A sensing and annotation system for recording datasets in multiple homes

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Abstract
Models for activity recognition require large annotated datasets. We describe our sensor and annotation system and give our experiences in recording datasets.

Keywords
Sensors, annotation, activity modeling, datasets.

ACM Classification Keywords
H5.2. Information interfaces and presentation (e.g., HCI): User interfaces.

Introduction
Research in human activity recognition in a home is a popular topic of research [3,5]. In most cases a model is used that relates the activity to sensor patterns. The learning of such models is usually done supervised and requires large annotated datasets recorded in different settings. Datasets currently available provide a good start, but often contain too little data [4], are not fully annotated [2] or are recorded in a single home [2,4]. We develop novel models for activity recognition from sensors. To train and test these models we developed a sensing and annotation system which we used to record multiple datasets. This paper describes our system and gives our experiences in recording these datasets.

Sensing and annotation system
Because we want to collect data in many homes, our sensor system was chosen based on ease of installation and minimal intrusion. It is combined with an efficient and inexpensive annotation method.

Sensing
The sensing method consists of wireless network nodes to which off-the-shelf sensors can be attached. They are manufactured by RFM and come with a very rich and well documented API. The standard firmware includes an energy efficient network protocol allowing a

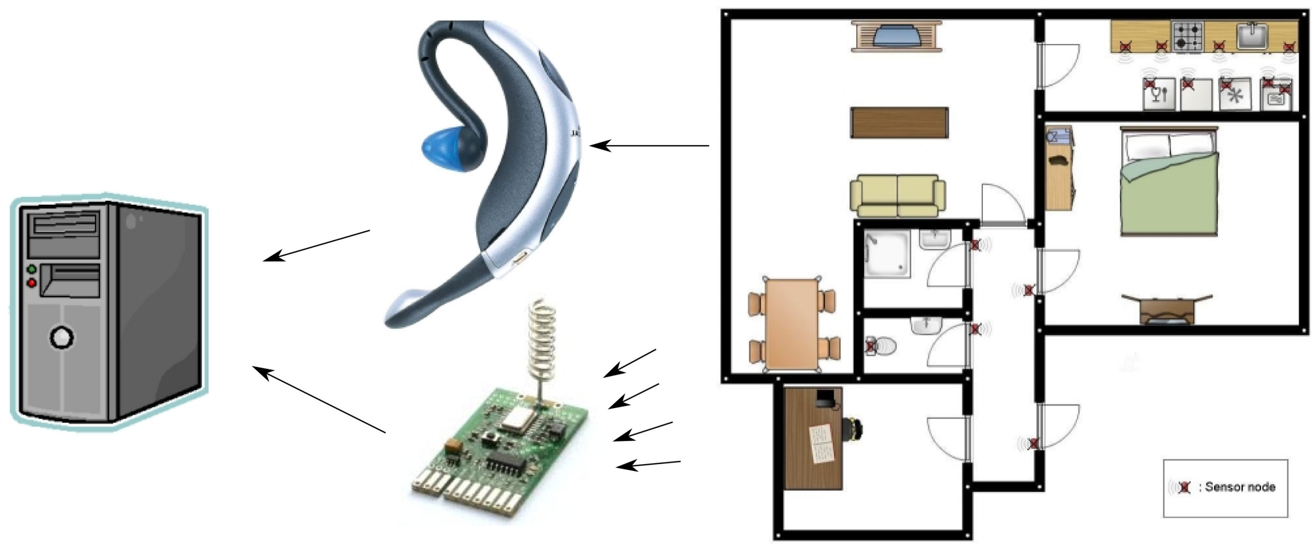

Figure 1: Our system, annotation is done using a headset; sensors send data to a gateway. Everything is stored on a central server.

long battery life. The nodes communicate wireless with a central gateway attached to a server on which all data is logged.

Each node can be equipped with an analog or digital sensor. An event is sent when the digital input changes state or when a threshold on the analog input is violated. Sensors we used include: reed switches to measure open-close states of doors and cupboards; pressure mats to measure sitting on a couch or lying in bed; mercury contacts for movement of objects (e.g. drawers); passive infrared (PIR) to detect motion in a specific area; float sensors to measure the toilet being flushed; temperature sensors to measure the use of the stove or shower. Further details about these sensors can be found in our technical report [6].

Nodes and sensors are installed using tape and depending on the type of sensor require one or more surface contact points.

We have recorded two datasets in the homes of members of our research team, one dataset in the home of an elderly lady and are currently recording two more datasets. Periods of recording range from one to four weeks and around twenty sensors are used in each home. One dataset consisting of 28 days of annotated sensor data is publicly available [5].

Annotation

Annotation is done using a bluetooth headset combined with speech recognition software. The start and end point of an activity are annotated using a predefined set of commands. Activities annotated are: Leave house, Toileting, Showering, Sleeping, Preparing breakfast, Preparing dinner and Preparing a beverage.

We used the Jabra BT250v bluetooth headset for annotation. It has a range of up to 10 meters and battery power for 300 hours standby or 10 hours active talking. The headset contains a button which we used to trigger the software to add a new annotation entry.

The software for storing the annotation was custom made by our research team. It uses the Widcomm bluetooth API to detect when the headset button is pressed and the Microsoft Speech API to perform the speech recognition.

The Microsoft Speech API provides the use of both speech recognition and text to speech. After pressing the button on the headset the speech recognition engine starts listening for commands. We created our own speech grammar, which contains possible combinations of commands the recognition engine could expect. By using very distinctive commands such as 'begin use toilet' and 'begin take shower', the recognition engine had multiple words by which it could distinguish different commands. This resulted in 95% accuracy in speech recognition during annotation. The recognized sentence is outputted using the text-to-speech engine. Any errors that occur can be immediately corrected using a 'correct last' command.

Our custom made annotation software is available for download from: http://www.science.uva.nl/~tlmkaste/

Lessons Learned

Building on previous lessons learned [1], we provide our insights and issues in recording a dataset.

1. To minimize installation time the number of surface contact points should be kept low. For example, reed sensors consist of two parts that need to be aligned. Proper installation and testing can take up to 15 minutes per sensor. Mercury contacts (shake sensors) are easier to install, however, reed sensors provide more information (i.e. door open or closed, instead of door moved).

2. The tape used to install sensors sometimes fails after a few days. It is difficult to predict which sensor will stick due to differences in surfaces. More tape helps, but requires more installation time.

3. The energy efficient firmware causes sensors to wake up on an input event, send the current state and go back to sleep. Sensor data is stored on a central server and the wireless communication works very well.

4. The pressure mats, float sensors and passive infrared sensors work very well. We used some tape on the passive infrared sensor to limit its field of view allowing us to monitor a specific area (e.g. the bathtub). The mercury sensors varied strongly in sensitivity, some required a strong push of the drawer to register the movement. We believe mercury sensors have a great potential to sense the movement of objects, but more sensitive sensors are required. We used the temperature sensor to measure the stove and the warm water pipe leading to the shower. Large differences in temperature due to central heating made it difficult to set a proper threshold.

5. We advise to let the software automatically check the status of the sensors on an hourly basis. By sending an email when any of the sensors fail to report faulty sensors can be quickly detected.

6. The location of the sensors is of great importance for the performance of the recognition system. This is more relevant in small homes where multiple activities occur in a single space, while large homes consist of separate areas for different activities.

7. Annotation using a headset is very efficient because it requires very little post processing. However, our subject reported the active form of annotation as a tiring experience. This is caused by the constant awareness that each activity has to be annotated. An experience sampling method in which the system asks the user the activity performed based on observed sensor data can solve this issue.

Discussion

We feel the most important contribution of this workshop would be to agree on a collection of datasets that will be used as a standard for evaluating models for activity recognition. This will allow us to easily compare different approaches.

The activities of interest depend strongly on the application in mind. What activities do we want annotated in our datasets?

The location of sensors and the type of sensors used strongly influence recognition performance. How do we decide on which sensors to use and where to install them?

The development of tools for visualizing and inspecting sensor data will lead to a standard data structure for storing datasets. This will make it easier to share datasets.

Acknowledgements

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