Activity Analyzing with Multisensor Data Correlation

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Abstract. In an ambient assisted living project, a novel way to be proposed in order to protect privacy, increase comfort and safety: a system that with different kinds of sensors installed in the living environment and observe the daily activities of the elderly. Based on the daily activities of the user an activity model will be build. In case of unusual activities the system will send alarm signal to caregiver according the build activity model.

The huge amount data from sensors is a computational burden for the system and an obstacle for the system to get character parameters to build activity model. In the paper data correlation is used to deal with the data and detect the relationship between sensors. In predefined time interval the data from sensors is correlated. The huge amount data is translated to a few correlation parameters between sensors. Furthermore the values of correlation parameters between sensors are changing in different time interval. That means different activities of the user are detected by the system.

Keywords: Activity model, Ambient Assisted Living, Data Correlation, Sensor fusion

1 Introduction

There are many papers about sensor fusion, sensor data correlation: in paper [1] sensor fusion architecture designed to bridge the gap between low-level sensor data and the high-level knowledge. The authors in paper [2] present a probabilistic approach to alert correlation, extending ideas from multisensor data fusion. Paper [3] shows how the spatial correlation can be exploited on the Medium Access Control (MAC) layer. The authors in paper [4] define the concept of sensor databases mixing stored data represented as relations and sensor data represented as time series. Techniques that exploit data correlations in sensor data to minimize communication costs were designed in paper [5]. The authors describe a system that provides a unified view of data handling in sensor networks, incorporating long-term storage, multi-resolution data access and spatio-temporal pattern mining in paper [6]. Some papers in ambient assisted living domain: in paper [7] a project was described that concern the ability to locate and track people within their homes, which based on a standard ceiling mounted camera, an on body accelerometer and simple yet robust image processing. Paper [8] provides a survey on Wireless sensor networks for healthcare. Paper [9] investigates the development of systems that involve different types of sensors, monitoring activities and in order to detect emergency situations or deviations from desirable medical patterns, just like papers [10], [11], [12] from project ATTEND (AdapTive scenario recogniTion for Emergency and Need Detection).

2 Contribution and Innovation

This paper is a further research related my earlier papers [10], [11], [12] based on the same idea: a system observes the activities of the user and builds the daily activities model of the user. According the model in case of unusual activities happened the system will send alarm signal to caregiver. But in papers [10], [11], [12] only motion detector is used to observe the activities of the user all the time. For a more flexible, robust, and accurate observation result many different types of sensors were installed in the living environment of user. For example passive infrared sensor (motion detector), door contactor, accelerometer, temperature sensor, light sensor. Each sensor sends signal to controller when it gets information from environment, such as: person movements, door closed or opened, vibration in the environment, temperature, and light. There are nearly 10,000 signals that the sensors send to controller every day in a real test experiment. How to deal with the huge data and furthermore find the relationship between these sensors are great challenges. In this paper data correlation is used to solve the problem.

Don't like some other ambient assisted living projects in the project ATTEND will be without camera and microphone are used. This is because of privacy issues of the user. At the same time nothing should be wear on the body of the user and nothing should be activated by the user in case of emergency [10]. All of these measures make the user more comfortable but a great challenge to realization. In the following figure 1 the experiment environment and these different types of sensors will be introduced at first. There are sensors installed in different locations of the rooms: at the entrance is sensor 1, at WC is sensor 2, at bathroom is sensor 3, at kitchen are sensors 4 and 5, at living room are sensors 6, 7, 8, 9 and 12, at bedroom is sensor 13, and at restrooms are sensor 10 and 11. Each sensor is multisensor, which means each of them can detect some of the following information: movement, vibration, contactor of the door, temperature and light. For example sensor 1 at the entrance can get all the 5 physical parameters. Sensor 2 at WC has without the ability to detect movement of the user in WC. Sensor 6 in living room can only get information about light, temperature and vibration in the environment.

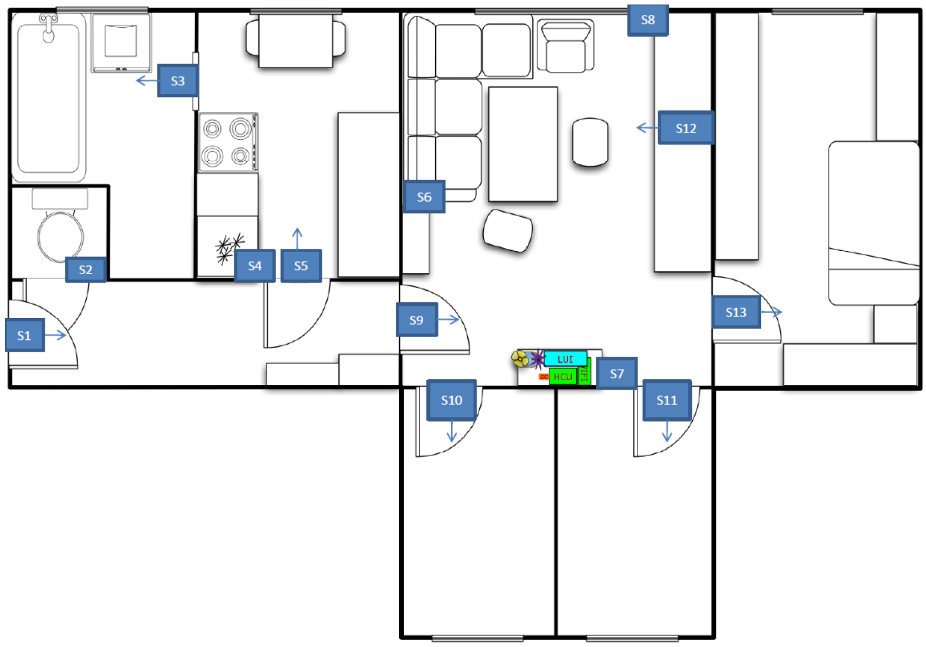

Fig. 1. The experiment environment with different types of sensors.

3 Data Correlation in Predefined Time Interval

Data correlation is used here to measure the relationship between different types of sensors. Because the user has activities in different areas in the rooms in different time of the day, for example at noon the user cooks for lunch, so perhaps activities from the user will be detected by sensor 4 and 5; in the evening the user watches TV in living room, so perhaps sensor 6, 7, 8, 9, and 12 detect activities from the user; at night the user sleeps at bedroom, so perhaps only sensor 13 detects activities from the user, but if the user goes from living room to WC, then goes to bathroom, then comes back to living room, so most of the sensors will be detect activities of the user. With sensor data correlation the relationship between these sensors will be find out.

Because of the user have activities in different areas in different time. So the relationship between sensors changes from time to time, in this paper we predefine a time interval (T_{int}), and try to find out the sensors relationship in the time interval. For example the sensor 1 has value $X=[x_1, x_2,\ldots x_t]$; the sensor 2 has value $Y=[y_1, y_2,\ldots y_t]$; Sensor 1 and 2 compose a set pair $[x_t, y_t]$ in time interval T_{int}.

1) The variance of X and Y

$$Var(X) = E[(X-\mu_x)];\ Var(Y) = E[(Y-\mu_y)] \qquad (1)$$

Here μ_x and μ_y are the mean value of X and Y.

2) The covariance of X and Y

$$Cov(X,Y) = E[(X-\mu_x)(Y-\mu_y)] \tag{2}$$

3) The correlation coefficient between X and Y

$$R_{xy} = Cov(X,Y) / \sqrt{Var(X)Var(Y)} \tag{3}$$

Because of Cauchy-Schwarz inequality $|Cov(X,Y)| \leq \sqrt{Var(X)Var(Y)}$, so $-1 \leq R_{xy} \leq 1$. If sensor data X and Y without relationship (they are independent) $Cov(X,Y)=0$, so $R_{xy} = 0$. If sensor data X and Y are the same values in time interval T_{int}, because of $Cov(X,Y)=E(XY)-E(X)E(Y)$, so $Cov(X,X)=E(XX)-E(X)E(X)=E(X^2)-(E(X))^2 = Var(X)$. So $R_{xy} = 1$.

In above figure 1 there are not only 2 sensors 1 and 2 but totally 13 sensors, so the correlations between sensors have to be done between each pair of the sensors. That means sensor 1 correlates with sensor 2, gets value $R_{1,2}$, then sensor 1 correlates with sensor 3 and gets value $R_{1,3}$, till all other sensors correlated with sensor 1. Then sensor 2 will be correlates with all other sensors and gets $R_{2,n}$. Here n means other different sensors. The correlation result shows in the following paragraph.

4 Result and Discussion

The figure 2 shows the sensors data correlation result. Here T_{int} is predefined as 15 minutes. The figure 2 displays the sensor data correlation result in the evening from 22:00 to 22:15. In the figure sensor 6 correlated with sensor 7, 8, and 13 with the same value 0.7008. Sensor 7 correlated with sensor 8 and 13 with value 1, with sensor 6 with value 0.7008. Sensor 8 correlated with sensor 7 and 13 with value 1, with sensor 6 with value 0.7008. Sensor 13 correlated with sensor 7 and 8 with value 1, with sensor 6 with value 0.7008. The result illustrated that the user has activities from 22:00 to 22:15 and the activities happened in living room and bedroom.

The figure 3 shows the sensor data correlation result in another time interval from 1:30 to 1:45. Figure 3 demonstrates that the sensors 6, 7, and 8 in living room correlated well with value 1. At the same time interval sensor 1 and 2 correlated too with value 0.8345. Furthermore the sensors in living room correlated with the sensor 2 at WC. So from the correlation result the system can judge that the user through living room goes to WC at night.

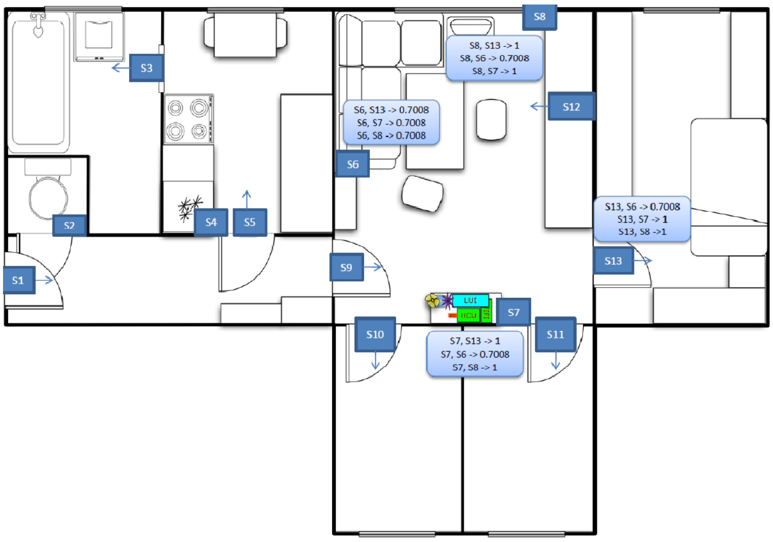

Fig. 2. The sensor data correlation result in the evening

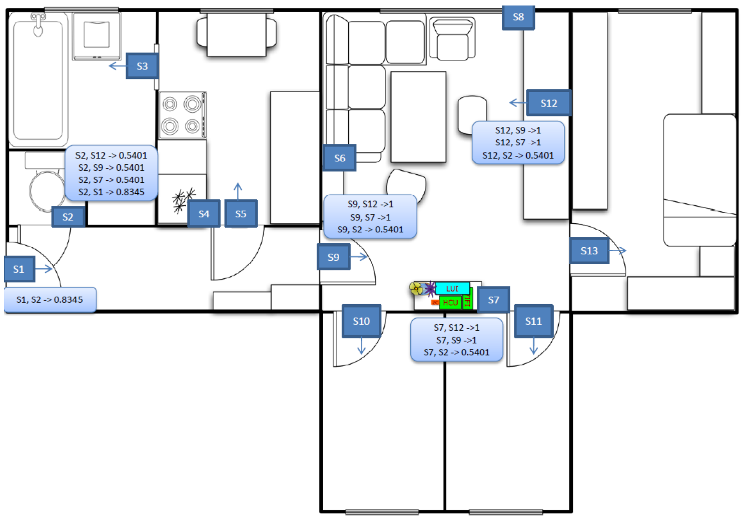

Fig. 3. The sensor data correlation result at night

The above two examples illustrated that sensor data correlation cannot only detect the relationship between sensors but also when and where the activities happened by the user. Through comparing the result from figure 2 and 3 we can see that the correlation value changed in different time interval. This is because each sensor has limited observation area and the activities from the user are perhaps different in different time interval. If the activities happened at noon in kitchen so sensors 4 and 5 should be correlated. If the activities happened in the evening at living room so sensors 6, 7, 8, 9 and 12 should be correlated. But if the activities changed from time to time, even at the same location the correlation result should be not the same in different time interval.

5 Conclusion and Further Work

In this paper we illustrated sensor data correlation for ambient assisted living: sensor data from different types of sensors correlated in predefined time interval, and detected the relationship between sensors in the whole living environment of the user. According the correlation result the system knows when and where the activities happened. With the correlation result we can furthermore to search and build the activities model of the user. This is the work in the next step. Communicating sensor fusion and hidden Markov model together build flexible, robust, and as possible as accurate activities model of the user.

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