A PSL-based Approach to Human Activity Recognition in Smart Home Environments

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***Abstract*—Human activity recognition is widely used in smart cities, public safety and other fields, especially in smart home systems where it has a pivotal role. The study addresses the shortcomings of Markov logic networks for human activity recognition and proposes a human activity recognition method in smart home scenarios - an activity recognition framework based on Probabilistic Soft Logic (PSL). The framework is able to deal with logical uncertainty problems and provides expression and inference mechanisms for data uncertainty problems on this basis. The framework utilizes Deng entropy evidence theory to provide an evaluation method for sensor event uncertainty, and combines event calculus for activity modeling. Comparing the PSL method with three other common recognition methods, Ontology, Hidden Markov Model (HMM), and Markov logic network, on a public dataset, it was found that the PSL method has a much better ability to handle data uncertainty than the other three algorithms. The average recognition rates on the ADL and ADL-E sub datasets were 82.87% and 80.33%, respectively. In experiments to verify the ability of PSL to handle temporal complexity, PSL showed the least significant decrease in the average recognition rate and maintained an average recognition rate of 81.02% in the presence of concurrent and alternating activities. The human activity recognition method based on PSL has a better performance in handling both data uncertainty and temporal complexity.**

***Keywords*—Human activity recognition; probabilistic soft logic; MAP inference; temporal complexity; data uncertainty**

I. Introduction

With the rise of smart cities and smart homes and the rapid development of related technologies, human activity recognition has become a hot topic of research for many researchers [1]. In the smart home environment, human activity recognition can help the smart home system to form a human "understanding" based on the activities being performed by the residents, and then provide better and smarter living services to the residents [2-3]. With the new iteration of wireless sensing devices, the research focus of smart home systems is gradually shifting from data collection to high-level information integration and activity recognition [4]. Human activity recognition includes sequential activity recognition and composite activity recognition, while the latter is more in line with the alternating and concurrent characteristics of daily activities [5-6]. Problems related to activity recognition have been classified into 12 main research types based on three different metrics: number of recognized users, activity complexity and perceptual patterns [7]. In order to further optimize the structure and function of smart home systems and provide a more convenient, comfortable, and safe living environment for people with inconvenience, especially the elderly, the study focuses on the identification of complex activities based on dense sensing in a single user environment of smart home systems. Firstly, a human activity recognition framework based on Probabilistic Soft Logic (PSL) is proposed, and an event preprocessing mechanism is proposed based on the characteristics of dense sensing. The reduction of irrelevant and redundant data is achieved through fragment partitioning and event merging. In addition, an event uncertainty calculation method based on DS evidence theory is proposed for data uncertainty in activity recognition, and activity modeling is carried out by combining Event Calculus (EC) and PSL. It is expected that the ability to relax first-order logical constraints through PSL and the ability to describe event persistence through EC will allow for conflicts in the knowledge base, enhance the freedom of the activity model, and further enhance its ability to handle logical uncertainty and temporal complexity problems.

Section II of the article describes the relevant work, focusing on the current research status at home and abroad, and provides a detailed explanation of the improvements and technical roadmap of the research. The first section of Section III proposes a human activity recognition framework based on PSL, which provides a detailed introduction to segment partitioning, event merging, and calculation methods for event uncertainty. Subsection B of Section III provides an activity modeling method based on PSL-EC and proves the equivalence between PSL-EC and complex activity descriptions. Section IV verifies the effectiveness of the PSL method through experiments and compares it with current mainstream activity recognition methods. Section V summarizes the research methods and results, and concludes by summarizing and organizing them.

II. Relative Work

Human activity recognition is an important research field in the Internet of Things, especially in smart homes, which focuses on understanding human behavior and further predicting human action intentions and motivations. A deep neural network model using convolutional neural networks and gated recurrent units was proposed by Dua et al. for activity time series data collected by wearable sensors, and the model was used to automatically extract and classify human activities. More than 95% accuracy was obtained on all three datasets, demonstrating the excellent recognition and classification performance of the model [8]. Zhang et al. proposed an approach combining convolutional neural networks and activity recognition attention mechanisms for sensors and mobile devices in smart healthcare applications and systems. The approach incorporates attention into a multi-headed neural network to improve the accuracy and feature extraction of activity recognition [9]. Bianchi et al. designed an activity recognition system combining a wearable device with deep learning, where the wearable system embeds an inertial measurement unit and WiFi to send the collected data to a cloud service. The system minimizes inference resources, saves cost, and achieves 97% accuracy in the recognition of 9 activities [10]. Agarwal and Alam propose a lightweight deep learning model for human activity recognition based on the feature that edge computing can reduce communication latency and network traffic, which overcomes the disadvantages of deep learning computationally intensive. Experimental results obtained on six daily activity data from testers show that the proposed model extends the ability to handle data uncertainty in activity recognition due to most existing machine learning and deep learning techniques [11]. Artikis et al. by defining the probability of maximum intervals and the confidence rate of such intervals. A linear time algorithm is then proposed to compute the full probabilistic time intervals for a given dataset and the performance of the method is evaluated on a benchmark activity recognition dataset [12].

Due to the uncertainty and temporal complexity of human daily activities, two main activity recognition methods, data-driven and knowledge-driven, have been derived. Data-driven methods mainly include Hidden Markov Model (HMM), support vector machine, dynamic Bayesian model, etc. Tran et al. investigated multiple recognition methods in multi-user scenarios and conducted evaluation experiments on the same dataset, while exploring the effectiveness and recognition efficiency of temporal learning algorithms using sequential data and non-temporal learning using temporal manipulation features the effectiveness and recognition efficiency of algorithms [13]. Li et al. proposed a method to analyze the significance of sensor data contribution based on sensor state frequency and inverse type frequency for daily behavior recognition of a single user in a multi-tenant smart home scenario Xi'an. The method is used to measure the contribution of specific types of sensors to a certain type of behavior recognition, and then construct a spatial distance matrix based on the layout of environmental sensors to achieve context awareness and reduce data noise. Based on this, an activity recognition algorithm based on wide time domain convolutional neural network and multi-environmental sensor data for daily activity recognition is also proposed [14]. Scholars such as Ashari P have conducted in-depth analysis of data fusion and multi classifier system technologies for human activity recognition, particularly systems based on mobile and wearable devices, focusing on sensor pattern based activity monitoring and classification methods used for behavior analysis, environmental monitoring, and other activities in smart home environments. They have identified the advantages, applications, and shortcomings of deep learning fusion methods for human activity recognition [15]. Asghari et al. proposed an online application of hierarchical HMM to detect the current activity in a real-time stream of sensor events, and also to detect activities that occur during an activity, i.e., interrupted activities. The proposed approach is validated on two different smart home datasets and the experimental results demonstrate its effectiveness and superiority [16]. The knowledge-driven recognition approach reduces the dependence on data for activity recognition and usually uses Ontology or rules for activity modeling and reasoning. Zhang et al. proposed a knowledge-based multi-intelligence collaboration approach. This layered architecture for smart homes that combines Ontology and multi-intelligence technologies aims to automatically acquire semantic knowledge and support heterogeneous and interoperable services. A generic inference algorithm based on the properties of disordered actions and activity events is proposed in this architecture for real-time inference of continuous composite activities and personalized services. Then a new idea is introduced to allow intelligences to learn knowledge of human activities autonomously and to transform them. The feasibility, effectiveness and stability of the proposal are verified through an extensive experimental evaluation at [17].

Comprehensive domestic and international related research can find that most of the commonly used recognition models are hybrid-driven approaches that mix two modeling methods, such as Markov Logic Networks (MLN). However, although MLN is used as an effective framework to address uncertainty and complexity, it adopts hard constraints on closed atoms and cannot effectively describe continuous variables of sensor data classes, resulting in low efficiency and inability to meet real-time requirements. Therefore, in view of the shortcomings of MLN method for human activity recognition, a PSL based activity recognition framework is proposed. PSL adopts Lukasiewicz logic instead of Boolean logic to transform integer linear programming problem into convex optimization problem for solution. Then, DS evidence theory was used to compensate for the lack of measurement of event uncertainty in PSL, and the activity modeling method PSL-EC was proposed in conjunction with EC, aiming to achieve efficient and accurate human activity recognition.

III. PSL-BASED HUMAN ACTIVITY RECOGNITION IN SMART HOMES

A. PSl-Based Human Activity Recognition Framework

In smart home systems, especially in most voice-activated systems, a key part of implementing an intelligent control system is the recognition of human activities [18]. Many researchers have proposed many excellent recognition frameworks for different environments, but most of these frameworks focus on the monitoring of the user's own characteristics and are weak in monitoring situational information. To address the uncertainty and complexity issues in daily activities, a PSL based activity recognition framework is proposed. From an application perspective, the framework divides the smart home control system into data collection layer, event management layer, and application layer. This section mainly studies the event management layer, which is divided into three sub tasks: event preprocessing, activity modeling, and activity inference. Event preprocessing is further divided into three parts: fragment partitioning, event merging, and event uncertainty calculation. Firstly, this section adopts a dynamic fragment partitioning method based on information quantity to address the characteristic of the unfixed sampling rate of raw sensor data. Then merge the redundant information within the fragments and consider the triggering frequency of the event; Finally, evaluate the uncertainty of these events based on DS evidence theory. The structure of the human activity recognition framework based on PSL is shown in Fig. 1.

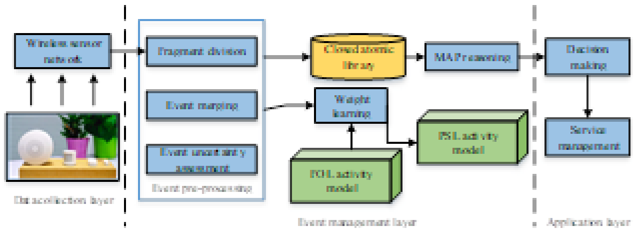

Fig. 1. Human activity recognition framework based on PSL.

In Fig. 1, the framework divides the smart home control system into a data collection layer, an event management layer, and an application layer. The data collection layer is responsible for collecting scenario information in the smart home environment and transmitting it to the event management layer through the wireless sensor network, which includes both sensors and network components deployed in the environment. The event management layer is responsible for transforming the received raw data into high-level scenario information, which can be divided into three parts by function: event pre-processing, activity modeling, and activity inference. The application layer is responsible for integrating the identified user activities and requests and is divided into two subtasks: decision making and service management. Event pre-processing is responsible for converting raw data into probabilistic events, which mainly includes three parts: fragmentation, event merging and event uncertainty calculation. Due to the sensor inexpensiveness and activity complexity in the smart home environment, usually a single behavior can be sensed by multiple sensors. Therefore, the study divides the relationship between sensors and activities into two categories: one sensor sensing multiple activities and multiple sensors sensing one activity. For the PSL model, the size of the problem increases exponentially with the number of formulas and the sensor information is susceptible to multiple factors. Therefore, the study first excludes irrelevant scenario information by segmenting the original sensor data, and then merges the sensor events within the segments to approximate the redundant information. Finally, the credibility of the observed evidence is measured by calculating the uncertainty of the events. Common segmentation methods include the interactive window method and the segmentation method based on unique attributes. The sensor trigger moments when a particular user performs a specific activity in the experimental dataset are shown in Fig. 2.

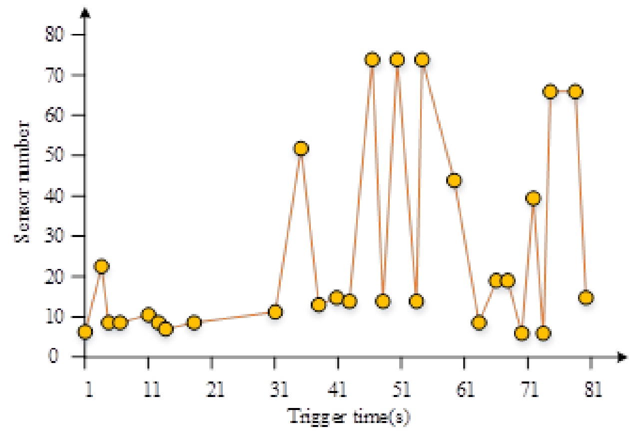

Fig. 2. Sensor trigger time chart when a user performs a specific activity.

By observing the sensor triggers when users perform different activities in the experimental dataset, it can be seen that the number of sensors triggered by different activities is stable at around 55. Therefore, the study adopts a fragmentation method based on the number of sensors based on the feature that the number of sensors triggered by different targets in the activity is more average. The method constitutes a range of values for the window length based on the average number of sensors triggered by the activities counted in the training data, and the window length is dynamically selected based on the current sensors, and the computational expression is shown in Equation (1).

$$L_s^* = \arg\max_{ws_l} \left\{ P\left(ws_l / A_m \right) \right\} \tag{1}$$

In Equation (1), L_s^* is the optimal window length corresponding to the active A_m . ws_l The range of values is $\left[ws_1, ws_l \right]$, where $ws_1 = \min\left\{ \overline{ws}\left(A_1\right), \overline{ws}\left(A_2\right), \cdots, \overline{ws}\left(A_m\right) \right\}$, $ws_l = \text{median}\left\{ \overline{ws}\left(A_1\right), \overline{ws}\left(A_2\right), \cdots, \overline{ws}\left(A_m\right) \right\}$, and $\overline{ws}\left(A_m\right)$ represent the average of the number of sensors triggered by the activity A_m . The expression of the relationship between sensors and activities is shown in Equation (2).

$$A^* = \arg\max_{A_m} \left\{ P\left(A_m / S_i \right) \right\} \tag{2}$$

A^* in Equation (2) represents the optimal activity of the sensor S_i . Combining Equation (1) and Equation (2) yields the probability estimation formula for the sensor and window length as shown in Equation (3).

$$ws^* = \arg\max_{ws_l} \left\{ P\left(ws_l / S_i \right) \right\} = \arg\max_{ws_l} \left\{ P\left(ws_l / A_m \right) \times P\left(A_m / S_i \right) \right\} \tag{3}$$

There is still a large amount of redundancy in the segmented data, so event merging is required before modeling to avoid overly bloated recognition models. Most traditional merging methods address the case where multiple sensors are triggered at the same time and can therefore be merged into one event, generalizing the sensor data associated with one event and ignoring the temporal impact range of sensor events. To address this problem, the study proposes an STF-EC algorithm that considers sensor trigger time and frequency in event merging. The algorithm first sets a time decay function to limit the impact range of the event, and then marks the recurring sensor events and records the number of times the sensor triggers. The impact range is calculated as shown in Equation (4).

$$R\left(e_i^a, e_j^a\right) = \begin{cases} 1, e_i^a.SID \in Uact_l \ \&\& e_j^a.SID \in Uact_l \\ 0, otherwise \end{cases} \tag{4}$$

In Eq. (4), $R\left(e_i^a, e_j^a\right)$ represents the sensor dependence between two atomic events e_i^a and. e_j^a $R\left(e_i^a, e_j^a\right) = 1$ Then it indicates that two sensors correspond to one event and can be combined if they are within the time constraint. The time dependence of the two atomic times is calculated as shown in Equation (5).

$$T\left(e_i^a, e_j^a\right) = \exp\left(-\delta \left| e_i^a.T - e_j^a.T \right|\right) \tag{5}$$

The final uncertainty event corresponding to that atomic time is generated and the number of occurrences of that event is recorded. The study calculates the event uncertainty based on the evidence fusion mechanism in DS evidence theory. First, we assign weights to sensor information based on Dun entropy theory, and then combine the weights and observations to calculate the uncertainty of the event. Dun entropy is a generalized version of information entropy, which is defined as shown in Equation (6).

$$DS = -\sum_{i=1}^{N} m\left(H_i\right) \log_2 \frac{m\left(H_i\right)}{2^{H_i^*} - 1} \tag{6}$$

In Equation (6), DS denotes the Dun entropy. denotes the H_i i th proposition in the identification framework, and H_i^* denotes the number of elements in the proposition. The relationship between sensor weights and Dun entropy is defined as shown in Equation (7).

$$r_i^{pst} = f\left(DS^*\right) = \left(1 - DS^*\right) \exp\left(DS^*\right) \tag{7}$$

In equation (7), DS^* is the normalized Dun entropy. In the problem of activity identification, the sensors used as evidence have different levels of reliability, so the uncertainty of the events is calculated using a weighted fusion as shown in Equation (8).

$$\hat{u} = \sum_{i=1}^{n} \alpha_i x_i \tag{8}$$

In Equation (8), $\hat{u}$ is the uncertainty of the event, x_i indicates the sensor measured data, and α_i is the weight of the data in the fusion. n indicates the number of sensors corresponding to the sensor event x_i .

B. Combining PSL and EC for Human Activity Modeling and Inference Methods

Unlike general machine learning methods, PSL is essentially a first-order logical knowledge base with weights, so the process of activity modeling is similar to the construction of a knowledge base. In the application environment of smart home, the daily life has the characteristics of alternation and concurrency, and the activity model can directly determine the accuracy of activity recognition[19-20]. The way of rule definition also largely determines the scale of the problem in PSL reasoning, which in turn affects the recognition efficiency of the recognition framework. Therefore, the study proposes the activity modeling method PSL-EC, which combines PSL and EC, to solve the problem of logical uncertainty and temporal complexity in daily activities by using the logical expression uncertainty of PSL and the characteristics of EC for activity persistence modeling. The activity modeling part includes two sub-tasks: rule definition and weight learning, and the rules in PSL can be classified into soft rules and hard rules by rule type, which are used to describe the uncertainty relationship between “event” and “activity” and the domain knowledge of activity recognition, respectively. The activity modeling approach of PSL-EC uses the classical discrete event algorithm as a template to define rules based on specific problems in the activity recognition domain and to model the continuity of activities. Then existing parametric learning methods for first-order logic formulas are used to deal with logical uncertainty. In daily life, users perform activities characterized not only by temporal complexity, but also by diversity in daily life based on different execution habits. The sensor events and durations triggered by different users performing the same activity are shown in Fig. 3.

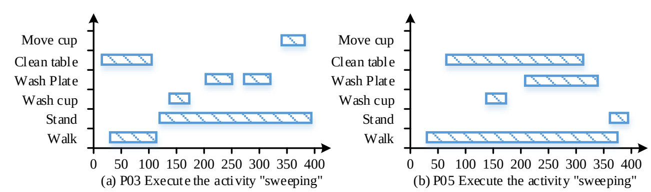

Fig. 3. Sensor events and duration triggered by different users performing the same activity.

Daily activities may seem to be irregular, but different users often have certain patterns embedded in their starting and ending actions when performing a particular activity. Assuming that daily activities are only related to start and end actions, the predicates in the event algorithm can be approximately reduced, thus streamlining the predicate structure. The study defines the start and end conditions of an activity as soft rules, and assigns weights to the formulas through parameter learning. The core of the event algorithm lies in the use of the law of inertia to describe the continuity of events, i.e., the state of an activity is determined only by its start and end conditions. The study defines hard rules based on the axioms of event algorithms and the law of the number of event triggers. The defined soft rules and hard rules are shown in Table I.

TABLE I. SOFT AND HARD RULES OF FRAMEWORK

Rule type	Number	Describe
Soft rule	1	$\forall Timestept : Happens\left(pa_1, t\right) \wedge Happens\left(pa_2, t+1\right) \rightarrow Initiates\left(a, t+1\right)$
	2	$\forall Timestept : Happens\left(pa_1, t\right) \wedge Happens\left(pa_2, t+1\right) \rightarrow Terminates\left(a, t+1\right)$
	3	$\forall Timestept : Happens\left(pa_1, t\right) \wedge \left[pa_1, \, frequency > K\right] \rightarrow Terminates\left(a, t+1\right)$
Hard rule	1	$\forall Timestept_1, t_2 : HoldsAt\left(\text{'close the front door'}, t_1\right) \wedge \left(t_1 + 1 \leq t_2\right) \rightarrow HoldsAt\left(\text{'open the front door'}, t_1\right)$
	2	$\forall Timestept_1, t_2 : HoldsAt\left(\text{'set the table'}, t_1\right) \wedge \left(t_1 + 1 \leq t_2\right) \rightarrow HoldsAt\left(\text{'eat breakfast'}, t_1\right)$
	3	$\forall Timestept_1, t_2 : HoldsAt\left(\text{'eat breakfast'}, t_1\right) \wedge HoldsAt\left(\text{'clear the table'}, t_1 + 1\right) \rightarrow HoldsAt\left(\text{'eat breakfast'}, t_1 + 1\right)$

The original version of the PSL model can be generated by rule definition, and these formulas are often given the same weights, so more appropriate weighting is needed through parameter learning. Commonly used weight learning methods are maximum likelihood estimation and maximum pseudo-likelihood estimation, and weight maximum pseudo-likelihood estimation uses pseudo-likelihood probabilities instead of likelihood probabilities. PSL-based inference needs to be performed in a closed PSL, so its inference problem is similar to that of probability maps. Activity inference is another important part of the study, and the activity inference mechanism in PSL includes maximum posterior probability inference and marginal probability inference. The PSL model constructed by activity modeling is defined as $P = \left(F_i, W_i\right)$, where F_i is the formula template in the model and W_i is the corresponding weights. The first step in performing Maximum A Posteriori Probabilistic Inference (MAP) is to convert the arithmetic and logical rules in PSL into a linear constraint form. This form of rule can be easily converted into the form of Horn clause as shown in Equation (9).

$$\left(\underset{i \in I_j^+}{\vee} l_i\right) \vee \left(\underset{i \in I_j^-}{\vee} \neg l_i\right) \tag{9}$$

In Eq. (9), L denotes the set of all words l_i included in a clause, and I_j^+ and I_j^- denote the set of non-negative and negative words, respectively. The PSL model includes soft and hard rules, both of which can be transformed into potential functions ϕ and inequality constraints φ as shown in Eq. (10).

$$\begin{cases} \phi\left(y, x\right) = \max\left\{1 - \sum_{i \in I_j^+} l_i - \sum_{i \in I_j^-} \left(1 - l_i\right), 0\right\} \\ \varphi\left(y, x\right) = 1 - \sum_{i \in I_j^+} l_i - \sum_{i \in I_j^-} \left(1 - l_i\right) \leq 0 \end{cases} \tag{10}$$

In PSL, the MAP inference problem can be described as finding the maximum probability distribution of possible worlds with the set of variables Y given the sequence of observations $X = \left\{x_1, x_2, \cdots x_m\right\}$, where the normalization factor Z is fixed, as shown in Equation (11).

$$\arg\max_{s \in S} P\left(S = s\right) = \arg\max_{y \in Y} P\left(y \middle| x\right) \tag{11}$$

According to Equation (11), it can be learned that the maximum probability distribution of possible worlds is equal to the distance between that world and the closure rule is minimized, so the MAP inference problem in PSL can be defined as shown in Equation (12).

$$\begin{cases} \arg\max_{s \in S} P\left(S = s\right) = \arg\min_{y} f_w\left(y, x\right) \\ s.t \varphi_k\left(y, x\right) = 0, \forall k \in \varepsilon \\ \varphi_k\left(y, x\right) \leq 0, \forall k \in I \end{cases} \tag{12}$$

In Equation (12), S represents the set of possible worlds consisting of x and y, and ε and I represent the set of equational constraints and inequality constraints in PSL, respectively. The MAP inference problem in PSL is a convex optimization problem rather than an integer linear programming, thus giving birth to a consistent optimization algorithm for efficiently solving large-scale optimization problems. The core of this algorithm is the Alternating Direction Multiplier Method (ADMM). Assuming that the hidden predicates constituting the soft and hard rules in the model are different, let y_j be the state variable appearing in the potential function $\phi_j\left(y, x\right), j = 1, 2, \cdots, m$ and y_{k+m} be the state variable appearing in the hard constraint $\varphi_k, k = 1, 2, \cdots, r$. For each hard constraint define an indicator function I_k as shown in Equation (13).

$$I_k\left[\varphi_k\left(y_{k+m},x\right)\right]=\begin{cases}0,\text{the congstraint is satisfied}\\ \infty,\text{otherwise}\end{cases} \tag{13}$$

Finally, the variable Y_i is set to be a copy of the variable y_i $i=1,2,\cdots,m+r$, so the MAP problem in PSL can be defined in the form shown in Equation (14).

$$\begin{cases}\arg\min_{y_i\in[0,1]}\sum_{j=1}^{m} ws_j\phi_j\left(y_i,x\right)+\sum_{k=1}^{r} I_k\left[\varphi_k\left(y\left(L,k+m\right),x\right)\right]\\ s.ty_i=Y_i\end{cases} \tag{14}$$

Combining Eq. (12) and Eq. (14), it can be seen that it is feasible to solve the MAP problem in PSL according to the ADMM approach. The data flow of the human activity recognition framework based on PSL is shown in Fig. 4.

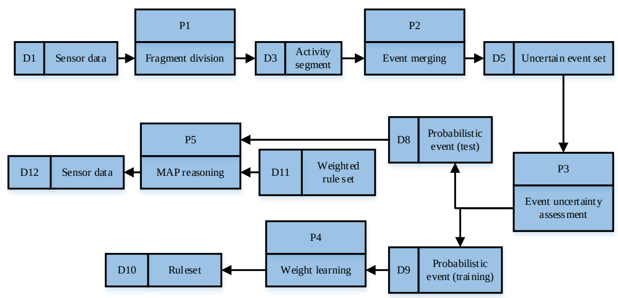

Fig. 4. Data flow of human activity recognition framework based on PSL.

As shown in Fig. 4, there are five core processing modules of the recognition framework, of which the weight learning and MAP inference modules use the platform's original approach. The sensor data is segmented by calculating the window length corresponding to the sensor through the fragment partitioning module. Then, the sensor and time dependencies of the event are calculated in the event merging module, and uncertain events are generated by merging based on the event dependency. In the event uncertainty evaluation module, the corresponding relationship between the event and the sensor is first calculated and stored, and then the uncertainty is evaluated based on the calculated comprehensive weights. Finally, human activity recognition can be achieved through weight learning and MAP inference modules.

IV. Results of PSL-based Human Activity Recognition in a Smart Home Environment

In the superiority test of the PSL-based activity recognition method, the practicality test of the PSL method for solving the data uncertainty problem and the temporal complexity problem was focused on, and a comparative experiment was conducted with three existing recognition methods (Ontology, HMM, MLN) under two datasets. The datasets for the validity experiments are collected in the TWSTBED apartment of the WSU CASAS project, where 78 sensors including motion sensors, kettle sensors, faucet sensors, pillbox sensors, temperature sensors, etc. are deployed.The validation experiments of the PSL method's ability to deal with data uncertainty use the ADL activity dataset containing the error data set, including both ADL and ADL-E The ADL dataset contains 6415 data obtained by 24 testers performing 5 different activities, while ADL-E is obtained by performing artificial activity omissions and errors based on ADL. The experiments to verify the ability of the PSL method to handle temporal complexity take the Interweaved ADL activity dataset with alternate execution activities, which consists of two parts of data obtained by 21 testers executing sequentially and by executing 8 activities in any order. Both sets of experiments were conducted using the ten-fold cross-check method, i.e. the data were equally divided into 10 parts, of which 9 parts were used as training data and 1 part was used as test data. The activities in the ADL dataset and the Interwoven ADL dataset are shown in Table II.

TABLE II. List of Activities in the ADL Dataset and Interwoven ADL Dataset

ADL dataset		Interweaved ADL Dataset	
Number	**Activity**	**Number**	**Activity**
SA1	Make a phone call	AC1	Fill medication dispenser
SA2	Wash hands	AC2	Watch DVD
SA3	Cook	AC3	Water plants
SA4	Eat	AC4	Answer the phone
SA5	Clean	AC5	Prepare birthday card
/	/	AC6	Prepare soup
/	/	AC7	Clean
/	/	AC8	Choose outfit

The performance evaluation indicators of other methods use the common F1 score, which is calculated as shown in formula (15).

$$F1=\frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{15}$$

In Equation (15), $\text{Recall}=TP/\left(TP+FN\right)\text{Precision}=TP/\left(TP+FP\right)$, TP is the number of correctly identified activities, FN is the number of unidentified activities, and FP is the number of incorrectly identified activities. The experiments started with event pre-processing of the data, and the average duration of the activities and the number of triggered sensors in the CASAS dataset is shown in Fig. 5.

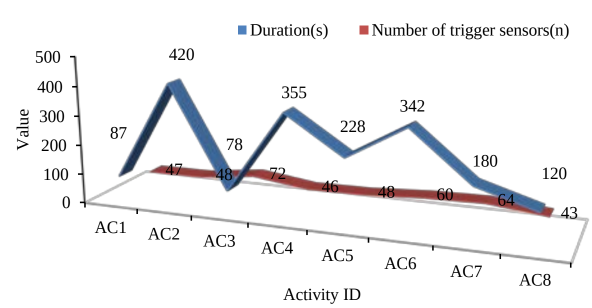

Fig. 5. Average duration of activity and number of triggered sensors in the CASAS dataset.

According to Fig. 5, the sensor corresponds to a window length in the range of [43, 54]. Then, event merging and uncertainty calculation are performed to transform the sensor data into probabilistic events. After defining the activity rules of the model, the PSL activity model is generated by learning the weights of the soft rules based on the training data. Finally, test data and PSL activity model are input, MAP inference is performed and the identification results are compared with the correct results. Experiment 1 verifies the ability of PSL method to handle data uncertainty, and the experimental results under ADL dataset and ADL-E dataset are shown in Fig. 6.

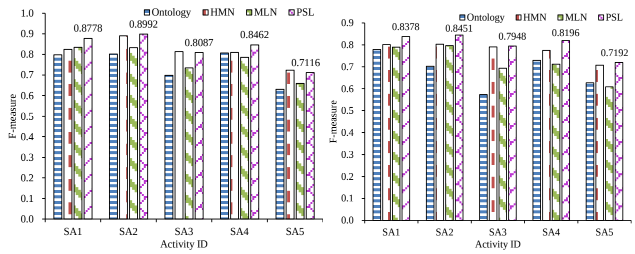

Fig. 6. Results to verify the ability of PSL method to deal with data uncertainty.

According to the experimental results of each method in Fig. 6(a) and Fig. 6(b) on the ADL dataset, it can be seen that the PSL method has good recognition performance for various activities, especially for activities SA1, SA2, and SA4. The average recognition rate for the three activities on the ADL dataset reached 87.44%, and even on ADL-E, it can maintain an average recognition rate of 83.42%. The execution methods of activities SA3 and SA5 have diversity, while the rules of PSL and MLN are manually defined, so the recognition performance of these two methods for SA3 and SA5 is slightly worse. The method of HMM is to establish recognition models based on training data, so the recognition rates for activities SA2 and SA5 are both above 70%. According to the experimental results on the ADL-E dataset in Fig. 6(b), it can be seen that the recognition rates of all methods have decreased, especially the Ontology method which decreased by 8.38%, followed by the MLN method which decreased by 5.76%, while the PSL method has the least significant decrease, with an average recognition rate of only 2.54%. The experimental results show that PSL has the best comprehensive recognition performance and can maintain good recognition performance even in the presence of erroneous activities, with a certain degree of recognition stability. The average recognition rate of each activity in two datasets using different recognition methods is shown in Fig. 7.

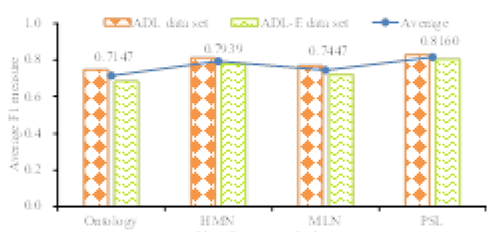

Fig. 7. Average recognition rate of activities in two data sets by different methods.

In Fig. 7, the PSL method achieved the highest average recognition rate, with an average recognition rate of 82.87% and 80.33% on the ADL and ADL-E datasets, respectively, while the Ontology method had the lowest recognition rate, with 74.73% (ADL) and 68.20% (ADL-E), respectively.

The average recognition rates of the four recognition methods on two datasets were 71.47% (Ontology), 79.39% (HMN), 74.47% (MLN), and 81.60% (PSL), respectively. The experimental results further demonstrate that the PSL method can maintain excellent recognition performance even in the presence of erroneous data, and verify the effectiveness of PSL in dealing with data uncertainty. The validation results of the ability of different algorithms to deal with temporal complexity are shown in Fig. 8.

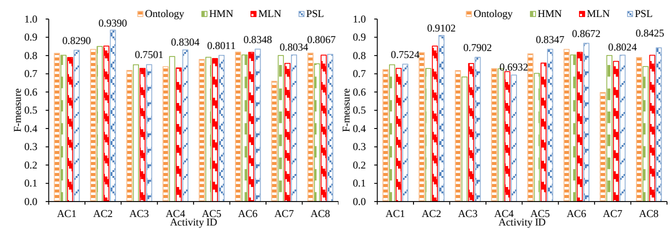

Fig. 8. Results of verifying the ability of different algorithms to deal with temporal complexity.

As shown in the experimental results of each method on the Sequential dataset in Fig. 8(a), PSL has the highest recognition rate among the four methods for 7 activities other than activity AC8, and the recognition rate for all other activities except for activity AC3 is above 80%. In the experimental results of each method on the interleaved dataset in Fig. 8(b), although the recognition rate of PSL for activities decreased under alternating and concurrent execution, the average recognition rate for activities is still the highest among the four methods, with an average recognition rate of 81.16%. The average recognition rate of each activity in two datasets using different recognition methods is shown in Fig. 9.

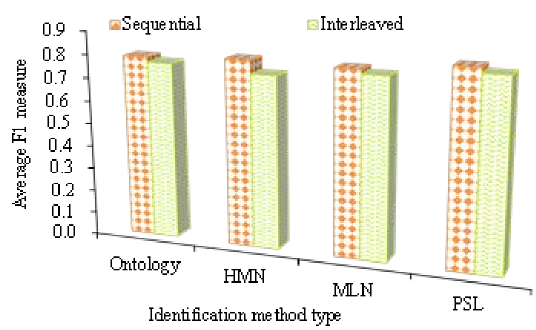

Fig. 9. Average recognition rate of each activity in two data sets by different recognition methods.

From Fig. 9, When there are alternating and concurrent recognition actions, the average recognition rate of the four activity recognition methods has decreased, with the HMM method showing the greatest decrease in recognition rate, with the average recognition rate decreasing from 80.32% to 74.65%. Although the average recognition rate of PSL on the Interleaved dataset has also decreased, it only decreased by

2.17%, and the decrease is not significant. It is still the highest average recognition rate among the four methods, maintaining an average recognition rate of 81.02%. The experimental results show that PSL can maintain the stability of activity recognition even when there are alternating and concurrent actions in recognition, verifying the effectiveness and superiority of PSL in processing temporal complexity data.

V. Conclusion

With the emergence and rapid development of smart cities and smart homes, ambient intelligence is widely used in various fields as an important part of artificial intelligence research. The study proposes a PSL-based activity recognition framework for human activity recognition in smart home scenarios, gives an evaluation method for sensor event uncertainty using DS evidence theory, and proposes an activity modeling method PSL-EC in conjunction with EC. the PSL method is compared with three other common recognition methods Ontology, HMN, and MLN on a publicly available dataset for experiments. to verify the ability of PSL to handle data uncertainty and temporal complexity. the ability of PSL to handle data uncertainty is far superior to the other three algorithms, with average recognition rates of 82.87% (ADL) and 80.33% (ADL-E) on the two sub-datasets. the average recognition rate of PSL decreases in the presence of concurrent and alternating activities is the least significant among the four methods, with declined by 2.17% and maintained the average recognition rate of 81.02%. The comprehensive experimental results show that the PSL-based human activity recognition method has excellent performance for both data uncertainty and temporal complexity. The different perception modes in the current smart home environment have their own advantages, so there is a trend towards a mixed use of multiple perception modes. However, these different patterns of scenario information exhibit heterogeneity, and current methods lack effective measures for processing these heterogeneous information. As an effective tool for eliminating information heterogeneity, ontology methods have been widely applied in other fields. However, the ability of ontology reasoning to handle uncertain information is poor, so future research can focus on the combination of ontology with methods such as MLN and PSL.

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References

[1] Y. Cui, L. Zhang, Y. Hou, G. Tian, Design of intelligent home pension service platform based on machine learning and wireless sensor network, Journal of Intelligent & Fuzzy Systems, 40(2): 2529-2540, 2021.

[2] S. Wan, L. Qi, X. Xu, C. Tong, Z. Gu, Deep learning models for real-time human activity recognition with smartphones, Mobile Networks and Applications, 25(2): 743-755, 2020.

[3] P. Asghari, E. Soleimani, E. Nazerfard, online human activity recognition employing hierarchical hidden Markov models, Journal of Ambient Intelligence and Humanized Computing, 11(3): 1141-1152, 2020.

[4] K. Ramirez-Amaro, Y. Yang, G. Cheng, A survey on semantic-based methods for the understanding of human movements, Robotics and Autonomous Systems, 119: 31-50, 2019.

[5] A. Prati, C. Shan, K. I. K. Wang, Sensors, vision and networks: from video surveillance to activity recognition and health monitoring, Journal of Ambient Intelligence and Smart Environments, 11(1): 5-22, 2019.

[6] L. K. Wang, R. Y. Liu, Human activity recognition based on wearable sensor using hierarchical deep LSTM networks, Circuits, Systems, and Signal Processing, 39(2): 837-856, 2020.

[7] D. Arifoglu, A. Bouchachia, Detection of abnormal behaviour for dementia sufferers using Convolutional Neural Networks, Artificial Intelligence in Medicine, 94: 88-95, 2019.

[8] N. Dua, S. N. Singh, V. B. Semwal, Multi-input CNN-GRU based human activity recognition using wearable sensors, Computing, 103(7): 1461-1478, 2021.

[9] H. Zhang, Z. Xiao, J. Wang, F. Li, E. Szczerbicki, A novel IoT-perceptive human activity recognition (HAR) approach using multihead convolutional attention, IEEE Internet of Things Journal, 7(2): 1072-1080, 2019.

[10] V. Bianchi, M. Bassoli, G. Lombardo, P. Fornacciari, M. Mordonini, I. D. Munari, IoT wearable sensor and deep learning: an integrate d approach for personalized human activity recognition in a smart home environment, IEEE Internet of Things Journal, 6(5): 8553-8562, 2019.

[11] P. Agarwal, M. Alam, A lightweight deep learning model for human activity recognition on edge devices, Procedia Computer Science, 167: 2364- 2373, 2020.

[12] A. Artikis, E. Makris, G. Paliouras, A probabilistic interval-based event calculus for activity recognition, Annals of Mathematics and Artificial Intelligence, 89(1): 29-52, 2021.

[13] S. N. Tran, D. Nguyen, T. S. Ngo, X. S. Vu, L. Hoang, Q. Zhang, M. Karunanithi, On multi-resident activity recognition in ambient smart-homes, Artificial Intelligence Review, 53(6): 3929-3945, 2020.

[14] Y. Li, G. Yang, Z. Su, S. Li, Y. Wang, Human activity recognition based on multienvironment sensor data, Information Fusion, 91: 47-63, 2023.

[15] Nweke H F, Teh Y W, Mujtaba G, Al-garadi M A. Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions. Information Fusion, 46: 147-170, 2019.

[16] P. Asghari, E. Soleimani, E. Nazerfard, online human activity recognition employing hierarchical hidden Markov models, Journal of Ambient Intelligence and Humanized Computing, 11(3): 1141-1152, 2020.

[17] Y. Zhang, G. Tian, S. Zhang, C. Li, A knowledge-based approach for multiagent collaboration in smart home: from activity recognition to guidance service, IEEE Transactions on Instrumentation and Measurement, 69(2): 317-329, 2019.

[18] X, Guo, Z. Shen, Y. Zhang, T. Wu, Review on the application of artificial intelligence in smart homes, Smart Cities, 2(3): 402-420, 2019.

[19] A. Keshavarzian, S. Sharifian, S. Seyedin, modified deep residual network architecture deployed on serverless framework of IoT platform based on human activity recognition application, Future Generation Computer Systems, 101: 14-28, 2019.

[20] Y. Xu, T. T. Qiu, Human activity recognition and embedded application based on convolutional neural network, Journal of Artificial Intelligence and Technology, 1(1): 51-60, 2021.