Tracking and Recognizing the Activity of Multi Resident in Smart Home Environments

Raihani Mohamed, Thinagaran Perumal, Md Nasir Sulaiman, Norwati Mustapha, Syaifulnizam Abd. Manaf

Department of Computer Science, Faculty of Computer Science and Information Technology,
Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia
raihanim@gmail.com

***Abstract*—Tracking and recognizing the functional activities in a smart home environment using ambient sensor technology is becoming an interesting field to discover. Its passive and unobtrusive in nature has made it impossible to infer the resident activities. The problems are becoming complex when it is involving multi resident living together in the same environment. Existing works mainly manipulate data association and algorithm modification on extra auxiliary of graphical nodes to model human tracking information in an environment to incorporate with the problems. Thus, recognizing activities and tracking which resident perform the activity at the same time in the smart home are vital for the smart home development and future applications. This paper goal is to perform accurate tracking and recognizing of individual's ADL of multi resident setting in the smart home environment. Also enable to foresee the patterns of everyday activities that commonly occur or not in an individual's routine by considering the simplification and efficient method using the multi label classification framework. We perform experiments on real world multi resident on ARAS Dataset and shows that the LC (Label Combination) using Decision Tree (DT) as base classifier can tackle the above problems.**

***Index Terms*—Activity Recognition; Label Combination; Multi Label Classification; Multi Resident; Smart Home Environment.**

I. Introduction

Activity recognition research in a smart home has been evolved due to demand growth in many modern applications today. The elderly population is getting prominent, thus there are increasing needs to expand the quality of life and promote the health monitoring and assistance for them to stay longer and secure at home. Sensor based activity recognition approach leads the ambient intelligent in many ways either deployment of sensor technology into the environment or carries them around. Sensor type technology such as video based sensor and wearable sensor such as CCTV [1], accelerometer and gyroscope [2] are among the common type applications. Consequently, when dealing with elderly people, they are more comfortable with technology that is resilience in nature and inviolate their privacy. Thus, an ambient sensor that embedded in the smart home environment is passive in nature are appropriate and recommended for them to track their functional activities. Examples of research areas resulted from the technology such as monitoring of elderly in activities of daily living (ADL) [3], early detection of the elderly decline in health [4] as well as the efficiency of energy management at homes [5], [6]. The information is vital for the caregiver and the family member for detection and automatic health monitoring, identifying the resident pattern and behaviour as well as tracking who and what activities the resident engaged in.

Tracking the ADL functionalities of single resident in the environment seems a simpler task to handle, however, it is significantly complicated to cope with the multi resident in the same environment. Previous works focusing on increasing the activity recognition accuracy of the single resident [7][8]. Thus, the applications in the smart home required the recognition the activities of a multi resident in the same environment. Tracking and recognizing the individual resident in the same environment using single type ambient sensor technology required more effort to tackle the problems. It is a challenging task due to diversity and complexity level of human activity and resident identification using only binary data type. A strong assumption is needed on the identification of which resident performing the activity. Many approaches such as data association and algorithms modification are considered to track individual activities in multi resident scenarios. Hence, expanding the problem using multi label classification approach is worth endeavour.

The multi-label problem is introduced to tackle the multi-label issues and is relevant to many applications domains such as text classification [9], scene classification [10] and genomics [11], [12]. All multi-label problems can be transformed into one or more single-label problems via some problem transformation and algorithm adaptation [13]. In smart home activity recognition scenarios, tracking the individual functional activities in multi resident setting can be tackled with supervised learning. In this paper, we introduce the MLC method of supervised learning to track and recognize the individual functional activities in a multi resident setting in a smart home environment that address the above issues. Label Combination (LC) approach operates every label into unique combination as a separate class and trains as a single multi-class classifier on the classes. Multi label problems using LC approach generalized the multi residents in smart home problems and offer the time efficiency and complexity reduction at the pre-processing stage.

We apply our approach in the context of ARAS Datasets involving two smart homes [14]. The model provides an ability to foresee the pattern of the residents' behaviour through its tracking and recognizing the functional activities. Thus, this study is able to identify frequent activities that naturally occur in an individual's ADL. Specifically, we hypothesize that smart home ambient sensor data that has been embedded in the environment and computational tools can be used to effectively tracking the individual types of activities of multi resident in everyday environments. To validate the hypothesis, this paper will deliberate into two contributions. First, we track and recognize activities of more than one resident in the same environment with the supervised learning of MLC using large datasets. Second, able to predict the individual activity pattern based on what activity mostly perform and least perform in their daily ADL using Label Combination (LC) of MLC approach.

This paper is organized as follows; Section 2 explains the related works. Section 3 describes the research methodology. Section 4 discusses the experimental results and analysis and Section 5 presents the conclusions and future work.

II. Activity Recognition in Smart Home

Smart home activity recognition problems have been evolved parallel with the complexity of activities among the resident especially with the elderly adult resides with others in the same smart home environment. Previous works address more on the single resident activity recognition in order to simplify the problems [8], [15]–[19]. Hence, the problems are becoming complicated and required to solve in efficient and real-time way. Tracking and recognizing individual's ADL is a fundamental problem in ubiquitous and pervasive computing. Generally, easy tracking and recognizing activities of individual residents are based on location sensing technologies and GPS signal to infer what activities performed by that particular person [20], combinations of video-camera and audio to recognize pattern of interactions of residents in the smart environments [21], RFID technology for indoor activities [22] and wearable sensor with accelerometer [23]. However, tracking and recognizing of individual's ADL based on list signal of passive binary sensors such as motion, pressure resistors, pressure mats, contact sensors and proximity sensors are becoming a headache when it's involving the multi resident in the same smart home environment.

Due to this issue, most researchers tackled the issue by algorithmic modification on graphical nodes with a probabilistic model. To cater the multi resident problem, mostly overcome with multi types of sensor technology that mixed the ambient sensor with wearable sensor [24]. Meanwhile, using a single type of sensor, the ambient sensor technology to model activity recognition of multi resident mostly using data association and graphical nodes with a probabilistic model such as HMM [25], CRF [26]. Other than that, the activity also recognized by prior knowledge on the individual and cooperative pattern using a combination of HMM and CRF to infer the activity and model the accuracy [27]. Alemdar et al. propose two methods to prove that the personal identification of individual resident from a specific sensor signals for that activity is a certain using algorithm modification factorial hidden Markov model (FHMM) and nonlinear Bayesian tracking for decomposing the observation space into the number of residents with the help of data association for multi sensor readings for multi target problems [28]. The E-ID5R (Extension of ID5R) is used to accommodate the incrementally new instances and new activities as it becomes available over time to recognize the activity but not the resident appropriately [29]. Hence, the works mentioned focused on activity recognition, not the residents. These efforts required a lot of pre-processing strengths in order to model the tracking and activity recognition at the same time. Mohamed et al. [30] consider the multi resident problems as multi label problem by recognizing the multi resident and types of interaction between the resident. The model performance reported was around 89%. Though, the detail activities were not shown through the model. However, Kumar et al. [31] propose the multi label learning to tackle the issue and successfully mapping the activities to its residents.

A. Multi Label Learning

Multi Label Classification (MLC) offers the efficient approach and reduces the efforts and time to tackle the complexity of data at the pre-processing stage. Previous works model the multi user and interaction of the residents in smart home and treated the residents and their interaction as labels [30]. They experimented using the three labels with many MLC approach and results showed that the Classifier Chains (CC) MLC method using random forest as base classifier topped among others.

MLC is an extension of single-label classification problem that has limitations on single label l that is chosen from a previously known finite set of labels L. In smart home with multi resident scenarios, the activities of resident A and activities of resident B are classified with a subset of labels $S \subseteq L$. For an observation sequence $x_{1:T} = \{x_1, x_2, \ldots, x_T\}$, it is a single-label problem if there is a sequence of labels $y_{1:T} = \{y_1, y_2, \ldots, y_T\}$, where $y_{t,}$ $t = 1, 2, \ldots, T$, are single-label vectors that best explains the sequence, and it is Multi-label problem if there is a sequence of labels $y_{1:T} = \{y_1, y_2, \ldots, y_T\}$, where $y_{t,}$ $t = 1, 2, \ldots, T$, are multi-label vectors that best explains the sequence.

Learning algorithms of MLC can be categorized as problem transformation method, algorithm adaptations and ensemble method. Most of the algorithm adaptation methods have some connection with problem transformation [32]. Hence, the proposed learning algorithms that will be experimented in this paper are categorized under problem transformation method.

III. Methodology

In this section, the overall approach involves in this study are explained comprehensively. Figure 1 presents its processes and details explanations are described in the subsection.

A. ARAS Datasets

In this study, we use public datasets from ARAS Human Activity Datasets [33] specifically using ambient sensor technology involving a multi resident setting in the smart home. The datasets consist of 20 types of sensor signals in 30 separate files indicating of multi resident activities in a daily format. It was labelled activities of two resident in two real houses, House A and B. Every file contains 86,400 instances. This study is a comprehensive study experimented on both houses and it is considered as large datasets since the total of instances are 5,184,000. There are 27 types of activities have been performed by each resident with a total of 54 type of activities captured almost every day. The 20 sensors consisting of resistors, pressure mats, contact sensors, proximity sensors, sonar distance sensors, photocells, temperature sensors, and infrared receivers.

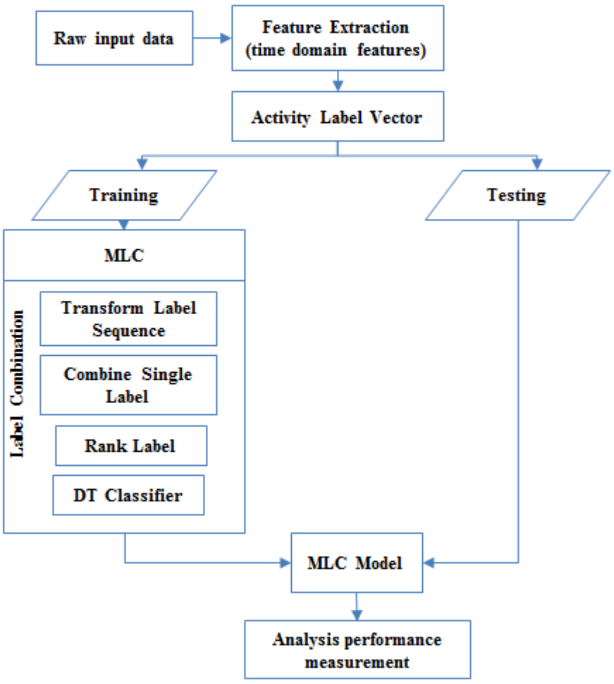

Figure 1: Proposed MLC using label combination approach

1) Data Pre-processing

The features extraction for this dataset consists of 20 sensor signals with its activity labels. In the labelling process, the residents are donated as A and B respectively followed by the activity ID as in Table 1.

2) Multi Label Classification (MLC)

Multi label problem is consisting of a sequence of labels $y_{1:T} = \{y_1, y_2, \dots, y_T\}$, where $y_{t,}$ $t = 1, 2, \dots, T,$ are multi-label vectors that best explains the sequence.

Table 1
The Activity ID and Its Activity Type

ID	Activity	ID	Activity
1	Other	15	Toileting
2	Going Out	16	Napping
3	Preparing Breakfast	17	Using Internet
4	Having Breakfast	18	Reading Book
5	Preparing Lunch	19	Laundry
6	Having Lunch	20	Shaving
7	Preparing Dinner	21	Brushing Teeth
8	Having Dinner	22	Talking on the Phone
9	Washing Dishes	23	Listening to Music
10	Having Snack	24	Cleaning
11	Sleeping	25	Having Conversation
12	Watching TV	26	Having Guest
13	Studying	27	Changing Clothes
14	Having Shower		

3) Label Combination Approach

Label Combination (LC) is under category problem transformation method [13], [34], is a simple but effective and efficient which has been the focus of several works [35]. LC transforms a multi-label problem into a single-label (multi-class) problem by treating all label combinations as atomic labels, i.e. each label set becomes a single class label within a single label problem. Thus, the set of single class labels represents all distinct label subsets in the original multi-label representation. For example, the multi-label set *{p, q, r}* would become a single label *pqr*. Hence the set of all distinct multi-label sets is transformed into a set of possible single labels *L* to be considered by the single-label classifier. Given a new instance, the single-label classifier of LC outputs the most probable class, which is actually a set of labels. If this classifier can output a probability distribution over all classes, then LP can also rank the labels. To obtain a label ranking we calculate for each label the sum of the probabilities of the classes that contain it. This way LC can solve the complete label correlations task.

B. Performance Measurement

MLC requires different evaluation measures than traditional single-label classification can generate. Hence there are important to measure the performance of the proposed method to evaluate its performance. This paper will measure based on example-based and label-based measures [13] and ranking-based measures [12]. For the purpose of comparison, we used five different multi-label evaluation measures [36][37], specifically:

Accuracy per label

$$:= \frac{1}{L}\sum_{n=1}^{L} Acc_{(n)} = \frac{1}{N}\sum_{i=1}^{N} \delta\left(\hat{y}^{(n)}, y^{(n)}\right), \tag{1}$$

$$\text{Accuracy } := \frac{1}{N}\sum_{i=1}^{N} \frac{|y^{(n)} \wedge \hat{y}^{(n)}|}{|y^{(n)} \vee \hat{y}^{(n)}|} \tag{2}$$

where $[\boldsymbol{A}]$ is an identity function, returning 1 if condition $\boldsymbol{A}$ is true, whereas ∧ and ∨ are the bitwise logical AND and OR operation respectively.

$$\text{Hamming Score} := \frac{1}{NL}\sum_{n=1}^{N}\sum_{j=1}^{L}\left[y_j^{(n)} = \hat{y}_j^{(n)}\right], \tag{3}$$

$$\text{Exact match } := \frac{1}{NL}\sum_{n=1}^{N}\left[y^{(n)} = \hat{y}^{(n)}\right], \tag{4}$$

Table 2
Performance Measure of House A and B

Day	House A			House B		
	Accuracy	Hamming Score	Exact Match	Accuracy	Hamming Score	Exact Match
1	0.819	0.97	0.704	0.927	0.978	0.867
2	0.819	0.972	0.765	0.942	0.984	0.893
3	0.844	0.975	0.642	0.982	0.994	0.972
4	0.844	0.975	0.642	0.969	0.994	0.955
5	0.766	0.976	0.67	0.978	0.993	0.967
6	0.798	0.973	0.621	0.992	0.998	0.987
7	0.787	0.973	0.688	0.992	0.998	0.987
8	0.829	0.977	0.755	0.95	0.992	0.947
9	0.705	0.958	0.53	0.985	0.996	0.976
10	0.821	0.981	0.776	0.967	0.993	0.955
11	0.806	0.972	0.637	0.956	0.989	0.932
12	0.785	0.969	0.656	0.98	0.996	0.976
13	0.837	0.983	0.735	0.986	0.997	0.983
14	0.746	0.964	0.648	0.99	0.996	0.983
15	0.776	0.965	0.581	0.951	0.988	0.944
16	0.8	0.969	0.691	0.946	0.989	0.874
17	0.839	0.978	0.672	0.943	0.988	0.908
18	0.834	0.971	0.658	0.986	0.997	0.979
19	0.697	0.97	0.584	0.977	0.994	0.96
20	0.731	0.959	0.542	0.973	0.994	0.963
21	0.726	0.959	0.542	0.917	0.988	0.915
22	0.832	0.972	0.724	0.946	0.991	0.92
23	0.781	0.965	0.603	0.956	0.988	0.941
24	0.855	0.977	0.69	0.958	0.991	0.931
25	0.776	0.965	0.576	0.985	0.995	0.976
26	0.793	0.968	0.635	0.983	0.995	0.97
27	0.869	0.983	0.807	0.974	0.993	0.952
28	0.792	0.967	0.597	0.911	0.983	0.844
29	0.786	0.968	0.726	0.956	0.986	0.935
30	0.888	0.981	0.839	0.942	0.989	0.932

IV. RESULTS AND DISCUSSIONS

The experiments accomplished by day involving House A and B and evaluated by 5 times fold cross validation (CV) on each dataset. A decision tree is employed as a single label classifier for LC method. As a result, Table 2 indicates the classification performance in daily basis presented the activity done resident A and B respectively accumulated in 30 days. The residents indicated as A and B, meanwhile, the numbering donates the activity types. Here, we can track that how many days the same activity performed within 30 days and some were not performed at all by the respective resident. From the activity tracking and recognizing we can envisage that the resident A of House A and B were probably a female resident and resident B were male. It was because both were found not shaving (A20). Most of the activities executed by the resident A of house A were house chores. Besides, Resident B was working outside thus the activity such as preparing lunch (B5), having lunch (B6), cleaning (B24) and having guest (B26) were not performed at all by him. For house B, activities like laundry (B19), listening to music (B23), cleaning (B24) and having guest (B26) were not performed by the Resident B. Thus, indicating that most of the time he was outside. We also found that having lunch (B5), prepare dinner (B7), washing dishes (B9), having snack (B20), talking on the phone (B22) by resident B were rarely (1 or 2 days) performed.

Table 3
Activity Accuracy of House A and B
(NA= Not Available)

Activity Label	Hs A				Hs B			
	Res A	Day Act	Res B	Day Act	Res A	Day Act	Res B	Day Act
1	0.97	30	0.99	24	0.98	30	0.99	26
2	0.91	27	0.86	27	0.98	26	0.98	25
3	0.99	26	1.00	3	0.99	21	1.00	3
4	0.98	27	1.00	4	1.00	22	1.00	19
5	0.98	19	***0.00***	***NA***	0.98	6	1.00	2
6	0.99	18	***0.00***	***NA***	0.99	6	0.99	5
7	0.98	18	0.98	11	0.99	11	1.00	2
8	0.99	19	0.99	13	1.00	9	0.99	6
9	0.99	29	1.00	21	1.00	12	1.00	2
10	0.99	24	0.98	22	1.00	9	1.00	2
11	0.93	30	0.92	27	1.00	28	1.00	25
12	0.93	30	0.95	25	0.98	25	0.99	19
13	0.94	18	0.98	2	0.98	18	0.96	2
14	0.99	23	0.99	17	1.00	10	1.00	3
15	0.99	30	0.99	27	1.00	30	0.99	25
16	0.97	6	0.93	13	***0.00***	***NA***	0.99	3
17	0.94	28	0.97	20	0.99	5	0.99	18
18	0.97	16	0.99	12	0.99	11	0.97	8
19	0.98	5	0.99	3	0.99	2	***0.00***	***NA***
20	***0.00***	***NA***	1.00	21	***0.00***	***NA***	0.99	2
21	0.99	30	1.00	26	1.00	21	1.00	4
22	0.97	30	0.98	21	1.00	1	1.00	1
23	0.98	10	1.00	1	1.00	1	***0.00***	***NA***
24	0.95	2	***0.00***	***NA***	0.94	1	***0.00***	***NA***
25	0.99	15	0.99	14	1.00	11	1.00	10
26	0.99	3	***0.00***	***NA***	***0.00***	***NA***	***0.00***	***NA***
27	0.99	25	0.99	26	1.00	27	1.00	23

V. CONCLUSION

In this work, we present an extensive experimental evaluation of MLC methods to infer and track human activity in multi resident of smart home environment setting. ARAS datasets consist from large datasets, thus the results showing a positive indication that the model can cater the multi resident problem using ambient sensor technology with the result of 0.971 and 0.992 hamming score on the both houses. The simplification in computation and generality in labels correlation is suitable using the LC method. Consequently, this method can present details activity taken by which resident. Thus, we also can predict who is the multi resident, either Resident A is female or male. The complexity of multi resident also increasing from day to day, thus, there is a need to track and monitor what activity performed by the resident and what not on a daily basis. We believe that this activity recognition and tracking are valuable for providing health monitoring and assistance and alternative health interventions by providing the activity profiling technology in an individual's everyday assisted living.

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