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Activity Recognition in Smart Homes Based on Second-Order Hidden Markov Model

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Abstract

Hidden Markov Model is an important approach applied to activity recognition. In the first-order Hidden Markov Model, there is the hypothesis that the transition probability of state and the output probability of observation are only dependent on the current state of the model, which debases the precision of information extraction comparatively. In second-order Hidden Markov Model, the relevance between the current state and its previous two states is considered. Also, the relevance between the current observation and its previous state is considered. So second-order Hidden Markov Model has stronger performance of recognition of incorrect information. In my paper, second-order Hidden Markov Model is applied to activity recognition. The experiments show that our approach has higher precision than those approaches based on first-order Hidden Markov Model and based on Conditional Random Fields.

Keywords: *Activity Recognition; Smart Homes; Second-Order Hidden Markov Model*

1. Introduction

As the rate of birth declines and the life of people is prolonged owning to the progress of science and technology, our society is becoming aging one. By Economic and Social Affairs Committee of the United Nations, the number of elderly people in the world is 7.37 hundred million. If the trend is going on, the number would be 20.2 hundred million in 2050. Elderly people run into all sorts of barriers in performing their daily routine tasks such as bathing, toileting, driving, cooking and handling finances. While aging society makes plenty of accepting public pensions, there's more demand of social care services and technical assistances.

In order to assist elderly people in daily living effectively, the concept of smart home is proposed. In a smart home, many sensors are installed in rooms. These sensors are context-awareness. The variations of context such as change of temperature, open or close of doors or water faucet can be caught. By analyzing the variations, computers can know activities of resident. Thus, some corresponding assistance services are activated.

Obviously, it is a key premise to recognize their daily activities in smart home. Activity recognition aims to build models and algorithms and infer the goals of individual subjects by data by sensors. Hidden Markov models (HMMs) and Conditional Random Fields (CRFs) are the mainstream techniques for recognizing activities with graphical models. But by our survey, the recognition precision is not high in previous approaches especially in class rate. So in our paper, a second-order Hidden Markov model is applied to activity recognition in order to improve the recognition precision.

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This paper is organized as follow. We introduce related works in Section 2. Activity recognition in smart homes is described in Section 3. Second-order Hidden Markov Model and its application in activity recognition are highlighted in Section 4. Experiments analysis is given in Section 5 and conclusion and the next work are arranged in the last section.

2. Related Work

There are two kinds of approaches to activity recognition. One is based on visual sensing facilities to monitor an actor's behavior and environmental changes [1, 2]. Computer vision techniques are used to analyze video and thus recognize activities [3, 4]. The other is based on data analysis. Data mining and machine learning technologies are used to analyze data and thus recognize activities. Wearable sensors often use inertial measurement units and RFID tags to gather an actor's behavioral information [5]. Approaches based on data can be generally classified into three categories. The first is based on probabilistic model such as Markov models [6] and Bayesian networks [7]. Generally, a small subset of sensor data is extracted as training data. The initial values of the parameters of the probabilistic models are determined. Activities are recognized by those models. The second is based on rules such as neural networks, linear or non-linear discriminant learning. They use machine learning techniques to extract ADL patterns from observed daily activities, and later use the patterns as predictive models [8, 9]. The approaches require large datasets for training models, thus suffer from the data scarcity or the "Cold Start" problem. It is also difficult to apply model and learning results from one person to another. The third approach is based on logic formulas such as event calculus [10] and lattice theory [11]. Although these logic models have more semantic information which is directly related to high recognition precision, it is more harder to build logic model.

3. Activity Recognition in Smart Homes

As you see in Figure 1, some sensors were installed in rooms of smart homes. These sensors are classified into six kinds. They are monitor motion (M), temperature (T), water (W), burner (B), phone (P), and item use (I), respectively. The motion sensors are located on the ceiling approximately 1 meter apart to locate the resident, the Voice over IP (VOIP) technology captures phone usage and switch sensors to monitor usage of the phone book, a cooking pot, and the medicine container. Some activities Telephone Use, Hand Washing, Meal Preparation, Eating and Medication Use and Cleaning need be recognized by these data provided by sensors.

Definition1: **Activity Recognition** is defined as $(a_1,a_2,\ldots,a_n)=R(o_1,o_2,\ldots,o_t)$, where $(o_1,o_2,\ldots,o_t)$ is a group of observations provided by sensors, $(a_1,a_2,\ldots,a_n)$ is a group of activities, R is recognition function.

4. Second-Order Hidden Markov Model and its Application in Activity Recognition

4.1. One-Order Hidden Markov Model (HMM$^{(1)}$)

HMM$^{(1)}$ is essentially an invisible Markov chain. Also, HMM$^{(1)}$ is a group of random processes of observations which are associated to a group of states. HMM$^{(1)}$ has two layers which are observations layer and hidden layer, respectively. Observations layer is usually represented as a sequence of observations, each of which has an emission probability. Hidden layer is Markov process described by transition probability.

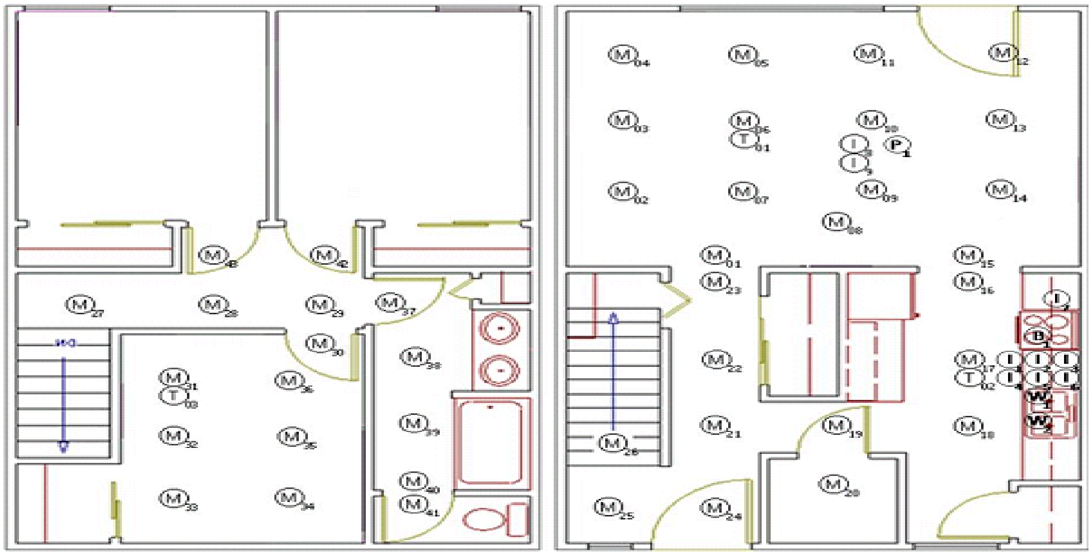

Figure 1. Sensors in a Smart Home, Monitor Motion (M), Temperature (T), Water (W), Burner (B), Phone (P), and Item Use (I)

Formally, HMM(1) is a 5-tupples $\{S, V, A, B, \pi\}$.

- $S=\{S_1,S_2,\ldots,S_N\}$;S is a set of states.
- $V=\{V_1,V_2,\ldots,V_M\}$;V is a set of observations.
- $A=\{a_{ij}=P(q_{t+1}=S_j|q_t=S_i),1\le i,j\le N\}$, A is a transition probabilities. Each a_{ij} represents the probability of transition from state S_i to S_j.
- $B=\{b_{jk}=P(o_t=V_k|q_t=S_j),1\le j\le N, 1\le k\le M\}$, B is emission probabilities. Each b_{jk} represents the probability of observation V_k being emitted by S_j.
- $\pi=\{\pi_i=P(q_t=S_i), 1\le i\le N \}$,$\pi$ is initial state distribution. Each π_i represents the probability that S_i is a start state.

The essential of building HMM(1) is how to evaluate these parameters of HMM(1). Maximum Likelihood(ML) algorithm is often used to solve it. ML algorithm may usually be expressed by three formulas as follows.

- Evaluating π

$$\pi_i=\frac{Init(i)}{\sum_{j=1}^{N} Init(j)},1\le i\le N$$ Formula (1)

$Init(i)$ of Formula (1) is the frequency of S_i occuring as a start state in training set. $N=|S|$. We use Formula (1) to evaluate each π_i of π.

$$a_{ij}=\frac{C_{i,j}}{\sum_{k=1}^{N} C_{i,k}},1\le i, j\le N$$ Formula (2)

- Evaluating A

$C_{i,j}$ of Formula (2) is the frequency of transition from state S_i to S_j in training set. We use Formula (2) to evaluate each a_{ij} of A.

- Evaluating B

$$b_{jk} = \frac{E_j(V_k)}{\sum_{t=1}^{M} E_j(V_t)}, 1 \le j \le N, 1 \le k \le M \quad \text{Formula (3)}$$

$E_j(V_k)$ of formula (3)is the frequency of observation V_k emitted by S_j in training set. We use Formula (3) to evaluate each b_{jk} of B.

4.2. Second-Order Hidden Markov Model(HMM$^{(2)}$)

HMM$^{(2)}$ is derived from HMM$^{(1)}$. Two extensions are made in HMM$^{(2)}$. For one, HMM$^{(2)}$ is based on second-order Markov chain, which say that state S_t is related to states S_{t-1} and S_{t-2}. For the other, the emission probability of an observation o in state q_t is related to state q_{t-1}.

Formally, HMM$^{(2)}$ is a 7-tuples $\{S, V, A_1, A_2, B_1, B_2, \pi\}$. S, V, A_1, B_1 and π are same to S, V, A, B and π in HMM$^{(1)}$, respectively.

- $A_2=\{a_{ijk}=P(q_{t+1}=S_k|q_t=S_j,\ q_{t-1}=S_i), 1\le i,j,k\le N\}$, A is a transition probabilities. Each a_{ijk} represents the probability of transition from states S_i, S_j to S_k .
- $B_2=\{b_{ijk}=P(o_t=V_k|q_t=S_j,\ q_{t-1}=S_i), 1\le i,j\le N,\ 1\le k\le M\}$, B is emission probabilities. Each b_{ijk} represents the probability of observation V_k being emitted by S_i, S_j.
- Evaluating A_2

$$a_{ijk} = \frac{C_{ijk}}{\sum_{u=1}^{N} C_{iju}}, 1 \le i, j, k \le N \quad \text{Formula (4)}$$

C_{ijk} of Formula (4) is the frequency of transition from state S_i, S_j to S_k in training set. We use Formula (4) to evaluate each a_{ijk} of A_2.

- Evaluating B_2

$$b_{ijk} = \frac{E_{ij}(V_k)}{\sum_{t=1}^{M} E_{ij}(V_t)}, 1 \le i, j \le N, 1 \le k \le M \quad \text{Formula (5)}$$

$E_{ij}(V_k)$ of formula (5)is the frequency of observation V_k emitted by S_i, S_j in training set. We use Formula (5) to evaluate each b_{ijk} of B_2.

4.3. Viterbi$^{(2)}$ Algorithm

Viterbi$^{(2)}$ algorithm is used to find an optimal sequence of states from HMM$^{(2)}$. Formally, for a sequence of observations $V=(V_1,V_2,\ldots,V_T)$ and a HMM$^{(2)}$ $\lambda=(\pi,A_1,A_2,B_1,B_2)$, Q^* is the optimal sequence of states iff $\forall Q \in perm(Q)$, $p(Q|V, \lambda)\le p(Q^*|V, \lambda)$ holds.

Let $\delta_t(i,j)$ be max probability of observation V emitted by states path $q_1, q_2, \ldots, q_{t-1}=S_i, q_t=S_j$ at time point t. $\delta_t(i,j)$ can be calculated by Formula (6). In a similar way, $\delta_t(i,j)$ can be calculated by Formula (7).

$$\delta_t(i, j) = \max_{q_1,\ldots q_{t-1}} P\left(q_1,\ldots,q_{t-1} = S_i, q_t = S_j, V \mid \lambda\right), 1 \le i, j \le N, 2 \le t \le T \quad \text{Formula (6)}$$

$$\delta_{t+1}(j,k)=\max_{1\le i,j\le N}[\delta_t(i,j)a_{ijk}]b_{ijt+1},1\le j,k\le N,2\le t\le T-1 \quad \text{Formula (7)}$$

Viterbi[2] algorithm is described as follow.

Step 1: initialization

$$\delta_2(i,j)=\pi_i a_{ij} b_{ii} b_{ij2},1\le i,j\le N \quad \text{Formula (8)}$$

$$\Psi_2(i,j)=0,1\le i,j\le N \quad \text{Formula (9)}$$

Step 2: recursion

$$\delta_{t+1}(i,j)=\max_{1\le i,j\le N}[\delta_t(i,j)a_{ijk}]b_{ijt+1},1\le j,k\le N,2\le t\le T-1 \quad \text{Formula (10)}$$

$$\Psi_{t+1}(j,k)=\arg\max_{1\le i\le N}\left[\delta_t(i,j)a_{ijk}\right],1\le i,j\le N,2\le t\le T-1 \quad \text{Formula (11)}$$

Step 3: terminal

$$P^*=\max_{1\le i,j\le N}[\delta_T(i,j)] \quad \text{Formula (12)}$$

$$q_T{}^*=\arg\max_{1\le i,j\le N}[\delta_T(i,j)] \quad \text{Formula (13)}$$

Step 4: finding an optimal sequence of states

$$q_{t-1}{}^*=\Psi_{t+1}\left(q_t{}^*,q_{t+1}{}^*\right),t=T-1,T-2,\ldots,2 \quad \text{Formula (14)}$$

4.4. Algorithm of Activity Recognition

Step 1: Building HMM[2].

(1)Initializing the parameters *S* and *V* of HMM[2]. An activity is explained as a state. A sensor data is explained as an observation.

(2)Applying algorithm ML[2] to compute the parameters A_1, A_2, B_1, B_2, π.

(3)Outputting HMM[2].

Step 2: Recognizing Activities by Viterbi[2] algorithm.

5. Experiments

5.1. Raw Data for Experiments

This subsection will present two datasets which are collected in ambient intelligence environments. One is kasteren Dataset [12] which is collected in a three-room apartment where a 26-year-old man lives and there are 14 state-change sensors were installed in this apartment. Another dataset is “WSU Apartment Test bed” which is collected in a smart apartment testbed located on the WSU campus [13]. This dataset is built to recognize and assess the consistency of Activities of Daily Living that individuals perform in their own homes.

5.2 Measurement Criteria

Two criterion are used to evaluate the performance of our models, time slice accuracy and class accuracy. The formulas are given in formula (15) and (16).

The time slice accuracy and the class accuracy are defined as follows:

$$\text{Time slice rate} = \frac{\sum_{n=1}^{N}\left[\text{inferred}(n)=\text{true}(n)\right]}{N} \qquad \text{Formula(15)}$$

$$\text{Class rate} = \frac{1}{C}\sum_{c=1}^{C}\left\{\frac{\sum_{n=1}^{N_c}\left[\text{inferred}_c(n)=\text{true}_c(n)\right]}{N_c}\right\} \qquad \text{Formula(16)}$$

where N is the total number of time slices, C is the number of classes and N_c the total number of time slices for class c.

5.3. Experiment Result

We compare the extraction result based on HMM, CRF with $HMM^{(2)}$. Table 1 shows that average precision rate of $HMM^{(2)}$ is 2.43, 0.34 percent higher than that of HMM, CRF in time slice rate. Average precision of $HMM^{(2)}$ is 11.23, 1.14 percent higher than that of HMM, CRF in class rate. Figure 2 and Figure 3 shows precision of every activity. From Figure 2 and Figure 3, $HMM^{(2)}$ is weak better than CRF and normal better than HMM in precision rate.

Measurement Criteria on kasteren Dataset	HMM	CRF	$HMM^{(2)}$	Measurement Criteria on WSU Apartment Test bed	HMM	CRF	$HMM^{(2)}$
Time slice rate	93.26%	97.11 %	98.45%	Time slice rate	80.58%	86.71%	98.33%
Class rate	52.17%	62.89 %	74.63%	Class rate	74.92%	82.47%	87.12%

Table 1. Time Slice and Class Accuracies for the Three Models On Kasteren Dataset and WSU Apartment Test Bed

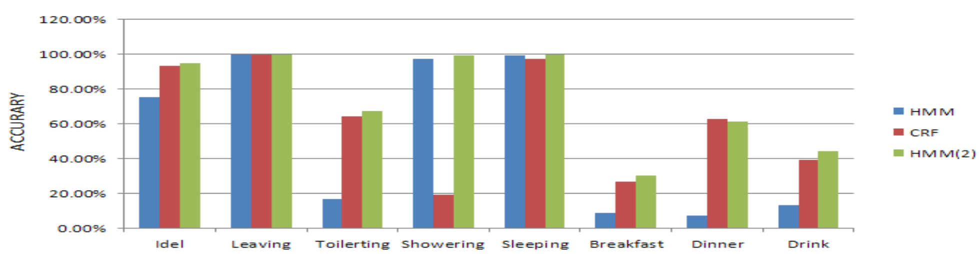

Figure 2. The Precisions of HMM, CRF and $HMM^{(2)}$ for Every Activities

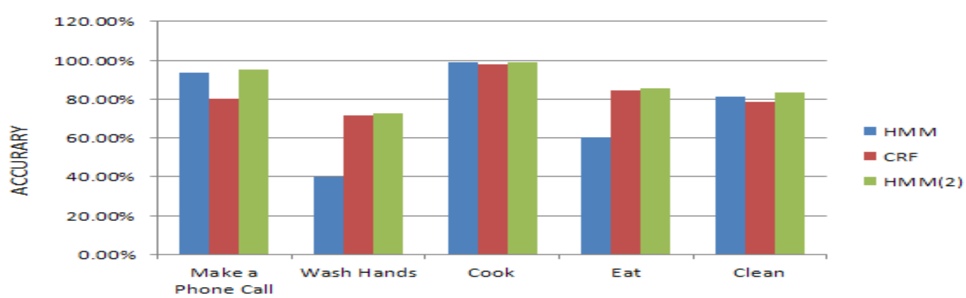

Figure 3. The Precisions of HMM, CRF and $HMM^{(2)}$ for Every Activities

This is because the activities that likely have sub-activities and complex structures tend to be recognized by $HMM^{(2)}$ when considering accuracies of individual activities. For activity 'dinner', CRF performs better than $HMM^{(1)}$ and $HMM^{(2)}$.

Figure 3 is comparison of recognition accuracy for $HMM^{(1)}$, CRF and $HMM^{(2)}$ in the five activities from which we can see the recognition accuracies of $HMM^{(2)}$ are always better than CRF and four of five are better than HMM.

6. Conclusion and Future Work

In this paper, we applied second-order Hidden Markov Model to activity recognition. The relationship between the probability and the model's historical states is considered reasonably. Our approach shows higher precision than previous approaches by experiments.

But in our experiments, we find that precision become lower with the increase of distribution complexity of observations. It reveals that Second-order hidden Markov model needs be optimized. In next work, we will focus on optimization of parameters in hidden Markov model. We will try to propose a hybrid approach which integrates Maximum Entropy with Second-order hidden Markov model to recognize activities in smart home.

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