A Sensor Network System for Event Attribution in Multi-user Home Environment

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Abstract - *This paper presents a sensor network system for detecting multiple user activity in a home environment. Recognizing Activities of Daily living (ADLs) by deploying sensors in the environment is very challenging. The task becomes more challenging when multiple inhabitants co-exist due to the noise introduced by the other users. We propose that each user carries an ID sensor and environmental sensors can recognize the user who activated them. The idea can effectively solve the event attribution problem for multi user activity recognition.*

Keywords: Activity Recognition, Activity of Daily Living (ADL), ID Sensor, Sensor, Wireless Sensor Network, Cluster.

1 Introduction

Recognizing activity of daily living is of particular interest to researchers for its various application domain, especially in healthcare industry. Detecting and learning the daily activities of elderly person, can save the caregiver's time and give the elderly more independence.

There are three basic method of detecting Activities. Video Based activity recognition though good at recognition accuracy, is usually not deployable for detecting ADLs because of privacy issue. Wearable sensors can also detect a set of fundamental set of ADLs like walking, standing etc. Wearable sensors have limitations in detecting more advanced set of activities like cooking, hygiene. Moreover, users are usually reluctant to wear sensors in special positions and orientations in their body needed for the specific recognition algorithm. So, sensor deployed in the environment is more desirable for detecting ADLs.

In a typical setup, various types of simple sensors, especially binary on-off state sensors, are deployed in the environment. The sensors are supposed to be deployed and forgot. So, the system needs to gather training data over a period of time. Sensor activation sequences are then fed to the system to train and test the classifier. Due to unavailability of any special features, the sensor states of the whole house are usually taken as the observation at a time instance.

Recognizing ADLs with environmental sensors is very challenging as a small set of training data cannot capture all the variations of a user activity. But the data itself might not be representative of the activities performed. This is because users are forgetful and usually interleave between activities. So, users unintentionally insert noise to the data. Figure 1 shows an example of noise in the data collected in MIT Data [13].

```
//Toilet_Flush is on while breakfast is being prepared or user is dressing//

Preparing_breakfast   4/1/2003    6:36:18   6:40:38
75      53      55      84      73      145     60      60      137     91
Drawer  Cabinet Cabinet Drawer  Cabinet Cereal  Contner Contner FreezerRefrgr
6:35:42 6:36:51 6:36:59 6:37:02 6:37:10 6:37:18 6:38:14 6:38:59 6:39:05 6:39:11
6:35:56 6:36:59 6:37:01 6:37:05 6:38:04 6:37:59 6:38:48 6:39:00 6:39:10 6:39:29
Dressing  4/1/2003   6:32:57   6:36:05
96            75       75       75       53       55       84
Exhaust_Fan   Drawer   Drawer   Drawer   Cabinet  Cabinet  Drawer
6:32:15       6:33:48  6:34:10  6:35:42  6:36:51  6:36:59  6:37:02
6:58:00       6:33:56  6:34:14  6:35:56  6:36:59  6:37:01  6:37:05

Toileting  4/1/2003   6:07:15   6:15:58
67       58           57           81        100              101
Cabinet  Med_cabinet  Med_cabinet  Closet    | Toilet_Flush | Light_switch
6:07:52  6:09:47      6:09:48      6:13:26   | 6:14:36      | 6:14:40
6:07:55  6:09:48      6:53:28      6:13:34   | 6:57:39      | 6:57:58



//medicine cabinet is on during toileting and preparing snacks //

Preparing_a_snack4/2/2003    16:45:53  16:46:59
58                57                    73        72        84
Medicine_cabinet  | Medicine_cabinet |  Cabinet   Cabinet   Drawer
16:45:09          | 16:45:43         |  16:45:57  16:46:00  16:46:10
16:45:42          | 20:51:52         |  16:46:04  16:46:27  16:46:14

Toileting  4/2/2003   16:44:14  16:45:44
88        68        58           57               73        72        84
Sf-cold   Sf-hot    Med_cabinet  | Med_cabinet |  Cabinet   Cabinet   Drawer
16:44:51  16:44:53  16:45:09     | 16:45:43    |  16:45:57  16:46:00  16:46:10
16:45:01  16:45:02  16:45:42     | 20:51:52    |  16:46:04  16:46:27  16:46:14
```

Figure 1. A data snippet from MIT data [13]

It can be observed that Toilet flush is on while the user is preparing breakfast or dressing. This might happen due to the forgetfulness of the user. Again, medicine cabinet is open during preparation of snack. The user might have interleaved between snack preparation and taking medicine. But the cabinet remains open when he is toileting.

So, noise is obvious in the data gathered and it needs to be eliminated. However, if multiple users are present, the noise can be from another user's activity also. If one user is cooking and another user is picking up the phone, the combination will not mean cooking for the first user, if training data did not contain this specific case. As one user's activity becomes another user's noise, we need a sensor event association mechanism.

A usual suggestion can be using a tracking system to separate out the sensors activated by a particular user. However, tracking fails for ADLs. Let us assume a scenario. In the morning Alice and Bob wakes up from sleep. Alice goes to kitchen to make breakfast and Bob to toilet. Suddenly the telephone rings. Usually Bob picks up the phone but this time Alice goes to pick up. While Alice is going to pick up the phone, Bob comes out of the toilet and goes to kitchen to open the fridge. Bob opens the fridge before Alice picks up the phone.

Both Alice and Bob usually go to toilet after waking up. So, the tracking system will be confused to detect who is making the breakfast and who is in toilet. Suppose this time the tracking identified the user right knowing that Alice usually makes the breakfast. Then the system will make a mistake in the second case. It will find Alice still making breakfast and Bob picking up the phone.

Let us assume that the tracking system does not have any knowledge about user activity pattern; it can only detect separate users doing activity using its domain knowledge. Then the tracker will take just an arbitrary decision about who picked the phone up, because from both kitchen and toilet it is possible to go to pick up the phone. The tracker even fails when the phone is cordless. In real activity recognition problem, the system should detect Alice picking up the phone and her breakfast making is paused temporarily.

To associate sensor states with users, each sensor should know who activated it. We propose each user carries an ID sensor with him which broadcasts a short range beacon periodically. Ideally, the sensors activated, should associate its state with the user sending the beacon. But engaging each sensor in the task is communication intensive. We provide a simple maximum neighborhood based clustering scheme that elects a leader for the association task. This does not hamper the 'deploy and forget' principle for environmental sensors. The proposal for using ID sensor and clustering algorithm for sensor event attribution facilitating multi-user activity recognition is a novel idea. We pursue the idea because of the failure of tracking system in detecting ADLs as shown in Alice and Bob scenario. The scenario we described is also a contribution of this work.

The rest of the paper is organized as follows. Section 2 provides some related works. We describe our main idea in section 3. Section 4 and 5 presents simulation and implementation results respectively. Section 6 is the conclusion.

2 Related Works

The most desirable setup for Activity of Daily Life (ADL) at home environment is to deploy simple ubiquitous sensors. MIT has been working to make a Living Laboratory [1,2] from where naturalistic data can be collected. Work [3] has used sensors deployed on the doors to detect few ADLs. However, it has been pointed out in [2] that if multiple users are present, the second user inserts noise in the data collected which significantly reduces the accuracy of the training of the classifier and recognition of ADL. So, ID sensor can necessarily solve this problem.

Passive RFID deployed with household utensils and users carrying the reader could be a good solution for reducing noise from other users [4]. However, RFID tags cannot be attached with all the utensils, such as mug that is put inside the micro woven. The observation was pointed out in [2].Moreover, RFID reader needs to be in close contact with the tags that discourages tag deployment in doors and furniture. So, a mixed deployment of sensors and RFID tags are more likely where users carrying ID sensors are very much helpful. Without loss of generality, RFID tag readers can be augmented with a beacon sensor and can work both as ID sensors and RFID readers. Neighboring clusters receiving the broadcasts (ID and tag information) can do the association task and also generate proximity information for the RFID tags.

Researchers [5,6] are also experimenting with body wear sensors for detecting few ADLs like dietary activity due to the fact that body wear sensors provide higher accuracy for fine grained activities as such. A prototype has also made to detect activities by embedding sensors on mobile phone [6]. So, it is not much demanding a beacon sensor to be carried by the user.

Interestingly, all the above approaches are essentially trying to solve the problem of single user activity. Multi object recognition problem can be approached with tracking and filtering.

Tracking can detect key location based activity detection. Work [7] proposes a location based tracking and activity detection. But the idea does not scale to the environment with many simple sensors deployed. Because, the filtering algorithms used for tracking needs input of domain or common sense knowledge otherwise the reasoning may take huge computation and memory and can in fact become intractable. For deployed sensors there are enormous ways of interacting with them that restricting the search space for the filtering algorithm is difficult and hence the system may make wrong decision about users' activities as depicted in the scenario of Alice and Bob. ID sensor can generate proximity event along with user's identification. So, the system is not left with guessing about users' movements. The failure of tracking system for multi user activity detection in home environment is the main motivation for us to propose ID sensors.

Attributing events to individuals in multi-inhabitant environment has recently been addressed in [9]. The work proposed users past behavior information be used to for the event association. But it is not pragmatic, what if the users change their behavior as in the case of Alice and Bob. The solution suffers the same problem as tracking.

Our clustering algorithm is not for wireless sensor network in harsh environment where focus is on maximizing network lifetime by balancing the assignment of cluster heads and reducing the energy expenditure for the sensor nodes (see [11,12] for an overview of some clustering algorithms in WSN). Rather, our focus is to group sensor nodes, in near proximity, under a cluster head. The cluster head is supposed to have unlimited power supply. Our contribution is not in the wireless sensor network, rather use of the clustering algorithm and ID sensor for the sensor event attribution problem facilitating multi-user activity recognition.

3 Main Idea

We assume a home where simple ubiquitous sensors are deployed for everyday activity detection. The users are carrying ID sensors with them, so that sensor activation can be associated with them. It is possible that passive sensors like RFID may also be installed within the system. RFID are usually tagged with moving objects and in such a case users are supposed to be carrying RFID readers with them [4]. The reader can easily act as an ID sensor. The functionality of the ID sensor is just to transmit beacon periodically in a short range of about 1~1.5 meter. The transmission range of 1~1.5 meter is based on the fact that human being walks at a speed of 4-5 km/hour in an open space which is equivalently 1-1.5m/sec. Hence a beacon signal should remain valid for 1 sec. If a beacon signal is not received after 1 sec, the user is supposed not to be present there.

The beacon signals can be received by the sensors and if this sensor is activated, it is associated with the user carrying the ID sensor. But, it is communication intensive for the sensors to send the beacons received, to the sink node. Even if sensor keep the beacon received with itself, until it is activated, the sensor has to stay awake. This is also costly. So, we propose a maximum neighbor based clustering algorithm for our problem. Maximum neighbor based algorithm is because sensors are usually deployed in small clusters in the household utensils and the algorithm will usually select only one cluster head for a group of sensors. The cluster heads will be receiving and associating the beacons with the activated sensors. Otherwise cluster heads and sensors activated can send their information directly to the sink node where the association task can be performed. We propose selecting cluster heads because, only those sensors are entrusted with high communication responsibilities and need unlimited power source. The proposal works in two phases. In the first phase, the clustering algorithm is run to select the cluster heads. The heads show signs to the user, so that they are provided unlimited power supply. Then the sensors enter into second phase when usual sensors wait for events, cluster heads receive the beacon signals and ID sensors broadcast periodically. There is a possibility that a sensor is activated but the cluster head has not got any beacon signal. In such a case, the beacon signal of previous second can be used. Otherwise, the event is associated with anonymous user.

A sensor node declares itself as cluster head if it has the maximum number of neighbors and has the minimum id among its neighboring sensors. Initially all the sensors set their transmission range to 1 meter and broadcast their ids. Neighboring sensors count number of neighbors and broadcast the numbers. Based on the information and its own id, a sensor can decide whether to claim the cluster head. There might be a case that no neighbor claims the cluster head. In that case the sensor itself (whatever may be the number of neighbors and id) claim the cluster head. Once the cluster heads are decided, they are given unlimited power supply. So, the cluster heads can provide distributed computing power facilitating distributed lightweight activity recognition such as [8,10].

If the cluster heads are to process the sensor events, they associate the events received from neighboring sensors with the users by using their beacon information received from ID sensors. Sometimes beacons might be missing in which case previous seconds beacon is used.

Phase I: clustering algorithm

```
1.  for each sensor except the ID sensors do
2.      Set the transmission range of the sensors to 1 meter;
3.      while  timer1 != TIME_OUT1 do(parallel)
4.          broadcast the id;
5.          save the broadcasts received;
6.      end
7.      count the number of neighbors (including itself);
8.      while timer2 != TIME_OUT2 do
9.          broadcast the number of neighbors;
10.     end
11.     if this sensor has the lowest id among the sensors having
        maximum neighbors do
12.         claim cluster head;
13.         while timer3 != TIME_OUT3 do ( parallel)
14.             Broadcast the claim;
15.             receive and save neighbors' messages joining the
                cluster;
16.         end
17.     else if no neighbor claimed cluster head do
18.         wait(TIME_OUT3);
19.         same as lines 12~16;
20.     else
21.         wait for some sensors to claim the cluster head;
22.         send joining message to the cluster head;
23.     end
34. end
```

Phase II:

```
1.  for each ID sensors do
2.      broadcast the ID;
3.      wait(1 sec);
4.  end
```

```
//Scenario I (distributed processing):
for each cluster head do (parallel)
    listen to beacons;
    store the beacons received until invalidated; keep history of
    previous 1 second beacon;
    listen to the sensor events from neighboring sensors;
    associate the event with current beacon(s) or previous second's
    beacon(s), if there is no current beacon;
    send the association to the sink;
end
for each sensor do
    send the state change events to the cluster head;
end
```

4 Simulation

We designed a simulation program to judge the practicability of the idea. It simulates simple user movement patterns in a 10X10 square meter space with 100 sensors. The space represents a typical small apartment. We also augmented our work with an implementation prototype.

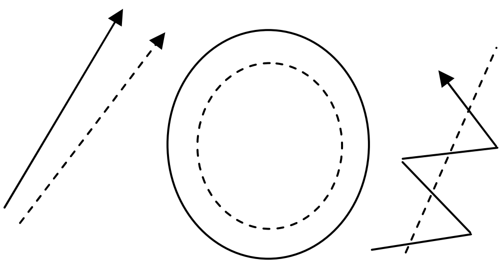

Figure 2. User Movement Pattern

The sensors' deployed coordinates are assumed randomly and then cluster head selection process is run. After that ID sensor's movement pattern is performed as straight lines in different directions, circles of different radius and zigzag pattern with a maximum deviation from the main axis. After every simulation time unit, the ID sensor's position is calculated with different walking speed of 0.5 meter (walking slowly) to 3meter/second (running fast). Simulation time unit is chosen to be 0.5 sec. Then ID sensor's beacon is broadcasted (after every alternative simulation unit). Cluster heads keep the ID, with a probability of [1-P(Beacon Loss)], if The ID sensor is within the range selected for the particular simulation (1 and 1.5 meter). Whether not to activate any sensor is determined by P(Not Activate) and the rest of the probability is distributed uniformly among the sensors within the reach. After a sensor is decided to be activated, its cluster head associate the event with the beacon(s)/ID(s) the head has in its list according to our algorithm.

Table I: Simulation Parameters

Parameter	Value
P(Beacon Loss)	1/10
P(Not Activate)	1/20
Walking speed	0.5~3 meter/sec
Beacon Valid period/ Broadcast Interval	1 sec
Beacon range	1meter and 1.5 meter
Simulation time unit	0.5sec
Stopping criteria	1000 sensor event
Number of simulation runs	200

The simulation was evaluated using two parameters: False Negative and False Positive event. False Negative occurs when the user activates a sensor but the event is not attributed to him. False Positive means the opposite, i.e. the user did not trigger an event but the event is attributed to him.

With a single user roaming around, the simulation results shows that there is no False Negative except 1% and 0.5% for walking speed of 3meter/sec and beacon range of 1 and 1.5 meter respectively. However, with slow walking speed of 0.5 meter/sec or fast walking speed of 3 meter/sec, there are False Positives (0.5%) when two users are present. Though 3 meter/sec is a very unlikely speed for a person in home, 0.5 meter/sec is very common. However, the slow walking speed means the users are socializing closely and no algorithm can reduce this error margin.

5 Implementation

We implemented a simple setup with 9 sensors from Crossbow's WSN Kit. We used MIB520 as interfacing board and MPR2400CA as zigbee sensors. We created two clusters each consisting of 3 sensors. Of the 3 sensors, one is the cluster head. The cluster heads do not have any sensing functionality except receiving the beacon signals and the sensor events and do the association. We took two ID sensors to simulate two moving users. Sensing nodes implement user proximity by short range infrared light sensors. When a user with ID sensor walks around any sensing node, sensing node sends the proximity event. The cluster head receives the beacons and the association is done. The association information is then sent to sink node for logging.

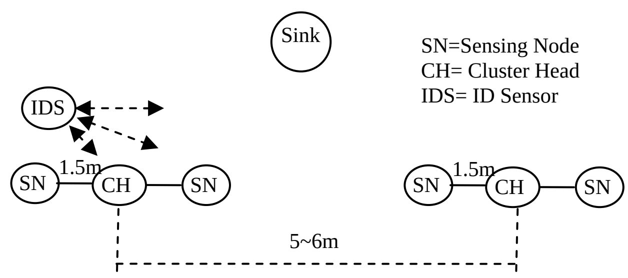

Figure 3. Implementation Scenario

Sensing nodes are placed at a distance of around 1~ 1.5 meters from the cluster head and opposite to each other. Two clusters are placed around 5~6 meter apart. ID sensors have a transmission range of 1~1.5 meter. The range was set experimentally by using the function CC2420Control.setRFPower(unit8_t) and passing para-meter 3. The function can receive parameters from 3~31. 3 means -25dBm and 31 equals to max power (0dBm). The sensor API did not have any function to set the range exactly. So, we had to verify the transmission range for different parameters by putting the sensors at different distances. To be best of our knowledge, we did not find any sensor API that can guarantee the transmission range to a fixed range.

In the real environment, the users were asked to move freely for 5 minutes. The movements were video recorded with timestamps to cross verify the association. On an average, we got False Positives and False Negatives of 0.5% each.

6 Conclusion

We propose a mechanism that will facilitate multiple user activity recognition in a home environment by ensuring correct attribution of events to users. We propose to use ID sensor and a maximum neighborhood based clustering algorithm in the deployed sensor network for the purpose. Simulation and simple implementation assert the validity of the idea.

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