Zone-Based Living Activity Recognition Scheme Using Markov Logic Networks

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Abstract. In this paper, we propose a zone-based living activity recognition method. The proposed method introduces a new concept called activity zone which represents the location and the area of an activity that can be done by a user. By using this activity zone concept, the proposed scheme uses Markov Logic Network (MLN) which integrates a common sense knowledge (i.e. area of each activity) with a probabilistic model. The proposed scheme can utilize only a positioning sensor attached to a resident with/without power meters attached to appliances of a smart environment. We target 10 different living activities which cover most of our daily lives at a smart environment and construct activity recognition models. Through experiments using sensor data collected by four participants in our smart home, the proposed scheme achieved average F-measure of recognizing 10 target activities starting from 84.14 % to 94.53 % by using only positioning sensor data.

Keywords: Daily living activity recognition · Markov Logic Networks · Smart home · Activity zone

1 Introduction

Recently, sensing various contexts in households as human activities and device usage conditions became available in addition to the existing environmental information such as temperature and humidity. Therefore, various daily living support context-aware services including energy-saving appliance control in homes [1], elderly monitoring systems [2], and context-aware appliance setting recommendations can be provided. Due to the presence of such services, which require highly accurate living activity recognition rate, the needs of new daily living activity recognition systems have become one of the greatest concerns in building a smart environment.

Many studies have been proposed for activity recognition [3–8]. Most of existing works suffer from the following problems: (1) high deployment and maintenance costs due to many sensors used [4]; (2) privacy intrusion due to utilization

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of cameras and microphones [3]; (3) few recognizable activities or low recognition accuracy; and (4) using Support Vector Machines which can not represent temporal and uncertain information in an efficient way [6]. So, we propose a new zone-based living activity recognition method for solving the aforementioned problems. The proposed method uses Markov Logic Network (MLN) [9] for handling uncertainty information in living activities and enhancing the recognition capability of the system through its rules by representing common sense knowledge (i.e. area of each activity).

2 Proposed Activity Recognition Scheme

In this section, we will introduce our proposed living activity recognition scheme called *Zone-Based Living Activity Recognition Method* (ZLAR) that constructs a reusable and efficient contextual activity model. Here, we assume that only one object is involved in each activity, so a complex activity taking place over multiple objects is out of scope of this paper and it will be part of our future work.

Basic Idea: The basic idea of ZLAR is based on two aspects: (1) representing all available knowledge which are related to a habitant behavior as relationship with objects, position, time, duration, area for each activity, and consumed power and (2) representing uncertainty information by using MLNs rules [9]. To represent all available knowledge as the area for each activity, the temporal information as a time and duration for doing a certain activity by a habitant, and the total amount of consumed power by an object to do its related activity, ZLAR proposed a new concept called activity zone which defines the location and the area of a certain activity that can be done by a habitant inside the smart environment. For example, activity "dining" happens in a zone near "dining table". This activity zone has a geometric shape which depends on the properties of its related activity object (ao) as object location and object mobility. For example, the zone of watching TV activity is related to the location of TV object inside a home and it may have a fixed shape and location; if the location of TV object is not changed. While, the zone of listening music activity is related to the location of an audio device (e.g. Stereo or iPod) inside a home and it may have a variable shape and location based on the mobility of this audio device. By using this activity zone, ZLAR builds a new data and knowledge-driven system by using MLN rules to represent uncertainty information in a system. So, ZLAR defines two features for each activity as follows.

(1) *Time interval*, $TI(u, Z_{ao}, t_{in}, t_{out})$, which represents the time duration value taken by a habitant u inside an activity object zone Z_{ao} for doing its related activity, where a habitant enters a zone at time t_{in} and he leaves a zone at time t_{out}.

(2) *Consumed power*, $PW(ao, t_{in}, t_{out})$, which represents the consumed power value by an activity object ao during the interval $(t_{out} - t_{in})$ to execute its related activity.

2.1 Proposed Activity Zone Concept

ZLAR uses activity zone concept to determine all possible positions of a habitant that he can do a certain activity inside a smart environment. This activity zone is defined by the location of activity object *ao* and the area that exists around *ao* which covers all possible positions of a habitant for this activity. As a result, this area has a plane geometric shape as a circle, rectangle, square, triangle, polygon, ellipse, or others. In this paper, for the sake of simplicity, we represent each activity zone as a circle with a certain radius value, ZR_{ac}. However, it is important to find the most suitable zone shape for each activity. This will be part of our future work. We assume that the locations of activity objects inside a smart environment are given by a user in advance. By knowing the locations of these objects, ZLAR can determine the center of each activity zone. As shown in Fig. 1, the location of activity object *ao* inside a zone has a two cases: (1) the location of *ao* exists on the circumference of activity zone which is called *edge activity zone* as the zone of watching TV activity with TV object (Fig. 1(a)). This case means that the activity can be done only if a user exists at a location in front of its object inside the activity zone. (2) the location of *ao* exists at the center of its activity zone which is called *centroid activity zone* as the zone of taking a meal activity with a dining table object (Fig. 1(b)). This case means that the activity can be done if a habitant exists at any position inside the activity zone relative to its center. So, one of ZLAR advantages that it uses a relative user position instead of his/her absolute position. Here, the problem is how to get the most suitable radius of each activity zone, ZR_{ac}. To solve this problem, ZLAR proposes a new optimization process by using a set of training datasets. This process will be explained in Sect. 2.3.

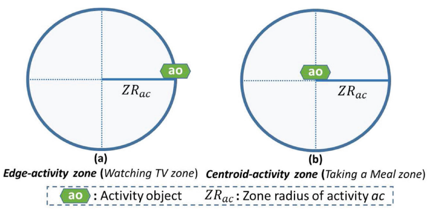

Fig. 1. Two cases of activity zone in ZLAR

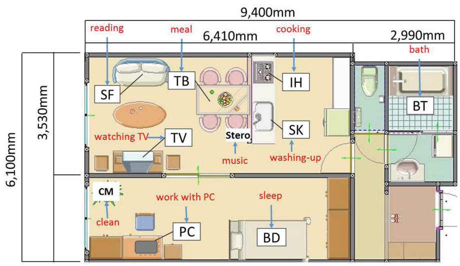

Fig. 2. A used smart home

2.2 Proposed Markov Logic Network Rules

ZLAR constructs two MLN rules which are based on activity zone, Z_{ao}, time duration feature, $TI(u, Z_{ao}, t_{in}, t_{out})$, and consumed power feature, $PW(ao, t_{in}, t_{out})$. These two rules are defined as follows.

(•) ***Rule 1:*** The first MLN rule of ZLAR deals with objects that must consume power to execute their related activities as watching TV or listening music. This consumed power by objects is associated with the time duration of a user existence inside their activity zones. This rule is defined as follows.

R1: $TI(u, Z_{ao}, t_{in}, t_{out}) \geq OT_{ac} \wedge PW(ao, t_{in}, t_{out}) \geq OP_{ac} \Rightarrow DoActivity(u, ac_{ao})$

(•) ***Rule 2:*** The second MLN rule of ZLAR deals with objects that do not need to consume any power to execute their related activities as taking a meal or reading a book. So, this rule depends only on the time duration of a user existence inside their activity zones. This rule is defined as follows.

R2: $TI(u, Z_{ao}, t_{in}, t_{out}) \geq OT_{ac} \Rightarrow DoActivity(u, ac_{ao})$

Here, OT_{ac} and OP_{ac} are the values of time duration and consumed power thresholds for each activity which will be determined by using our proposed optimization process in Sect. 2.3. $DoActivity(u, ac_{ao})$ represents the doing activity ac_{ao} of an object ao by a user u if the rule features are met.

2.3 Proposed ZLAR Architecture

ZLAR designs a new living activity recognition architecture which consists of the following three processes:

(1) Optimization Process: In ZLAR, the activity zone of a certain object has a circle shape with a specific radius value, ZR_{ac}, as described in Sect. 2.1. Also, the two MLN rules of ZLAR contain time duration OT_{ac} and consumed power OP_{ac} thresholds as described in Sect. 2.2. Here, the main problem is how to find the most suitable values of zone radius ZR_{ac}, time duration OT_{ac}, and consumed power OP_{ac} thresholds. To solve this problem, ZLAR proposes a new optimization process by using a set of training datasets based on two issues: (i) using one of optimization algorithms and (ii) formulating a suitable fitness function to find optimal values of ZR_{ac}, OT_{ac}, and OP_{ac}. These two issues are described as follows.

- **(a)** *Optimization algorithm:* Here, ZLAR uses evolution algorithm called *Differential Evolution* algorithm (DE) [10] which is one of the most efficient algorithms for optimization problems. DE is a genetic method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality and is used for multidimensional real-valued functions.
- **(b)** *Optimization Fitness function:* Based on the set of training datasets, ZLAR formulates its fitness function, which will be used by DE algorithm, for each activity ac in the system. We assume that the following: (1) there is a training dataset $TData_u$ for a user u; (2) the real time durations for every activity ac in $TData_u$ are $<1, 2, ..., h, ..., H>$; (3) a set of real location instances of a user u at interval h for activity ac is $RL^u_{ac}(h)$; (4) a set of real time instances of a user u at interval h for activity ac is

$RI^u_{ac}(h)$; and (5) a set of real power instances for using an activity object ao by a user u at interval h for activity ac is $RP^u_{ac}(h)$. The proposed fitness function, $F^u_{ac}(ZR_{ac}, OT_{ac}, OP_{ac})$ is defined as follows.

$$F^u_{ac}(ZR_{ac}, OT_{ac}, OP_{ac}) = \frac{\sum_{h=1}^{H} V^u_{ac}(ZR_{ac}, OT_{ac}, OP_{ac}, h)}{H} \quad (1)$$

and

$$V^u_{ac}(ZR_{ac}, OT_{ac}, OP_{ac}, h) = \frac{1}{R}\left(\frac{|L^u_{ac}(ZR_{ac}, h)|}{N_h} + \frac{|I^u_{ac}(OT_{ac}, h)|}{M_h} + \frac{|P^u_{ac}(OP_{ac}, h)|}{K_h}\right) \quad (2)$$

where $L^u_{ac}(ZR_{ac}, h) \subseteq RL^u_{ac}(h)$ is a set of real location instances that are covered by optimized radius ZR_{ac}, $I^u_{ac}(OT_{ac}, h) \subseteq RI^u_{ac}(h)$ is a set of real time instances that are covered by optimized time duration threshold OT_{ac}, $P^u_{ac}(OP_{ac}, h) \subseteq RP^u_{ac}(h)$ is a set of real consumed power instances that are covered by optimized consumed power threshold OP_{ac}, and R represents the number of optimized parameters. The value of R equals 3 (radius, time duration, consumed power), if the activity object uses a power threshold. If the activity object does not use a power threshold, the value of R equals 2 (radius, time duration) and $\frac{|P^u_{ac}(OP_{ac}, h)|}{K_h} = 0$ in Eq. 2. Also, N_h, M_h, and K_h represent the number of real instances that exists in $RL^u_{ac}(h)$, $RI^u_{ac}(h)$, and $RP^u_{ac}(h)$, respectively.

The fitness function F^u_{ac}, in Eq. 1, determines the total number of accumulated real instances of user location, activity time, and consumed power that are covered by the optimized values of ZR_{ac}, OT_{ac}, and OP_{ac}. Here, our goal is maximizing the value of F^u_{ac}. Note that, the value of F^u_{ac} is a ratio $\in [0, 1]$. Finally, the optimization process of ZLAR uses F^u_{ac} as a fitness function in DE algorithm to find the most suitable values of ZR_{ac}, OT_{ac}, and OP_{ac} for each activity and its related proposed MLN rules.

(2) Weight Learning Process: In this process, ZLAR executes a specific weight learning algorithm to find a value of the associated weight with each proposed MLNs rule based on a set of training datasets. There are a lot of weight learning algorithms for MLNs rules. In ZLAR, the Diagonal Newton discriminative learner as described in Lowd and Domingos [11] is used to get a suitable weights for the proposed rules.

(3) Recognition Process: In this process, ZLAR executes a specific inference algorithm based on a set of testing datasets by using proposed MLN rules with their optimization values of time duration threshold with/without consumed power threshold to recognize a habitant's activities. There are a lot of inference algorithms that can be used for MLNs inference process. In ZLAR, the Maximum a Posteriori Estimation (MAP) inference algorithm called WalkSAT [12] is used in its recognition process.

3 Experimental and Qualitative Evaluations

3.1 Experimental Outline and Results

The experiment targeted to recognize 10 types of activities which classified into two groups: (1) *Powered group*: {*Cooking*, *WatchingTV*, *WashUp*, *Bath*, *Clean-*

ing, *PC*, *Music*} which uses time duration and consumed power features and (2) *Nonpowered group*: {*Meal*, *Reading*, *Sleeping*} which uses only a time duration feature. Four participants *U1*, *U2*, *U3*, and *U4* (three males and a female in twenties) lived for three days each in our smart home which was built in Nara Institute of Science and Technology, Japan. Each of the participants wore an ultrasonic position transmitter and they performed normal daily activities at home as usual. Data were collected for a total of twelve days. After collecting the data, we labeled the sensor data according to activity type using the living activity labeling tool which was proposed in [6]. All labeled sensor data were divided into 30 s intervals (time window) and manually labeled each interval with an appropriate activity using this labeling support tool. Figure 2 shows the location of appliances and furniture used for the activities in the smart home. To validate the proposed ZLAR method, we designed our own GUI application based on *Tuffy* which is an open-source Markov Logic Network inference engine [13]. We evaluated four scenarios **S1**, **S2**, **S3**, and **S4** as cross validation experiment. In each evaluated scenario, we used all data for three participants (total of nine days) in optimization and weight learning (WL) processes of ZLAR. For testing phase, we used the forth user data(total of three days) in recognition process of ZLAR. Finally, the evaluation results were measured by *Precision*, *Recall* and *F-measure* as defined in [6]. The results based on this scenario as follows.

(1) Optimization results: The optimization results for ZR_{ac} (millimeter), OT_{ac} (seconds), and OP_{ac} (power unit) of 10 activities were {[1220, 4700], [128, 488], [1.3, 4]}, {[1000, 4500], [168, 488], [1, 10]}, {[1700, 4000], [125, 488], [1, 8]}, and {[1000, 4940], [110, 488], [1.3, 9]} by using **S1**, **S2**, **S3**, and **S4**, respectively. As a result, the optimized values of $ZR_{ac}, OT_{ac}, OP_{ac}$ for different scenarios are different, this is because ZLAR uses different training datasets in its optimization process.

(2) Weight learning results: By using the training datasets, the weight learning results of **R1** and **R2** were [10.7282,11.4248] and [10.7282,11.7654] by using **S1**, [10.8617,11.2491] and [10.2502,11.8668] by using **S2**, [11.0477,11.3491] and [11.0656,12.1762] by using **S3**, and [11.0779,11.3378] and [11.0477,11.8792] by using **S4** for the 10 activities. As shown from these results, the weight of each MLN rule depends on the training datasets of each scenario.

(3) Recognition results: Table 1 shows the results of Precision, Recall, and F-measure by using time duration and consumed power thresholds (**R1**) for bath, cleaning, cooking, watching TV, PC, music, and Washing up activities and using time duration threshold (**R2**) for sleeping, meal, and reading activities. In Table 1, we set *None* for the activity, if the testing user did not do this activity during his stay inside the smart home. As shown in Table 1, the values of Precision, Recall, and F-measure were between [92.02 %, 97.41 %], [76.56 %, 82.4 %], and [83.74 %, 88.78 %] on average, respectively. As a result, ZLAR can recognize living activities with high F-measure accuracy by using only two types of sensors. This is because, ZLAR can efficiently represent all available knowledge in smart environments as area of activity, consumed

Table 1. Precision (P), Recall (R), and F-measure (F) results for **S1**, **S2**, **S3**, and **S4** by using **R1** and **R2**

Activity (Rule)	Using S1			Using S2			Using S3			Using S4		
	P	R	F	P	R	F	P	R	F	P	R	F
Bath (R1)	100	62.07	76.6	100	67.78	80.79	100	70.83	82.94	100	94.87	97.37
Cleaning (R1)	91.67	100	95.65	None	None	None	100	79.52	88.59	97.5	100	98.73
Cooking (R1)	100	75.9	86.3	94.74	61.29	74.43	96.23	73.1	83.09	95.56	61.22	74.63
WatchTV (R1)	99.5	71.17	83.98	98.55	81.18	89.02	98.61	91.43	94.88	96.52	78.9	86.83
PC (R1)	99.06	71.62	83.13	100	92.98	96.36	100	87.36	93.25	98.85	75.94	85.9
Music (R1)	99.03	65.61	78.92	97.89	79.17	87.54	99.62	88.63	93.8	94.81	59.08	72.8
WashUp (R1)	100	68.52	81.32	95.45	84.62	89.71	93.75	76.19	84.06	88.1	77.78	82.62
Sleeping (R2)	99.84	68.49	81.25	None	None	None	None	None	None	None	None	None
Meal (R2)	93.84	80.66	86.75	97.18	97.93	97.56	83.33	66.67	74.07	66.4	56.31	60.94
Reading (R2)	90.7	93.48	92.07	95.45	94.29	94.87	99.66	100	99.83	90.42	97.56	93.85
Average	97.09	76.56	84.86	97.41	82.4	88.78	96.8	81.53	88.28	92.02	77.96	83.74

power by activity object, and time duration of using activity object for doing its related activity. In addition, using MLN rules in ZLAR gives a good representation ability of uncertainty information for each living activity. Also, F-measure precision of all activities was not 100 %, this is because some activities were mistakenly classified to another activity due to overlapped zones of those activities. So, ZLAR misrecognized the current activity. Solving this overlapped zones problem will be part of our future work. In addition, we conducted another experiment by using time duration threshold only (**R2**) for all activities and the values of Precision, Recall, and F-measure were between [87.23 %, 97.19 %], [81.55 %, 92.73 %], and [84.14 %, 94.53 %] on average, respectively. As a result, the Recall value increased for all activities in case of using time duration threshold only for MLN rule (**R2**). Therefore, the value of F-measure increased. This is because, some of real activity instances, which do not meet the consumed power threshold in MLN rule (**R1**), were added to the recognized instances when the consumed power threshold did not be considered.

3.2 Qualitative Evaluation

Here, the evaluation results based on qualitative metrics is presented to show the efficiency of ZLAR compared to some of existing simple activity recognition schemes. The evaluation process requires studying the schemes and finding their attributes that satisfy a certain evaluation criteria. We assume that the best evaluation criteria must take into account accuracy, number of recognized activities, deployment and maintenance (D&M) costs, privacy intrusion, representing uncertainty, and reusability as qualitative metrics. The optimal values for this evaluation criteria are *High* accuracy, *Many* recognized activities, *Low*

Table 2. Qualitative performance comparison

Qualitative metric	Accuracy	# recognized activities	D&M costs	Privacy intrusion	Representing uncertainty	Reusability
[3]	Approx. High	Few	Average	Yes	No	No
[4]	Low/High	Many	High	No	No	No
[5]	High	Few	Average	No	No	No
[6]	Approx. High	Median	Low	No	No	No
[7]	Approx. High	Many	Average	Yes	Satisfies	No
[8]	Medium	Median	Average	No	No	No
ZLAR	High	Many	Low	No	Satisfies	Satisfies

deployment and maintenance costs, *No* privacy intrusion, *Satisfies* representing uncertainty, and *Satisfies* reusability. Table 2 shows the qualitative performance comparison based on these qualitative metrics. As shown in Table 2, none of existing schemes can meet all qualitative metrics of the required criteria. While, ZLAR meets all the required qualitative metrics. As a result, ZLAR has a high qualitative performance compared to existing schemes.

4 Conclusion

In this paper, we proposed a zone-based living activity recognition method called ZLAR. ZLAR outperforms most of existing schemes by achieving the following issues: (1) using a relative position of a user position instead of his/her absolute position, (2) minimizing the cost of deployment and maintenance costs, (3) achieving a high recognition accuracy, and (4) representing the temporal information of activities and the habitant efficiently by using MLN. In addition, the best benefit of ZLAR is the possibility used for different users, places and environments without having to repeat the learning process of ZLAR. So, the overhead cost due to collection of sensor data is limited. In our future works, we will study the effect of changing the locations of objects inside the smart environment on the performance of ZLAR method.

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