with CH completed all the DOTs.

Generally speaking, Parkinson's disease (PD) could evolve into dementia with high risk and could be sensed and classified by the smart home system [25]. As a result, Cook *et al*. [26] proposed another system to investigate the impact of the elders with CH, MCI, and PD. The proposed system only required elders to perform some activities including IADL, timed up and go (TUG), and DOT in a smart home environment, and its classification had good accuracy based on features of individual activity with several additional processes such as principal component analysis (PCA), k means clustering, and random resampling. However, its performance was not very well when handling with the original features of individual activity.

Another related work proposed by Dawadi *et al*. [2] classified 65 elders with CH and 14 elders with dementia. Elders were asked to perform eight activities selected from IADL, and there are 14 kinds of features extracted from each activity. However, the accuracy for classifying elders with CH was good, but to classify elders with dementia was not. All of these studies needed to consider the time of completing each activity. Therefore, elders who had mobility problems, such as degenerative joint diseases, could not join the tests. Moreover, those studies used many types of ambient sensors including motion sensors, item sensors which are infrared sensors affixed to items in order to detect the items that were taken, and door sensors. Such heterogeneity of deployed sensors makes the same classification system hardly replicable in other environments unless they are almost identical to the ones set up.

In this article, we proposed a supporting system that can classify the elders as either dementia or nondementia with high accuracy after a short amount of monitoring time. The ambient sensors are chosen as they can capture the motion trajectory of the elders, and the elders might feel more comfortable because they do not need to wear the sensors on their bodies. In addition, the system is designed not to impose any hardship to elders who might have mobility problems such as degenerative joint diseases, which make the system be able to admit more elders either with dementia or nondementia. Our proposed work and mechanism can address the challenges of assessing whether an elder has dementia quickly and conveniently.

III. Problem Setup

A. Indoor Wandering Pattern

The previous study by Alzheimer's Association shows that roughly 60% of people with dementia will have experience of wandering [27]. Note that wandering is a syndrome of dementia-related locomotion behavior which exhibits some movements being frequent, repetitive, temporally-disordered, and/or spatially-disoriented [28]. Furthermore, wandering may be purposeful or maybe not, and it may be a behavior of which a person is aware or is unaware, such as that of exploring a new area, escaping from a place, looking for something, pacing mindlessly, and meandering to fill time [29]. If elders with dementia perform the assigned activities in the smart home environment, they would very likely forget the locations of items or the instructions of activities. Under this circumstance, they would walk around and try to look for something in order to recall what they have forgotten. Therefore, we can record the elder's movement trajectory and detect his/her repetitive movements, if they take place, based on k-repeating substrings features, which will be clear in the sequel, according to the nature of wandering.

In general, there are four kinds of indoor wandering patterns, including direct, pacing, lapping, and random [30], and these patterns may happen to elders with dementia. These four patterns were defined: 1) direct: travel from one location to another location without diversion; 2) pacing: repetitive back-and-forth movement within a limited area; 3) lapping: repetitive travel characterized by circling large areas; and 4) random: roundabout or haphazard travel to many locations within an area without repetition. The patterns of pacing and lapping from elders with dementia could be significantly different from the same patterns but from elders without dementia. Note that the identical characteristic in these two patterns is repetitive movement.

In our proposed system, we detect indoor wandering patterns by passive infrared (PIR) motion sensors mounted on the ceiling. The status of the motion sensor will transfer from "OFF" to "ON" when an elder moves to the sensing area of that motion sensor. If the elder leaves that area or does not perform significant movement right under the same motion sensor over a period of time, the status of that corresponding motion sensor will transfer from "ON" to "OFF." For the latter situation, the sensor status would transfer to "ON" again if the elder starts to move.

B. K-Repeating Substrings

K-repeating substrings are all substrings that take place no greater than k times in the input string [31]. It is originally used to detect textual data based on the assumption that such rare sequences may contain sensitive information such as names of people. However, we can hypothesize that the movement trajectory generated by an elder is a long string. Each letter in the string is the location that the elder had traveled through. In that case, we can use the algorithm to detect repetitive movements from the movement trajectory.

If there is an example for an elder who moves through 11 locations in a smart home, the sequence of motion sensors which are triggered will be {M001, M002, M010, M001, M003, M001, M004, M001, M002, M010, M001}. The letter "M" refers to the motion sensor. Different numbers following the letter mean different locations. Therefore, the movement trajectory consists of 11 motion sensor events in this example. We can extract K-repeating substrings with this movement trajectory by setting the value of k from 1 to 4. For 1-repeating substrings, the repetitive number of "M001" is 5, the repetitive number of "M002" is 2, and the repetitive number of "M010" is 2. The repetitive numbers of "M003" and "004" are both 0 because these two motion sensors are not repetitive in this trajectory. Thus, the total number of 1-repeating substrings is 9. For 2-repeating substrings, the number of repetitive

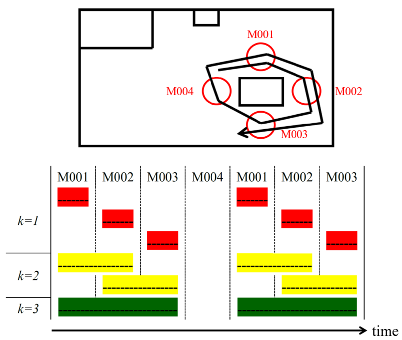

Fig. 1. Wandering detection with K-repeating substrings.

Time	ID, Status	Message
15:13:34.687	M001 ON	start
15:13:37.186	M005 ON	
15:13:49.487	M001 OFF	
15:13:55.59	M005 OFF	
15:14:56.685	M005 ON	
⋮	⋮	⋮
15:15:17.515	M008 OFF	
15:15:49.26	M001 ON	end

Trajectory of the activity: {M001,M005,M005,……,M001}

Fig. 2. Trajectory extracted from the motion sensor.

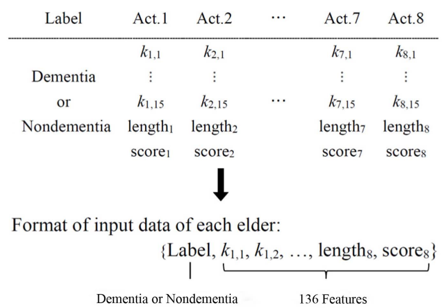

Fig. 3. Features for each elder.

movements from "M001" to "M002" is 2, the number of repetitive movements from "M002" to "M010" is 2, and the number of repetitive movements from "M010" to "M001" is 2. Thus, the total number of 2-repeating substrings is 6. For 3-repeating substrings, the total number of the 3-repeating substrings is 4. For 4-repeating substrings, the total number of the 4-repeating substrings is 2. Consequently, we can know how many times an elder repeatedly appears in the same locations with 1-repeating substring and moves to the same trajectory segments, of which each refers to some k-repeating substrings where $k > 1$.

There is an example for lapping as shown in Fig. 1. There are four motion sensors whose sensing areas are surrounding an object in the room (say, desk). If an elder walks through sensing areas of motion sensor "001," "002," "003," to "004," and walks again through sensing areas of motion sensor "001," "002," to "003," we can then obtain his movement trajectory which will be denoted in a simple fashion as "001, 002, 003, 004, 001, 002, 003," involving these seven motion sensor events. If we detect wandering behaviors with k-repeating substrings by setting the values of k from 1 to 5, the total number of 1-repeating substrings which are labeled as red will be 6; the total number of 2-repeating substrings which are labeled as yellow will be 4; the total number of 3-repeating substrings which are labeled as green will be 2; and the numbers of 4-repeating substrings and 5-repeating substrings are both 0. It means that we extract repetitive locations by 1-repeating substrings and repetitive movement paths together by 2-repeating substrings and 3-repeating substrings.

C. Feature Extraction

In this proposed monitoring system, each activity is annotated the time of start and time to end by the experimental conductors who stays outside the sensing range and observes the entire experiment process where every elder performs several assigned activities. According to the times of start and end of each activity, the motion trajectory of each activity is extracted. There are many motion sensors deployed in the experimental environment, each of which is indexed with a different ID. The ID of motion sensor whose status is "ON" is added to the trajectory of an activity if the event triggering of the motion sensor takes place between the time of start and the time end of the corresponding activity, as shown in Fig. 2. In this method, the duration of an activity and that of an event which triggers the motion sensor are not considered. In other words, only the elder's movement trajectory of each activity is considered. Therefore, if an elder has a mobility problem and walks slowly with the assistive device, he/she will still be able to do the test with this proposed monitoring system.

In this article, the value of k is set from 1 to 15 for each trajectory in order to cover all of short and long repetitive movement paths no matter what space size of the experimental environment is, where $k_{i,j}$ represents the jth-repeating substrings of the ith activity. The length of each trajectory and the score of each activity are also adopted as features. Thus, there are 17 features for each activity including 15 k-repeating substrings, one trajectory length, and one activity score. There are totally 136 features for each elder, as shown in Fig. 3 since there are in total of eight activities. The label, which is dementia, MCI or CH, is given by doctors and is used to train the quick monitoring model.

The number of motion sensors and the IDs of motion sensors that should be deployed, in which locations are not considered in this method because we only consider the occurrence sequences of motion sensors or identical trajectories. Therefore, the thing we only have to do is deploy motion sensors as a matrix on the ceiling of each experimental room to make sure that the system can record the information from motion sensors and label start and end of each activity. Then, we will be able to start the monitoring system. Moreover, the sensor layout is very simple, and thus, this system and the method of feature extraction can be easily duplicated in many smart home environments.

D. Classification Algorithm

In Section III-C, our smart home environment monitors the elders' movement trajectories which ask them to perform several assigned daily activities. Moreover, the presented detection algorithm allows us to detect the distribution of k-repeating substrings of the movement trajectory of each elder. Now, what is left is how we should classify the elders as dementia group or the opposite using the distribution record. In fact, there are many machine learning algorithms that can be used to help proceed the classification task as just mentioned for our proposed system. Apparently, we should choose a suitable one that can fully leverage the characteristics of the mentioned k-repeating substrings features. Langarizadeh and Moghbeli [32] reviewed 23 studies published between 2005 and 2015 and concluded that to predict diseases based on a Naïve Bayes algorithm would demonstrate the best performance in most disease predictions in comparison with other algorithms because Naïve Bayes algorithm works better than other algorithms in most cases based on the reported accuracy. A possible explanation is that there were not enough patients for each prediction model of a disease, and Naïve Bayes requires a small amount of training set for classification [33], [34]. According to these reviews [32], Naïve Bayes could perform well because the prediction model was built with prior knowledge in the case of just a few samples, whereas other algorithms selected in these reviews did not build a better prediction model.

However, Naïve Bayes assumes each feature is independent of one another. It means that each feature contributes to each class with an independent probability. According to our features extracted, namely, k-repeating substrings, there are hardly relations among k-repeating substrings of each activity. It is generally conceived that if there are relations between different k-repeating substrings of each activity, Bayesian network can be the best methodology to build the classifier because that algorithm will be able to classify elders according to the dependencies of features. Our previous work was done by the Bayesian network [14]. However, the numbers of subjects in the data set are not enough to build a Bayesian network with high confidence. Furthermore, we are lacking an expert who can build a suitable Bayesian network for us according to our selected features. There are two reasons prevent us from using the Bayesian network to establish the classifier in our system. As a result, we select Naïve Bayes as the method for constructing the classifier in our proposed system in order to simplify this problem, and these dependencies are not handled.

In general, Naïve Bayes is used as a methodology for our required classifier because it is straightforward to build and performs relatively well in real problems [35]. It can rapidly infer which features are crucial to classify the data properly. As a consequence, Naïve Bayes has been used in many domains for classification and prediction, including bioinformatics. There are four advantages for Naïve Bayes: 1) it can easily and quickly be constructed from data; 2) it is compact in terms of space complexity; 3) it can rapidly infer the relations between input and output; and 4) it requires small amount of training set for classification [33], [34], [36]–[38].

For Naïve Bayes-based classifier, if attributes are quantitative, the classification performance will tend to be better when the attributes are discretized [39]. The method of discretization can directly handle continuous variables, and

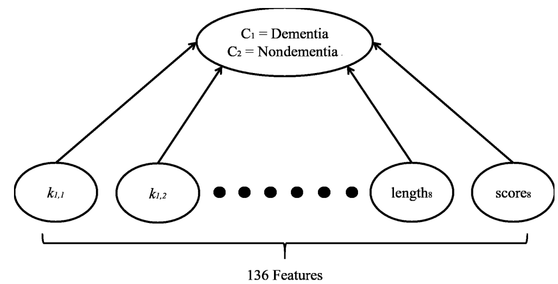

Fig. 4. Elder is classified with the Naïve Bayes classifier.

the performance of classification algorithms will be impacted by using discretization for analyzing high-dimensional biomedical data [40]. Our features extracted with k-repeating substrings are all quantitative. Therefore, we preprocess our features by discretization. There are two methods for discretization. One is unsupervised discretization, and the other one is supervised discretization. Unsupervised discretization does not use any information in the target variable. It discretizes data based on equal width or equal frequency. Supervised discretization considers the information in the target variable, and the performance for classification is more beneficial than that by the unsupervised discretization. Therefore, we use supervised discretization to preprocess our features and minimum description length principle (MDLP) to decide the partitioning of interval in this article [41]. MDLP tends to form qualitative attributes with few values, which, however, does not lead to the lowest distortion error as compared to other methods in general. Nevertheless, the least number of values has the benefit of classification with small data size. References [42] and [43] have also shown that it can achieve very high performance in many classification problems.

If there are two classes, C_1 = dementia and C_2 = nondementia, for classification, and an elder, $E = (x_1, x_2, \ldots, x_{136})$, is input to the system, all 136 features of the elder will contribute probabilities, p, to each class independently, as shown in Fig. 4. The elder will be classified as dementia if $f_{\mathrm{nb}}(E)$ is greater than or equal to 1, or it will be classified as nondementia, where $f_{\mathrm{nb}}(E)$ is shown in the following equation:

$$f_{nb}(E) = \frac{p(C_1)\prod_{i=1}^{136} p(x_i|C_1)}{p(C_2)\prod_{i=1}^{136} p(x_i|C_2)}. \tag{1}$$

IV. System Overview

Fig. 5 shows the system's overview. There are two parts for our system, as illustrated below.

A. Model Training

1) Diagnose: The participant who is an elder has to be diagnosed first by a doctor. The diagnosis result, dementia or not, is the ground truth for machine learning.

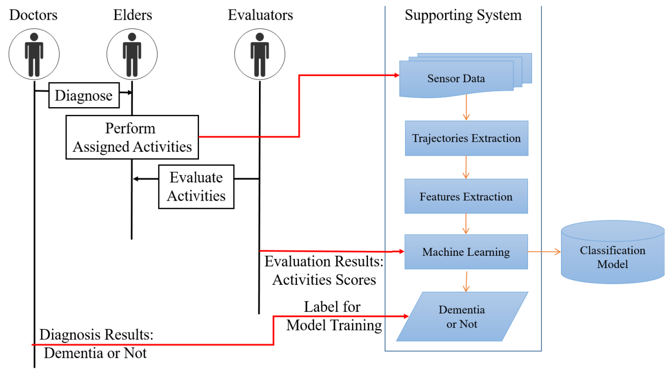

Fig. 5. System overview.

2) Perform Assigned Activities: Several activities are selected from IADL according to the suggestions from medical doctors, and a smart home environment is carefully designed so as to monitor how these activities are performed by the participating elders in this environment.

3) Evaluate Activities: There are several instructions for each activity, and the score for how an elder performs each activity depends on the completeness of these instructions [44]. There are totally five levels of a score as shown below.

- Score level 1: All activities are completed without any errors. An error could be noncritical omissions, noncritical substitutions, irrelevant actions, or inefficient actions.
- Score level 2: All activities are completed with 1–2 errors.
- Score level 3: All activities are completed with ≥ 3 errors.
- Score level 4: More than 50% of the activities are completed.
- Score level 5: Less than 50% of the activities are completed.

4) Sensor Data: Many kinds of sensors could be deployed in a smart home for monitoring, such as motion sensors, switch sensors, and current sensors. In this work, only the motion sensors are installed, and their data for each activity are extracted as inputs.

5) Trajectories Extraction: A trajectory for an elder given an activity is extracted by integrating the motion sensor data collected while he/she is performing that activity. If the status of a motion sensor is "ON," its corresponding ID is added to the trajectory. Under this circumstance, a trajectory appears as a text string.

6) Features Extraction: K-repeating substrings from each trajectory [31] are extracted as features for each activity, and then, features and scores of all activities are combined together for one participant as input for machine learning.

7) Machine Learning: The machine learning algorithm selected to train models in this work is Naïve Bayes [45].

8) Classification Model: The trained model is used to quickly classify the participant with dementia. There are two classes of the model as the trained result, namely, "dementia" and "nondementia." Section IV-B will illustrate the details.

B. Classification

1) Process of Quick Monitoring: This process involves performing certain assigned activities belonging to IADL, evaluation of activity performance, sensor data collection, trajectory extraction, and features extraction. The participant who wants to do the quick monitoring needs to do the same activities as has been introduced in Section IV-A. Conceivably, we will extract the same features while monitoring the participant.

2) Classification: The features extracted in the last step are the input to the model trained in Section IV-A to classify the participant.

3) End Result: The classification result for each participant can only be dementia or nondementia based on the features extracted from motion sensor data about the participant's behaviors in those assigned activities.

If a medical doctor applies the system to an elder and later concludes with his further diagnosis, which amounts to providing ground truth, we can use this case as an additional data input to retrain the model again.

V. Data Acquisition

In this article, there are two data sets used to evaluate the monitoring system and its classification capability in the experiment. The first one is a public data set from the Center for Advanced Studies in Adaptive Systems (CASAS), Washington State University, Pullman, WA, USA, which is an on-campus smart home test-bed [1]. The second one is a data set collected by ourselves from ZS Senior Home, subjected to IRB approval.

A. CASAS Data Set

There are many groups in this data set, including elders with dementia, elders with MCI, younger adults with CH, elders aged between 45 and 59 years with CH, elders aged between 60 and 74 years with CH, and elders aged over 75 years with CH. We choose the elders aged between 60 and 74 years because much fewer elders aged younger than 59 years suffer from dementia, and elders aged over 75 years would have other nondementia diseases which might affect their performing of the selected activities. As a result, there are totally 157 elders selected from CASAS data set in our experiment, including 20 elders with dementia, 55 elders with MCI, and 82 elders aged between 60 and 74 years with CH. Our proposed quick monitoring system requires elders be able to perform all activities, i.e., excluding the cases where some elders might not be willing to perform the assigned activities, or some elders with dementia are not able to complete all of the assigned activities. One reason for this is that if an elder with dementia is not able to perform all activities, he/she could be more easily classified as dementia by a doctor because of the correlation between the cognitive impairment and disorganized behavior. Therefore, from the data set, we purposely remove several subjects so long as their data collection including scores and labels of some of the eight activities is incomplete. More precisely, we exclude the subject cases where the activity scores are not recorded, or some sets of sensor data fail to have the annotation about start or end of an activity. After screening, there are 122 remaining elders including 7 with dementia, 43 with MCI, and 72 with CH for our experiment.

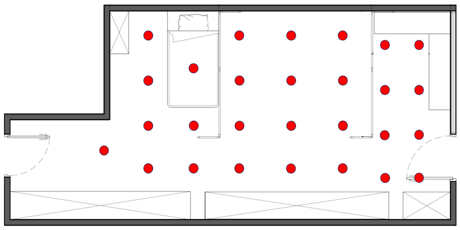

Fig. 6. Motion sensors deployment at ZS.

The smart home environment at CASAS is a two-story apartment. The environment contains a living room, a dining area, a kitchen on the first floor, and three bedrooms and a bathroom on the second floor. There are eight categories of sensor data collected from the smart home environment in the data set, including motion sensor, item sensor, door sensor, burner sensor, hot water sensor, cold water sensor, temperature sensor, and the whole-apartment electricity usage. Our proposed system only uses the motion sensor data to extract features. There are 4–6 motion sensors in each area and slightly more in the living room. The motion sensors are set up in a matrix pattern in the room and a line pattern in the hallway, where the spacing between two adjacent sensors is about 1.5 m. The eight activities performed by the elders are selected from the IADL list by a professional psychologist.

B. ZS Data Set

There are totally 30 elders aged between 68 and 97 years in the ZS data set, including 9 elders aged between 68 and 97 years with dementia and 21 elders aged between 68 and 97 years without dementia. There are 5 males including 3 aged between 71 and 97 years with dementia and 2 aged between 88 and 90 years without dementia, and 25 females including 6 aged between 68 and 87 years with dementia and 19 aged between 68 and 97 years without dementia. The diagnosis of dementia is to follow dementia diagnosis manual [46] provided by the Ministry of Health and Welfare of Taiwan, and it is based on the core clinical criteria recommended by the National Institute on Aging-Alzheimer's Association (NIA-AA) [47]. All of the nine elders with dementia are diagnosed by doctors. Their clinical dementia rating (CDR) scores are between 0.5 and 2. The score of CDR is from 0 to 3, where 0 means normal, 0.5 means very mild dementia, 1 means mild dementia, 2 means moderate dementia, and 3 means severe dementia. Moreover, two elders with dementia and four elders without dementia use assistive devices for walking, such as walking sticks and wheelchairs. They do move slowly when they are asked to perform the assigned activities.

The smart home environment at ZS is a studio simulating one-story apartment, and the layout of the installed motion sensors at ZS is shown in Fig. 6. The environment contains a bedroom, a living room, and a kitchen. The motion sensors are set up on the ceiling in a matrix pattern, where every two adjacent sensors are spaced about 1.5 m in order not to let the respective detection areas overlap. In other words, only one motion sensor would be triggered if an elder walks through the sensing area covered by all the motion sensors. Next, all elders are asked to perform eight activities selected form IADL set as follows.

- Sweep all the rooms and dust the living room.
- Obtain a set of medicines, read instructions, and fill the dispenser with medication.
- Write a birthday card, enclose a check, and address an envelope.
- Find the assigned DVD, watch the news clip, and select assigned TV channel.
- Obtain a watering can and water all plants in the living space.
- Answer the phone and respond to questions pertaining to the activity which is finding DVD, watching the news clip, and selecting TV channel.
- Steam a sweet bun using electric pot.
- Pick an assigned outfit from the wardrobe.

All of these activities are similar to the ones in CASAS data set except the seventh activity. Elders prepared a cup of soup using the microwave in the CASAS data set but steamed a sweet bun using electric pot in the ZS data set. The reason why we here change microwave to electric pot because many elders in Taiwan do not know how to use the microwave but do know how to use electric pot. Moreover, since details of each activity are designed by ourselves, such as item location and type of medicine, we put different items in different locations in each complex activity in order to observe the potential wandering pattern. For example, the card, envelope, and check are put in different cabinet drawers in the third activity. DVD, newspaper, and remote controller are put on different shelves and tables in the fourth activity. A sweet bun is put in the living room, and the electric pot is in the kitchen in the seventh activity. Under these circumstances, elders have to move more in order to complete the assigned activities. These activities are redesigned after discussing with the experts in our team. Before every participating elder performs each of the activities, that activity is demonstrated at the experimental home setting to the elder to make sure that the elder knows how to complete the assigned activity. Afterward, the experimenter will stay outside the experimental home invisible by the elder to annotate the start and end time of that activity. In short, this experimenter will observe the entire process of the experiment, ask the elder to perform the eight assigned activities, and make their scores. Under this circumstance, the ordering of activities and the level of familiarity with the environment problem do not affect the performance of the activities, leading to the fact that these eight activities are independent of one another.

VI. Result and Discussion

The machine learning algorithm selected in the proposed system to classify elders is Naïve Bayes. We also compare Naïve Bayes with other algorithms such as support vector machines (SVMs) with linear kernel and random forest (RF). The performance is quantified by precision (2), recall (3), and the area under the ROC curve (AUC-ROC) with leave-one-out cross-validation. ROC curve is called the sensitivity versus (1 − specificity) plot. In these equations, TP stands for true positive, TN stands for true negative, FP stands for

TABLE I

RESULT OF CLASSIFYING SEVEN DEMENTIA AND 115 NONDEMENTIA (43 MCI AND 72 CH) FROM THE CASAS DATA SET

		Naïve Bayes	SVM	RF
Precision (%)	Dem.	83.3	37.5	100
	Nondem.	98.3	96.5	95.8
	Avg.	97.4	93.1	96.1
Recall (%)	Dem.	71.4	42.9	28.6
	Nondem.	99.1	95.7	100
	Avg.	97.5	92.6	95.9
AUC-ROC		0.848	0.693	0.951

*Dem. = Dementia *Avg. = Average (All elders)

false positive, and FN stands for false negative. The value of AUC-ROC is from 0 to 1. The higher AUC-ROC value means that the classifier adopted to classify elders is more reliable

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{recall} = \text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}. \tag{4}$$

A. Classification With CASAS Data Set

In the CASAS data set, the result of classifying seven elders with dementia and 115 elders without dementia, including MCI and CH, is shown in Table I. The classification is done by leave-one-out cross-validation because there are fewer elders with dementia in the experimental data set. For Naïve Bayes, the precision and recall for classifying elders with dementia are 83.3% and 71.4%, respectively, whereas those for classifying elders without dementia are 98.3% and 99.1%, respectively. The average precision and recall of classifying all elders are 97.4% and 97.5%, and the value of AUC-ROC is 0.848 representing high reliability of this proposed quick monitoring system. For SVM, the precision and recall for classifying elders with dementia are 37.5% and 42.9%, respectively, whereas those for classifying elders without dementia are 96.5% and 95.7%, respectively. The average precision and recall of classifying all elders are 93.1% and 92.6%, and the value of AUC-ROC is 0.848. For RF, the precision and recall for classifying elders with dementia are 100% and 28.6%, respectively, whereas those for classifying elders without dementia are 95.8% and 100%, respectively. The average precision and recall of classifying all elders are 96.1% and 95.9%, and the value of AUC-ROC is 0.951. The variations of precision and recall for classifying elders with dementia are more significant than those for classifying elders without dementia because the number of elders with dementia is less than the number of elders without dementia. Therefore, the precision and recall for classifying elders with dementia are important here. The precision–recall (PR) curves for these three classifiers are shown in Fig. 7.

In order to know which classifier performs better, we can calculate the area under PR curve (AUC-PR) for each classifier. The AUC-PR with Naïve Bayes labeled as the blue line, RF labeled as the red line, and SVM labeled as the green line are 0.770, 0.715, and 0.194, respectively. It turns out that Naïve Bayes leads to the best precision and recall for classifying elders with dementia, whereas RF is slightly inferior to Naïve Bayes, and SVM performs the worst. A possible explanation is that there are not enough elders to build a good model with SVM or RF. On the other hand, Naïve Bayes performs better than SVM and RF possibly because its model is built with prior knowledge. The testing data are classified based on the observation of training data.

We also classify elders with dementia and only CH as shown in Table II and elders with dementia and only MCI as shown in Table III. For Naïve Bayes, the precision and recall of the former for all elders are both 97.5% with the value of AUC-ROC being 0.855, whereas those of latter are 93.8%

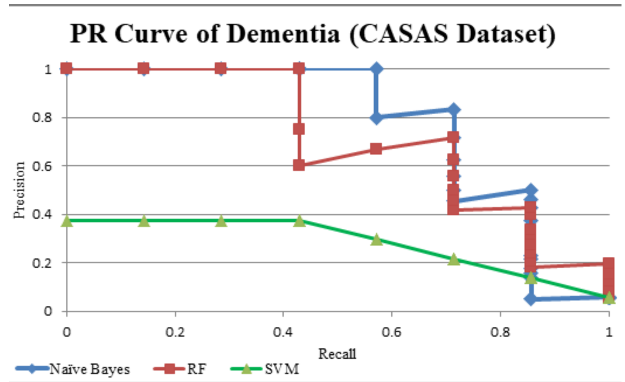

Fig. 7. Precision–recall curves for classifying elders with dementia from 122 elders in the CASAS data set.

TABLE II

RESULT OF CLASSIFYING SEVEN DEMENTIA AND 72 CH FROM THE CASAS DATA SET

		Naïve Bayes	SVM	RF
Precision (%)	Dem.	100	50.0	66.7
	CH	97.3	94.5	93.4
	Avg.	97.5	90.6	91.1
Recall (%)	Dem.	71.4	42.9	28.6
	CH	100	95.8	98.6
	Avg.	97.5	91.1	92.4
AUC-ROC		0.855	0.693	0.961

TABLE III

RESULT OF CLASSIFYING SEVEN DEMENTIA AND 43 MCI FROM THE CASAS DATA SET

		Naïve Bayes	SVM	RF
Precision (%)	Dem.	83.3	28.6	100
	MCI	95.5	88.4	87.8
	Avg.	93.8	80.0	89.5
Recall (%)	Dem.	71.4	28.6	14.3
	MCI	97.7	88.4	100
	Avg.	94.0	80.0	88.0
AUC-ROC		0.837	0.585	0.849

TABLE IV

RESULT OF CLASSIFYING SEVEN DEMENTIA, 43 MCI, AND 72 CH FROM THE CASAS DATA SET

		Naïve Bayes	SVM	RF
Precision (%)	Dem.	66.7	28.6	66.7
	MCI	47.5	44.2	57.1
	CH	69.7	65.3	68.1
	Avg.	61.7	55.7	64.2
Recall (%)	Dem.	57.1	28.6	28.6
	MCI	44.2	44.2	37.2
	CH	73.6	65.3	86.1
	Avg.	62.3	55.7	65.6
AUC-ROC		0.586	0.576	0.637

TABLE V

RESULT OF CLASSIFYING 43 MCI AND 72 CH FROM THE CASAS DATA SET

		Naïve Bayes	SVM	RF
Precision (%)	MCI	63.4	45.7	56.0
	CH	77.0	68.1	67.8
	Avg.	71.9	59.7	63.4
Recall (%)	MCI	60.5	48.8	32.6
	CH	79.2	65.3	84.7
	Avg.	72.2	59.1	65.2
AUC-ROC		0.522	0.571	0.589

TABLE VI

RESULT OF CLASSIFYING SEVEN DEMENTIA AND 225 NONDEMENTIA (43 MCI AND 182 CH) FROM THE CASAS DATA SET

		Naïve Bayes	SVM	RF
Precision (%)	Dem.	71.4	14.3	100
	Nondem.	99.1	97.3	97.4
	Avg.	98.3	94.8	97.5
Recall (%)	Dem.	71.4	14.3	14.3
	Nondem.	99.1	97.3	100
	Avg.	98.3	94.8	97.4
AUC-ROC		0.846	0.558	0.923

TABLE VII

RESULT OF CLASSIFYING SEVEN DEMENTIA AND 182 CH FROM THE CASAS DATA SET

		Naïve Bayes	SVM	RF
Precision (%)	Dem.	83.3	28.6	100
	CH	98.9	97.3	97.3
	Avg.	98.3	94.7	97.4
Recall (%)	Dem.	71.4	28.6	28.6
	CH	99.5	97.3	100
	Avg.	98.4	94.7	97.4
AUC-ROC		0.852	0.629	0.884

and 94.0%, respectively, with the value of AUC-ROC being 0.837. These results show that the activity behaviors of elders with dementia are different from those of elders with MCI and those of elders with CH.

In order to know whether the activity behaviors of elders with MCI are different from those of elders with CH, we classify elders into three classes, which are dementia, MCI, and CH, as shown in Table IV. The precision and recall are not satisfactory because some elders with MCI had just slight neuropsychiatric symptoms (NPS) [48], which would not cause the activity behaviors of elders with MCI significantly different from those of elders with CH if they only perform simple activities in short period of time. However, if we classify elders into two classes, which are MCI and CH, as shown in Table V, the precision and recall are better than the results from the earlier case shown in Table IV. The results may represent that the activity behaviors of elders with MCI are slightly different from those of elders with CH, but not directly correlated with those of elders with dementia provided only some simple activities are performed in short period of time. This hypothesis may need to be verified by further experiments. For example, we can assign more complex activities to elders or extract other features. According to these experimental results, we could classify elders with MCI by two steps in our supporting system: 1) we can first quickly classify elders into dementia and nondementia groups with the results as shown in Table I and 2) we can then further classify elders without dementia into MCI and CH groups according to the results as shown in Table V.

Tables VI and VII show the classification results with more elders with CH being added from the same data set, while no more elders with dementia can be added. These additional elders with CH are 56 younger adults, 28 elders aged between 45 and 59 years, and 26 elders aged over 75 years. Therefore, there are totally 232 elders, including 7 elders with dementia, 43 elders with MCI, and 182 elders with CH. For Naïve Bayes, the precision and recall shown in Table VI for all elders are both 98.3% with the value of AUC-ROC being 0.846, whereas those shown in Table VII are 98.3% and 98.4%, respectively, with the value of AUC-ROC being 0.852. The recall values of classifying elders with dementia are the same as those in Tables I and II, which means that adding more elders with CH will not degrade the performance of classifying elders with dementia. The precision of classifying the elders with dementia declines obviously because the number of elders with dementia is much less than the number of elders without dementia. The precision will decline a lot as long as one elder with CH is classified as FP of dementia. The PR curves for classifying dementia with these three classifiers are shown in Fig. 8. The AUC-PR with Naïve Bayes labeled as the blue line, that with RF labeled as the red line, and that with SVM labeled as the green line are 0.705, 0.490, and 0.046, respectively. Apparently, Naïve Bayes also has the best precision and recall for classifying elders with dementia, whereas RF is worse than Naïve Bayes, and SVM is the worst.

Given the above results, we only focus on Naïve Bayes method, i.e., we show the confusion matrix of classifying 232 elders' movement trajectories from CASAS data set only using the Naïve Bayes classifier. In order to make our system more human labor-free, we remove the scores of all activities regarded as a feature because the scoring needs human evaluation. On the other hand, since the trajectories are more objective because they are performed all by elders

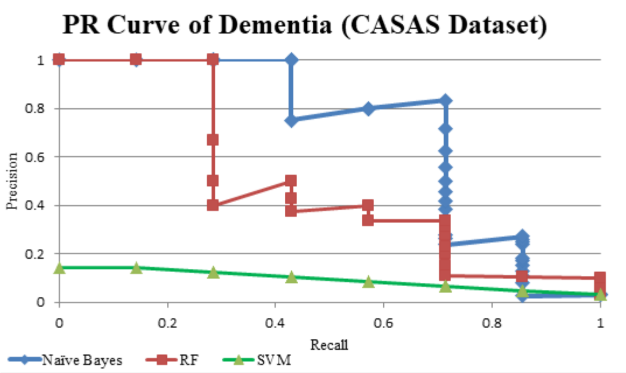

Fig. 8. Precision–recall curves for classifying elders with dementia from 232 elders in the CASAS data set.

TABLE VIII
CONFUSION MATRIX OF CLASSIFYING SEVEN DEMENTIA AND 225 NONDEMENTIA ONLY WITH MOVEMENT TRAJECTORIES FROM THE CASAS DATA SET

Classified as \ Ground Truth	Dementia	Nondementia
Dementia	4	3
Nondementia	3	222

TABLE IX
CONFUSION MATRIX OF CLASSIFYING SEVEN DEMENTIA AND 225 NONDEMENTIA WITH ALL FEATURES FROM THE CASAS DATA SET

Classified as \ Ground Truth	Dementia	Nondementia
Dementia	5	2
Nondementia	2	223

TABLE X
RESULT OF CLASSIFYING NINE DEMENTIA AND 21 NONDEMENTIA FROM THE ZS DATA SET

		Naïve Bayes	SVM	RF
Precision (%)	Dem.	87.5	66.7	80.0
	Nondem.	90.9	85.7	80.0
	Avg.	89.9	80.0	80.0
Recall (%)	Dem.	77.8	66.7	44.4
	Nondem.	95.2	85.7	95.2
	Avg.	90.0	80.0	80.0
AUC-ROC		0.921	0.762	0.929

themselves, the classification results will be more likely free of subjectivity bias. After comparing the confusion matrix only with movement trajectories as shown in Table VIII and the confusion matrix with all features including movement trajectories and the aforementioned human-made scores as shown in Table IX, we find that their differences are only one elder with dementia and one elder without dementia. Thus, the trajectories extracted by the system can be shown to be quite useful to classify elders with dementia.

B. Classification With ZS Data Set

In order to validate our proposed system, we use the second data set, ZS data set, to train and test the model. In the ZS data set, the result of classifying 9 elders with dementia and 21 elders without dementia is shown

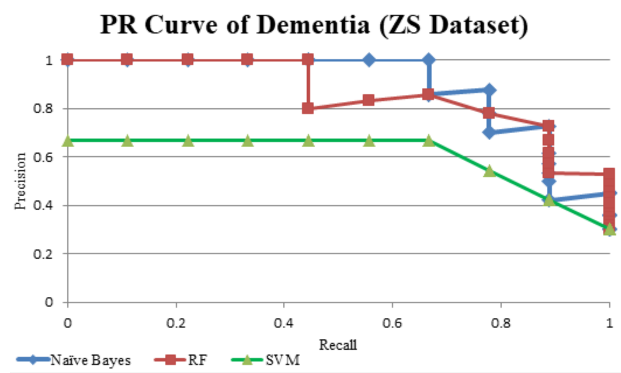

Fig. 9. Precision–recall curves for classifying elders with dementia from 30 elders in the ZS data set.

TABLE XI
CONFUSION MATRIX OF CLASSIFYING NINE DEMENTIA AND 21 NONDEMENTIA ONLY WITH MOVEMENT TRAJECTORIES FROM THE ZS DATA SET

Classified as \ Ground Truth	Dementia	Nondementia
Dementia	7	2
Nondementia	2	19

in Table X. The classification is also done by leave-one-out cross-validation because of the few subjects. Naïve Bayes also has the highest accuracy for classifying elders with dementia and without dementia. The precision and recall for classifying elders with dementia are 87.5% and 77.8%, respectively, whereas those for classifying elders without dementia are 90.9% and 95.2%, respectively. The PR curves for classifying dementia from the ZS data set are shown in Fig. 9. The AUC-PR with Naïve Bayes labeled as the blue line, that with RF labeled as the red line, and that with SVM labeled as the green line are 0.895, 0.858, and 0.544, respectively. Naïve Bayes also has better precision and recall for classifying elders with dementia than those with RF or SVM.

Moreover, we also show the confusion matrix of classifying 30 elders only with movement trajectories from the ZS data set using the Naïve Bayes classifier. After comparing the confusion matrix only with movement trajectories as shown in Table XI and the confusion matrix with all features including movement trajectories and scores as shown in Table XII, we find that there is only one elder without dementia with the wrong classification in Table XI. Thus, we can make a brief summary that the proposed classification system for dementia, MCI, and CH groups based on Naïve Bayes does not require a large number of subjects for training and can perform accurate classification only taking movement trajectories as features, without human-made scores.

C. Discussion

According to the inference with the model of Naïve Bayes, we can find out which activity is important among these eight assigned activities in each data set, and that activity is called key activity. Because the ZS data set is under our handling,

TABLE XII

CONFUSION MATRIX OF CLASSIFYING NINE DEMENTIA AND 21 NONDEMENTIA WITH ALL FEATURES FROM THE ZS DATA SET

Ground Truth / Classified as	Dementia	Nondementia
Dementia	7	1
Nondementia	2	20

we only discuss the elders' behaviors in this activity set. More specifically, we would like to give some more insight about why the activities are important for extracting features and classifying elders with dementia.

Note that there are two key activities, namely, the 3rd and 4th activities in the ZS data set, where the 3rd activity is to write a birthday card, encloses a check, and addresses an envelope, whereas the 4th activity is to find the assigned DVD, watches the news clip, and selects the assigned TV channel. These two activities are the most complex ones among these eight activities because the items elders have to fetch in each activity are all placed in different locations. When elders perform these two activities, the wandering patterns are exhibited obviously if the elder could not find the items he/she has to use. In fact, in our experiment, we have already told the elder what he/she had to do and where the items were placed more than twice before each activity was started. However, the elders who had dementia easily forgot what he had to do and the locations where the items were placed. Thus, they would walk around and attempt to find something they remembered.

In the CASAS data set, the 7th activity, to prepare a cup of soup using the microwave, is the key activity. However, the 7th activity in the ZS data set is not a key activity because of different details of the designed activity and environment. For example, elders took more time to wait for steaming with electric pot in the ZS data set than the time taken for elders to heat the soup with microwave in the CASAS data set. On the other hand, during the waiting time, the elder would watch TV, walk around to see the environment, see the view outside the window, sit on the bed, and so on. However, these movement trajectories are hard to classify dementia and nondementia groups. A possible mitigation of this is to add some subactivities during the waiting time.

As for other activities in the ZS data set, the 1st activity is to sweep and dust, but the elders' habits might affect their performances. For example, most females perform such activity more carefully than males. Thus, it is harder for the movement trajectories extracted from this activity to classify elder with dementia effectively. In the 5th activity, which is about watering plants, most elders could complete this activity without making too much error because it is quite easy. In the 2nd activity, obtaining medicine, the 6th activity, answering the phone, and 8th activity, picking an outfit, elders only move to the destination directly to perform these activities. Therefore, the differences of trajectories between elders with dementia and those of elders without dementia do not seem to be significant. Therefore, it is generally hard to classify the elders with dementia from those without only based on movement trajectories; instead, the useful feature here is scores of those activities.

Overall, we find from our own experiment using the self-collected ZS data set that the wandering patterns will appear when elders forget something and will walk around to see anything in order to recall what they need to do. Despite that the activity with complex instructions (such as to grab something in different rooms and different locations) is efficient to classify dementia and nondementia, some simple activities still need to be added in during the test in order to let elders gain more sense of self-achievement. If we do that, more elders will be willing to do the test.

VII. CONCLUSION

The contribution of this article is we have proposed a set of useful features, which is applied to a supporting system that can help doctors who do not know the elder's recent activity behaviors to quickly classify him/her to assess the likelihood of having dementia. Our system only requires elders to perform some activities selected from IADL within 2 to 4 hours in a smart home environment where only motion sensors are deployed on the ceiling. Under this circumstance, elders may feel more comfortable when they perform activities in the environment because they do not need to wear any sensor. Then, we generate elders' movement trajectories by integrating data from motion sensors and extract "k-repeating substrings" features from the trajectories focusing on finding wandering patterns. The features and evaluated scores for each activity are fed into a machine learning algorithm, Naïve Bayes, to classify elders into groups with and without dementia. Such a proposed system is systematic and scientific with the motion detection, which tries to track the behavior marker of the dementia patients. There are two data sets used to validate the supporting system, including CASAS data set, which is a public data set from Washington State University, and the ZS data set, which is designed and collected by us at ZS Senior Home. In the CASAS data set, there are 7 elders with dementia and 115 elders without dementia, including MCI and CH, aged between 60 and 74 years. We also choose another 110 elders with CH aged either younger than 59 years or older than 75 years from the same data set. The average precision and recall for classifying 122 elders are 97.4% and 97.5%, respectively, with the value of AUC-ROC being 0.848. The average precision and recall for classifying 232 elders are both 98.3% with the value of AUC-ROC being 0.848. In the ZS data set, there are 9 elders with dementia and 21 elders without dementia aged between 68 and 97 years. The average precision and recall for classifying these 30 elders are 89.9% and 90.0%, respectively, with the value of AUC-ROC being 0.921. Moreover, we find that wandering patterns will easily be exhibited if elders forgot the instructions of activities or the locations of items in the ZS data set. They would try to walk around to recall their previous memories. As a result, our proposed detecting system does extract useful features from the information collected from the motion sensors. To sum up, the advantages of our proposed system are: 1) these extracted features are useful and easy to be obtained; 2) the total amount of time taken to monitor an elder is relatively short; and 3) the outcome of our system can be quite supportive for, say, family doctors.

In the future, we can try to build a smart home environment in the hospital with motion sensors only based on the proposed design to support doctors to tell whether an elder with dementia is getting worse or not. Thus, many patient subjects visiting the hospital can join the experiment so that more data can be collected in order to promote the proposed system. We will also analyze feedbacks from doctors about the plausibility of the proposed supporting system and improve it further.

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