Activity Recognition Based on Importance Degree Reduction of Decision Table

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Abstract: Recently, people pay more attention to quality of life in the smart home, so activity recognition based on sensors become research hotspot. In the past study, people care more about the recognition accuracy rather than recognition data. Few researches consider the problem that recognize based on reduced and characteristic sensor data. In the paper, an activity recognition method which based on importance degree reduction of decision table is proposed. By the method characteristic sensors can be found. The experiment results show that recognition accuracy is promoted based on characteristic sensors than all the sensors.

Key Words: Activity Recognition, Importance Degree Reduction, Decision Table, Characteristic Sensors

1 INTRODUCTION

In recent years, more and more people pay their attention to activity recognition. Most activity recognitions are based on visual instrument, such as video. There are many algorithms which be used to recognize activities in this research area [1]. But in most situation, people don't like their life be exposed to the others. And under some special situation, the site need to be protected or kept absolutely secret. So the activity recognition based on video is limited in such particular area.

With the development of the wireless sensor technology, it is possible that recognition based on sensors. This recognition technology is widely used in smart hospitals [2], assisted living [3], physical and sport activities [4] and other fields. Now the main activity recognition methods are supervised, semi-supervised and unsupervised recognition. Common machine learning methods such as Naive Bayes (NB), Decision Trees (DT) and K-nearest Neighbor (KNN) are supervised methods. Hidden Markov Models (HMM), Conditional Random Fields (CRF) and their deformable models which consider the action sequence during recognition are generally used in supervised activity recognition. In terms of semi-supervised and unsupervised recognition, similarity comparison, mine and cluster methods always be used.

The supervised activity recognition research in smart house always need a large number of labeled data which collected from sensors in the smart situation. In the process of recognition, classify is based on all the sensor data. But in fact, not all the sensor data are needed, some special sensors which are very important for one activity and can distinguish from other activities are what we really need. We call them characteristic sensors. P. Rashidi and Diane J. Cook found that the number of sensors can be reduced in the process of recognition during the experiments in [5]. In other words, activities can be classified by a few of characteristic sensors, not by all the sensors. In reality, some sensor data affected the identification results and made recognition rate decline. In the past study, people care more about the recognition accuracy rather than recognition data. Few researches consider the problem that recognize based on reduced and characteristic sensor data. Most research of activity recognition is based on all the information of sensors which installed in the smart home. The related study of recognition based reduced sensor data is very scarce. If we can find the few characteristic sensors which can make one activity be distinct to the others, and make the recognition accuracy keep not decrease, the number of sensors installed in the smart home can be cut down. Accordingly, the cost of build smart home and recognition time will be decrease.

To address these issues, we propose an activity recognition method which based on importance degree reduction of decision table in the paper. By the method characteristic sensors can be found. Then we make activity classify based on machine learning methods such as NB, KNN and SVM. The experiment results show that recognition accuracy is promoted based on characteristic sensors than all the sensors.

The article structure specific arrangement is as follows. The data structure and the process of build decision table is introduced in section 2. The importance degree reduction algorithm is explained in section 3. In section 4, contrast classify experiments are be implemented which based

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characteristic sensors and all the sensors by using different machine learning methods. Then we include the paper in section 5.

2 PRELIMINARIES

In this section, at first we introduce the data in our paper. Second, the process of build decision table from source data is explained.

2.1 Data Description

The data in this paper come from the Center for Advanced Studies on Adaptive Systems (CASAS) smart environment project [6] at Washington State University. We choose three data sets which come from three single resident smart home. The detailed information of data sets is as Table 1.

Table 1. Data Description

Dataset	Days	Sensor events	Activities	Sensor numbers
Dataset1	60	108999	974	111
Dataset2	60	112198	1070	105
Dataset3	60	95465	708	70

Considering that the activities of every resident in daily life are different, six common activities are chose in the paper. There are Toilet, Dress, Cook, Eat, Wash_Dishes and Read. Three data sets are about 60 days life data. The data structure is as Table 2.

Table 2. Data Structure

Timestamp	Sensor ID	Sensor value or status	Label
2013-03-01 14:11:34.208204	D002	OPEN	Enter_Home="begin"
2013-03-01 14:11:34.230416	T102	26	
2013-03-01 14:11:45.448647	LS021	46	
2013-03-01 14:12:13.960323	M002	ON	
2013-03-01 14:12:20.346595	M002	OFF	
2013-03-01 14:12:23.944549	LS001	12	
2013-03-01 14:12:23.969737	M001	ON	
2013-03-01 14:12:26.36553	M001	OFF	
2013-03-01 14:12:27.500524	M001	ON	
2013-03-01 14:12:28.616375	M001	OFF	
2013-03-01 14:12:29.176738	M001	ON	
2013-03-01 14:12:29.985345	D002	CLOSE	
2013-03-01 14:12:30.307932	M001	OFF	Enter_Home="end"

2.2 Decision Table Building

In this paper, we don't care the timing sequence of sensor events. In order to find the characteristic sensors, the times which the sensors are triggered is important for our researches. So we statistics the times of the sensors triggered in one activity which is labeled between begin and end. The result of above count is a decision table like Table 3.

Table 3. Decision Table

D002	T102	LS001	LS021	M001	M002	Activity Name
1	1	1	1	3	1	Enter_Home
0	0	2	2	0	1	Eat
0	0	1	3	0	4	Toilet

Table 3 is composed by n columns. The first $n-1$ columns are all the sensors in one dataset. The value is their triggered times. If one sensor in an activity is not be triggered, the value is zero. The second line of Table 3 come from Table 2. The triggered times of sensors in every activity are counted and changed to the line of the decision table like Table 3. According above method, we change three data sets to three decision table, in which sensors are condition attribute and activity is decision attribute. Obviously, activity can be decided by sensors. Through above abstract, we can get three decision tables which respectively include 974, 1070 and 708 data lines instead of their primary hundreds of thousands of lines. It make the problem become easy.

3 IMPORTANCE DEGREE REDUCTION MODEL OF DECISION TABLE

In this section, the definitions of decision table and importance degree are given. The importance degree reduction algorithm is detailed explained. At last, we propose a method based on mutual information to deal with the situation which importance degree of several sensors are equal at the same time.

Definition 1 ([7]). For a decision system $DT=\{U, C\cup D, V, f\}$, $B(B\subseteq C)$ is a subset of condition set and $a(a\in C \; but \; a\notin B)$ is any condition attribute. The importance degree of a relative to decision set D is as follow:

$$sig(a, B; D)=\gamma_{B\cup\{a\}}(D)-\gamma_B=\frac{|POS_{B\cup\{a\}}(D)|-|POS_B(D)|}{|U|}$$

In our work, condition attribute set C is the set of all the sensors, and decision attribute set D is activity set. Value set V means the times which sensors are triggered in the activities. So the problem of sensor reduction is changed into the problem of decision table reduction. Then we can use importance degree algorithm. The algorithm based on above definition is as follow:

Algorithm 1. Importance Degree Reduction Algorithm

Input: $DT=\{U, C\cup D, V, f\}$
Output: A reduction set of $B((B\subseteq C)\wedge(B\in RED_C(D)))$ of DT
Step 1: Calculate the core C relative to the D $CORE_D(C)$;
Step 2: Let $B=CORE_D(C)$,
If $POS_{IND(B)}(D)=POS_{IND(C)}(D)$
Turn to step 5;
End if
Step 3: For $\forall a_i\in C-B$
Calculate $sig(a,B;D)=\gamma_{B\cup\{a\}}(D)-\gamma_B(D)$;
Let $a_m=\arg\max_{a_i\in C-B} sig(a_i,B;D)$
Let $B=B\cup\{a_m\}$
Step 4: If $POS_{IND(B)}(D)=POS_{IND(C)}(D)$
Turn to step 5;
Else
Turn to step 3;
End if
Step 5: Return $B\in RED_C(D)$

In above algorithm, the new attribute is added based on the core of decision table. In the process of finding the attribute every time, the attribute which the importance degree is max always is chose. But sometimes, this situation will happen that the importance degree of several attributes is same at the same time. In the normal importance degree algorithm, we can choose any one of these attributes to add to set B. But in actual situation, such method is not reasonable. So we propose a method based on max mutual information to deal with this situation.

Definition 2. The mutual information for each sensor is as follow:

$$MMI_a = \sum_{d \in D} P(a,d) * \log \frac{P(a,d)}{P(a)P(d)}, \quad a \in C$$

In above definition a means a sensor in the condition set C. d is an activity in decision attribute set. Definition 2 give out the mutual information of sensor a for the activities, which the sum of sensor a for each activity. When the importance degree of several attributes is same at the same time during calculation according algorithm 1, the sensor which has the max mutual information will be chose. So in our work the reduction set is only one not multiple.

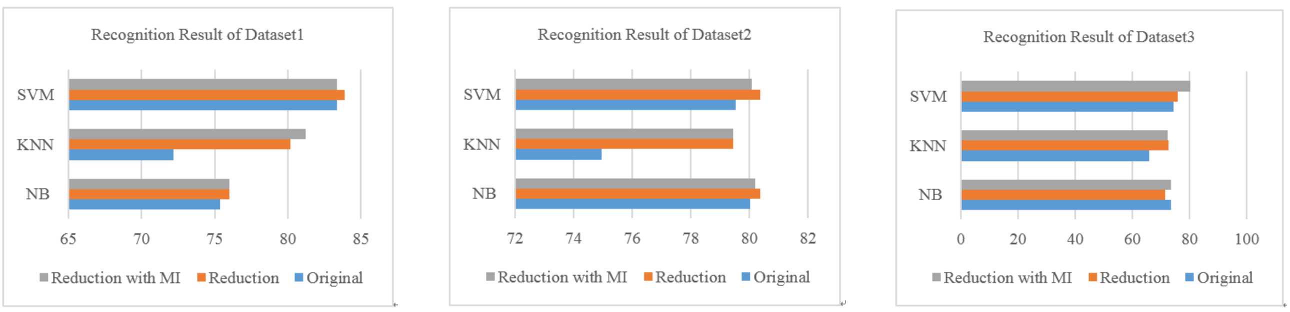
4 EXPERIMENTS

In our experiments, the residents in the three apartments have different living habit and schedules. The sensors which installed in the smart apartments are not the same. All the data used in the experiments are all labeled. The results based on importance degree reduction is as Table 3. The sensor numbers is significantly reduced. Before reduction they respectively are 111, 105 and 70. Now we get 23, 33 and 19 sensors in three datasets which we called characteristic sensors.

Table 3. Sensor Reduction Result

Dataset	Sensor numbers		
	Original	Reduction	Reduction with MI
Dataset1	111	22	23
Dataset2	105	33	33
Dataset3	70	19	19

In the experiments, machine learning methods such as NB, KNN and Lined SVM are used. Above methods are respectively used on original data sets and data sets based on importance degree reduction. The recognition results has been shown in Figure 1. From the figures we can find that the recognition accuracy after reduction is better than the original, in spite of the decrease in the number of sensors. The reduction with mutual information is always better or equal to the simple importance degree reduction. When the simple importance degree reduction is worse than original, the reduction with mutual information is also better.



(1) Dataset1 (2) Dataset2 (3) Dataset3

Fig 1. Recognition accuracy in original datasets, reduced datasets and reduced with mutual information datasets.

Table 3. Activity Recognition Result

Dataset	Method	Correctly Recognized Activity Numbers																	
		Original						Reduction						Reduction with MI					
		Toilet	Dress	Cook	Eat	W_D	Read	Toilet	Dress	Cook	Eat	W_D	Read	Toilet	Dress	Cook	Eat	W_D	Read
Dataset1	All	256	117	248	110	117	126	256	117	248	110	117	126	256	117	248	110	117	126
	NB	256	117	119	102	87	53	256	116	109	106	95	58	256	117	109	106	96	56
	KNN	241	105	165	73	47	72	252	109	183	84	54	99	255	114	184	84	57	97
	SVM	256	111	185	92	63	105	256	113	200	91	51	106	255	116	186	89	59	107
Dataset2	All	342	148	233	149	138	60	342	148	233	149	138	60	342	148	233	149	138	60
	NB	341	146	50	144	118	57	340	146	56	144	117	57	340	146	55	143	117	57
	KNN	307	131	145	114	60	45	327	133	152	128	57	53	326	133	153	128	57	53
	SVM	340	115	180	136	26	54	341	121	204	136	4	54	341	121	203	136	2	54
Dataset3	All	221	71	157	66	186	7	221	71	157	66	186	7	221	71	157	66	186	7
	NB	220	71	38	49	142	1	216	70	35	36	149	0	216	70	36	50	149	0
	KNN	208	61	65	42	90	1	218	64	69	55	106	2	218	62	70	53	106	2
	SVM	218	70	49	61	126	3	217	70	52	61	134	3	217	70	43	62	137	2

So from the experiments, we can get a conclusion that during the activity recognition process not all the sensors are important, the characteristic sensors play a crucial role in the recognition. The characteristic sensors can be get by reduction. Although the sensor numbers is decreased, but the identification accuracy is increased.

In Table 3, the detailed information about correctly recognized activity numbers is shown. We find that the activities Cook and Wash_Dishes can not be distinguished very well, because they have similar characteristic sensors. But the activities such as Toilet and Dress get a higher recognition rate because their characteristic sensors are great differences. By the importance degree reduction with mutual information, the correctly recognized activity numbers rise.

5 CONCLUSIONS

Traditional activity recognition methods is always based on all the sensors data in the smart house. It will spend a lot of time on labeling data. And some data is noise data which will affect the identification accuracy. We first build a decision table through changing the source data, then propose an importance degree reduction method to extract the characteristic sensors. At last the mutual information is added to the reduction method to get the more accurate reduction results. Through the experiments prove the result that the recognition accuracy after reduction is better than the original and the reduction with mutual information is always better or equal to the simple importance degree reduction. But the activities Cook and Wash_Dishes can not be distinguished very well, because they have similar characteristic sensors. So we need to find other methods to process such problem.

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