



Multi-resident type recognition based on ambient sensors activity[☆]

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ABSTRACT

With the development of sensing and intelligent technologies, ambient sensor-based activity recognition is attracting more attention for a wide range of applications. One of the technology challenges is the recognition of the activity performer in a multi-occupancy scenario. This paper proposes a multi-label Markov Logic Network classification method to recognize resident types based on their activity habits and preference. The activity preference mainly includes time sequence preference, duration and period preference, and the location preference of a basic entity or action events. According to the resident type (gender, age bracket, job), the further reasoning work is the family role (mother, father, daughter and so on.) recognition. We have designed simple and combined preferences to test and evaluate our proposed method. Initial experiments have produced good performance in many cases proving this solution is an efficient and feasible method for resident type recognition which could be applied to real-world scenarios.

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1. Introduction

Activity of Daily Living (ADL) recognition is discovering the action intent, living habits, and health status. In recent years, since people have paid more and more attention to privacy protection, the non-obstruct (non-vision) ambient sensors have been increasingly deployed in our life. The non-obstruct sensors are not interfering with their traditional life which are more comfortable and flexible for all users, especially for newcomers. However, there are many technical challenges for the researchers to handle. The most apparent problem is distinguishing the resident of activity with a low correlation between sensor data and resident. Many proposed solutions try to build a high correlation. For example, Chao-Lin Wu et al. have presented an activity recognition system which adopts the wearable devices to identify the user [1]. Minh-Son et al. have adopted the voice biometrics to identify resident [2,3]. Similarly, Eunju Kim also realized multi-resident

recognition by using the video data [4]. As a result, utilizing non-obstruct sensors to establish the resident label is a suitable solution for residents. While, all the previously mentioned solutions produce a new burden of deployment, computational, and even storage. Adopting the ambient sensors which has been used for activity recognition is a better way for resident recognition. Therefore, using their internal relationships between resident preference and temporal-spatial attributes of sensors is a breakthrough to build the correlation. This paper presents a multi-classification solution, which establishes the resident recognition model based on the ambient sensors' activity model.

The multi-resident scene is more complicated than the single-resident scene which not only requires the simple spatial-temporal characteristic, but also the high-dimensional features, like duration, time series and so on. Geetika Singla et al. have concerned the average time feature to recognize the resident in one activity. However, it is difficult to recognize in the approximate preference situation. In addition, this feature is not fixed and cannot handle the dynamic scenes [5]. Shuai Zhang et al. have adopted the duration feature for daily activity recognition. While this method just sets three durations which just keeps the arithmetical operation result but ignores the temporal feature and does not have the efficient ability for the resident recognition [6]. Nicholas et al. [7] have adopted the time sequence and duration features to identify the resident's habit by clustering method. This method has a good performance for new comers, but it is

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an unsupervised algorithm and gives three resident types, but it cannot identify the habit details. To sum up, establishing a supervised or semi-supervised method with flexible high-dimensional temporal features, including time sequence, duration and period, is an efficient method for multi-resident scene.

Many algorithms are being adopted by researchers. Based on the process of model establishment, we can divide them into two types. One type is called as data-driven methods, such as clustering, recurrent neural network, Hidden Markov Model (HMM), and other probabilistic methods. The other one is defined as knowledge-driven methods, such as Activity Features (AFs), formal concept analysis, and other semantic expert systems. Tran et al. have contrasted different algorithms and selected the recurrent neural network with recurrent units which makes it better than other models. Then, the performance has been verified after deploying in three people families' houses, but is not good enough [8,9]. Geetika Singla et al. have established the models by HMM for each resident, but not all the results were good with the unsufficient and unrepresentative training data [5]. Yi-Ting Chiang et al. have extended coupled hidden Markov models by adding some vertices to realize a dynamic network which has 80% precision approximately. The complex interaction activities model cannot be learned from the small data [10]. Alemdar et al. have proposed a method which is factorial hidden Markov model. It consists of multiple independent Markov chains for two residents which achieved 62.7% and 61.2% accuracy respectively. They evaluated their method in their own dataset which does not have enough individual features to distinguish the residents [11]. As shown in previously, Data-driven methods have obvious disadvantages. The knowledge-driven methods on the other word, have been more and more popular in recent researches. Shahi et al. have divided the processing into two stages. Firstly, establishing the AFs and classifier model, and then, segmenting the sensor data dynamically based on the first step [12]. Hao et al. have proposed a knowledge-driven solution based on formal concept analysis and incremental lattice search strategy which showed a promising solution for sequential event mining [13]. Comparing these knowledge-based methods, the deficiencies have following, (1) completeness of the rule base is difficult to realize, especially for the rapid changing world where more and more new activities are born; (2) the lack of robustness, like some newcomers have the different actions; (3) the poor universality, some rules are not suitable for everyone, etc.; (4) high dependency for expert rules, poor adaptative for the changing rules, and so on. Therefore, adopting a hybrid algorithm is a well-considered way for activity recognition. Kuo-Chung et al. have utilized transition table and conditional random field with iterative inference to decompose the data of two residents [14]. Gayathri et al. [15] have adopted Markov Logic Network (MLN) which combined the first-order logic and Markov Network to recognize the activities but set the weights manually without statistical probability which is not the real combination. In 2019, we have adopted MLN to handle the noisy and data missing problems in activity recognition which get good performance [16]. We adopt the MLN in resident recognition in this paper which will be detailed introduced in Section 2.

There are some typical datasets of multi-resident, like CASAS of WSU [5] and ARAS [17]. Based on these datasets, some researchers have evaluated their solutions. For example, Raihani Mohamed et al. have designed a multi-label classification framework based on the classifier chains approach [18,19]. Wang et al. have utilized multi-task learning and zero-shot learning to recognize the multi-resident and unseen classes [20]. Prosssegger et al. also have a proposed extension of ID5R based on multi-label [21]. Benmansour et al. have combined activity label with a resident label to represent the activity [22]. While these datasets have two

residents, their solutions preferred to establish the individual's resident model which is small-scale. In multi-resident situation, the dynamic numbers (more than 2 persons) and the roles of residents are more common in our daily life. Therefore, building a scalability dataset with the generalizing labels for residents is the trend for further research. In this paper, we deploy the multi-sensor in the family home which has been shown and evaluated in Section 4. In order to improve the dataset scalability, we label their activities with the resident type (more numbers and roles of residents) which will be introduced in Section 3.

We establish the resident model of activity where the residents have been represented by type labels, then sampling the data of residents to set up the different probabilities. The flow chart is shown in Fig. 1. The inference results consist of multi-label, so we can infer the resident type based on the labels. These labels represent the resident type which are more flexible for the newcomers and have stronger scalability.

The remaining part of this paper is organized as follows; In Section 2, we introduce the inference algorithm. Then, we deploy it in our home to represent the resident model. After that, we use the multi-resident to train the probability of rules in Section 3. We add the multi-sensor to the multi-resident family in order to collect data and do an experiment to verify this solution in Section 4. In Section 5, we present the conclusion and the future prospects.

2. Basic theory - Markov Logic Network

In this section, the basic algorithm of resident recognition will be explained which will deepen the understanding and build the better family MLN to enhance the inference accuracy.

Markov Logic Network (MLN) is a combination of First-order Logic (FoL) and Markov Network (MN) [23]. FoL is a predicate calculus set with area knowledge. MN is an algorithm for joint distribution with an undirected graph G and related potential function ϕ_k . MLN is composed of two parts, the first part is logic represented by a set of pairs (F_i, ω_i) , and the second part is a finite set of constants $(C = c_1, c_2, \dots, c_{|C|})$. Hence, MLN can be defined as $M_{L,C}$, where L represents logic, and C represents a constant set.

The main predicate symbols consists of action, activity, resident label, and other keywords. The resident label represents the main work of this paper. It could be a role, a gender, an age bracket, or a job which, in turn, has various combinations to represent the resident type. The supplementary part contains multi-feature, the traditional temporal-spatial attribute, sequence, and coherence attributes. The large amounts of resident labels and features are going to generate more predicates. Therefore, using abstractive and general rules is more practical. Generalization specific rules for the resident labels and features has two works, one is the abstraction of resident class, the other is the abstraction of attributes. The resident is defined as a constant symbol, like, Bob, Ammy, Juli, etc. The attribute is defined as a constant symbol too, like, 09/05/2019, Kitchen Room, etc. These constant symbols start with an uppercase letter or a number. The generalization of constant symbols is a variable symbols which start with lowercase characters, like, resident, time, student, etc.

FoL consists of predicate symbols (quantifiers) and connectives. The presentation, symbol, and meaning of connectives are shown in Table 1 [24]. The predicate symbols have been connected by connectives which reflects the particular relationships.

In order to improve the algorithm efficiency, the uniform format of FoL is adopted. Usually, we transform all the FoLs to disjunctive normal form (DNF) which means converting all conjunction to disjunction literally [25].

Then, establishing the MN need to draw the graph for FoL which is the key technology of this solution. Therefore, we draw

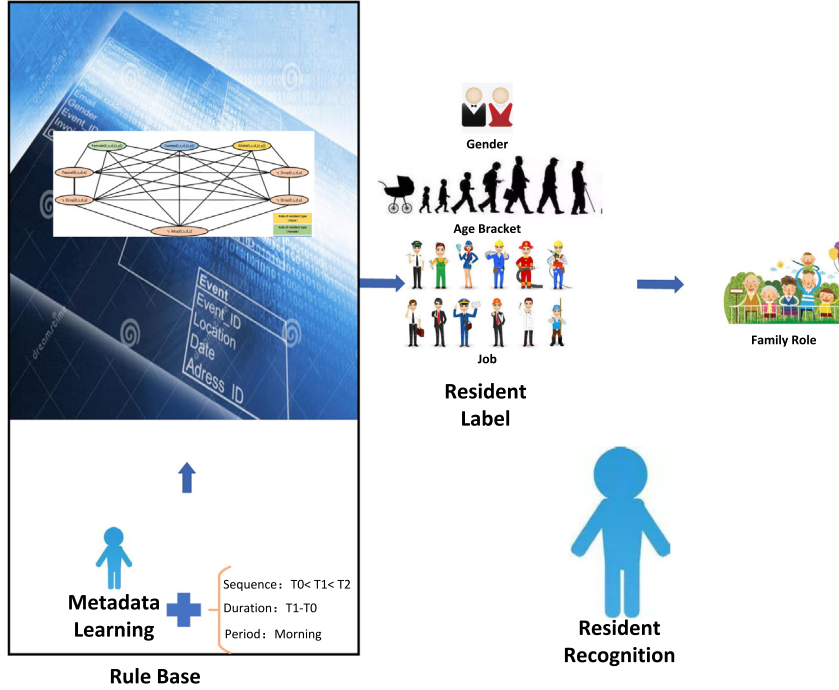


Fig. 1. Flowchart of resident recognition.

Table 1

Connectives	Symbols	Meaning
Negation	\neg	Antonym
Conjunction	\wedge	Simultaneous
Disjunction	\vee	One satisfaction
Implication	\rightarrow	Deduce
Equivalence	\leftrightarrow	Equal in value

the all-connected graph based on one rule. Then we build the entire graph iteratively and incrementally based on the rule base.

As we all know, MN is a probabilistic graphical model which requires the related potential function. The potential function of each rule is different and learned from small data of the resident which has their trait. The potential function reflects the probability or intensity of true, so it has been called as “weight”. Learning the weight by maximizing the likelihood is a process of obtaining extremum points for convex, which also can be called as “convex optimization” [26]. The usual weight solution is gradient descent algorithm, which is a first-order class searching optimization method. The weight “ ω ” has been defined as the following formula with the learning rate “ η ” and gradient “ g ” [27].

$$\omega_{t+1} = \omega_t - \eta g \quad (1)$$

The gradient “ g ” is obtained by taking the derivative for the conditional probability of the unknown results and known evidences.

$$\begin{aligned} g &= \frac{\partial}{\partial \omega_i} (-\log P_{\omega}(Y = y | X = x)) \\ &= -n_i(x, y) + \sum_{y'} P_{\omega}(Y = y' | X = x) n_i(x, y') \\ &= E_{\omega, y} [n_i(x, y)] - n_i(x, y) \end{aligned} \quad (2)$$

After realizing the MLN, the next step will be inferencing which generates two types of results; the first type is most likely state, and the other one is a conditional probability. In our work,

we only calculate the conditional probability. This conditional probability is different from that in the gradient descent process regardless of using the similar function. MN with weight logic rule is the final model for inference. The conditional probability works with the unknown results and Markov blanket. Markov blanket of one predicate is the minimal set which renders the predicate of the remaining network. That means the outer edge of this set gives the accurate value which cannot be changed by the remaining predicates. The probability of a ground predicated X_i when its Markov blanket B_i is in state b_i is illustrated in (17). F_i is the set of ground formulas in which X_i appears, and $f_i(X_i = x_i, B_i = b_i)$ is the value of i_{th} ground formula when $X_i = x_i$ and $B_i = b_i$.

$$\begin{aligned} P(X_i = x_i | B_i = b_i) &= \frac{\exp(\sum_{f_i \in F_i} \omega f_i(X_i = x_i, B_i = b_i))}{\exp(\sum_{f_i \in F_i} \omega f_i(X_i = 0, B_i = b_i))} \\ &\quad * \frac{1}{\exp(\sum_{f_i \in F_i} \omega f_i(X_i = 1, B_i = b_i))} \end{aligned} \quad (3)$$

Nevertheless, solving the conditional probability is a non-deterministic polynomial (NP)-hard formula which can be solved by data directly. Sampling algorithms are commonly used in such situation. There are many sampling methods, like Gibbs sampling, Markov Chain Monte Carlo with satisfiability testing, Simulated Tempering and so on [28].

3. Family MLN based on individual characteristics and high-dimensional features

In this section, we introduce a method for resident type recognition based on MLN described by typical individual characteristics at home as shown in Fig. 1. The flow chart of the whole data processing is shown in Fig. 2.

• FoL Rule Base

Entity events or action events build the original rules of activities. Then this paper adds the individual characteristics

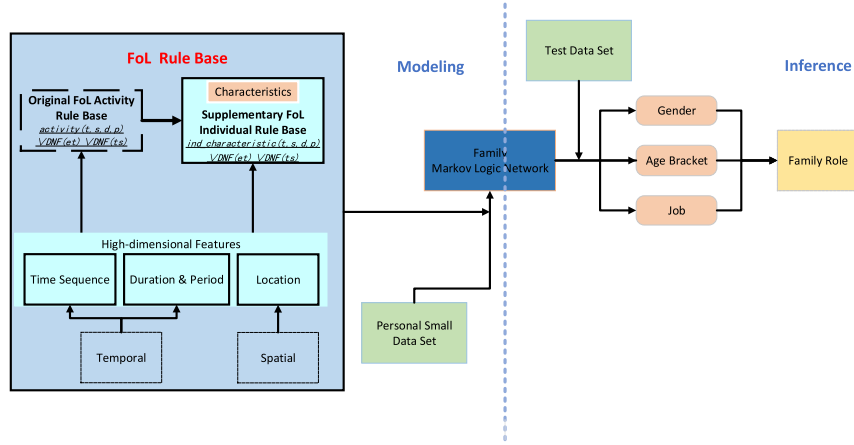


Fig. 2. Data processing flowchart for resident type recognition.

rules to be the supplement as innovating. In order to ensure the completeness of rule base, we build the new rules by replacing the activity using the new characteristics one by one. Specifically, the traditional rules of the activities, now, have been expended to several rules, where each rule has one new characteristic.

The general rules for one activity are generated as follows; the first rule is the original activity rule which is represented by DNF, the second rule replaces *activity* (t, s, d, p) by all *ind_characteristic* (t, s, d, p)s which reflects the relationship between the individual characteristic and entity events, t is the abbreviation of the temporal feature, s is the abbreviation of the spatial feature, d is the duration of the spatial feature, and p is the period feature. The individual characteristics consist of gender, age bracket and job which are also the query nodes for inference. The kinds of all individual characteristics are shown in Table 2.

Among them, $DNF(ts)$ is the DNF of the Time Sequences (ts) feature. For the variable, when starting with a lowercase letter (*activity*, t , d , p , *entityevents*(et), *timesequences* (ts), *ind_characteristic*), that means they are generalized variables. There are also listing some representative examples, including the cooking, cleaning, drinking three activities rules, and the gender characteristic rules of them.

$$activity(t, s, d, p) \vee DNF(et) \vee DNF(ts) \quad (4a)$$

$$ind_characteristic(t, s, d, p) \vee DNF(et) \vee DNF(ts) \quad (4b)$$

$$Cook(t, s, d, (x, y)) \vee \neg Holloware(t, s, d, x) \quad (5a)$$

$$\vee \neg Gas(t, s, d, y) \vee \neg Before(x, y) \quad (5b)$$

$$Female(t, s, d, (x, y)) \vee \neg Holloware(t, s, d, x) \quad (5c)$$

$$\vee \neg Gas(t, s, d, y) \vee \neg Before(x, y) \quad (5d)$$

$$Male(t, s, d, (x, y)) \vee \neg Holloware(t, s, d, x) \quad (5e)$$

$$\vee \neg Gas(t, s, d, y) \vee \neg Before(x, y) \quad (5f)$$

$$Sweep(t, s, d, (z, y)) \vee \neg Faucet(t, s, d, x) \vee \neg Drop(t, s, d, y) \quad (6a)$$

$$\vee \neg Mop(t, s, d, z) \vee \neg Before(z, x) \vee \neg Before(x, y) \quad (6b)$$

$$Female(t, s, d, (z, y)) \vee \neg Faucet(t, s, d, x) \vee \neg Drop(t, s, d, y) \quad (6c)$$

$$\vee \neg Mop(t, s, d, z) \vee \neg Before(z, x) \vee \neg Before(x, y) \quad (6d)$$

$$\begin{aligned} & Male(t, s, d, (z, y)) \vee \neg Faucet(t, s, d, x) \vee \neg Drop(t, s, d, y) \\ & \vee \neg Mop(t, s, d, z) \vee \neg Before(z, x) \vee \neg Before(x, y) \end{aligned} \quad (6e)$$

$$\begin{aligned} & DrinkTea(t, s, d, (x, y)) \vee \neg TouchCup(t, s, d, x) \\ & \vee \neg MoveCup(t, s, d, y) \vee \neg Teabag(t, s, d, z) \end{aligned} \quad (7a)$$

$$\vee \neg Before(x, z) \vee \neg Before(z, y) \quad (7b)$$

$$Female(t, s, d, (x, y)) \vee \neg TouchCup(t, s, d, x) \quad (7c)$$

$$\vee \neg MoveCup(t, s, d, y) \vee \neg Teabag(t, s, d, z) \quad (7d)$$

$$\vee \neg Before(x, z) \vee \neg Before(z, y) \quad (7e)$$

$$Male(t, s, d, (x, y)) \vee \neg TouchCup(t, s, d, x) \quad (7f)$$

$$\vee \neg MoveCup(t, s, d, y) \vee \neg Teabag(t, s, d, z) \quad (7g)$$

$$\vee \neg Before(x, z) \vee \neg Before(z, y) \quad (7h)$$

• Family MLN

The completeness rules illustrate that there is no discriminant ability because of the high degree of complementarity. Therefore, the intensities of rules must be in an uneven level, MLN is a useful probability graph model used to address this issue. Small resident data set assists the weight learning which reflects the resident's habit and preference.

The original first-order logic (FoL) activity rule base and individual FoL rule base together make up the MN. Then, the small data set of the real residents can be built a family MLN, and the supervised learning for weight can generate an inference model with preferences. Each rule is being linked to its weight which can be used to predict the activity and the performer. When multi-resident have different preferences, the rules are being labeled by their different individual characteristics. When the marked difference is not available, we infer that the performer of the activity has the equal probability which cannot be inferred.

The family MLN is the resident model based on the combination algorithm of data-driven and knowledge-driven methods. Each family has its own particular model which can express its relationships precisely. The MLN of the three sweep rules in formula (6) has been shown in Fig. 3.

• Multi-label Inference based on MLN

There are three types label of resident, gender, age bracket and job. The label of age bracket has many kinds, for example, infant, adolescent, young, middle-aged, and elderly. Sometimes, we can find a marked difference between them. Labeling the residents by these different labels can help

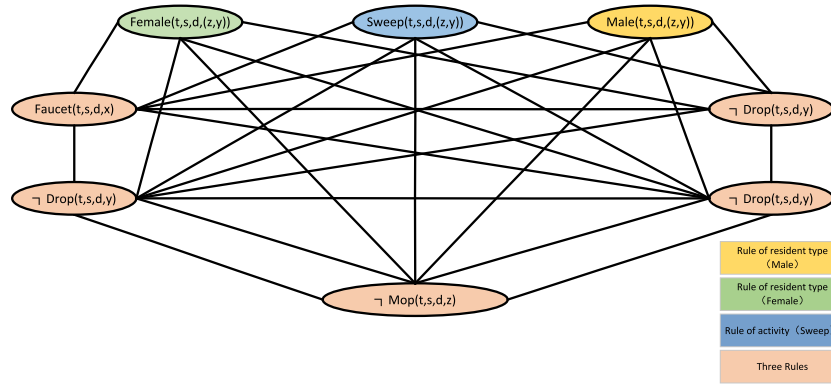


Fig. 3. The simple MLN of three sweep rules.

Table 2

Individual characteristics labels.

Characteristic	Labels
Gender	female, male
Age Bracket	infant, adolescent, young, middle-aged, agedness
Job	worker, teacher, student, doctor

us to find the performer. The other characteristics follow the same principle, labeling the performer at the obvious different situation. The difference between labels is affected by many factors, like temporal-spatial, time series, duration, periods, and other inner features. Usually, the difference between these labels is distinct. However, it is difficult to find the differences on rare occasions, which also can be accepted in our algorithm. Maybe every resident has the same habit for one specific activity, so we cannot distinguish the right one.

The further inference is the family role distinguishment, including father, mother, grandmother, grandfather, son, daughter, aunt, uncle and so on. There are many possible results which cannot get the unique one. But, the multi-label results also can be used to provide more accurate personalized service and warn the emergency in time. For example, the timely wake up service is effective for worker or student who gets up too late. The further inference is an optional result for the residents.

4. Experiments and results

4.1. Experiments tool and settings

In our experiments, we used Alchemy 2.0 which is a MLN engine used for inferencing. The raw data of sensor has been transformed into “.db” file by entity events representation. All rules of the activities and resident types are stored in “.mln” file written in FoL formats. Alchemy 2.0 has two main functions, one is learning the weight of rules (“.mln” file) by the entity database (“.db” file). The out result of this function is a weighted rules set (“out.mln” file). The other function is inferring the resident type by the weighted rules (“out.mln” file) for test database (“test.db” file). The output is “.result” file, which gives all possible results and their probabilities.

In order to evaluate the new comers, we have deployed new scene with multi-sensor in the kitchen of three-resident families. The smart kitchen covers three typical activities, cooking, cleaning, and drinking. The three activities have their own features. They may have the significant gender distinction (female, male),

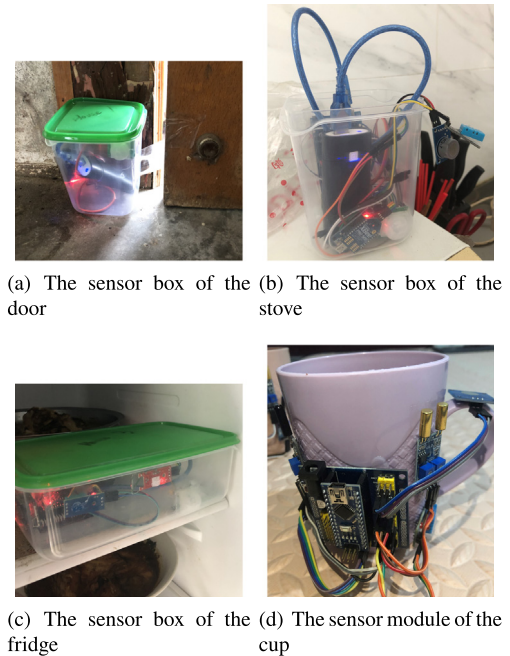


Fig. 4. The deployment of multi-sensor boxes and modules.

age bracket distinction (infant, young, middle-aged), job distinction (different working time, different jobs, like worker, student) which has relation with the time sequence preference (the time sequence for the entity events, even consists of different entity events), time duration (less than 1 h, 1 to 2 h, more than 2 h), time periods (breakfast, lunch, supper), and location preference (next to stove, next to faucet). These preferences can be randomly combined. Drinking is a usual activity which has the infinite possibilities. The performer of drinking activity cannot be inferred in some families.

The deployed sensors have been integrated into some boxes and put in fixed location in their kitchens in Table 3. The near door location deploys the infrared sensor, magnetic induction sensor, and other sensors which are shown in Fig. 4(a). The near stove location deploys the infrared sensor, temperature sensor, humidity sensor, and gas sensor as shown in Fig. 4(b). The inside fridge location deploys the magnetic induction sensor, temperature sensor, infrared sensor, and distance sensor as illustrated in Fig. 4(c). The cup model deploys the vibration sensor, touch sensor, infrared sensor, and tilt sensor which as shown in Fig. 4(d).

Table 3
Activities with their sensors.

Activity	Sensors	Data type	Train data	Test data
Cooking	infrared, temperature, magnetic induction, distance, humidity, gas...	TS A & DP A & LP A	288	145
Cooking	infrared, temperature, magnetic induction, distance, humidity, gas...	TS B & DP B & LP B	321	134
Cleaning	touch, tilt, vibration, infrared, humidity...	TS C & DP C & LP C	287	154
Cleaning	touch, tilt, vibration, infrared, humidity...	TS D & DP D & LP D	171	124
Drinking	vibration, touch, infrared, tilt, infrared, water, pressure...	TS E & DP E & LP E	641	231
Drinking	vibration, touch, infrared, tilt, infrared, water, pressure...	TS F & DP F & LP F	694	213

Table 4
The different time sequence preferences and different labels.

Time Sequence (TS)	Labels	Precision (without any preferences)	Precision	Further
Cooking with TS A	female, worker, middle	0.126	0.994	Mother
Cooking with TS B	male, student, Young	0.124	0.994	Son
Cleaning with TS C	male, Young	0.056	0.996	Son
Cleaning with TS D	female, middle	0.055	0.996	Mother
Drinking with TS E	male	0.055	0.568	None
Drinking with TS F	female	0.056	0.432	None

The first step of all is the pre-processing of the raw data. The raw data generated by a sensor includes the sensor name, location, and time. Considering using the semantic expression and simple inference in the pre-processing stage, the inference result of the semantic sensor data will be an entity or action event data. The activity can be divided into several entities or action events. The FoL rules of the activities link the entity events with activities using connectives. After that, they will be transferred to the standard DNF format.

We design the three kinds of experiments for time sequence preference, time duration and period preference, and location preference. The precision of preference experiments for the performers shows a good performance which proves that our design is efficient.

4.2. Experiments results

- Time sequence preference

There are three activities, concerning the different time sequence preferences, even the same sensor data without regarding the duration, which can easily label the activity. The results are shown in Table 4. Because of the difference between this work and other resident recognition, this work tries to inference the resident type, not resident role which cannot do the comparison experiments. We compared the results with the [16] model (without any preferences). We can easily find the [16] model (without any preferences) just has the bad performance because of the computation of classical probability, the comparison experiments will not be repeated anymore in the following experiments. The time sequence of an activity is a sequence of several ordered events, like, turning on faucet, feeling the dropping water, taking the mop, shaking the mop, and then pressing the mop. Those events are performed one after the other. Actually, this is the sequence order for doing cleaning, which has been represented by time sequence C. Other time sequences are the same with no further detailed description. The two typical probabilities of the results can be shown in Fig. 5, where, Fig. 5(a) illustrates doing the cooking with time sequence A, and, Fig. 5(b) represents time sequence B.

- Duration and Period preferences

The three activities results with the duration & period preferences and further conjecture are shown in Table 5.

- Location preference

The three activities results with location preference and further conjecture are shown in Table 6.

In the three different characteristics, all of the kitchen activities have been tested. The results show that our method

Table 5
The different duration, period preferences and the different labels.

Duration & Period (DP)	Labels	Precision	Further
Cooking with DP A	female, worker, middle	0.991	Mother
Cooking with DP B	male, student, Young	0.991	Son
Cleaning with DP C	female, middle	0.820	Mother
Cleaning with DP D	female, young	0.386	None
Drinking with DP E	male	0.923	Father/Son
Drinking with DP F	female	0.978	Mother/Daughter

Table 6
The different location preferences and the different labels.

Location Preference (LP)	Labels	Precision	Further
Cooking with LP A	female, worker, middle	0.988	Mother
Cooking with LP B	male, student, Young	0.988	Son
Cleaning with LP C	female, young	0.300	None
Cleaning with LP D	female, middle	0.477	Mother
Drinking with LP E	male	0.805	Father/Son
Drinking with LP F	female	0.687	Mother/Daughter

has a good performance, which is close to 100 percent, when the performer differentiates the activities clearly with other residents.

- Combined preference

When concerning one preference, for some special activities, the result showed terrible performance. After combining all the characteristics, there is just a probability of $\frac{1}{90}$ (Because the three types consist of 5 kinds (one is Null), 6 kinds (one is Null) and 3 (one is Null) kinds respectively, there will exist $5 \times 6 \times 3$ combinations) to get the identical habits, and the resident recognition precision will be improved greatly. The result of the three activities which have combined all characteristics are shown in Table 7.

5. Conclusion

In this paper, we study the recognition of activity performer in a multi-resident family home – the bottleneck problem for the ambient sensor-based environment. We have characterized activities of daily living in terms of their direct relations with the human type, and learned the personalized resident model from their small data set. We adopt multi-classification method, MLN, to establish the personalized model which is based on the general completeness rule base and then set the weight for each rule by small data set. The experiment results show good performance many times even when concerning only one characteristic. Therefore, after combining the three characteristics,

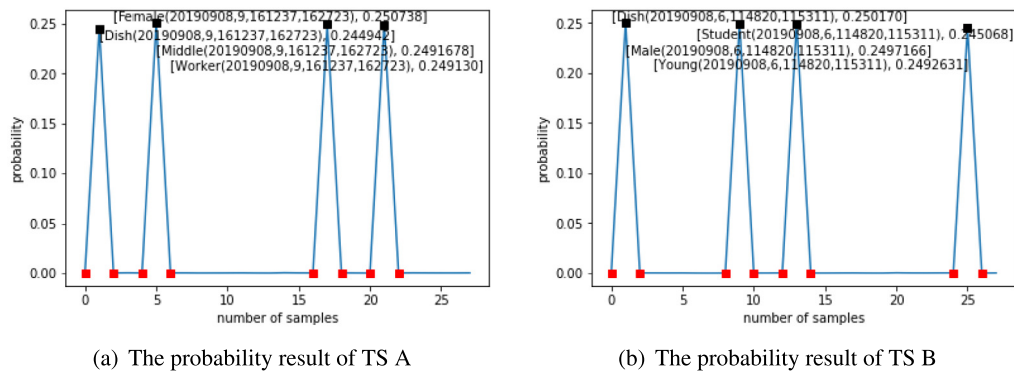


Fig. 5. The probability result of cooking activities with different time sequence preferences.

Table 7

The combined preferences and the different labels.

Combined Preference (CP)	Labels	Precision	Further
Cooking with CP A	female, worker, middle	0.994	Mother
Cooking with CP B	male, student, Young	0.994	Son
Cleaning with CP C	female, middle	0.996	Mother
Cleaning with CP D	male, Young	0.996	Son
Drinking with CP E	male	0.923	Father or Son
Drinking with DP F	female	0.978	Mother or Daughter

time sequence preference, duration and period preference, and location preference, the activities which are hard to identify show a better performance. Using data-driven and knowledge-driven combination method for the activities is an efficient solution for the user recognition, especially for the uncertain number and structures of residents, residents with the obvious individualities, which represent good robustness. Future work includes to mine more relations between characteristics with performers, and improve the performance of recognition of different residents and activities.

CRedit authorship contribution statement

Qingjuan Li: Conceptualization, Methodology, Software. **Wei Huangfu:** Supervision. **Fadi Farha:** Software. **Tao Zhu:** Supervision. **Shunkun Yang:** Supervision. **Liming Chen:** Funding acquisition. **Huansheng Ning:** Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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