A Novelty Approach to Enhance Activity Modeling

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Abstract

Objectives: Cognition-driven activity recognition is a very challenging study domain. There are two main approaches to enhance activity modelings such as context knowledge and sensor dataset. **Methods:** The existing system used cognition-driven tool to annotate sensor activity dataset. It used Semantic Activity Annotation algorithm to annotate dataset. This produced perfect and wrong activity paradigm. It does not found frequent activity sequences. **Findings:** A novel technique is used to enhance cognition-driven activity paradigm by using the data-driven method. The methodology consists of clustering activity where basic partial activity models established through management technologies. By using this find out action cluster that denotes activities and accumulates recent actions. A learning activity paradigms. This can be tested with sensor dataset and sensor dataset with noisy. **Applications:** It is mainly applicable for home-based rehabilitation, monitoring human activity and security-based applications.

Keywords: Activity Recognition, Activity Paradigm, Cognition-Driven, Data-Driven

1. Introduction

Activity recognition is an important and very challenging task in pervasive computing¹, the ambient intelligent system², context-aware computing³ and surveillance-based security⁴. In this field, two main approaches are used for activity recognition namely data-driven and cognitiondriven. To act upon activity recognition various kinds of sensors have to be set up in an environment to watch resident behaviors'. The information determined by those sensors has to be handled through data mining methodology. The scientific community has formulated to main methods to solve activity recognition. They are data-driven and cognition driven. The data-driven method uses alarge number of sensor dataset to make activity paradigm using various techniques. As an alternative cognition-driven make use of earlier knowledge in the domain to built activity paradigms using management technologies. Let us demonstrate the hybrid method by the following example. Figure 1. shows basic activity paradigm for MakeTea activity which is combined with the actions hastea and hascontainer. These are the needed action to run MakeTea activity, which shows up necessary actions of this activity. In Figure 1, where basic activity paradigm will only contain tea and container, the system learns that how to make tea in two ways: in the first case the user make tea using milk and sugar while in the second case user use only sugar. Hence, finalize and specialized activity paradigm is acquired.



Figure 1. The system uses BAM and user-generated data as input, learn to finalize and specialized activity pattern.

Various types of sensors used to recognize activity. First, one is vision-based; it is to capture user activity and environmental changes. The second one is to monitor actor behavior by using various sensor technologies⁵. There are two techniques to recognize activity by using sensors. They are data-driven and cognition driven. The data-driven method uses alarge number of sensor dataset to make activity paradigm using various techniques. Based on modeling two main types are found. They are generative and discriminative methods. The generative method is to provide finalize description of input, typically with a probabilistic pattern. The other generative methods are Naïve Bayes and Hidden Markov Model. These are very easy to recognize activity. The discriminative method uses the conditional random field for mapping inputs to outputs^{6.7}. The main demerit of the data-driven method is a cold-start problem and annotation problem. This can be arising due to data needed to model activity. On the other hand transfer of learning use data-driven method for activity recognition. The main objective is to train the new user and it can be transfigured to another user. The demerits of this approach are not able to handle uncertainty and temporal data. There is a little hybrid approach to aim at gathering merits of both data-driven and cognitiondriven, combine them as a single one named ontology based activity modeling.

2. Ontology-Based Activity Pattern

Ontology-based activity paradigms give correct and meaningful paradigms. Substitute some rules there are some definitions:

2.1 Axiom 1(Sensor Activation)

Device activation establishes when the device changes from one position to another position. Example: when a user takes remote, sensor activation is named as remotesens.

2.2 Axiom 2(Events)

Events are the main objective for activities and it is attached to object activation.

2.3 Axiom 3(Kind)

It denotes the type of activities depends on the environment.

2.4 Axiom 4 (Basic Activity Model)

Basic Activity Model (BAM) denotes the sequence of actions that can be performed with an estimation of time. Within that time, only that activity can be performed.

2.5 Axiom 5(Enhanced Activity Model)

A conclude and a particular version of the BAM. By concluding means all events can be performed for that activity and particular version means if you can be performed an activity with various two or more action sequences.

3. Methods to Enhance Activity Modeling

Two methodologies are used to enhance activity paradigm. They are

- 1. Context knowledge: equipped by the expert system. It includes precedent knowledge about activities, object, and sensors.
- 2. Activation dataset: it denotes activation of each sensor labeled with an activity.

3.1 Architecture of Proposed System

The proposed architecture to enhance activity paradigm is as shown in Figure 2. It takes input as sensor dataset by using synthetic dataset generator. Then clustering method is run, using expert knowledge. Clustering proceeds in following ways (a) semantic activity annotation algorithm uses BAM to find out the unlabeled activity and set action cluster (b) Action grouping is to elaborate BAM. Finally, Activity Model Learner is to separate out false action sequences.

3.2 Semantic Activity Annotation

Semantic Activity Annotation Algorithm is used to initialize clusters⁸. It uses BAM to annotate datasets. It show activity



Figure 2. Architecture for proposed system.

paradigm with positive sensor noise and missing sensor noise. The result of this algorithm is where actions are named with an activity. Otherwise, it can be named as none.

3.3 Action Grouping

Semantic activity annotation is elaborated using prior knowledge about activities, object and sensors and time slots for action grouping⁹. A most usable clustering algorithm such as k-means, SA3 immediately preparing the number of clusters for each sensor data set and set centroids. Then it groups them to most suitable one based on time metrics. SA3 find out activities such as B1 and B2 in that sequence of actions. Each action that is contained by B1 or B2, but is not in their BAM is an insider and out of find out activities is an outsider.

3.3.1 Insider

The compatibility function is used to added activity to wrapping activity. It is stated as

$$com(B,a) = Loc(B,a) \wedge Kind(B,a)$$

Where *B* is an activity and *a* is an action. *Loc* (*B*, *a*) denotes compatibility function of location among activity and action. *Kind* (*B*, *a*) defines compatibility function of a kind among activity and action. It is processed by making the junction of activity and action. Hence, an insider added to activity, if *Com* (*B*, *a*) =True. Otherwise, it can be labeled as none.

3.3.2 Outsider

It was grouped to next or earlier activity. This is processed by using candidate function.

$$Can(B,a) = Com(B,a) \wedge InRange(B,a)$$

This produced the result only both conditions are true. Otherwise, it cannot be processed. An outsider action *a* and activities *B1* and *B2* can be employed in four cases by using candidate function.

- 1. $Can(B_1, a) = Can(B_2, a) = False \rightarrow a \text{ is noise}(None label)$
- 2. $\operatorname{Can}(B_1, a) = \operatorname{True} \bigwedge \Box \operatorname{Can}(B_2, a) = \operatorname{False} \rightarrow \operatorname{group} a$ to B_1
- 3. $\operatorname{Can}(B_1, a) = \operatorname{False} \bigwedge^{\square} \operatorname{Can}(B_2, a) = \operatorname{True} \Rightarrow \operatorname{group} a \text{ to} B_2$

4. $Can(B_1, a)=Can(B_2, a)=True \rightarrow need of a new method$

The first three supply classification. In the fourthcase, a new method is to be defined. To implement these, three-timeslots are used. They are

1. Classic time slot: classic time slot between action time and center of the activity as given by *SA*³

$$\Delta_t(B,a) = |C_B - t_a| \text{ where } C_B = \frac{t_{end}^{SA3} - t_{start}^{SA3}}{2}$$

2. Normalized time slot: Above distance is normalized by using duration of that activity

$$\Delta_t(B,a) = \frac{|C_B - t_a|}{Duration_B} \text{ where } C_B = \frac{t_{end}^{SA_3} - t_{start}^{SA_3}}{2}$$

3. Dynamic center time slot: it finds out the center of the activity and it can be applied to the next or previous activity.

$$\Delta_t(B,a) = \frac{|C_B - t_a|}{Duration_B} \text{ where } C_B = \frac{t_{start}^{AG} + Duration_B}{2}$$

3.4 Activity Pattern Learner

It includes all action sequences for each activity. Depend on results find out false paradigm due to sensor noise and grouping error. The aim of activity paradigm learner is to acquire false action sequences. There are three methods to avoid this. First, one is to emit repeated action sequence. Second, one is to joined same action sequences as one.

4. Implementation

The experiment depends on synthetic dataset generator. It provides various datasets based on needed, where all sensors are named with an activity name and several users performing several activities are available. Using this technique, two evaluation schemes are set. The first one is the standard scheme, it does not include any sensor noise and easy to learn. The second one is the finalize scheme, it include a noisy sensor and difficult to learn. The experiment consists of:

- 1. Activities of daily living
- 2. Two schemes: the standard scheme and finalize scheme.

The synthetic generator tool produced clustering results to each sensor activation.

5. Results and Discussion

The experiment is setup first, and then it can produce sensor dataset for each user. It accommodates 2400 sensor dataset for standard scheme and finalize scheme has 3500 datasets, which provides clear thought of positive sensor noise. Table 1. and Table 2. show the output with classic time-slot in the standard and finalize schemes. Next, Table 3. and Table 4. show output for normalized time slot. Table 5. and Table 6. show output for dynamically normalized time slot. Table 7. and Table 8. show precision, recall, and performance for all methodologies. Table 9. and Table 10. shows finalize model for EAM (Enhanced Activity Model). Finally, Table 11. shows a mean value of actions acquired by the system.

Table 1.Using classic time slot, mean outcome for 4users of clustering activity for standard scheme

Activity	True positive (%)		False positive (%)		False negative (%)	
	SA ³	AG	SA ³	AG	SA ³	AG
MakeTea	55.05	98.67	0	0	44.95	1.33
Make Whipped Cream	75.12	100	0	0	24.88	0
Wash Legs	90.91	96.8	0	0	9.1	3.2
Brush Teeth	74.93	99.87	0.1	13.12	25.07	0.14

Table 2.Using classic time slot, mean outcome for 4users of clustering activity for finalize scheme

True		ue	False		False	
Activity	positive (%)		positive (%)		negative (%)	
	SA ³	AG	SA ³	AG	SA ³	AG
MakeTea	54.73	97.76	1.2	2.86	45.27	2.24
Make Whipped Cream	71.13	100	0	0	28.87	0
Wash Legs	91.18	96.97	0.28	0.41	8.82	3.03
Brush Teeth	75.12	98.45	0.69	12.6	24.88	1.53

Table 3.Using normalized time slot, mean outcomefor 4 users of clustering activity for standard scheme

	True		False		False	
Activity	positive (%)		positive (%)		negative (%)	
	SA ³	AG	SA ³	AG	SA ³	AG
MakeTea	55.05	98.67	0	0	44.95	1.33
Make Whipped Cream	75.12	100	0	0	24.88	0
Wash Legs	90.91	96.57	0	0	9.1	3.43
Brush Teeth	74.93	99.86	0.1	14.27	25.07	0.14

Table 4.Using normalized time slot, mean outcomefor 4 users of clustering activity for finalize scheme

	True positive		False		False	
Activity	(%	%)	positive (%)		negative (%)	
	SA ³	AG	SA ³	AG	SA ³	AG
MakeTea	54.73	97.76	1.2	2.86	45.27	2.24
Make Whipped Cream	71.13	100	0	0	28.87	0
Wash Legs	91.18	96.7	0.28	0.41	8.82	3.3
Brush Teeth	75.12	99.83	0.69	13.99	24.88	1.55

Table 5.Using dynamic center normalized time slot,mean outcome for 4 users of clustering activity forstandard scheme

	True positive		False		False		
Activity	(%	(%)		positive (%)		negative (%)	
	SA ³	AG	SA ³	AG	SA ³	AG	
MakeTea	55.05	98.67	0	0	44.95	1.33	
Make Whipped Cream	75.12	100	0	0	24.88	0	
Wash Legs	90.91	98.27	0	0	9.1	1.73	
Brush Teeth	74.93	99.72	0.1	5.1	25.07	0.27	

Table 6.Using dynamic center normalized time slot,mean outcome for 4 users of clustering activity forfinalize scheme

	True positive		False		False		
Activity	(%	(%)		positive (%)		negative (%)	
	SA ³	AG	SA ³	AG	SA ³	AG	
MakeTea	54.73	97.76	1.2	2.64	45.27	2.24	
Make Whipped Cream	71.13	100	0	0	28.87	0	
Wash Legs	91.18	98.43	0.28	0.41	8.82	1.57	
Brush Teeth	75.12	98.37	0.69	4.55	24.88	1.63	

Table 7.Clustering activity in the finalize schemeprovide comparative results for three time slots

	Mean outcome of precision	Mean outcome of recall
time1	95.72%	97.18%
time2	95.59%	97.16%
time3	96.75%	97.25%

Table 8.Using mean average and mean precision forfinalize scheme, performance of SA3 and clusteringactivity is obtained

	Mean outcome of precision	Mean outcome of recall
SA3	97.93%	68.69%
Complete Clustering	96.75%	97.19%

Activity	Correct models	False models	Total models	Average number of patterns
MakeTea	1	0	1	1
Make Whipped Cream	1.14	0	1.14	1.14
Wash Legs	1.25	0.47	1.72	1.25
Brush Teeth	1	0.25	1.25	1

Table 9. Using standard scheme mean outcome for 4users of EAM (*Enhanced Activity Model*) activity

 Table 10.
 Using finalize scheme mean outcome for 4

 users of EAM (*Enhanced Activity Model*) activity

Activity	Correct models	False models	Total models	Average number of patterns
MakeTea	1	1.2	2.2	1
Make Whipped Cream	1.14	0.89	2.03	1.14
Wash Legs	1.25	1.17	2.42	1.25
Brush Teeth	1	0.75	1.75	1

Table 11.Mean outcome for sequence of actions relatedto sequence of actions in BAM of definite activities

Activity	Sequence of actions in BAM	Mean number of learned actions
MakeTea	3	5.7
Make Whipped Cream	3	2.54
Wash Legs	3	3.6
Brush Teeth	2	2.78

6. Conclusion

This paper includes innovation method to get finalize and specialized activity paradigm by using data-driven methodology. This can be available using partial activity paradigm in cognition -driven activity recognition system learns finalize and specialized activity paradigm. Two step grouping is used, which has knowledge about activities to find action cluster for each activity and name with a corresponding activity. Those can be used to enhance cognition driven activity paradigm.

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