DETECTION OF COMPLEX ACTIVITIES USING AAL ORIENTED SENSOR NETWORK

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I. Introduction

The concept, Ambient Assisted Living (AAL) aims to utilize the recent technological achievements. These made possible to create systems, which can enhance the quality of living, without requiring any direct interaction between the system and the person. Our research aims to create methods and a system, which monitors an elderly person in order to observe his or her daily activities [1][2]. A short-term observation can prevent or detect accidents; a long-term observation can detect the first signs of dementia or other disorders. To specify the exact aims of the activity detector, the following activities are detected in the current version:

- Entering or leaving the apartment
- Sleeping or resting
- Using the toilet or bathroom
- Dining
- Dangerous situations (Not moving for a long time, heater left on, fridge left open)

This paper presents an initial method for detecting activities and based on that experiences we show some future development ideas.

II. Description of the system

Our test environment/laboratory contains motion, contact, load cell (strain gauge) and electric consumption sensors. The contact sensors are used to monitor the state of doors and windows, like the apartment door, or the fridge door. The load sensors are monitoring some furniture, like the kitchen chair and the bed (their outputs are binary). Most of the sensors are "off-the-shelf" products, communicating over a wireless network. The coordinator of the network is a PC, with Linux operational system. The signals of the sensors are transferred to a system bus, called the DBUS, which is designed for inter-process communications. The transfer to the DBUS made by device manager software which is specialized to these sensors. If we would like to introduce a new type (or a brand new) sensor, we have to implement an additional device manager to the new sensors, but modification of the other parts of the system is not necessary. This is possible due to the well-defined signal structure on the bus.

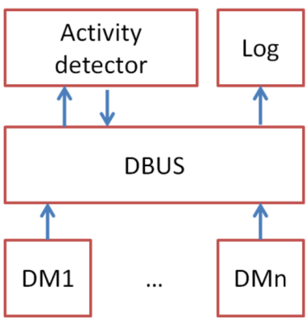

Figure 1: The layered design of the system (DM=Device manager)

The activity detector software is attached to the DBUS and it is subscribed to the relevant sensor interfaces, when a signal on DBUS is sent, a callback function will be activated.

III. Principle of the activity detection

To describe the events we specified an event (e.g. the breakfast) descriptor, looks like:

	Start event	Required sequential event(s)	Required not ordered event(s)	Likely event(s)	Unlikely event(s)	Final event
Event name(s)	*Entering kitchen*	-	*[Using heater, using fridge, using chair]*	-	-	*Leaving kitchen*
Earliest start time	*6:00 AM*	-	-	-	-	-
Latest start time	10:00 AM	-	-	-	-	-
Min. duration [minute]	-	-	[5,1,5]	-	-	-
Max. Duration [minute]	-	-	[20,5,30]	-	-	-

Table 1: The activity descriptor of breakfast

For each activity we have to define the descriptor shown above. For the detection, we used a Finite State Machine (FSM), but it is extended with uncertain states. Uncertain states have a number of sub-states, each sub-state has a probability, these probabilities sum up to 1. When the system enters an uncertain state, one of the sub-states becomes active; the selection of the sub-state is based on its prior probability. Further sensor events can influence the sub-states probability values, therefore they can change the active sub-state. We can influence the probabilities with the elapsed time in the sub-state or with the time of the day as well. The update of the sub-state probabilities uses the following Bayesian method that can be shown most easily by an example. Assume that, when the patient is on the bed, there are 3 possible activities: resting (RT), reading (RD) or sleeping (S) and we have 2 sensors: a motion (M) sensor pointed to the bed and an electric consumption meter, so we can tell when the reading lamp (L) is on. For example the updated probability value of the sleeping (P(S|M,L)) sub-state can determined with the following formula:

$$P(S|M,L) = \frac{P(M,L|S)\cdot P(S)}{P(M,L|S)\cdot P(S)+P(M,L|RD)\cdot P(RD)+P(M,L|RT)\cdot P(RT)} \quad (1)$$

where the P(S) is the prior probability of the sleeping sub-state, and the measurement was moving and lamp on (M,L). In the nominator the prior probability of the sub-state is multiplied with the conditional probability of the measurement. The denominator only contains the normalization, to ensure:

$$P(S) + P(RD) + P(RT) = 1 \quad (2)$$

The conditional probabilities of the measurements can be determined with statistical methods, or if we are lack of samples we fill the conditional probability table (CPT) based on earlier experiences. With this simplification the resulted values are not probabilities, rather scores. For example:

	Moving	~Moving
Sleeping	P(M|S)=0.1	P(~M|S)=0.9
~Sleeping	P(M|~S)=0.7	P(~M|~S)=0.3

Table 2: An example of CPT for binary case

In more complex instances the CPT can be very large; to avoid filling all values we made another simplification in the activity detector software. By the configuration of the software, the expert user only has to give that the specific sensor event increases or decreases the score of a sub-state. If we have more sensors of the same type, we can assign weight values for the sensors. From these inputs, the CPT can be generated automatically, after that we can still modify particular values, if it is necessary.

As we mentioned earlier the score of a sub-state is influenced by time too. We achieved this by adding time as a virtual sensor, so there is a time related score in the CPT's. This score is a function of the elapsed time in the actual active sub-state and time-of-the-day, this two parts are calculated separately. To get the aggregated time related score, these two values are multiplied. For the calculation of each score, we composed two logistic functions (Fig. 2.), so the time related score is calculated from 4 logistic curves. There are 5 time related parameters for each sub-state:

- Earliest start time (center of the 1st curve)
- Latest start time (center of the 2nd curve)

Time-of-the-day related score (Fig. 2.)

- Minimal duration (center of the 3rd curve)
- Maximal duration (center of the 4th curve)

Elapsed time related score

- Steepness of the logistic curve (usually constant for all sub-states)

It is possible to make time independent sub-states probabilities, e.g. bathroom usage can happen any time in a day.

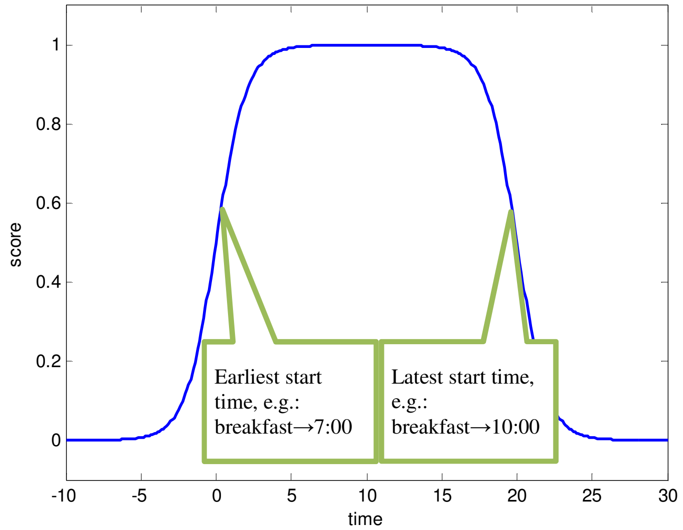

Figure 2: The logistic functions for the calculation of the time-of-the-day related score

Another extension is that we can add conditions for state transitions, a transition can only fire, when a particular state was active. This is useful when there is a precondition for an activity. The FSM can model these preconditions without conditional state transitions, but it needs more states, and the complexity of the FSM should be limited, because a human expert has to handle it.

The output of the activity detector is a DBUS signal for each activity we would like to detect. We can send event signals and activity signals, the difference between them is that the activity signal contains a duration parameter, the event signals are related to momentary events. We can attach an event signal sending method to every state transition, or an activity signal sending method to every state leaving event, where we can send the elapsed time in the state.

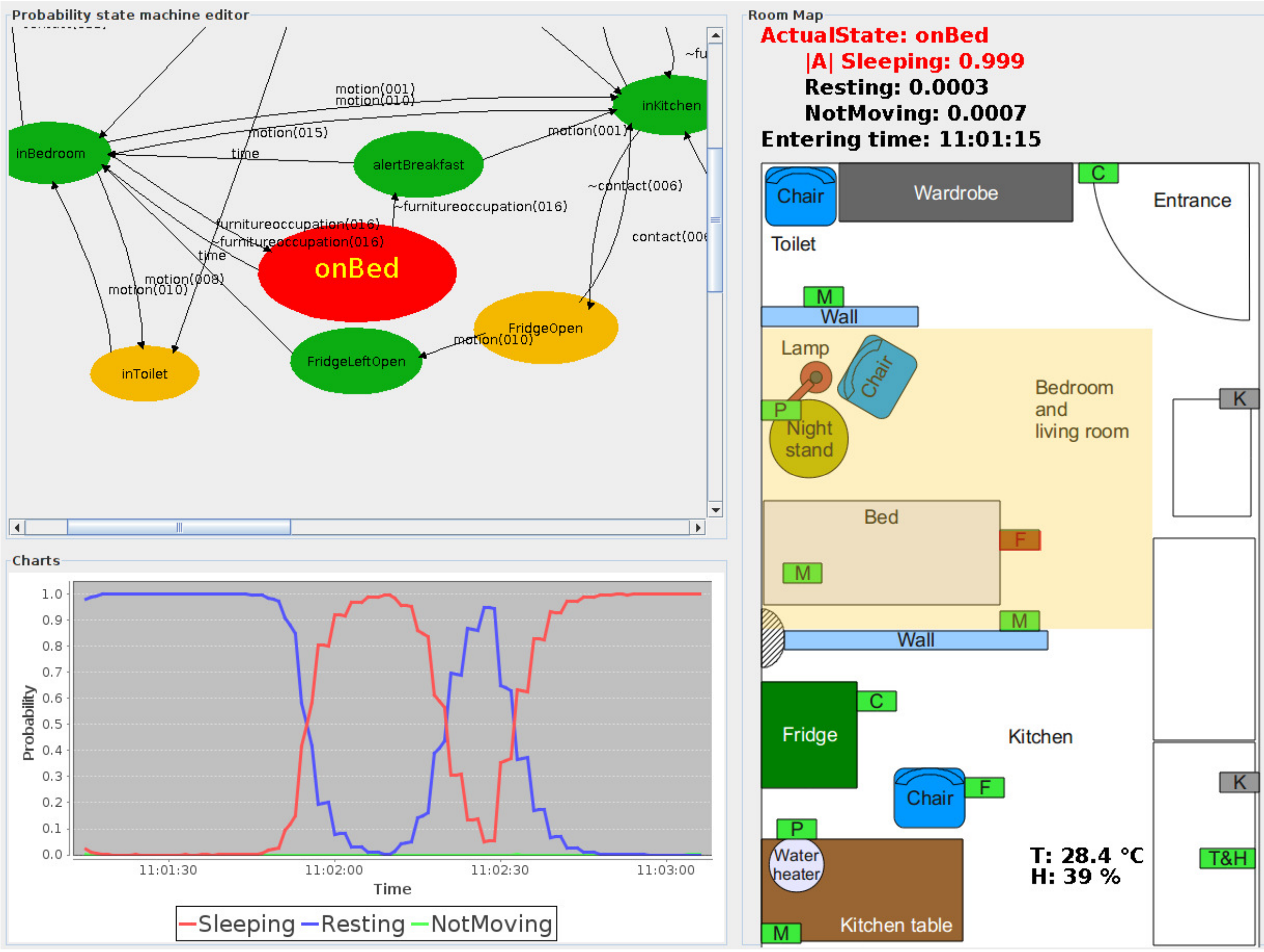

Figure 3: The screenshot of the activity detector

IV. Conclusion and Further Work

This system was successfully tested in our laboratory, and it can detect activities we mentioned above. We used a 10 minutes long test scenario to validate the activity detector's proper operation. A test patient is entered the apartment, then started activities like sleeping, using the bathroom and having breakfast. We implemented three alert events: the system is alerted the patient when the fridge door is left open and an alert was sent to the observers when the patient was in the bed, but no movement happened for a given time. At the end of the test, the patient left the apartment, and an SMS alert was sent to the observers.

The main drawback of the FSM model is that, the number of states can explode, when we would like to detect parallel activities or asynchronous events. A second version of the activity detector is being developed and analyzed. It models the activities in the apartment as probability processes. The outputs of the processes are connected to an evaluation module, which output is the probability of the current activity.

References

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[2] Emmanuel Munguia Tapia Stephen S. Intille Kent Larson, "Activity Recognition in the Home Using Simple and Ubiquitous Sensors", *Lecture Notes in Computer Science*, 2004, Volume 3001/2004, 158-175