2023 62nd IEEE Conference on Decision and Control (CDC)
December 13-15, 2023. Marina Bay Sands, Singapore

A Probabilistic Finite-State Automata Framework for Monitoring Long-Term Activities of Daily Living

Mianjun Li and Peter C. Y. Chen

***Abstract*— Aging is an increasingly challenging healthcare issue with long-term sociopolitical implications, requiring more sophisticated management of healthcare services for the elderly. A key element in managing such services is the knowledge about a typical elderly person's Activities of Daily Living (ADLs). However, there is little study on the model-based objective and standardized ADLs assessment. This paper presents the concept of tracking the health status of the elderly by monitoring their individual patterns of ADLs: the specific pattern of the elderly model as probabilistic state-transition structures, and the transition probabilities in such a probabilistic model are considered as a representation of the health status of a typical older person. The typical pattern of ADLs changes with the health status due to changes in the residential environment, progressive aging, or the onset of certain diseases. Such changes are reflected (over time) in the model, and therefore monitoring the transition probabilities to assess ADLs represents a possible way to track the health status of an older person and to alert relevant health service professionals if some change that warrants subsequent careful medical attention.**

I. INTRODUCTION

According to information from the World Health Organization (WHO), by 2050, one out of every six people in the world will be 65 years old (16%) or older, and this number was 1 out of 11 (9%) in 2019 [1], [2]. For the elderly, demographic and epidemiological changes are accompanied by risk factors and lifestyle changes that make chronic diseases such as diabetes more prevalent [3]. When coupled with aging, these underlying factors can lead to a worrying state of frailty [4] in older people. Frailty is a dynamic process that worsens or reverses over time, which makes individuals more vulnerable to stressors and adverse health outcomes, such as falls, comorbidity, disability, and death [5]. Age-appropriate improvements to living conditions and long-term health checks are ways to pull the elderly back from the brink of frailty [6].

An important indicator of health and non-pathological functional status for elderly health detection in mainstream studies of this process is Activities of Daily Living (ADLs) [7], which describes the ability of older people to perform basic and routine tasks independently (e.g.: grooming, dressing, self-feeding, toileting, transferring, walking) [8]. During the process of becoming older and frailer, older people's ability to perform ADLs deteriorates, making them more dependent on caregivers and physical assistance, which

Mianjun Li is with Department of Mechanical Engineering, National University of Singapore, 117575, Singapore limianjun@u.nus.edu
Peter C. Y. Chen is with the Department of Mechanical Engineering, National University of Singapore, 117575, Singapore mpechenp@nus.edu.sg

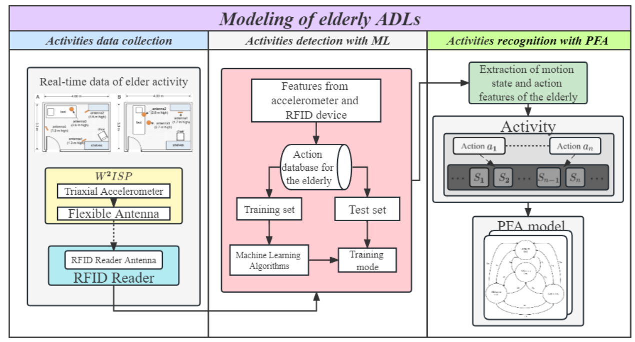


Fig. 1: Framework of monitoring and analysis of the ADLs for the elderly.

results in unsafe conditions and a poor quality of life. In the past decade, numerous investigations have been conducted on the continuous monitoring of ADLs of the elderly, with emphasis on smart homes, abnormal behavior detection, or remote activity monitoring [9], [10]. In addition, long-term ADLs monitoring the changes in daily activity patterns and functional abilities of the elderly can facilitate healthcare professionals to inform decision-making, enabling them to monitor deterioration in health status or assess response to treatment. ADLs-based elderly health assessment scales are experimentally validated and widely recognized in ADLs monitoring, such as the Barthel Index (BI) [11] and the Katz Index of Independence in Activities of Daily Living (Katz ADL) [12].

As the monitoring techniques advance, the ADLs evaluation methods have limitations. Implementing these scales, which quantify the performance of ADLs to describe the health status and mobility of older adults, is subject to human factors that require trained professionals for direct observation and management. Meanwhile, non-standard and contextual factors constitute general limitations that affect ADLs monitoring accuracy and reliability.

In this paper, probabilistic model-based assessment methods are presented, with the goal of eliminating subjectivity introduced by human factors and the lack of standardized situational factors by mathematical demonstration model. A framework for the general implementation of ADLs monitoring, analysis, and evaluation based on this assessment method is introduced as a practical example. In such a framework, biometric information about the activities of the elderly is provided by wearable devices, while machine learning (ML) methods are used to extract activities from the raw data. Modeling and simulation of the ADLs provide evidence for age-friendly living environment assessment and long-term health monitoring by caring for changes in the behavior patterns of the elderly and assessing "how well" an elderly person accomplishes ADLs. Due to the mental health status, personalities, or even irrationality of the elderly, representation of such knowledge requires a scheme capable of considering probabilistic events.

The key contribution and novelty of our work are to propose the concept of assessing the health status of the elderly by monitoring their individual patterns of ADLs (modeled as probabilistic state-transition structures). Such a concept introduces the use of probabilistic models to construct a standardized assessment method through the activities of the elderly for the health status of the elderly. And the specific pattern of the transition probabilities in such a probabilistic model represents the health status of a typical older person. Our proposed approach fills the crucial gap in the existing literature by addressing the limitations of sensor-based behavior recognition and health status linkage, as well as the traditional manual ADLs evaluation. It provides a more comprehensive and accurate representation of elderly activities, enhancing the effectiveness of health monitoring systems.

The remainder of this paper is structured as follows: Section II provides an overview of the ADLs-related research in Activity Discovery (AD) and Activity Recognition (AR). Section III describes the problem statement and recalls the fundamental concepts and notations of PFA. Section IV proposes an ADLs assessment method based on PFA. A study case is presented in Section V in order to show the efficiency of the proposed method and present the data analysis and the evaluation of the results. Finally, Section VI draws the conclusions.

II. Background

Since how Activities of Daily Living (ADLs) is related to health status has been widely recognized, research on monitoring, analysis, and evaluation of ADLs has been the focus of researchers. In addition, the tremendous progress in semiconductors and MEMS [13], combined with the resolution of power and communication issues through passive RFID technology [14] drive the growth of wearable devices.

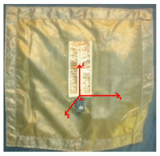
M. Saleh et al.[16] proposed a wearable devices-based ADLs analysis dataset for human fall detection. The authors evaluated the effectiveness of the proposed approach on a dataset collected from a group of individuals. In comparison to the videos-based and audios-based methods, wearable devices-based have the advantage of protecting the privacy of the users while monitoring their ADLs.

In addition to the development of the ADLs monitoring technique, as discussed in [17], studies about ADLs analysis and understanding are divided into two parts: Activity Discovery (AD) and Activity Recognition (AR). AD enables the direct discovery of activity patterns from low-level sensor data, free from prior assumptions or models. In the study of D. J. Cook [18] and E. Rogers [19], the generally accepted approach to AD involves the utilization of unsupervised machine learning classification techniques that search the mapping of sensor event sequences to corresponding activity labels in increasing length order. Conversely, AR prioritizes accurate human activity detection through predefined models and aims to establish a high-level conceptual model for a universal system's implementation [17], [18]. Researchers widely recognize the probabilistic models in AR for their ability to model activity patterns and exploit temporal dependencies between activities. Hidden Markov Model (HMM) and Conditional Random Fields (CRF) are mainly used probabilistic models among them [20]. M. V. Albert et al. [21] and T. Van Kasteren [22] describe the emission distribution of HMM by applying the Viterbi algorithm [23] and merging multimodal accelerometers and video features and classifying and identifying test segments [9].

Compared to the development of ADLs monitoring, analytical methods, as opposed to the mining and evaluation of ADLs information provided by monitoring and analysis, have received less attention. Traditional assessment methods, such as manual observation or questionnaires, map the health condition of the elderly to the caregiver's experience, which is then reflected in the summary scores of ADLs assessment tables. It is important to note that these tasks are time-consuming and susceptible to observer bias. There still needs to be a gap in the literature when it comes to evaluating ADLs using activity models. Probabilistic models offer a transparent and interpretable approach to modeling complex systems. Because probabilistic models explicitly incorporate uncertainty, enabling the evaluation of ADLs more objectively and consistently, bypassing the subjective human judgment, which biases or other factors can influence.

Consider that in an HMM, the state transition probabilities depend on and only on the previous state. In CRF, it is unsuitable for unknown words, and the training phase can be computationally complex. Consider again that the system's state space is partially or completely unknown. The state variables must incorporate both the previous state and observed events, and the events depend only on the model's current state. These considerations suggest using the grammatical inference approach of Probabilistic Finite-State Automata (PFA) [25], which allows for intuition and experience-based models so that qualitative information can be processed.

To assess the validity and accuracy of the model, we examined the similarity properties and the degree of fit, which are related to the model architecture. By comparing the Kullback - Leibler divergence of the layout from different probability models [24], theoretical support is provided for effectively evaluating the effects of the probability models. PFA addresses the challenge of modeling structured spaces with probabilistic elements by incorporating probabilities into the underlying structure, enabling accurate modeling of elderly ADLs as automata [26]. By setting ADLs as the states of the PFA model, the practical significance of the transition probability describing the state change after an event is shown as the execution probability of these ADLs. Moreover, the hitting time of a Markov chain refers to the number of time it takes for the chain to reach a specific state



(a) The Cartesian coordinate direction of the sensor

(b) A participant with the W2ISP at the sternum level

Fig. 2: Illustration of the W2ISP module [30].

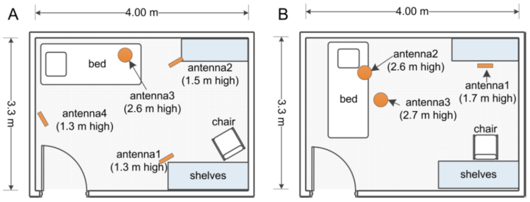


Fig. 3: The two-room configurations with different antenna settings and orientations of the furniture.

[27], which is a predetermined subset within the initial "hit" state space of the process and this concept draws inspiration for a valid path to calculate the expectation of the ADLs state. The hitting probability, characterized by the ability of the modeled object to perform ADLs, is determined by ADLs serving as states in the PFA model.

III. Problem Statement and Methods

A. Problem statement

Due to the change in the residential environment, progression of aging, or the onset of some illness, the typical patterns of ADLs in person will change. For example, people with Alzheimer's disease tend to experience a decline in their ability to perform ADLs as the disease progresses[28], and weight gain increases the risk of high blood pressure and lipid levels can limit people's mobility. Similarly, unfriendly environments for the elderly can lead to an increase in their burden of executing ADLs, not only affecting their quality of life but also directly impacting their health over time.

This section presents an overview of the current challenges in the field, as well as the methods proposed to address them, based on the underlying assumptions:

i) The collection of elderly activity data needs to be non-invasive, ensuring the privacy of the elderly and not affecting the ADLs of the elderly. This consideration enables the adoption of wearable sensors.

ii) Elderly behavior pattern is not static and can be affected by age or environment. Therefore, robust AD algorithms are selected and their effects are verified through different environmental configurations to maximize the robustness and applicability of the framework.

iii) Assessing the framework for long-term monitoring of elderly ADLs requires long-term detection and evaluation. Unfortunately, this information is challenging to obtain due to the limited experimental conditions. To corroborate the concept of ADLs telemonitoring and assessment proposed in this paper, the changes in ADLs resulting from environmental factors are widely used to equivalent to those caused by aging. Therefore, two different clinical environment configurations are adopted to capture variations in the ability to perform ADLs and validate the effectiveness of the monitoring approach.

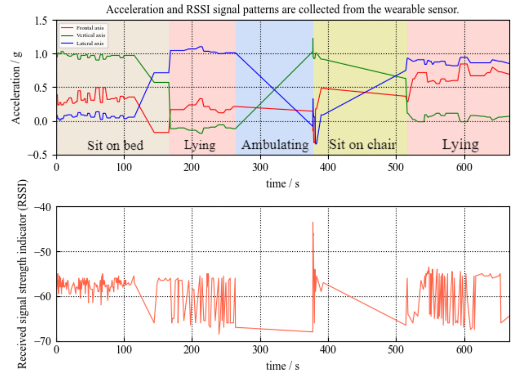


Fig. 4: Raw data of triaxial acceleration collected by wearable sensors.

Although some new techniques have been proposed for both monitoring and analysis of ADLs, the framework of ADLs that combines monitoring, analysis, and objective evaluation based on a probability model is novel. The proposed framework, shown in Fig. 1, involves wearable-based ADLs monitoring methods to give a set of activity data of healthy elderly individuals. The ADLs analysis part performs AD using a machine learning classification algorithm, and the resulting model is represented in the form of a PFA model for the AR. Through the AR, exhibited the typical activity patterns for healthy elderly individuals and comparing changes in activity patterns with different room configurations, we seek to evaluate variations in the ability of elderly individuals to perform ADLs and to assess their health status.

B. Dataset

This paper utilizes the UCI data set of "Activity recognition with healthy older people using a batteryless wearable sensor" to perform an experimental analysis of the proposed study on activity data for older adults [29]. The data set collected activity data from 14 healthy male and female elders between the ages of 66 and 86 years. Data collection using a Wearable Wireless Identification and Sensing Platform (W2ISP) device developed, based on [30].

Since people spend more than 80% of their daily activities indoors, which is even higher for elders with ADLs difficulties, living alone, or with chronic medical conditions [31]. The data set is carried out in two different configurations of the indoor environment with a length of 4m x 3.3m, similar to the Elizabeth Hospital clinical environment. Different positions and orientations of the furniture result in different activity spaces for the elderly. Notably, the activity space in Room 2 is observed to be smaller than in Room 1. Since the layout of the clinical environment of nursing homes and hospitals can meet the basic living requirements of the elderly, the method for detecting the activities of the elderly based on simulating such an environment can be generalized. The activities and states of the elderly captured from the data set are: sitting on bed, sitting on chair, lying, and ambulating, and a group of actions is: getting up, getting out of bed, lying down, and sitting down.

C. PFA: Basic Definitions and Notation

A PFA consists of states, events, and transition probability tables. Each state has an entry event and an exit event. PFA defines a tuple $E = \{Q_E,\ \varepsilon,\ \delta_E,\ I_E,\ P_E,\ F_E\ \}$:

- Q_E: is a finite set of elderly states.
- ε: is the alphabet representing events that transfer between states.
- $\delta_E \subseteq Q_E \times \varepsilon \times {Q_E}'$: is a set of finite transitions that characterize the transition from the previous state to the next state after the occurrence of an event.
- $I_E:\ Q_E \to \mathbb{R}^+$: the initial-state probabilities
- $P_E:\ \delta_E \to \mathbb{R}^+$: is a set of the probability of transition from the previous state to the next state after the event.
- $F_E:\ Q_E \to \mathbb{R}^+$: the final-state probabilities.

The state transition table of the PFA model is based on factual logic and calculates the probability associated with each transition of the PFA model. Let $a_i,\ a_j$ be the two events of alphabet ε, q_0 be the initial state, $q_i,\ q_j$ be the two states after the event $a_0,\ a_1, q_0,\ q_i,\ q_j \in\ Q_E$.

$$P_E\{q_0,\ a_i,\ q_i\} = P_E(q_0 \to\ q_i\ ,\ a_i) \tag{1}$$

$$= \frac{\mathcal{N}(q_0 \to\ q_i\ ,\ a_i)}{\sum_{a\in\varepsilon,\ q'\in Q_E} \mathcal{N}(q \to q'\ ,\ a)} \tag{2}$$

$$= \frac{\mathcal{N}(q_0 \to\ q_i\ ,\ a_i)}{\mathcal{N}(q_0 \to q_i,\ q_0) + \mathcal{N}(q_0 \to q_j\ , a_j)} \tag{3}$$

where $\mathcal{N}(q_0 \to\ q_i\ ,\ a_i)$ indicated the number of occurrences of transitions from q_0 to q_i after event a_i.

For the initial state, the following laws should be met statistically and probabilistically:

$$\sum_{q\in Q_E} P\{I_E(q)\} = 1 \tag{4}$$

For the end state, the following laws should be met statistically and probabilistically:

$$P(F_E(q)) + \sum_{a\in\varepsilon,\ q'\in Q_E} P_E\{q, a, q'\} = 1,\ \text{for}\ q \in\ Q_E \tag{5}$$

Property 1. If a PFA-based model generates a finite-length path string via a finite number of events: $\alpha = \left(q_0 \overset{a_0}{\to} q_1 \overset{a_1}{\to} q_2 \overset{a_2}{\to}\ \ \cdots \overset{a_{n-2}}{\to} q_{n-1} \overset{a_{n-1}}{\to} q_n\right)$, the probability of generating the path is

$$P_\alpha = I_E(q_0) \times \left[\prod_{i=1}^{n} P_E\{q_{i-1}, a_{i-1}, q_i\}\right] \times F_E(q_n) \tag{6}$$

Property 2. Defined a PFA model α, the set of all valid paths from initial state q_0 to final state q_n, with step size i is $\Phi_\alpha(i, q_0, q_n)$. For the event set designed and used in this experiment is $\varepsilon_\alpha = (a_0,\ a_1, \cdots, a_{j-1})$ and assumed to be complete, that is, the maximum likelihood estimated probability distribution function of the effective path is defined as:

$$Optimal_{\Phi_\alpha}(i, q_0, q_n) = \underset{\forall q_0, q_n \in Q_\alpha}{\operatorname{argmax}}\ P_{\Phi_\alpha}(i, q_0, q_n) \tag{7}$$

$$= \max_{\forall q_0, q_n \in Q_\alpha, a\in\varepsilon_\alpha} I_E(q_0) \times \left[\prod_{j=1}^{i} P_E(q_{j-1}, a_{j-1}, q_j)\right] \times F_E(q_n) \tag{8}$$

The similarity measurement defines the similarity between PFA distributions under the same probability space by measuring its cross-entropy and comparing their correlation. In practice, we want to know whether the distribution after the probabilistic model is close to the original model. Therefore, in the task of learning and building PFA involved in this research, the results or quality can be measured by assessing the distributed similarity of the models.

Property 3. Based on Kullback-Leibler divergence, the normal distribution center of activity prediction model output is established.

$$d_{KL}(\mathcal{D}, \mathcal{D}') = \sum_{x\in\Sigma^\star} \mathrm{Pr}_{\mathcal{D}}(x) \cdot \ln \frac{\mathrm{Pr}_{\mathcal{D}}(x)}{\mathrm{Pr}_{\mathcal{D}'}(x)} \tag{9}$$

Considering the state transition chain sampled from the established PFA model, the probability distribution obtained after statistics is compared with the probability distribution of the data set:

$$d_{KL}(\mathcal{D}_{\mathcal{PFA}}, \mathcal{S}) = \sum_{x\in\Sigma^\star} \mathrm{Pr}_{\mathcal{D}_{\mathcal{PFA}}}(x) \cdot \ln \frac{\mathrm{Pr}_{\mathcal{D}_{\mathcal{PFA}}}(x)}{\mathrm{Pr}_{\mathcal{S}}(x)} \tag{10}$$

$$= \sum_{x\in\Sigma^\star} \left(\mathrm{Pr}_{\mathcal{D}_{\mathcal{PFA}}}(x) \cdot \ln \mathrm{Pr}_{\mathcal{D}_{\mathcal{PFA}}}(x) - \mathrm{Pr}_{\mathcal{D}_{\mathcal{PFA}}}(x) \cdot \ln \mathrm{Pr}_{\mathcal{S}}(x)\right) \tag{11}$$

IV. ADLs Assessment based on PFA

The relationship between ADLs and health status is widely recognized, and ADLs assessment is an essential aspect of the routine elderly assessment. This paper proposes a method to characterize the health status of the elderly by modeling the ADLs with transition probabilities in such a probabilistic model. A PFA model for the healthy elderly is developed based on the data set, and the state-transition probability pattern of the model is considered the "baseline". By detecting any significant changes in the state-transition probability of the probabilistic model to monitor the person's actual ADLs condition. Recall the concepts of expected hitting times and hitting (reachability) probability. The expected hitting time represents the expected number of times until the target state is reached from the initial state of the probabilistic model. On the other hand, the hitting probability refers to the likelihood of starting from the initial state and reaching the target state [32]. For a Markov chain X_n in state space S, the hitting time to hit the set $A \subset S$ is:

$$H_A = \inf\{n \in \{0, 1, 2, \cdots\} : X_n \in A\} \tag{12}$$

The hitting probability P_{iA} of set A starting from state i is:

$$P_{iA} = \mathbb{P}(X_n \in A \text{ for }\ \text{some } n \in \{0, 1, 2, \cdots\} | X_0 = i) \tag{13}$$

$$= \mathbb{P}(H_A < \infty | X_0 = i) \tag{14}$$

The expected hitting times e_{iA} of set A starting from state i is:

$$e_{iA} = \mathbb{E}\left(H_A | X_0 = i\right) \tag{15}$$

For a valid path to calculate the expectation of the ADLs state, characterized as the ability of the modeled object to perform ADLs. Now back to PFA, similar to the number of transitions from the q_i state to state q_j is regarded as a random variable H_{ij}, and the expectation of reachability from q_i to q_j defined as E_{ij} is:

$$E_{ij} = \mathbb{E}\left(H_{ij}\right) = \sum_{q \in Q_E,\ a \in \varepsilon} \left[H_{ij} \cdot P\left(q_i, q_j\right)\right] \tag{16}$$

For the probabilistic model of this project, the transition expectations from the initial state to the other state are: $\{E_0,\ E_1,\ E_2,\ E_3\}$, where E_2 is the only ADLs: ambulating. Other activities $E_0,\ E_1,\ E_3$ are not within the scope of ADLs. The assessment score consists of two parts: for activities belonging to ADLs, multiply the activity expectation with constant π_{ADLS}; for activities not ADLs, bring the expectation into a Gaussian function. The two parts are added to get the evaluation score. The expression of the Gaussian function is as follows:

$$f\left(x\right) = a * e^{-\dfrac{\left(x-b\right)^2}{2 * c^2}} \tag{17}$$

This evaluation method is adopted because for the elderly, the higher the expectations of ADLs, the higher frequency and probability that the elderly will complete ADLs. On the other hand, for activities that do not belong to ADLs, their expectations should be stabilized at an average level, which is more consistent with human behavior. That is, the action expectation falls near the peak of the normal distribution.

$$\varepsilon_{ADLS} = \pi_{ADLS} * E_j + \sum_i a_i * e^{-\dfrac{\left(E_i - b_i\right)^2}{2 * {c_i}^2}} \tag{18}$$

where $j \in ADLs$, $i \notin ADLs$, and the constant $\pi_{ADLS},\ a_i,\ b_i,\ c_i$ is based on the statistics of activity data of healthy older people. π_{ADLS} and a_i are the reward constants for daily activities of Basic Activities of Daily Living (BADLs) and non-BADLs, respectively, determined by the difficulty of completing each activity. In particular, π_{ADLS} represents the weight of ambulating and a_i means the weight of Lying, Sitting on bed, and Sitting on chair. b_i is the expected value of the maximum likelihood estimation of the daily activities of the elderly except for Basic Activities of Daily Living (BADLs), that is, the expected value of the highest probability density of other activities of the healthy elderly.

V. Case Study

A. Activity Discovering based on classification algorithms

In ADLs analysis, time window techniques are usually used to extract activity features from raw data. These techniques involve dividing the sensor signal into short time periods and then applying segmentation and classification algorithms in each window separately. Since the sampling frequency is 0.5Hz, when the slide time window method with the fixed size is used to preprocess the original data, the size of each window is 4 points. That is, the time of each window is 2 seconds. The overlap rate of the window is 50%, the activity data of all the elderly in each dataset are split and the time sequence is all scrambled. The time domain and frequency domain features are considered in data preprocessing.

Characterization	Type of feature
Time-domain	X-axis acceleration
	Y-axis acceleration
	Z-axis acceleration
	Resultant acceleration
	Mean value of each axis
	Standard deviation of each axis
	Variance of each axis
	Received signal strength indicator (RSSI)
	Phase
Frequency-domain	The Direct Current of FT
	The magnitude of FT

TABLE I: Combination of Data

Data Set	Classification algorithm	Accuracy	Time / second
Room 1	Support vector machine (SVM)	97.17%	7.97
	Multilayer perceptron (MLP)	97.68%	20.02
	Decision tree (DT)	98.8%	0.08
	K-Nearest Neighbors (KNN)	98.38%	0.59
	Bernoulli Naive Bayes (BNB)	58.17%	0.01
	Gaussian Naive Bayes (GNB)	93.0%	0.01
	Naive Bayes (NB)	58.44%	0.01
	Logistic regression (LR)	89.88%	1.22
	Random Forest (RF)	99.21%	2.21
	Adaptive Boosting (AdaBoost)	78.55%	1.15
	Extreme Gradient Boosting (XGBoost)	99.29%	2.49
	Light Gradient Boosting Machine (LightGBM)	99.28%	0.64
Room 2	Support vector machine (SVM)	98.46%	0.93
	Multilayer perceptron (MLP)	98.75%	8.77
	Decision tree (DT)	98.82%	0.04
	K-Nearest Neighbors (KNN)	98.36%	0.23
	Bernoulli Naive Bayes (BNB)	92.95%	0.001
	Gaussian Naive Bayes (GNB)	97.58%	0.01
	Naive Bayes (NB)	90.53%	0.001
	Logistic regression (LR)	97.65%	0.4
	Random Forest (RF)	98.83%	0.92
	Adaptive Boosting (AdaBoost)	93.29%	0.45
	Extreme Gradient Boosting (XGBoost)	99.03%	1.18
	Light Gradient Boosting Machine (LightGBM)	98.98%	0.33

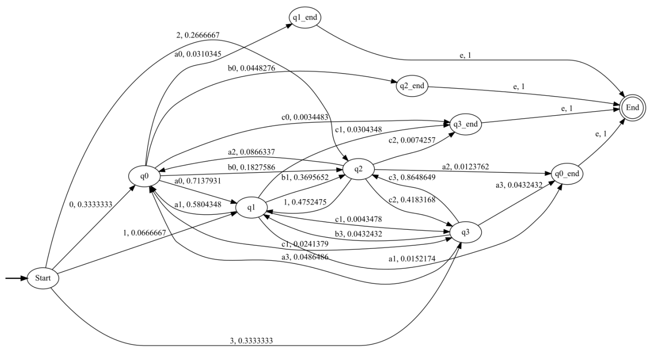
TABLE II: Accuracy and processing time of input composed of the data in each timestamp

For two room data sets, the accuracy and processing time using different classification algorithms are shown in the Table. II. Comparing the recognition accuracy of different datasets, by using Extreme Gradient Boosting for AD, dataset 1 reaches about 99.29% and 99.03% for dataset 2, which achieves the expected goal and confirms its robustness.

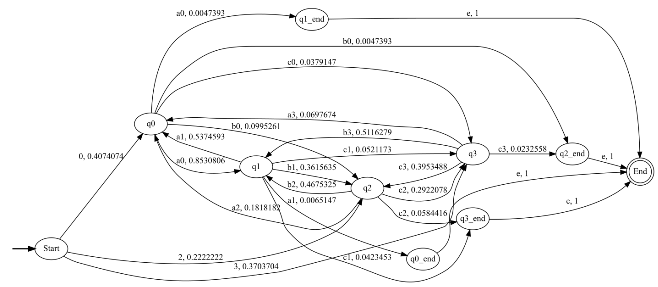
B. Generation of PFA Structure

After using the machine learning classification algorithm to complete the AD of ADLs, PFA is used to perform AR and generate the daily activity behavior patterns of the elderly PFA defines a tuple $E = \{Q_E,\ \varepsilon,\ \delta_E,\ I_E,\ P_E,\ F_E\}$:

1) The set of states of elderly Q_E is defined as: q_0 = "**Lying**", q_1 = "**Sitting on bed**", q_2 = "**Ambulating**", q_3 = "**Sitting on chair**". To facilitate the programing, four final states $q_{0_{end}},\ q_{1_{end}},\ q_{2_{end}},\ q_{3_{end}}$ are added to the state set as shown in Table.III.



(a) The PFA model for Room 1



(b) The PFA model for Room 2

Fig. 5: Events $0,\ 1,\ 2,\ 3$ are added to characterize the transition events of the PFA model from the **Start** to the four initial states, e stands for the event from the final state to the **End**.

The four final states respectively stand for the same events in the real space but represent the final state before the model ends. Then states set $Q_E = (q_0,\ q_1,\ q_2,\ q_3,\ q_{0_{end}},\ q_{1_{end}},\ q_{2_{end}},\ q_{3_{end}})$.

2) The set of event ε performed during the activity is then defined as a transition from one state to another by the occurrence of an event in the alphabet $\varepsilon = (a_0, b_0, c_0,\ a_1, b_1, c_1,\ a_2, b_2, c_2,\ a_3, b_3, c_3)$.
3) While defining the event set alphabet ε, the finite transition is determined as $\delta_E = (q, a, q')$, where: $a \in \varepsilon, (q,\ q') \in Q_E$, shown as TABLE IV.

State	Observed states in real space
q_0 and $q_{0_{end}}$	Lying
q_1 and $q_{1_{end}}$	Sitting on bed
q_2 and $q_{2_{end}}$	Ambulating
q_3 and $q_{3_{end}}$	Sitting on chair

TABLE III: Added state in the state set Q_E of PFA model

4) The ADLs of the elderly are fully modeled based on the PFA probabilities calculated from the transition probability table, and the model structure is generated and shown in Fig. 5.

State q	Alphabet ε	Event a	New state q'
Lying	a_0	Get up	Sitting on bed
Lying	b_0	Get out of bed	Ambulating
Lying	c_0	Move to chair	Sitting on chair
Sitting on bed	a_1	Lie down	Lying
Sitting on bed	b_1	Get out of bed	Ambulating
Sitting on bed	c_1	Move to chair	Sitting on chair
Ambulating	a_2	Lie down	Lying
Ambulating	b_2	Sit down on bed	Sitting on bed
Ambulating	c_2	Sit down on chair	Sitting on chair
Sitting on chair	a_3	Move and lie down	Lying
Sitting on chair	b_3	Move to bed	Sitting on bed
Sitting on chair	c_3	Get up	Ambulating

TABLE IV: Event set alphabet ε of PFA model

C. *Effectiveness evaluation*

This paper explores two evaluation methods for the evaluation of probabilistic models.

1) Probability distributed coverage. The sequence is sampled from the PFA to evaluate the precision rate and coverage of the model to the data set. The required sampling times can also show the fitting degree of the model to the behavior pattern. As shown in Fig.6, after 3,000 cycles, the PFA model has 100% coverage of the activity patterns of the elderly in the dataset. The coverage speed for Room 1 is faster than Room 2.
2) Similarity measurement. As elaborated in **Property.3**, the Kullback-Leibler divergence between PFA model and data set is 1.6010×10^{-2} for Room 1 and 4.3975×10^{-2} for Room 2, as shown in Fig. 7. This result can be recognized because Room 2 has fewer data than Room 1, according to which the validity of the programmed PFA can be demonstrated.

The collected number of state transitions sequence under different room configurations is: Room1 = 22.3, Room2 = 26.5. These longer sequences make PFA need more sampling to cover.

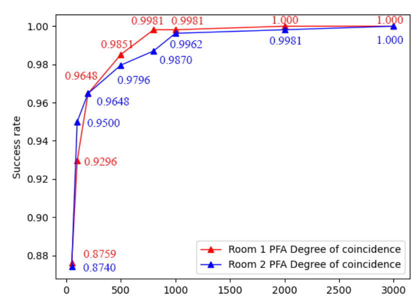
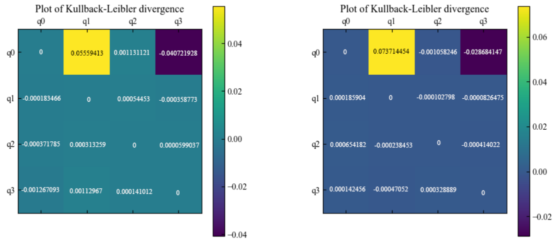


Fig. 6: Probability distributed coverage result

Based on the PFA models established based on the activity data of the elderly in different environmental configurations, the average behavioral expectations of the elderly are:

Room 1:

$$\bar{E_0} = 0.786553967,\ \bar{E_1} = 1.263318354,$$
$$\bar{E_2} = 1.492451072,\ \bar{E_3} = 0.457676607$$



(a) KL divergence map of Room 1

(b) KL divergence map of Room 2

Fig. 7: Similarity measurement result

Room 2:

$$\bar{E_0} = 0.795559565,\ \bar{E_1} = 1.83698028,$$
$$\bar{E_2} = 0.926778849,\ \bar{E_3} = 0.440681306$$

Recall the set of states of PFA: Lying, Sitting on bed, Ambulating, Sitting on chair, it can be found that the elderly in Room 1 prefer Ambulating, while the elderly in Room 2 prefer Sitting on bed. This is because, in the Room layout, Room 2 limits the activity space of the elderly, which leads to a change in their ADLs pattern. The results from the evaluation also reflect this change, indicating that it makes the elderly in Room 2 more reluctant to move, and the change in mobility ability will also directly affect their health status.

Since Room 1 is the more aging-friendly configuration, Let the PFA model of Room 1 be a typical pattern of ADLs for the elderly $b_0 = \bar{E_0},\ b_1 = \bar{E_1},\ b_3 = \bar{E_3},\ c_i = 1$, the evaluation formula will be:

$$\varepsilon_{ADLS} = \pi_{ADLS} * E_2 + a_0 * e^{-\dfrac{(E_0 - 0.7865)^2}{2}} + a_1 * e^{-\dfrac{(E_1 - 2633)^2}{2}} + a_3 * e^{-\dfrac{(E_3 - 0.4576)^2}{2}}$$

Let $\pi_{ADLS} = a_0 = a_1 = a_3 = 1$, the ADLs scores for the elderly under different room configurations are: $\varepsilon_{Room1} = 4.5$, $\varepsilon_{Room2} = 3.8$.

The activity model of the elderly needs to be updated at a fixed time interval for long-term ADLs monitoring of the elderly. Any significant change in the probability model state-transition probability will be reflected in different expectation values and scores. A red line (passing score on the scale) can be defined if clinical observations and records can be combined. Once the elderly ADLs below this score may require more attention and attendant care while increasing the provision of ADLs assistive devices.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we have proposed tracking the health status of the elderly by monitoring their individual patterns of Activity of Daily Living (ADLs). To provide a way to eliminate the impact of subjectivity and lack of standardization, the specific pattern of the elderly is modeled as probabilistic state-transition structures. To do that, a PFA-based ADLs assessment scale has been introduced, and the transition probabilities represent the health status of a typical older adult. The UCI data set involves two room configurations that capture the changes in the elderly's ability to perform ADLs and are used to verify the feasibility of the framework in this case. The framework for the ADLs could help to monitor the health status and facilitate healthcare professionals to inform decision-making.

Future work will enhance the proposed method and further refine the detection process.

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