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MOART: Multiple Occupants Activity Recognition and Tracking in Smart Home

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Abstract: Smart home aims to offer ambient assisted living environment to its occupants through the design of activity recognition system. Most of the existing works in smart home design is carried on single occupant monitoring and recognition. In reality, more than one occupant resides in a home environment and thus it essential to extend the activity recognition to multi occupancy. Sensor data association and occupant enumeration are the major concerns in the design of multi occupancy activity recognition system for smart home. Hence, the Multiple Occupants Activity Recognition and Tracking (MOART) framework is proposed for data association and enumeration using statistical and artificial intelligence techniques. Hidden Markov Model and Joint Probability Data Association approaches are used for activity recognition and data association respectively and is further enhanced using contextual approaches. Experiments are carried with the real time smart home dataset and the study shows that the proposed approach outperforms existing approaches.

Keywords: Smart home, Multioccupancy, Activity recognition, Occupant count.

I. INTRODUCTION

A Smart home is an automated home environment which is equipped with sensors and communication technologies to monitor the occupant's activities and to ensure their safety and security conditions. The aim is to recognize the sequence actions of a specific person using sensor readings. Most of the research has been devoted to activity recognition of single occupants. But, living environments are usually inhabited by more than one person results in multioccupancy. Smart home mainly improves the quality of life for the disabled and elderly people.Augusto et al. (2010). Smart home enhances their well-being and independent living. The most essential requirements of smart homes with ambient intelligence is the automatic human activity and behaviour monitoring capability.The main objective for the development of the smart home technologies is that the home environment has to increase the comfortability of its users with reduced minimal costs Alam et al. (2012), Augusto (2012). The difficulty of multioccupancy comes from mainly two aspects: resident identification, known as data association, and diversity of human activities Singla et al. (2010). Activities in smart home can be recognized in ambient or in mobile environment. Ambient sensing includes the following.Computer vision can be used to monitor the environment. But the use of camera in private environment is not feasible. Instead, the use of miniaturized sensors in the smart environment that can measure the conditions of the environment and the interactions of the inhabitants with it are preferred. This second branch of ambient sensing has started in early millennium and expanded quickly due to the advancements in the sensor and communication technology and having less privacy related problems. There is also an increasing trend in acoustic sensing of the activities in smart environments since the sound contains rich information about the environment and the activities performed.

Besides, speech is a natural way of interacting and communication. Understanding the speech and ambient sound is beneficial for many healthcare applications especially in the remote monitoring cases. On the mobile sensing track, the smart phones have abundance of functionality together with sensors which helps to recognize occupant activities. Although the mobility is one of the main advantages of smart phone based sensing that enables us to expand to outdoor environments as well as indoors.But it brings additional complexity processing of the data which affects on a battery life.Recently, the wearable devices gave rise to a whole new track of well-being applications that require automatic recognition of activities. These devices, which are originally started with simple accelerometer-based sensing of the activity levels, has expanded quickly to include many other physiological signs such as heart rate, blood pressure, and oxygen saturation levels. In our scenario, several ambient sensors are installed inside a smart home. These sensors measure the residents' interactions with the house. For example, the sensors can measure whether someone is sitting on a sofa, someone has opened the door or someone is in the kitchen. Identification mechanisms are not installed.

Sensor activity for a specific occupant is unknown. Activities may be sequential, interleaved, Concurrent, Parallel and Collaborative for modeling in multi-occupancy. Identifying residents and their corresponding events needs efficient and accurate tracking in smart environment. Cooperative activities are usually interdependent activities and interactions between individuals occur. In Sect. 2, A brief literature review on multioccupant tracking methods and data association methods used for multiple target tracking. In Sect. 3., describes our proposed system . Section 4 gives the details of our experiments with real world data. Finally, Sect. 5.concludes our proposed work.

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II. RELATED WORK

Alemdar & Ersoy (2017) on "Multiresident activity tracking and recognition in smart environments", describes,Multiple resident concurrent activity recognition problem in smart homes equipped with interaction-based sensors and with multiple residents.Experiments performed on real-world multi-resident Activity Recognition with Ambient Sensing data sets.

Benmansour et al. (2016) presented survey article on "Multioccupant Activity Recognition in Pervasive Smart Home Environments", it provides an overview of existing approaches and current practices for activity recognition in multioccupant smart homes.

Roy et al. (2016) on "Ambient and smartphone sensor assisted AD recognition in multi-inhabitant smart environments" proposed a hybrid approach for recognizing complex Activities Of Daily Living (ADL), This work combines smartphone data and ambient sensor data to improve the recognition accuracy of activities of daily living. Motion sensors are used to determine the location of the residents at the room level and they fuse this information with smartphone accelerometer data in order to infer the actual activities that the residents are engaged in, more accurately. Battery gets drained by using smart phone is the major issue.

Chen & Tong (2014) on "A two-stage method for solving multi-resident activity recognition in smart environments"describes a combined labeled method for tackling the problem and then apply hidden Markov model (HMM) and Conditional Random Field (CRF) models to the data with combined labels.The combined labels are the Cartesian product of the activities of multiple residents.It generates a new label for each pair of activities that belong to each resident. The explosion of the Cartesian product space prevents this method from scaling to environments where more than two residents live is the major issue. Experimental results reveal several segmentation problems with Cartesian approach.

Prossegger & Bouchachia (2014) on "A Multi-resident activity recognition using incremental decision trees" proposes a combined label approach with incremental decision tree model. Classification rates on ARAS data sets are reported as 40 and 82% in House A and House B

Guo & Miao (2010) on "Multi-person Activity Recognition through Hierarchical and Observation Decomposed HMM", proposes a hierarchical and observation decomposed hidden Markov model to classify multi-person activities.A multi-person activity recognition study using computer vision. Use of feature selection mechanism in order to decompose the observation space, and then use a Hierarchical Hidden Markov Model (HHMM) for activity recognition. The use of computer vision for activity recognition is the major issue.

Wang et al. (2009) "Sensor-Based Human Activity Recognition in a Multi-user scenario", proposes Coupled Hidden Markov Models (CHMMs) to recognize multi-user activities from sensor readings in a smart home environment. Multi-resident environments recognizes both single user and multi-user activities from sensor readings in a smart home environment. Coupled Hidden Markov Models (CHMMs) is used to recognize multi-user activity.Confusion takes place while predicting ADL is the major issue.

Alemdar et al. (2015) on "Daily Life Behaviour Monitoring for Health Assessment using Machine Learning: Bridging the gap between domain", proposed activities for grouping the daily livings in terms of their duration and frequency sensitivities. Hidden Markov Model (HMM) and Time Windowed Neural Network (TWNN) are the two methods used to evaluate the performance.Using the same single metric for all types of activities is the major issue.

Crandall & Cook (2009) "Coping with multiple residents in a smart environment" Collects a data set for multi-resident activity recognition in a controlled laboratory environment using a set of activities performed following a predefined scenario. The major issue is the use of pre-segmented data set reports an average accuracy for 14 activities. Hence, MOART mainly focuses on analyzing occupant count in the smart home and tracking of occupant activities.

III. PROPOSED WORK

In the proposed framework Figure3.1, Sensor data gets segmented and segmented sequence gets decomposed in data Association. Activity recognition system builds activity model for recognizing the activities of occupants. Set of heuristics are defined in contextual approaches data association and activity recognition system works with contextual approaches based on results occupant count and activity of each occupant gets recognized.

A. *Segmentation:* Data segmentation is the process of identifying, categorizing, labeling and processing specific elements or section of electronic data in order to provide precise control over who may use, view, access or manipulate specific bits of data.

- Fixed time interval: Splitting of data in fixed time intervals
- Location based sensor: Data gets splinted based on the location sensors
- Dominant sensor: Based on object sensor the data getsSegmented.

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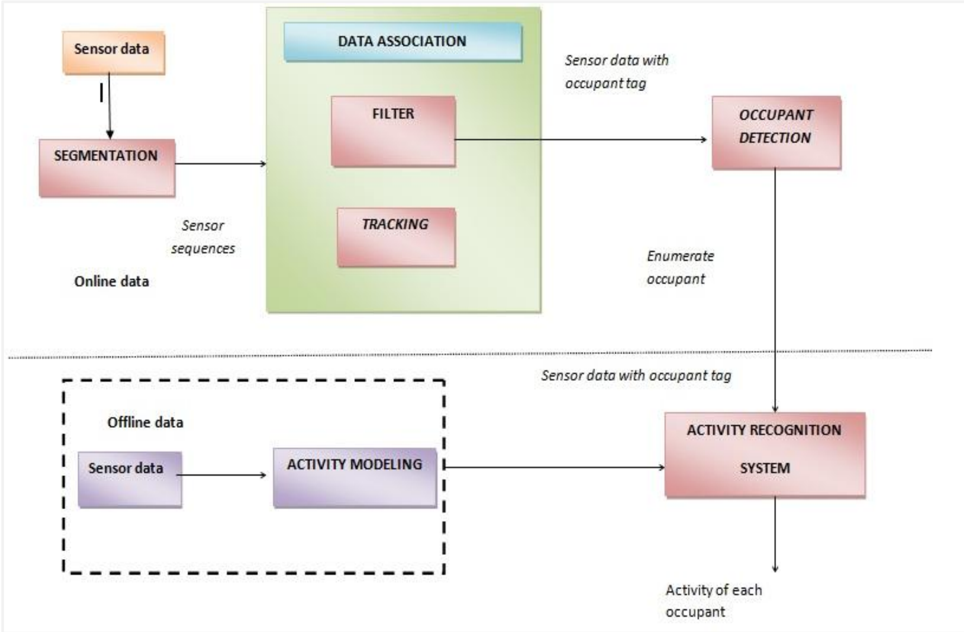

Fig 3.1 MOART Framework

B. *Tracking:* The Joint Probabilistic Data Association (JPDA) algorithm is used as a tracking algorithm. In jpda algorithm, joint posterior probabilities are computed for multiple targets. It incorporates all observations within a validation region about the predicted track position into the update of that track observation can be used to update multiple tracks.

C. *Occupant count*: Enumerates the number of occupants in smart home. By applying contextual method, occupant count can be detected.

D. *Activity recognition:* Activity recognition can be done by using activity model. The Hidden Markov Model (HMM) is a relatively simple way to model sequential data. A hidden markov model implies that the markov model underlying the data is hidden or unknown . More specifically, only observational data is known and not information about the states.

EXPERIMENTAL STUDY

Segmentation done on the basis of Fixed time interval approach. ARAS data set contains 86,400 (seconds)sequences for each day. Segmentation reduces data sequences to 1440(minutes). The JPDA algorithm is used for tracking purpose shows in figure 4.1.

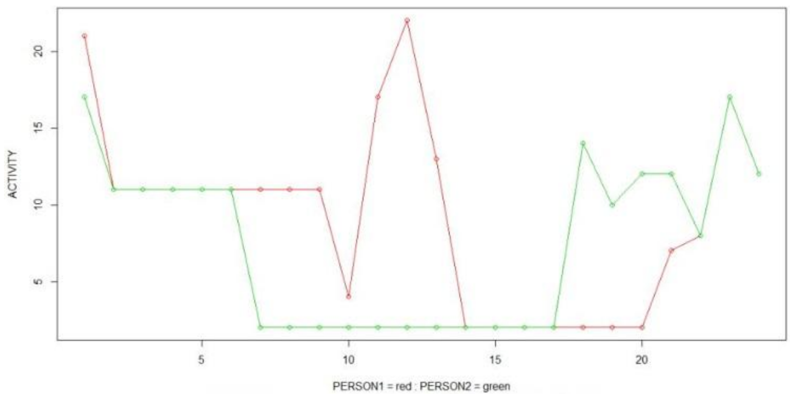

Fig 4.1 Tracking of occupants

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By applying herustics in the smart environment occupant count gets derived. Oucupant count derived for ARAS dataset House A shows in the Figure 4.2.occupant count is shown at the end of every hour.

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```
[1] "No. of hrs:1>> No. of occupants :2"
[1] "No. of hrs:2>> No. of occupants :2"
[1] "No. of hrs:3>> No. of occupants :2"
[1] "No. of hrs:4>> No. of occupants :2"
[1] "No. of hrs:5>> No. of occupants :2"
[1] "No. of hrs:6>> No. of occupants :2"
[1] "No. of hrs:7>> No. of occupants :2"
[1] "No. of hrs:8>> No. of occupants :2"
[1] "No. of hrs:9>> No. of occupants :2"
[1] "No. of hrs:10>> No. of occupants :2"
[1] "No. of hrs:11>> No. of occupants :1"
[1] "No. of hrs:12>> No. of occupants :0"
[1] "No. of hrs:13>> No. of occupants :1"
[1] "No. of hrs:14>> No. of occupants :1"
[1] "No. of hrs:15>> No. of occupants :0"
[1] "No. of hrs:16>> No. of occupants :1"
[1] "No. of hrs:17>> No. of occupants :1"
[1] "No. of hrs:18>> No. of occupants :1"
[1] "No. of hrs:19>> No. of occupants :3"
[1] "No. of hrs:20>> No. of occupants :3"
[1] "No. of hrs:21>> No. of occupants :2"
[1] "No. of hrs:22>> No. of occupants :2"
[1] "No. of hrs:23>> No. of occupants :2"
[1] "No. of hrs:24>> No. of occupants :2"
```

Figure 4.2 Occupant count

Activity is recognized based on the sensor triggered.Activity of person 1 and person 2 are calculated based on time series shows in the Figure 4.3 and Figure 4.4. And Table 4.1 shows activity id with their labels.

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

Table 4.1 Activity with their labels

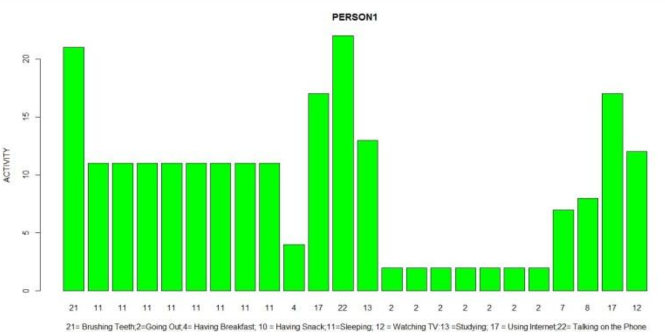

Figure 4.4 Activity of person 2

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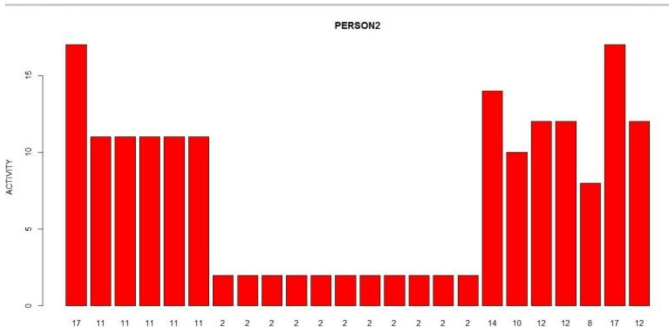

Figure 4.4 Activity of person 2

CONCLUSION

Ambient assisted living environment is offered to the occupants of smart home with the design of activity modeling and recognition system. To deal with the real time requirement of home environment, multi occupancy activity recognition system is presented in this work. The primary issue of data association and enumeration in multi occupancy recognition is addressed in the proposed design. The proposed framework MOART skillfully integrates data association and recognition within a single framework. The experimental study reveals the excellence of the proposed design in multi occupancy recognition. Future work would be to extend the activity modeling for recognizing co-operative activities.

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