Improving Multi-resident Activity Recognition for Smarter Homes

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Abstract

Recent growing interest in ambient intelligent environments has driven a desire for effective models to reason about behaviour of multiple residents. In this paper we show the preliminary results of combining different types of dependencies to capture the complexity nature of such environments for better activity recognition.

1 Introduction

In intelligent environments such as smart homes activity recognition plays an important role, especially when apply to health monitoring and assistance [Chernbumroong *et al.*, 2013; Mocanu *et al.*, 2011; Das and Cook, 2004]. Much effort has been spent on modelling the activities of residents in order to facilitate reasoning of their behaviour. The success of such models would result in reducing cost of traditional health care, a smarter and safer home for eldercare, and better assistance for patients. Activity recognition in ambient environment has been studied for years, most of that focus on single resident, aiming to support independent living [van Kasteren *et al.*, 2008]. However, in practice this is not always the case since modern smart environments should be able to support multiple occupants. As a result, there is a growing desire for a model that is capable of capturing the complexity nature of both independent and joint activities. In recent work, temporal approaches have been widely employed to model activities in smart homes [Singla *et al.*, 2010; Cook, 2012; Chen and Tong, 2014; Alemdar *et al.*, 2013; Chiang *et al.*, 2010; Wang *et al.*, 2011]. However, there still lacks a comprehensive study to fully understand the relations of residents' behaviours and how they are reflected through the sensors' states. In this paper, we show that such study is helpful not only in understanding the complexity of multi-resident activity modelling in ambient environments, but also in developing a novel model to improve prediction performance.

2 Smart Home Environments

Let us denote $a^{m,t}$ and o^t as the activity of resident m and the sensors' state at time t respectively. For ease of presentation we denote $\mathbf{a}^t = \{a^{1,t}, a^{2,t}, .., a^{M,t}\}$ as the activities of all M residents at time t. We use $t_1 : t_2$ to denote a sequence of events/states from time t_1 to t_2. For example, $\mathbf{a}^{t_1:t_2} = \{\mathbf{a}^{t_1}, .., \mathbf{a}^{t_2}\}$ is the sequence of activities performed by all residents from time t_1 to t_2.

For multiple residents there are three types of dependencies as being illustrated in the first row of Table 1, with two residents as an example. *Parallel dependency*: each resident's activities are seen as an independent Markov chain where there is no interactive link between them (left figure) . *Cross dependency*: activity of a resident at time t depends not only on his previous activity but also on the activities of the others (middle figure). *Group dependency*: consider the group of activities of all residents as a single random variable where their current combined activity depends on the previous one (right figure).

We now consider two types of interactions between activities and environment's states, as can be seen in the first column of Table 1. In the first case, each resident has his own interaction with the environment (top figure). This based on the fact that a sensor should only be triggered by a single person. In the second case, one may argue that since the environment is treated as one object, its states should reflect the whole dynamic in it. Therefore, in this case the environment's state is modelled to be dependent on the activities of all residents (bottom figure).

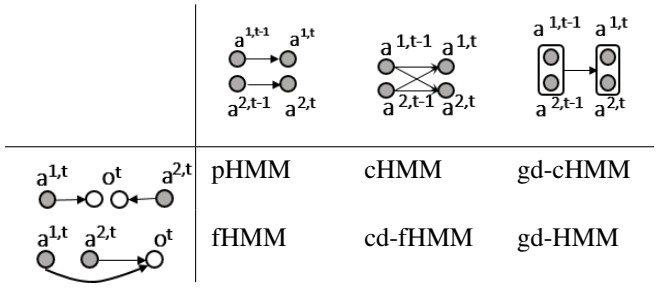

Table 1: First row (left to right): parallel dependency, cross dependency, group dependency ; First column (top to bottom): individual interaction, group interaction; pHMM: parallel HMM, cHMM: coupled HMM, gd-cHMM: coupled HMM with group dependency, fHMM: factorial HMM, cd-fHMM: factorial HMM with cross dependency, gd-HMM: HMM with group dependency

3 Multi-resident Activities Modelling

3.1 Hidden Markov Models

We show how to model the activities of multiple residents in smart homes by combining the dependencies discussed in previous section. Here, we can either use Conditional Random Fields (CRFs) or Hidden markov Models. We find that in previous works on the same problem as in this paper, CRFs do not show apparent advantage over HMMs [Cook, 2012; Wang *et al.*, 2011]. Therefore, we choose HMMs for efficient learning and reasoning. As the result, this leads to the construction of six different HMMs as shown in Table 1.

3.2 Mixed-dependency Models

We argue that the complexity of multi-resident activities would require more than one type of dependency for better reasoning. First we propose an ensemble of HMMs to combine different type of activity dependencies. Then we generalize the idea to propose another model that mixes the dependencies and subsumes the ensembles.

Let us consider an ensemble of gd-HMM, cd-HMM and fHMM where parallel dependency, cross dependency and group dependency are combined. We call this as md-HMM. The combined probability of this ensemble in log-space is:

$$\phi_{\text{md-HMM}} = \log p_{\text{gd-hmm}} + \log p_{\text{cd-hmm}} + \log p_{\text{fhmm}} \tag{1}$$

We observe that the emission probability table does not have important role as the transmission probabilities in activity modelling. We also find that the influence of each type of dependency varies in different environments, depending on the complexity of the occupants' activities. Therefore we generalize the log-probability in the ensemble such that each type of dependency is assigned with a different weights. This can be seen as a mixture of weighted log-probabilities which we call mixed-dependencies model (MDM). The combined log-probability of this model is:

$$\phi_{\text{MDM}} = \log p(o^t|\mathbf{a}^t) + \alpha \log p(\mathbf{a}^0) + (\beta+\gamma)\sum_m \log p(a^{m,0}) + \sum_t [\alpha \log p(\mathbf{a}^t|\mathbf{a}^{t-1}) + \sum_m \beta \log p(a^{m,t}|\mathbf{a}^{t-1}) + \gamma \log p(a^{m,t}|a^{m,t-1})] \tag{2}$$

where α, β, γ are arbitrary positive weights.

We can show that this MDM subsumes fHMM, cd-fHMM, gd-HMM and also the ensemble md-HMM. Indeed, the combined log-probability of MDM is equivalent to the log-probabilities of fHMM, cd-fHMM and gd-HMM with the assignments $(\alpha = 0, \beta = 0, \gamma = 1)$, $(\alpha = 0, \beta = 1, \gamma = 0)$ and $(\alpha = 1, \beta = 0, \gamma = 0)$ respectively. Similarly, if we set $\alpha = \beta = \gamma = 1/3$ we would have $\phi_{\text{MDM}} \propto \phi_{\text{md-HMM}}$. Interestingly, if we maximize the combined log-likelihood from ϕ_{MDM} given a constraint that $\alpha+\beta+\gamma = 1$ we end up in finding the best models among fHMM, cd-fHMM and gd-HMM.

4 Preliminary Results

4.1 Datasets

The CASAS data was collected in the WSU smart department Testbed with multi-residents where each resident performing 15 unique activities [Cook *et al.*, 2010]. The data is collect in 26 days in a smart home equipped with 37 ambient sensor.

The ARAS data[Alemdar *et al.*, 2013] is collected in two different houses, denoted as House A and House B, in 30 days. In these environments, there are 20 sensors for two residents in each house. Each resident is ask to perform 27 different activities.

4.2 Experimental Results

In the experiments we use leave-one-out cross validation for all datasets. In particular, the data of one day (one file) is employed for evaluation and the data of the other days are for training the models. We repeat the evaluation for every day and report the average accuracy as shown in Table 2. Here α,β and γ are selected empirically.

In CASAS dataset, gd-HMM achieves much higher performance than the other variants with 69.114% accuracy. In comparison with other work which use the same evaluation method, in [Hsu *et al.*, 2010] the iterative CRF achieves 64.16% and in [Chiang *et al.*, 2010] pHMM achieves 61.78% accuracy. In [Singla *et al.*, 2010] and [Chen and Tong, 2014], the authors report the accuracies of 60.60% and 75.77% but different from us they use threefold cross-validation. Also note that all these methods rely on the prior knowledge of data association while our HMMs do not. For completeness, we also report the results in [Alemdar *et al.*, 2013] with 61.5% and 76.2% for ARAS House A and ARAS House B respectively. Different from us, in that work the activities of each residents are grouped into 6 categories while we use all 27 activities

The ensemble model has good results in ARAS data but it seems not very useful in CASAS data. This is because there are many misclassified activities from the parallel part which performs poorly in this case. Our MDM achieves impressive results in all three environments, notably in ARAS data where it outperforms the others model with large margins. In particular, compare to the best HMMs from six variants MDM achieves higher accuracy of 0.221% in CASAS dataset, $\mathbf{31.638}\%$ in ARAS house A, and $\mathbf{8.104}\%$ in ARAS house B. This confirms our hypothesis that complexity of activities must be captured by multiple dependencies

5 Conclusions

This paper studies smart home environment with ambient settings, aiming to understand the insights of the behaviours of multiple residents. We show that by combining different types of dependencies better activity recognition can be achieved.

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	CASAS			ARAS House-A			ARAS House-B		
	R1	R2	All	R1	R2	All	R1	R2	All
pHMM	51.338	50.242	33.899	43.104	21.797	16.563	88.732	78.135	75.332
cHMM	62.661	63.887	46.321	43.724	23.969	17.110	88.823	78.049	75.306
gd-cHMM	70.760	69.144	59.330	43.606	24.024	17.039	88.752	78.101	75.305
fHMM	59.747	56.780	43.547	34.281	42.571	21.985	90.251	81.456	79.267
cd-fHMM	71.653	69.710	56.554	37.887	44.615	25.278	89.563	84.246	81.652
gd-HMM	77.368	78.267	69.114	38.017	45.398	25.487	89.449	84.318	81.717
md-HMM	57.939	60.567	47.314	45.369	52.850	31.857	90.227	86.035	83.173
MDM	**77.791**	**78.529**	**69.335**	**64.688**	**80.453**	**57.125**	**94.492**	**91.998**	**89.821**

Table 2: Evaluation results using leave-one-out validation. "R1", "R2" indicate the average accuracy for each resident and "All" indicates the accuracy for all residents.

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