# Collaborative Trajectory Mining in Smart-homes to Support Early Diagnosis of Cognitive Decline

Elham Khodabandehloo, Daniele Riboni

**Abstract**—Our ageing world population claims for innovative tools to support healthcare and independent living. In this paper, we address this challenge by introducing a novel system to recognize symptoms of cognitive decline by exploiting modern smart-home sensors. Since several studies indicate that cognitive issues are frequently associated to locomotion anomalies, our work relies on clinical models of wandering behavior. Previous works tried to recognize wandering of elderly people in outdoor environments, using GPS data and location trace analysis. However, the recognition of wandering indoors poses additional challenges. On the one hand, when moving in a restricted indoor environment, a system for wandering recognition may produce a large number of false positive, since a person's movements are frequently more intricate indoors than outdoors. On the other hand, several indoor movements resembling wandering may be actually due to the normal execution of daily living activities, or to the particular shape of the home. To address these challenges, we adopt a collaborative learning approach, using a training set of trajectories shared by individuals living in smart-homes. New wandering episodes are classified using a personalized model, built considering the homes' shape and the individuals' profiles. We apply a long-term analysis of classified wandering episodes to provide a hypothesis of diagnosis to be communicated to a medical center for further inspection. We implemented our algorithms and evaluated the system with a large dataset of real-world subjects, including people with dementia, MCI persons, and cognitively healthy people. The results indicate the potential utility of this system to support the early diagnosis of cognitive impairment.

**Index Terms**—Cognitive decline, Abnormal behavior detection, Activity recognition, Ambient intelligence.

## 1 Introduction

Due to the rapid increase of the population age, more and more people are going to experience cognitive issues that, especially if not diagnosed, may disrupt their quality of life and their ability of living independently. Since the senior population is projected to double as a percentage over the whole population in the next decades, this problem may ultimately challenge the sustainability of health systems [1]. Hence, it is of foremost importance to devise novel techniques to recognize early symptoms of cognitive decline in the elderly, in order to report them to the clinicians. Since it is a common situation for elderly people to live alone, periodic screening done by clinicians should be complemented by continuous cognitive assessment carried out using automatic tools, in order to trigger alarms when indicators of cognitive decline are observed [2].

In this paper, we face this challenge by exploiting the sensing infrastructures of modern smart homes, as well as artificial intelligence methods. Indeed, the increasing adoption of indoor positioning infrastructures in smart-homes paves the way to a plethora of intelligent applications to support the user's ageing and well-being [3]. In particular, we investigate the use of location data acquired from Passive Infrared (PIR) motion sensors and from other smart-home sensors to monitor the cognitive status of the inhabitant through collaborative trajectory mining. In fact, several studies confirm that a person's movements are impacted by his/her cognitive status [4]. As a consequence, different clinical models have been proposed to describe locomotion patterns of cognitively impaired people.

Algase et al. [5] define wandering as "a syndrome of dementia-related locomotion behaviour having a frequent, repetitive, temporally-disordered and/or spatially-disoriented nature that is manifested in lapping, random and/or pacing patterns". A popular clinical model is the one proposed by Martino-Saltzman in [6] to characterize wandering behavior frequently observed in cognitively impaired people. That model classifies movement traces in different pattern of wandering behavior. Wandering behavior is defined as *random walk* (going from an origin to a destination following a very inefficient path), *pacing* (repeatedly going back and forth from two places at a small distance), or *lapping* (repeatedly moving around a small area with circular movements or loops).

Hence, different previous works tried to recognize wandering behavior outdoors by means of positioning systems and location pattern mining [7]. Liao et al. proposed a GPS-based system to recognize typical routes and transportation modes based on the user's movement history, and to automatically detect deviations from the normal mode [8]. Lin et al. proposed a method to detect wandering behavior according to the Martino-Saltzman model, based on the angular sum of the GPS trajectory turning points [9]. However, fewer studies tried to apply the model-based approach in indoor environments. Kearns et al. proposed the use of ultra-wide band radio technologies deployed in common indoor living spaces for measuring wandering in people with dementia (PwD) [10]. Their method relies on measuring the number of turning points in the trajectory. Lin et al. used customized active infrared sensors to recognize spatio-temporal patterns

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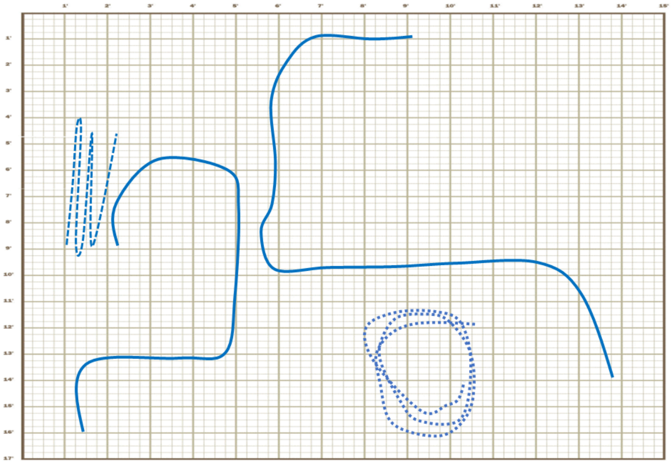


Fig. 1: Examples of human trajectories in a space. Without any context information, all of the four trajectories seem abnormal, according to well-known clinical models of wandering behaviors. Indeed, the two trajectories depicted with solid lines resemble a *random walk*; the one depicted with a dashed line resembles a *pacing* movement; the one depicted with a dotted line resembles a *lapping* movement.

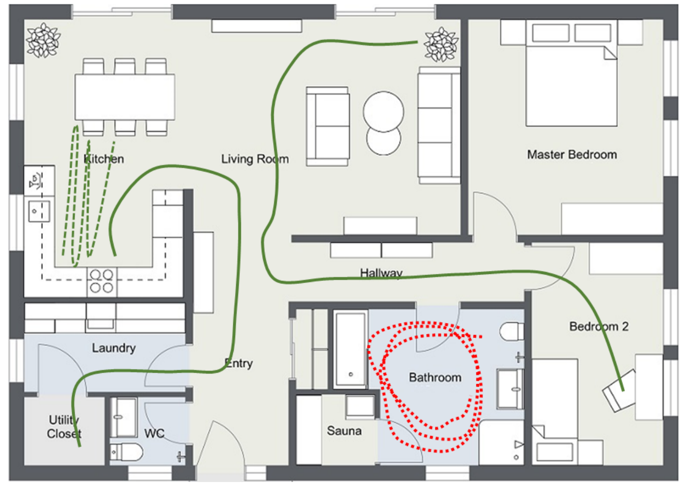



Fig. 2: The same trajectories illustrated in Figure 1, are shown in the context of the home floor plan. When put in context, only one trajectory out of four is likely abnormal. Indeed, the two trajectories depicted with solid lines, which resemble random walks when observed out of context, are actually the shortest paths from their source to their destination when observed in the context of the floor plan. The back-and-forth movement from the kitchen to the dining table, depicted with a dashed line, may actually be a normal movement executed by a person setting up the table for dinner. On the contrary, the repeated looping movement within the bathroom, depicted with a dotted line, is likely an abnormal trajectory corresponding to the *lapping* pattern, possibly due to cognitive issues.

of wandering locomotion in a smart home [11].

In other works, information acquired from PIR motions sensors was analyzed for supporting different healthcare applications. Suzuki et al. used PIR sensors mounted on the ceiling of rooms in a nursing home to monitor high-level activities of the inhabitants [12]. Recognition of abnormal behaviors was based on statistical deviation from the usual activity pattern of the subject. Yang et al. proposed a method to track the movements of people within smart-homes based on PIR sensors using an accessibility map and the $A^*$ algorithm [13]. The accessibility map was trained on the movements of the individual, while the $A^*$ algorithm was used to refine tracking. Other indoor localization technologies were proposed to support healthcare. Sun et al. presented a pressure sensing system based on fiber-optic to track the movements of people [14]. They used a space encoding scheme to retrieve the position of inhabitants, and mixture models on location information for recognizing behaviors. Other works, including the system proposed by Wang et al. [15], rely on cameras and computer vision tools for gait assessment of elderly people.

However, in a smart-home, accurate recognition of wandering patterns may not be sufficient to reliably recognize the cognitive decline of the inhabitant. When applied in smart homes, existing model-based methods can likely generate a large number of false positives. Indeed, several normal movements due to regular activity execution or due to the shape of the home may be recognized as wandering by the direct application of a clinical model. For instance, consider the four trajectories shown in Figure 1. Observed out of context, those trajectories may seem abnormal, since they resemble inefficient movement patterns. On the other hand, when observed in their smart-home context illustrated in Figure 2, only one out of four trajectories may be considered abnormal, while the other three are likely due to the floor plan of the smart home, or to normal activity execution.

Hence, an indoor system for detecting wandering episodes in smart-homes should include an effective method to sort out false positives. An obvious method to recognize false positives would be to rely on the smart-home floor plan to recognize inefficient paths due to the home shape, and on activity recognition systems [16] to detect abnormal paths due to normal activity execution. However, most existing smart-home systems do not include the apartment floor plan, and the accuracy of activity recognition systems may be insufficient to reliably sort out false positives.

In order to overcome this problem, in this paper we propose a collaborative machine learning approach to cognitive assessment based on smart-home positioning data. In particular, we acquire anonymous trajectories from a set of instrumented smart homes inhabited by both cognitively healthy and cognitively impaired people. We extract possible wandering episodes from those traces, and we label them according to the cognitive status of the individual. Then, we select trajectories according to the home shape and to the profile of the inhabitant, and we train a personalized model based on them. We classify new wandering episodes according to the personalized model, and we apply long-term analysis to produce a hypothesis of diagnosis about the cognitive status of the subject. We have implemented our algorithms, and performed experiments with a large real-world dataset acquired from different categories of users that underwent clinical assessment. The results indicate that our method can potentially provide useful information to the clinician for early detecting cognitive decline, and for supporting the clinical assessment.

The main contributions and innovation of our paper can be summarized as follows:

- We introduce an innovative architecture for supporting early detection of cognitive decline through collaborative trajectory mining in smart homes.
- We propose a novel wandering detection method, as well as a feature engineering technique to represent wandering episodes in a compact and expressive way.
- We illustrate a collaborative machine learning method to classify new wandering episodes, and a long-term analysis technique for continuous cognitive assessment.
- We perform extensive experiments with real-world data, which indicate the utility of our system.

The rest of the paper is structured as follows. In Section 2 we formalize the problem and we illustrate our system architecture. Section 3 describes the home wandering detection method. In Section 4 we explain the algorithms for classification of wandering episodes, and the long-term trajectory analysis method. Section 5 reports our experimental evaluation. In Section 6 we conclude the paper with final remarks and directions for future work.

## 2 Collaborative Cognitive Assessment System

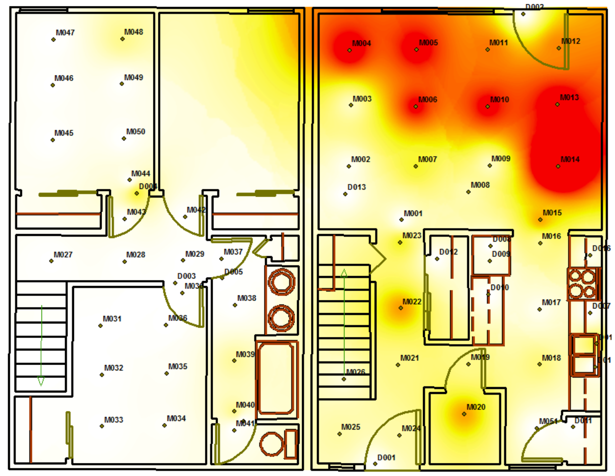
In this section, we formalize the addressed problem and we present our architecture for supporting early diagnosis of cognitive decline.

### 2.1 Smart home architecture and positioning system

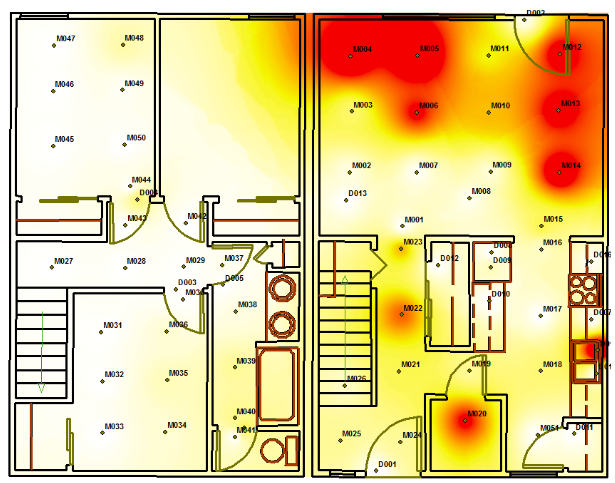
In our paper, we assume a typical smart home infrastructure, equipped with ambient sensors to monitor movements and interaction with furniture and appliances. In particular, we are interested in monitoring the position of the inhabitant and his/her movements within the home. For the sake of this work, we assume that the person is living alone in the home. Hence, we extract location information from the interaction of the user with every sensor having a fixed position in the home, and that fires only as a consequence of the user's presence or actions. For instance, if the fridge door sensor detects that the door has been opened at time $t$, and the relative coordinates of the fridge in the home are $(x, y)$, we infer (with good confidence and relatively small approximation) that the user's position at $t$ is $(x, y)$.

For the sake of this paper, we assume that the CASAS sensor infrastructure [18] is deployed in the smart-home. However, our methods and algorithms can be applied to any other indoor positioning system capable of accurately tracking the movements of the user within the home. In particular, our indoor positioning system acquires information about the user's location using the following sensors:

- passive infrared (PIR) motion sensors;
- door sensors to detect the interaction with certain furniture, such as medicine cabinets;
- door sensors to detect when a door is opened or closed;
- ambient sensors detecting the interaction with fixed devices or furniture, such as the fridge or the oven.



(a) Heatmap of a cognitively healthy inhabitant.



(b) Heatmap of a cognitively impaired inhabitant.

Fig. 3: The smart-home environment used in our experiments. The figure is taken from the documentation of the CASAS datasets described in [17]. Dots and labels represents the position of PIR sensors and other kinds of sensors. The heatmaps represent the distribution of movements of the inhabitant.

The CASAS infrastructure is illustrated in Figure 3. Labeled dots indicate the position of sensors used for determining the user's position. The heatmaps in Figures 3a and 3b indicate the typical distribution of movements of a cognitively healthy and of a cognitively impaired subject, respectively. The distribution of movements of the cognitively impaired subject is less homogeneous, possibly indicating the repeated execution of abnormal trajectories such as *lapping*.

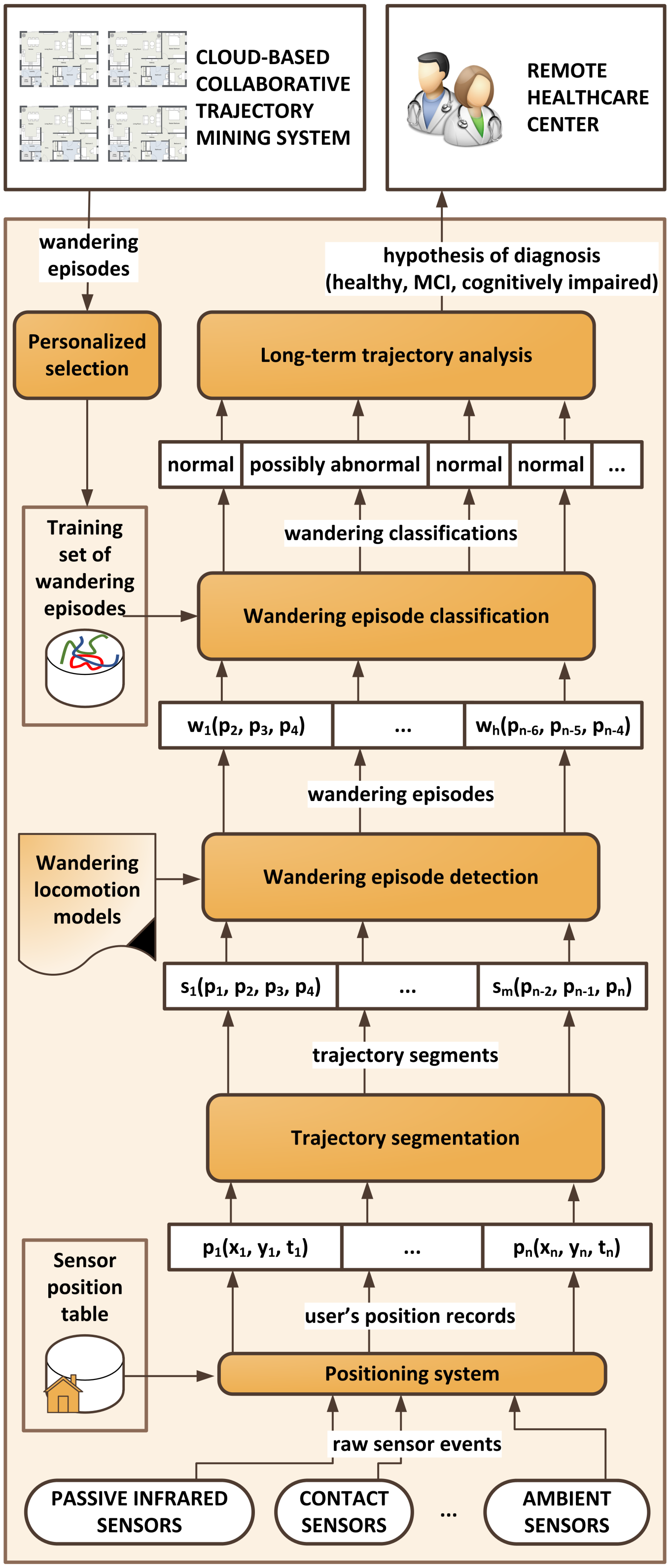



Fig. 4: Our overall framework.

## 2.2 Problem formalization and recognition system

Our overall framework is illustrated in Figure 4. Our system can be deployed either in the home or on the cloud. Each time a sensor fires, it sends a **sensor record** $sr$ to the home's POSITIONING SYSTEM:

$$sr = \langle t, s\_id, v \rangle,$$

where $t$ is the timestamp of firing, $s\_id$ is the sensor's unique identifier, and $v$ is the generated value.

The positioning system has a SENSOR POSITION TABLE $SP$ storing the relative position of each sensor in the home. A record of sensor position is a triple:

$$\langle s\_id, (x, y) \rangle,$$

where $s\_id$ is the sensor's unique identifier, and $(x, y)$ are the relative coordinates of that sensor in the home. Each time the positioning system receives a sensor record, it joins the record with the $SP$ table to add the $(x, y)$ coordinates, and projects the coordinates and timestamp values, to obtain a **user's position record** $p$:

$$p = \langle x, y, t \rangle,$$

where $x$ and $y$ are the relative coordinates of the user within the home at time $t$.

At run time, the positioning system communicates each position record to the TRAJECTORY SEGMENTATION module. That module stores the user's **position history** $H$, that is the whole temporal sequence of the user's positions within the home:

$$H = \langle p_1, p_2, \ldots, p_n \rangle.$$

The trajectory segmentation module is in charge of partitioning $H$ to identify **trajectory segments**; i.e., temporally contiguous sequences of positions which are likely related to the execution of a single activity or task. To execute this task, the trajectory segmentation module considers temporal information about the trajectory positions. In particular, the trajectory segmentation module partitions the position history $H$ in a set $S$ of trajectory segments:

$$S = \{s_1, s_2, \ldots, s_m\},$$

where each segment $s \in S$ is a temporal sequence of consecutive user's positions:

$$s_i = \langle p_j, p_{j+1}, \ldots, p_k \rangle,$$

and the last position of $s_i$ corresponds to the first position of $s_{i+1}$.

The temporal sequence of trajectory segments is sent to the WANDERING EPISODE DETECTION module. That module analyses each trajectory segment to find **wandering episodes**; i.e., temporal sequences of consecutive user's positions that resemble a wandering behavior according to a clinical model. A well-known clinical model for cognitive assessment is the Martino-Saltzman model of wandering behavior [6], which defines four patterns of paths: random, pacing, lapping, and direct. The categories of paths are illustrated in Figure 5. According to that model, the direct path is considered a normal behavior, while the other ones may indicate cognitive decline. In particular, the recognition of random walks in the home is very challenging, since tortuosity of movements may be due to several contextual facts such as furniture or presence of other obstacles. Hence, in this paper we concentrate on the recognition of pacing

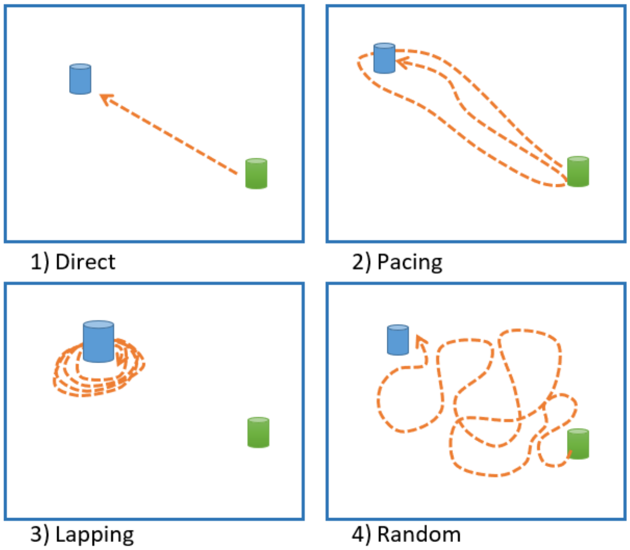



Fig. 5: Categories of paths according to the Martino-Saltzman model of wandering behavior [6]. Direct path is considered a normal behavior, while pacing, lapping, and random paths may indicate cognitive decline.

and lapping patterns; for the sake of simplicity, we call those patterns **loops**. We will investigate the recognition of random walks in future work.

Each wandering episode $w$ is sent to the WANDERING EPISODE CLASSIFICATION module, which applies a machine learning algorithm to classify the episode as normal, abnormal, or possibly abnormal. The classifier is trained using a set of trajectories collaboratively acquired in smart-homes having a similar shape and inhabited by people having a similar profile, in particular the same age range. The CLOUD-BASED COLLABORATIVE TRAJECTORY MINING SYSTEM collects anonymous wandering episodes from smart-homes. Episodes are labeled with the anonymous inhabitant's profile, home shape information, and his/her cognitive status. That system provides the PERSONALIZED SELECTION module with the available wandering episodes collected in homes that match the inhabitant's home shape. The latter module selects the episodes according to their inhabitant's profile. It provides the WANDERING EPISODE CLASSIFICATION module with a training set of selected wandering episodes. The training set is collected from heterogeneous people, including healthy elderly persons, people diagnosed with MCI, and cognitively impaired people.

Based on the received episodes, the wandering episode classifier provides the LONG-TERM TRAJECTORY ANALYSIS module with a stream of predictions. When a sufficient number of predictions has been acquired, that module produces a hypothesis of diagnosis of the person as cognitively healthy, mild cognitively impaired, or cognitively impaired. Hypothesis of diagnosis are communicated to the remote healthcare center of the user, for further investigation by the clinicians.

We point out that our system is not devoted to provide a definitive diagnosis. On the contrary, its goal is to raise an alarm when symptoms of cognitive decline are recognized, such that the individual can undergo a clinical evaluation.

# 3 PERSONALIZED WANDERING DETECTION

In this section, we explain how we perform trajectory segmentation and wandering episode detection in the smart home environment, and how we perform personalization.

## 3.1 Trajectory segmentation

The trajectory segmentation algorithm takes as input a temporal sequence of user's position records:

$$\langle p_1, p_2, \ldots, p_n \rangle.$$

We recall that its goal is to partition the sequence in trajectory segments, such that each segment is generated by a single activity instance. Hence, the algorithm needs to finalize a segment as soon as the individual stop executing his/her current activity. In a trajectory, both locomotion and non-locomotion phases may exist. Hence, we use the same method adopted in [19]: our algorithm partitions the trajectory such that each two consecutive positions in a segment have a temporal distance of less than one minute, and the distance between consecutive trajectories is one minute or more.

## 3.2 Wandering episode detection

Given a segment, the goal of this algorithm is to find wandering episodes. In each segment, it is possible to find several episodes. We define a loop as the largest continuous sequence of positions in the segment such that the locations of the start and end position are approximately the same. Hence, for recognizing loops, we consider linear misclosure by using partial coordinates. For this purpose, for each couple of consecutive positions in a sub-segment, we sum the positive and negative partial coordinates for $x$ coordinates ($\Delta x$) and $y$ coordinates ($\Delta y$). The sub-segment is a loop if and only if the algebraic sum of both $\Delta x$ and $\Delta y$ is close to 0, up to an approximation error $\epsilon$, according to these steps:

1) Calculate the algebraic sum between all consecutive positions in a sub-segment as $\Delta x$ and $\Delta y$;
2) The sub-segment is a loop iff $\sum \Delta x < \epsilon$ and $\sum \Delta y < \epsilon$.

## 3.3 Personalized selection of wandering episodes

As explained before, the wandering episode classifier is trained with anonymous examples in a personalized manner. Personalization is achieved by acquiring training samples from people having a profile similar to the one of the target user. Moreover, the home's shape may influence the kind of movement traces and the execution of daily living activities. Hence, training samples are acquired only from homes whose shape is similar to the one of the target user's home. For instance, a residence for elderly people may consist of several similar apartments; the inhabitants of those apartments may share their anonymous traces to collectively train personalized classification models based on their profile. Due to the nature of the dataset available for our experiments, in this work we assume that all trajectories are collected from homes having the same shape. When trajectories are collected from heterogeneous homes, a proper function or criteria should be devised for homes selection, but this aspect is out of the scope of this paper.

Ideally, in order to apply profile-based personalization, we should consider all those features of the inhabitant that affect his/her movement patterns, such as age, gender, and physical condition. However, due to the nature of our dataset, in this work we restrict personalization to the individual's age. Due to the relatively small number of individuals available in our dataset and to the lack of detailed profile information, we could manually divide the individuals in groups. However, when the number of individuals is large, and additional profile information is available, a standard clustering technique could be used to partition the inhabitants in homogeneous groups according to their features. Moreover, the number of trajectories obtained from cognitively healthy people, MCI subjects, and PwD should be well balanced to avoid the class imbalance problem [20].

We point out that indoor location traces may reveal sensitive information, such as personal routines, and physical or mental disabilities [21]. Hence, they are shared in anonymous form, without including explicit identifiers of the inhabitant. However, when matched with external data, profile information may easily enable the reconstruction of the inhabitant's identity. For this reason, the cloud-based collaborative trajectory mining system should adopt state-of-the-art techniques for identity anonymity, such as $l$-diversity [22] or $t$-closeness [23].

# 4 Cognitive assessment algorithm

In this section, we explain the algorithms for classification of wandering episodes and long-term trajectory analysis.

## 4.1 Wandering episode classification

The wandering episode classification module receives a training set of loops acquired from the CLOUD-BASED COLLABORATIVE TRAJECTORY MINING SYSTEM. Those loops are collected from three categories of users: cognitively healthy persons, people diagnosed with MCI, and cognitively impaired people. For each loop, the module builds a feature vector, which should represent in a compact yet expressive way the characteristics of the trajectory. Each vector is composed of the following features:

- area: the area of the loop;
- distance: the length of the loop;
- $x$ centroid: the relative horizontal centroid of the loop;
- $y$ centroid: the relative vertical centroid of the loop;
- time duration: the time taken by the user to walk the loop;
- other N features, each related to a single sensor, whose value counts the number of times that the sensor was activated by the user during the loop;
- class: the person's diagnosis.

The machine learning module uses the training set to build a statistical model of the wandering episodes generated by the different categories of people. When it receives a new wandering episode, it classifies it using that model. If the episode is classified as generated by a healthy subject, it is considered a *normal* episode. If it is classified as generated by an MCI person, the episode is considered *possibly abnormal*. If the episode is classified as generated by a PwD, it is considered an *abnormal* episode. The result of the classification of each wandering episode is sent to the module for long-term trajectory analysis.

## 4.2 Long term trajectory analysis

The goal of this module is to generate a hypothesis of diagnosis based on the predictions of the wandering episode classifier. In order to produce a reliable hypothesis, the module must accumulate a sufficient quantity of wandering classifications. For the sake of this work, we assume that the system uses all the available data to produce the hypothesis. In a real-world system continuously acquiring sensor information, the system should adopt more sophisticated techniques to consider only a sufficient quantity of recent wandering episodes classifications, in order to recognize changes in the cognitive performance. This aspect will be investigated in future work. Currently, the module analyses the whole history $EC$ of wandering episodes classifications:

$$EC = \{class_1, class_2, \ldots, class_h\},$$

where the value of $class_i$ may be either *normal*, *abnormal*, or *possibly normal*. The module formulates the hypothesis of diagnosis corresponding to the most frequent class. Formally, we define the prediction function $PF$, which computes the number of predictions of each class in $EC$:

$$PF : D \rightarrow \mathbb{N},$$

where $D$ is the domain of classes (in our case, $D$ = {normal, abnormal, possibly abnormal}). $PF$ is defined as follows:

$$PF(class) = |\{cl \in EC : cl = class\}|.$$

Then, the module computes the most frequent class $fc$:

$$fc = \underset{class \in D}{\arg\max}\ PF(class).$$

Finally, it formulates the hypothesis of diagnosis $h$ according to the following formula:

$$h = \begin{cases} \text{`healthy'} & \text{if } fc = \text{`normal'}, \\ \text{`MCI'} & \text{if } fc = \text{`possibly abnormal'}, \\ \text{`cognitively impaired'} & \text{if } fc = \text{`abnormal'}. \end{cases}$$

and communicates the hypothesis $h$ to the medical center.

# 5 Experimental evaluation

In this section, we report the experimental evaluation we carried out with real-world trajectories acquired in smart-homes from a large set of individuals. The dataset has been acquired and labeled by researchers of the Center for Advanced Studies in Adaptive Systems[1] (CASAS) at Washington State University (WSU). For the sake of privacy, explicit identifiers of the individuals involved in the study have been removed before releasing the data, while quasi-identifier personal data such as age have been generalized to avoid identity disclosure. The whole protocol of recruiting and data collection was approved by the Institutional Review Board of WSU [24].

1. http://casas.wsu.edu/

### 5.1 Smart home setup

Sensor data have been acquired while the participants individually performed several kinds of activities in a smart home apartment, partially shown in Figure 3. The smart home includes a kitchen, a living/dining room, a bathroom, and three bedrooms. The apartment is equipped with several kinds of sensors attached to doors, furniture, water taps, and items, to capture data about the actions of the inhabitant. Moreover, the smart home includes PIR motion sensors positioned on the ceiling. The average distance of PIR sensors is about 1 meter throughout the home. The setup of the smart home is described in detail in [25]. For the sake of our experiments, we relied on motion sensors and door sensors only. In total, the apartment includes 51 motion sensors and 16 door sensors. We disregard any other semantic information of the sensor events apart from location information.

We used that dataset to reproduce a residence for elderly persons, with apartments having identical shape and sensors, but inhabited by different individuals with heterogeneous profiles.

### 5.2 Participants recruiting and cognitive evaluation

Participants were recruited by WSU researchers through advertisements, physician referrals, and from past studies in their laboratories. Recruitment and data collection occurred over a period of two years. In total, 400 individuals were recruited to participate to the CASAS study. After obtaining informed consent, participants underwent multidimensional clinical assessment, which included both standardized and experimental neuropsychological tests. The cognitive health status of each participant was diagnosed by neuropsychologists. Participants were classified in three categories:

- Participants in the Dementia (category D) group met the DSM-IV-TR diagnostic criteria described in [26], which includes the observation of several cognitive deficits that negatively affect the normal execution of daily living activities and represent a decline from the previous health status of the subject. 36 Participants were classified in this group.
- Participants in the MCI category met the criteria defined by Petersen in [27] and those defined by the National Institute on Aging - Alzheimer's Association [28]. This group included 59 participants.
- 255 participants were diagnosed as cognitively Healthy (category H). Among them, 37 were middle aged persons (45-59 years old), 83 were young-old persons (60-74 years old), 44 were persons older than 75, and 91 were younger adults.

Among the remaining ones, 40 persons were diagnosed with "other conditions", and 10 persons had no diagnosis or were diagnosed as "at risk".

### 5.3 Day out tasks execution and data collection

After cognitive evaluation, participants were asked to execute Day Out Tasks (DOTs) in the smart home. DOTs are naturalistic tasks that require the ability to perform interleaved activities in order to reach a certain goal. Those activities are at the core of competency in everyday life [29]. DOTs were executed in a single day by each user according to a given script. Each DOT was described to the user as a complex activity composed by a number of simpler tasks. For instance, "Setup hands for a card game, answer the phone and describe the rules of the game" was composed by "move to the kitchen", "locate the deck of cards from kitchen cabinet", etc.

During the activity execution, the smart home infrastructure acquired the sensor data triggered by the movements of the participant in the home and by his/her interaction with furniture and appliances. For each sensor event triggered by a given user, the CASAS dataset reports the following sensor record: $\langle\ t \quad s\_id \quad v\ \rangle$, where $t$ is the timestamp of sensor firing, $s\_id$ is the sensor unique identifier, and $v$ is the emitted value. The domain of the value $v$ depends on the specific sensor; e.g., if a sensor is attached to a fridge door, the domain of $v$ may be {'open', 'close'}. For instance, the record ⟨ 08:30:00.27063 M08 ON ⟩ represents the fact that the motion sensor M08 emitted the value ON at 08:30:00.27063. Note that, since each user executed his/her activities in a single day, the information about the day is not necessary. The detailed description of tasks and the full dataset are available on the Web[2].

Despite several participants diagnosed with MCI or dementia were enrolled in the CASAS study, we were able to include in our experiments only part of them. Indeed, we had to exclude the data of different cognitively impaired persons that could not complete the required activities. Totally, among people having cognitive issues, we included in our experiments 17 PwD and 40 with MCI. We also excluded from our experiments the data of people with no diagnosis, or diagnosed as "other condition" or "at risk", since their cognitive diagnosis was missing or unclear.

### 5.4 Selection of wandering episodes

As explained in Section 3.3, the wandering episode classifier is trained with episodes collected from selected participants to enforce personalization and class balancing. In order to evaluate the effectiveness of selection, we considered the following setups.

- *Personalized selection*. Ideally, in order to keep the classes well balanced, we should consider the same number of individuals from PwD, MCI, and cognitively healthy persons. However, only 17 PwD were included in our experiments; as a consequence, with this strategy, only 51 people would be considered totally. In order to include a larger number of subjects in our experiments and to exploit additional training data, in this setup we relaxed the balancing constraint, and included the same number of cognitively unhealthy (i.e., MCI or PwD) and healthy subjects. The latter were randomly chosen among healthy people having a profile similar to the one of MCI persons and PwD. For privacy reasons, the CASAS dataset does not specify the age of MCI people and PwD. However, from the medical literature, it is well

2. http://casas.wsu.edu/datasets/assessmentdata.zip

known that MCI and dementia typically affect people aged 60 or older [26], [27]. We assume that the age of cognitively unhealthy subjects in the dataset falls in that range. Hence, the healthy individuals were randomly chosen among people aged 60 or older. This setup includes the trajectories of 17 PwD, 40 MCI, and 57 healthy people (114 persons totally).

- *Non-personalized selection*. This setup includes the same participants of the above setup, and 86 additional participants randomly chosen among healthy subjects aged 59 or younger. While it may exploit additional training data, this setup is not personalized, and classes are less balanced. This setup includes the trajectories of 17 PwD, 40 MCI, and 143 healthy people (200 persons totally).

### 5.5 Prototype and experimental setup

In order to detect the relative position of each considered sensor in the home, we imported the home map shown in Figure 3 in the ArcGIS software. We assigned to each sensor, identified by its marker's label in the map (M47, D-06, etc.), its $x$ and $y$ coordinates, in order to populate the SENSOR POSITION TABLE $SP$ introduced in Section 2.2. Figure 6 shows an excerpt of the imported map; green points indicate the sensors position.

We have developed a prototype of our system modules in Matlab, using the Weka [30] toolkit version 3.8.2 for executing the machine learning tasks. The code of our prototype is published on the Web[3]. For enabling reproducibility, the documentation of the code includes the pseudo-identifiers of those individuals whose data have been used in our experiments.

At first, our prototype takes CASAS datasets as input, and pre-processes them to map the sensor labels into their respective geometric coordinates. In particular, the code transforms each sensor record into the tuple: $\langle x, y, t\rangle$, where $(x, y)$ are the coordinates of the fired sensor, and $t$ is the time of firing. Note that the above tuple matches our definition of *user's position record*. For each user, the TRAJECTORY SEGMENTATION module is provided with the stream of his/her position records. That module performs segmentation and provides the WANDERING EPISODES DETECTION module with the trajectory segments. The latter module detects wandering episodes, transforms them into feature vectors, and provides the WANDERING EPISODE CLASSIFICATION module with them.

The latter uses the machine learning APIs of Weka to classify each wandering episode in three categories: N, PA, and A, according to the diagnosis of the person that walked along that loop: healthy subjects are supposed to generate *normal* loops (N); MCI subjects are supposed to generate *possibly abnormal* loops (PA), and PwD are supposed to generate *abnormal* loops (A). Hence, the problem tackled by that module is a three-class classification problem. In our experiments, we evaluated different machine learning algorithms for classification. Feature vectors of episodes are considered in temporal order of occurrence, one person at a time. Since very short loops are irrelevant, we disregarded loops shorter than 50 seconds. Then, we applied 100-folds

3. https://sites.unica.it/domusafe/tetc-code/

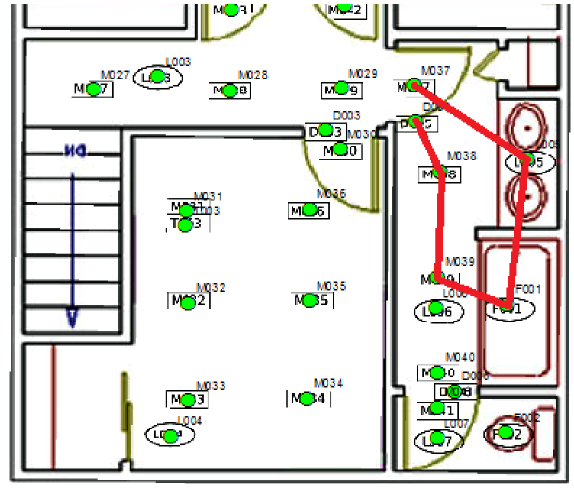



Fig. 6: The smart home map imported to ArcGIS for acquiring the sensor position information. Bright green marks indicate the positions of sensors. The red path illustrates a wandering episode identified by our system, which resembles a *lapping* episode possibly indicating wandering behavior according to the Martino-Saltzman model [6]. Note that the red path is identified as lapping even though its start and end point are not identical, but their distance is below a given threshold.

cross validation to evaluate the accuracy of the wandering episode classifier. For each subject, the wandering episodes classifications are passed to the LONG-TERM TRAJECTORY ANALYSIS module, which provides a hypothesis of diagnosis. The hypothesis is then compared with the ground truth to evaluate results.

For evaluating the overall performance of our algorithms, we used the standard metrics of accuracy (i.e., the percentage of correct predictions), precision, recall, $F_1$ score (i.e., the harmonic mean of precision and recall), true positive rate (TPR), and true negative rate (TNR).

In the following, we report the results obtained with cross-validation. In this work, we do not use a validation set, since our algorithms do not require tuning of hyperparameters. The only hyperparameter used in our algorithms is the parameter $\epsilon$ used for wandering episode detection (Section 3.2). However, the optimal value to assign to that parameter depends on the accuracy of the positioning system. Given the positioning infrastructure used in our experiments, we set $\epsilon$ to 30 cm and do not perform experiments with different values of $\epsilon$. Similarly, we keep the default parameters of the machine learning algorithms set by Weka. However, recognition rates could be possibly improved by fine-tuning the hyperparameters using a validation set.

### 5.6 Results of wandering episode classification

Initially, we evaluate the performance of the wandering episode classification method. In particular, we evaluate the ability of the classifier to correctly recognize the cognitive status of a person given the loop that he/she generated. We perform experiments with several state-of-the-art classifiers. Since the three classes are unbalanced, we apply the class balancing filtering operation of Weka, which changes the

| Class | TPR | FPR | Prec. | Rec. | $F_1$ |
|---|---|---|---|---|---|
| Normal | 0.673 | 0.352 | 0.650 | 0.673 | 0.661 |
| Possibly Abnormal | 0.588 | 0.241 | 0.585 | 0.588 | 0.586 |
| Abnormal | 0.412 | 0.074 | 0.476 | 0.412 | 0.441 |
| Avg. | 0.605 | 0.272 | 0.602 | 0.605 | 0.603 |

(a) Metrics

| Normal | Possibly Abnormal | Abnormal | ← classified as |
|---|---|---|---|
| **6611** | 2417 | 795 | Normal |
| 2544 | **4303** | 476 | Possibly Abnormal |
| 1017 | 632 | **1154** | Abnormal |

(b) Confusion matrix

TABLE 1: Personalized selection. Results of wandering episode classification using Random forest.

| Class | TPR | FPR | Prec. | Rec. | $F_1$ |
|---|---|---|---|---|---|
| Normal | 0.506 | 0.306 | 0.616 | 0.506 | 0.556 |
| Possibly Abnormal | 0.445 | 0.246 | 0.512 | 0.445 | 0.476 |
| Abnormal | 0.492 | 0.241 | 0.250 | 0.492 | 0.332 |
| Avg. | 0.482 | 0.275 | 0.526 | 0.482 | 0.495 |

(a) Metrics

| Normal | Possibly Abnormal | Abnormal | ← classified as |
|---|---|---|---|
| **4972** | 2474 | 2377 | Normal |
| 2312 | **3259** | 1752 | Possibly abnormal |
| 790 | 634 | **1379** | Abnormal |

(b) Confusion matrix

TABLE 2: Personalized selection. Results of wandering episode classification using $k$NN ($k = 5$).

| Class | TPR | FPR | Prec. | Rec. | $F_1$ |
|---|---|---|---|---|---|
| Normal | 0.374 | 0.288 | 0.558 | 0.374 | 0.448 |
| Possibly abnormal | 0.391 | 0.319 | 0.415 | 0.391 | 0.403 |
| Abnormal | 0.483 | 0.298 | 0.209 | 0.483 | 0.292 |
| Avg. | 0.396 | 0.301 | 0.457 | 0.396 | 0.409 |

(a) Metrics

| Normal | Possibly Abnormal | Abnormal | ← classified as |
|---|---|---|---|
| **3676** | 3262 | 2885 | Normal |
| 2231 | **2861** | 2231 | Possibly abnormal |
| 681 | 767 | **1355** | Abnormal |

(b) Confusion matrix

TABLE 3: Personalized selection. Results of wandering episode classification using Logistic regression.

| Class | TPR | FPR | Prec. | Rec. | $F_1$ |
|---|---|---|---|---|---|
| Normal | 0.381 | 0.337 | 0.523 | 0.381 | 0.441 |
| Possibly abnormal | 0.277 | 0.237 | 0.405 | 0.277 | 0.329 |
| Abnormal | 0.502 | 0.372 | 0.181 | 0.502 | 0.266 |
| Avg. | 0.36 | 0.305 | 0.431 | 0.36 | 0.375 |

(a) Metrics

| Normal | Possibly Abnormal | Abnormal | ← classified as |
|---|---|---|---|
| **3739** | 2392 | 3692 | Normal |
| 2613 | 2032 | **2678** | Possibly abnormal |
| 799 | 597 | **1407** | Abnormal |

(b) Confusion matrix

TABLE 4: Personalized selection. Results of wandering episode classification using Support Vector Machines.

| Class | TPR | FPR | Prec. | Rec. | $F_1$ |
|---|---|---|---|---|---|
| Normal | 0.274 | 0.273 | 0.493 | 0.274 | 0.352 |
| Possibly abnormal | 0.541 | 0.477 | 0.397 | 0.541 | 0.458 |
| Abnormal | 0.296 | 0.215 | 0.184 | 0.296 | 0.227 |
| Weighted Avg. | 0.375 | 0.34 | 0.414 | 0.375 | 0.373 |

(a) Metrics

| Normal | Possibly Abnormal | Abnormal | ← classified as |
|---|---|---|---|
| 2690 | **4861** | 2272 | Normal |
| 1954 | **3963** | 1406 | Possibly abnormal |
| 811 | **1162** | 830 | Abnormal |

(b) Confusion matrix

TABLE 5: Personalized selection. Results of wandering episode classification using Bayesian network.

weights of the data instances so that each class has the same total weight.

### 5.6.1 Personalized selection

At first, we consider the *Personalized selection* setup, described in Section 5.4. We achieve the best results using the Random forest classifier [31]. Overall, the classifier achieves an $F_1$ measure of 0.603. The specific metrics are reported in Table 1a, while the confusion matrix is reported in Table 1b. As it can be observed, only 1154 abnormal episodes out of 2803 are recognized as such, while the remaining 1649 are classified as either normal or possibly abnormal. However, among the three classes, the most frequently predicted class for abnormal episodes is the correct one. This consideration holds also for normal and possibly abnormal episodes. The best results are achieved for the recognition of normal episodes (relative $F_1$ = 0.661). The hardest category to recognize is abnormal (relative $F_1$ = 0.441), possibly because the number of PwD in the dataset is low. Results with a $k$NN classifier [32], reported in Table 2, achieve lower results, with an $F_1$ measure of 0.495. The other classifiers that we evaluated, including Logistic regression, Support Vector Machines, and Bayesian networks, achieved lower results. The respective results are shown in Tables 3 to 5.

### 5.6.2 Non-personalized selection

Then, we consider the *Non-personalized selection* setup. Overall, with this setup, the classifiers that we used achieve an average $F_1$ score higher than the one achieved by the same classifiers with the personalized selection setup. However, when we closely inspect the results, we notice that the increase in the average $F_1$ score is mainly due to the fact that the classifiers tend to recognize well the most frequent class N, while they obtain much lower recognition rates for the least frequent class A. Even with this setup, the classifiers obtaining the best results are Random forest and $k$NN. Their results are shown in Tables 6 and 7, respectively. However, with Random forest, only 704 abnormal episodes out of 2803 are correctly recognized. The most frequently predicted class for abnormal episodes is 'possibly abnormal', which is predicted in 1244 cases, while 'normal' is predicted in 855 cases. Also with the $k$NN algorithm, the most frequently predicted class for abnormal episodes is 'possibly abnormal'. All the other classifiers that we considered obtained lower recognition rates; we omit their results for lack of space.

| Class | TPR | FPR | Prec. | Rec. | $F_1$ |
|---|---|---|---|---|---|
| Normal | 0.816 | 0.263 | 0.916 | 0.816 | 0.863 |
| Possibly Abnormal | 0.681 | 0.178 | 0.422 | 0.681 | 0.521 |
| Abnormal | 0.251 | 0.035 | 0.320 | 0.251 | 0.281 |
| Avg. | 0.760 | 0.235 | 0.801 | 0.760 | 0.773 |

(a) Metrics

| Normal | Possibly Abnormal | Abnormal | ← classified as |
|---|---|---|---|
| **29129** | 5592 | 967 | Normal |
| 1808 | **4987** | 528 | Possibly Abnormal |
| 855 | **1244** | 704 | Abnormal |

(b) Confusion matrix

TABLE 6: Non-personalized selection. Results of wandering episode classification using Random forest.

| Class | TPR | FPR | Prec. | Rec. | $F_1$ |
|---|---|---|---|---|---|
| Normal | 0.684 | 0.178 | 0.931 | 0.684 | 0.789 |
| Possibly Abnormal | 0.588 | 0.225 | 0.332 | 0.588 | 0.424 |
| Abnormal | 0.385 | 0.129 | 0.163 | 0.385 | 0.229 |
| Avg. | 0.65 | 0.183 | 0.788 | 0.65 | 0.696 |

(a) Metrics

| Normal | Possibly Abnormal | Abnormal | ← classified as |
|---|---|---|---|
| **24420** | 7503 | 3765 | Normal |
| 1250 | **4304** | 1769 | Possibly Abnormal |
| 557 | **1168** | 1078 | Abnormal |

(b) Confusion matrix

TABLE 7: Non-personalized selection. Results of wandering episode classification using $k$NN ($k = 5$).

| Cogn. impaired | MCI | Cogn. healthy | ← classified as |
|---|---|---|---|
| **10** | 1 | 6 | Cogn. impaired |
| 0 | **29** | 11 | MCI |
| 1 | 3 | **53** | Cogn. healthy |

(a) Random forest. Overall accuracy: 80.7%

| Cogn. impaired | MCI | Cogn. healthy | ← classified as |
|---|---|---|---|
| **12** | 1 | 4 | Cogn. impaired |
| 4 | **26** | 10 | MCI |
| 4 | 6 | **47** | Cogn. healthy |

(b) $k$NN ($K = 5$). Overall accuracy: 74.6%

| Cogn. impaired | MCI | Cogn. healthy | ← classified as |
|---|---|---|---|
| **13** | 2 | 2 | Cogn. impaired |
| 9 | **21** | 10 | MCI |
| 9 | 20 | **28** | Cogn. healthy |

(c) Logistic regression. Overall accuracy: 54.4%

| Cogn. impaired | MCI | Cogn. healthy | ← classified as |
|---|---|---|---|
| **13** | 1 | 3 | Cogn. impaired |
| **18** | 4 | **18** | MCI |
| 26 | 4 | **27** | Cogn. healthy |

(d) Support Vector Machines. Overall accuracy: 38.6%

| Cogn. impaired | MCI | Cogn. healthy | ← classified as |
|---|---|---|---|
| 3 | **11** | 3 | Cogn. impaired |
| 1 | **35** | 4 | MCI |
| 3 | **53** | 1 | Cogn. healthy |

(e) Bayesian network. Overall accuracy: 34.2%

TABLE 8: Personalized selection. Long term trajectory analysis: confusion matrices for the algorithm on the whole set of available wandering episodes classifications.

### 5.7 Results of long-term trajectory analysis

In the following experiments, we use the predictions of the different machine learning algorithms to evaluate the performance of the LONG-TERM TRAJECTORY ANALYSIS algorithm.

#### 5.7.1 *Personalized selection*

At first, for each individual of the 'personalized selection' setup, we execute our algorithm using the whole set of classifications about his/her wandering episodes. The confusion matrix obtained applying the long-term trajectory analysis algorithm with the predictions of the Random forest classifier is reported in Table 8a. Out of 114 predictions, our algorithm provides 22 misclassifications. The worse results are obtained with PwD. In one case, a PwD is classified as MCI, while six PwD are classified as normal. We believe that this result is due to the low number of PwD involved in the study. Out of 40 MCI subjects, 29 are recognized as such, while 11 are classified as normal. Among the 57 cognitively healthy persons, 53 are correctly classified, while one is classified as PwD and three as MCI. Overall, the algorithm obtains a recognition rate of 80.7%.

The overall recognition rate obtained using the $k$NN classifier is 74.6%. The confusion matrix is shown in Table 8b. With that classifier, our algorithm obtains better results in recognizing cognitively impairment, since 12 out of 17 PwD were correctly recognized. However, the recognition rates for MCI and cognitively healthy persons were lower than those obtained using Random forest. Our algorithm achieves significantly worse results using the other considered classifiers, whose confusion matrices are shown in Tables 8c to 8e.

#### 5.7.2 *Non-personalized selection*

We execute the same experiment described in Section 5.7.1 with the non-personalized setup. With this setup, we achieve recognition rates significantly lower than those achieved using personalized selection. Results obtained using the predictions of Random forest and $k$NN are reported in Tables 9a and 9b. With the predictions of Random forest, the long-term analysis algorithm achieves an overall accuracy of $70.5\%$, with a decrease of more than $10\%$ with respect to the one achieved applying personalized selection. In particular, only 3 cognitively impaired individuals out of 17 were correctly recognized. Recognition rates of cognitively impaired people are not satisfactory also using the predictions of the $k$NN classifier, since only 6 PwD out of 17 are correctly recognized. With this setup, we also obtain a large number of misclassifications regarding cognitively healthy subjects. Indeed, using Random forest, 45 out of 143 cognitively healthy persons are classified as either PwD or MCI persons. Using $k$NN, 55 cognitively healthy people are misclassified. These results indicate the effectiveness of the personalized selection method described in Section 3.3.

#### 5.7.3 *Incremental recognition*

Finally, we measure the performance of our system based on the number of available classifications of wandering episodes. We consider the use of personalized selection, since it achieves the best results. Results are illustrated in

| Cogn. impaired | MCI | Cogn. healthy | ← classified as |
|---|---|---|---|
| 3 | **12** | 2 | Cogn. impaired |
| 0 | **40** | 0 | MCI |
| 2 | 43 | **98** | Cogn. healthy |

(a) Random forest. Overall accuracy: 70.5%

| Cogn. impaired | MCI | Cogn. healthy | ← classified as |
|---|---|---|---|
| 6 | **11** | 0 | Cogn. impaired |
| 1 | **39** | 0 | MCI |
| 2 | 53 | **88** | Cogn. healthy |

(b) $k$NN ($K = 5$). Overall accuracy: 66.5%

TABLE 9: Non-personalized selection. Long term trajectory analysis: confusion matrices for the algorithm on the whole set of available wandering episodes classifications.

Figure 7. As expected, the accuracy of our system tends to increase the more wandering episodes are considered by the long-term analysis module. The classifier obtaining the best result is Random forest, whose recognition rate increases significantly after having received about 200 classifications of wandering episodes. Using the other classifiers, the results exhibit a similar trend, even though the overall accuracy is lower. The only exception is when using the Bayesian network classifier, which achieved the worst results in our pool, since results do not improve with the number of available episodes.

### 5.8 Discussion

Overall, the results achieved by our system are promising. The recognition rate achieved by our long-term trajectory analysis method is high, even considering a limited number of wandering episodes. However, additional experiments are needed to thoroughly assess the potential of our approach. Indeed, the used dataset was acquired in a controlled environment. Moreover, activities were executed in semi-naturalistic conditions, since the participants were asked to execute a set of scripted activities and tasks. Our results should be confirmed by executing a trial in naturalistic environments. The introduction of noise due to naturalistic conditions may have a negative impact on recognition rates. However, recognition rates may increase if the system is executed for longer periods of time, and trained with additional trajectory data.

Currently, we have developed a prototype of all the algorithms of our system. The prototype is capable of analyzing the datasets of individuals' movements and to produce a hypothesis of diagnosis for each individual. However, in order to perform a large-scale trial in real-world conditions, our prototype implementation should be integrated in a whole system architecture. The architecture should take the raw data directly from a sensor infrastructure, share the data with the collaborative system, and communicate the diagnosis to the medical center. Currently, these modules are missing, and implementing the whole system will pose several challenges. In particular, sharing position data among participants will determine relevant issues regarding privacy and trust, which should be addressed through specific technological solutions, as those reported in [33]. Moreover, given the sensitivity of the involved data, it will be necessary to adopt specific measures to enforce security and compliance to regulations.

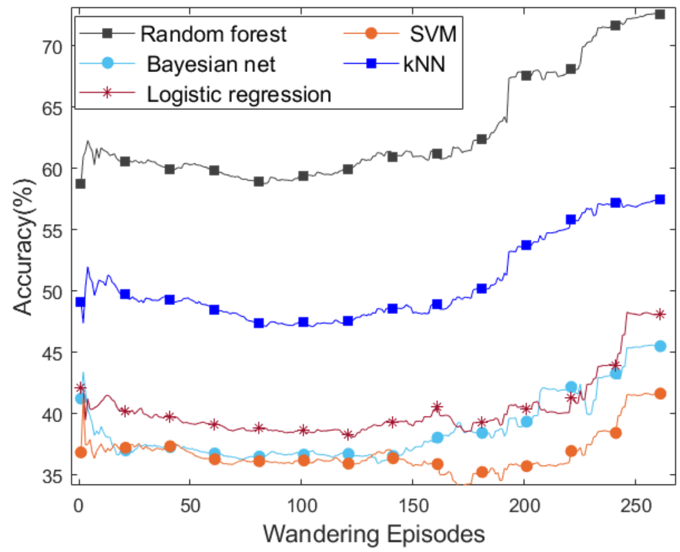



Fig. 7: Recognition rate of the long-term trajectory analysis algorithm based on the number of available wandering episode classifications per patient.

## 6 Conclusion and Future Work

In this paper, we have addressed the challenging issue of recognizing symptoms of cognitive impairment based on indoor location pattern mining. We have introduced a smart-home system equipped with position technologies and artificial intelligence capabilities to automatically provide hypothesis of diagnosis. Our system exploits collaborative learning to fine-tune recognition to the characteristics of homes and inhabitants. The results of experiments with a large dataset indicate the potential utility of our system to support the early recognition of cognitive decline.

Several research challenges remain open. First of all, our current recognition system assumes that a single person is living in the home. Multi-inhabitant scenarios introduce additional issues, since our method requires the identification of the respondent of location information. This issue could be addressed by using indoor positioning technologies that can recognize the identity of the person, possibly based on wearable devices such as beacons. Moreover, currently we assume that the configuration of sensors in the homes is fixed and identical. While this assumption may be valid for certain environments, such as nursing home facilities, we will investigate a more flexible technique to reuse training data across heterogeneous environments. Finally, the dataset we used in this paper was acquired in semi-naturalistic conditions, since activities were executed in a controlled environment for a short period of time. In the future, we will perform additional experiments with data acquired in fully naturalistic environments for longer periods of time.

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## References


[1] B. Rechel, E. Grundy, J.-M. Robine, J. Cylus, J. P. Mackenbach, C. Knai, and M. McKee, "Ageing in the European Union," *The Lancet*, vol. 381, no. 9874, pp. 1312–1322, 2013.

[2] G. Huzooree, K. K. Khedo, and N. Joonas, "Pervasive mobile healthcare systems for chronic disease monitoring," *Health Informatics Journal*, vol. 25, no. 2, 2019.

[3] U. Varshney, "Pervasive healthcare and wireless health monitoring," *MONET*, vol. 12, no. 2-3, pp. 113–127, 2007. [Online]. Available: https://doi.org/10.1007/s11036-007-0017-1

[4] K. Brittain, C. Degnen, G. Gibson, C. Dickinson, and L. Robinson, "When walking becomes wandering: Representing the fear of the fourth age," *Sociology of health & illness*, vol. 39, no. 2, pp. 270–284, 2017.

[5] D. L. Algase, D. H. Moore, C. Vandeweerd, and D. Gavin-Dreschnack, "Mapping the maze of terms and definitions in dementia-related wandering," *Aging & mental health*, vol. 11, no. 6, pp. 686–698, 2007.

[6] D. Martino-Saltzman, B. B. Blasch, R. D. Morris, and L. W. McNeal, "Travel behavior of nursing home residents perceived as wanderers and nonwanderers," *The Gerontologist*, vol. 31, no. 5, pp. 666–672, 1991.

[7] Q. Lin, D. Zhang, L. Chen, H. Ni, and X. Zhou, "Managing elders wandering behavior using sensors-based solutions: a survey," *International Journal of Gerontology*, vol. 8, no. 2, pp. 49–55, 2014.

[8] L. Liao, D. J. Patterson, D. Fox, and H. A. Kautz, "Learning and inferring transportation routines," *Artif. Intell.*, vol. 171, no. 5-6, pp. 311–331, 2007. [Online]. Available: https://doi.org/10.1016/j.artint.2007.01.006

[9] Q. Lin, D. Zhang, X. Huang, H. Ni, and X. Zhou, "Detecting wandering behavior based on GPS traces for elders with dementia," in *12th International Conference on Control Automation Robotics & Vision*. IEEE, 2012, pp. 672–677.

[10] W. D. Kearns, J. L. Fozard, V. O. Nams, and J. D. Craighead, "Wireless telesurveillance system for detecting dementia," *Gerontechnology*, p. 90, 2011.

[11] Q. Lin, W. Zhao, and W. Wang, "Detecting dementia-related wandering locomotion of elders by leveraging active infrared sensors," *Journal of Computer and Communications*, vol. 6, no. 05, p. 94, 2018.

[12] R. Suzuki, S. Otake, T. Izutsu, M. Yoshida, and T. Iwaya, "Monitoring daily living activities of elderly people in a nursing home using an infrared motion-detection system," *Telemed J E Health*, vol. 12, no. 2, pp. 146–155, 2006.

[13] D. Yang, B. Xu, K. Rao, and W. Sheng, "Passive infrared (pir)-based indoor position tracking for smart homes using accessibility maps and a-star algorithm," *Sensors*, vol. 18, no. 2, p. 332, 2018.

[14] Q. Sun, F. Hu, and Q. Hao, "Human movement modeling and activity perception based on fiber-optic sensing system," *IEEE Trans. Human-Machine Systems*, vol. 44, no. 6, pp. 743–754, 2014.

[15] F. Wang, E. E. Stone, M. Skubic, J. M. Keller, C. Abbott, and M. Rantz, "Toward a passive low-cost in-home gait assessment system for older adults," *IEEE J. Biomedical and Health Informatics*, vol. 17, no. 2, pp. 346–355, 2013.

[16] M. Li, M. O'Grady, X. Gu, M. A. Alawlaqi, G. O'Hare *et al.*, "Time-bounded activity recognition for ambient assisted living," *IEEE Transactions on Emerging Topics in Computing*, vol. in press, 2019.

[17] D. J. Cook, M. Schmitter-Edgecombe, A. Crandall, C. Sanders, and B. Thomas, "Collecting and disseminating smart home sensor data in the CASAS project," in *Proceedings of the CHI Workshop on Developing Shared Home Behavior Datasets to Advance HCI and Ubiquitous Computing Research*, 2009.

[18] D. J. Cook, A. S. Crandall, B. L. Thomas, and N. C. Krishnan, "CASAS: A smart home in a box," *Computer*, vol. 46, no. 7, pp. 62–69, 2013.

[19] A. Kumar, "A longitudinal study on identification of wandering patterns and their trends in elders with dementia residing in assisted living facilities," Ph.D. dissertation, Nanyang Technological University, 2018.

[20] N. Japkowicz and S. Stephen, "The class imbalance problem: A systematic study," *Intell. Data Anal.*, vol. 6, no. 5, pp. 429–449, 2002. [Online]. Available: http://content.iospress.com/articles/intelligent-data-analysis/ida00103

[21] D. Riboni, L. Pareschi, and C. Bettini, "Privacy in georeferenced context-aware services: A survey," in *Privacy in Location-Based Applications, Research Issues and Emerging Trends*, ser. Lecture Notes in Computer Science, vol. 5599. Springer, 2009, pp. 151–172.

[22] A. Machanavajjhala, J. Gehrke, D. Kifer, and M. Venkitasubramaniam, "l-diversity: Privacy beyond k-anonymity," in *Proc. of the Int. Conf. on Data Engineering (ICDE)*. IEEE Computer Society, 2006, p. 24.

[23] N. Li, T. Li, and S. Venkatasubramanian, "t-closeness: Privacy beyond k-anonymity and l-diversity," in *Proc. of the Int. Conf. on Data Engineering (ICDE)*. IEEE Computer Society, 2007, pp. 106–115.

[24] A. M. Seelye, M. Schmitter-Edgecombe, D. J. Cook, and A. Crandall, "Naturalistic assessment of everyday activities and prompting technologies in mild cognitive impairment," *J Int Neuropsychol Soc*, vol. 19, no. 4, pp. 442–452, 2013.

[25] P. Rashidi, D. J. Cook, L. B. Holder, and M. Schmitter-Edgecombe, "Discovering activities to recognize and track in a smart environment," *IEEE Trans. Knowl. Data Eng.*, vol. 23, no. 4, pp. 527–539, 2011.

[26] A. P. Association *et al.*, *Diagnostic and statistical manual of mental disorders*. American Psychiatric Pub, 2013.

[27] R. C. Petersen and J. C. Morris, "Mild cognitive impairment as a clinical entity and treatment target," *Archives of neurology*, vol. 62, no. 7, pp. 1160–1163, 2005.

[28] M. S. Albert, S. T. DeKosky, D. Dickson, B. Dubois, H. H. Feldman, N. C. Fox, A. Gamst, D. M. Holtzman, W. J. Jagust, R. C. Petersen *et al.*, "The diagnosis of mild cognitive impairment due to alzheimers disease: Recommendations from the national institute on aging-alzheimers association workgroups on diagnostic guidelines for alzheimer's disease," *Alzheimer's & dementia*, vol. 7, no. 3, pp. 270–279, 2011.

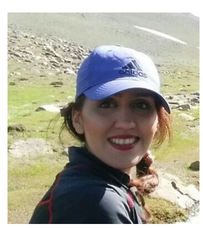
[29] P. W. Burgess, "Strategy application disorder: the role of the frontal lobes in human multitasking," *Psychological research*, vol. 63, no. 3-4, pp. 279–288, 2000.

[30] E. Frank, M. A. Hall, G. Holmes, R. Kirkby, and B. Pfahringer, "WEKA - A machine learning workbench for data mining," in *The Data Mining and Knowledge Discovery Handbook*. Springer, 2005, pp. 1305–1314.

[31] L. Breiman, "Random forests," *Mach Learn*, vol. 45, no. 1, pp. 5–32, 2001.

[32] D. W. Aha, D. F. Kibler, and M. K. Albert, "Instance-based learning algorithms," *Machine Learning*, vol. 6, pp. 37–66, 1991. [Online]. Available: https://doi.org/10.1023/A:1022689900470

[33] C. Bettini and D. Riboni, "Privacy protection in pervasive systems: State of the art and technical challenges," *Pervasive and Mobile Computing*, vol. 17, pp. 159–174, 2015. [Online]. Available: https://doi.org/10.1016/j.pmcj.2014.09.010

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