Walk-through the OPPORTUNITY dataset for activity recognition in sensor rich environments

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Abstract. We aim at activity and context recognition in opportunistic sensor setups. The system ought to make use of sensor modalities that just happen to be available, rather than to rely on specific sensor deployment. In order to assess opportunistic activity recognition methods, we collected a large-scale dataset of complex activities in a highly sensor rich environment, with 72 sensors of 10 modalities in the environment, in objects and on-body. The dataset contains composite and atomic activities in large numbers (>28000 hand interactions). We present the activity scenario and the sensor setup. We show the user's activities and the corresponding sensor signals side by side. We argue that such a visualization may be an efficient form of dataset documentation, especially when such a dataset is shared, as it gives an insight into the complexity of the activities and richness of the sensor setup.

1 Introduction

Typically, activity and context recognition methods rely on sensors placed at well-defined and constant ambient or on-body locations, such as to be able to use machine learning techniques to map sensor signal patterns to activity or context classes. Within the EU FP7 FET-Open project OPPORTUNITY we investigate ways to relax sensor placement constraints for activity and context recognition in pervasive and wearable computing, with new developments along self-organized sensing, opportunistic context recognition methods and autonomous adaptation to changes in the sensing environments [1]. Many sensors are already available (and trends indicate that numbers will increase) in the environment, in objects, and on body and in accessories we carry with us (e.g. mobile phones). Thus, rather than deploying a specific sensor setup for a given activity recognition task, an activity recognition system ought to make best use of available resources. Our current results cover ([1]): methods for sensors to automatically detect their on-body or ambient position, methods for sensors to autonomously learn from others how to recognize context (thus addressing the needs of operation in open ended environments), unsupervised methods to increase robustness to unpredictable sensor placement variability, and adaptive methods to turn an activity recognition system into an autonomic system capable of self-improvement, by using non-attentive brain-signal user feedback.

Eventually, new methods must be assessed and compared. Thus, we collected a large-scale dataset of human activities in a highly sensor rich environment. Opportunistic sensor setups are simulated offline by selecting desired sensor subsets. We present this data set: the activities it contains, the sensor setup, and we visualize some activities and the corresponding sensor signals.

2 Background

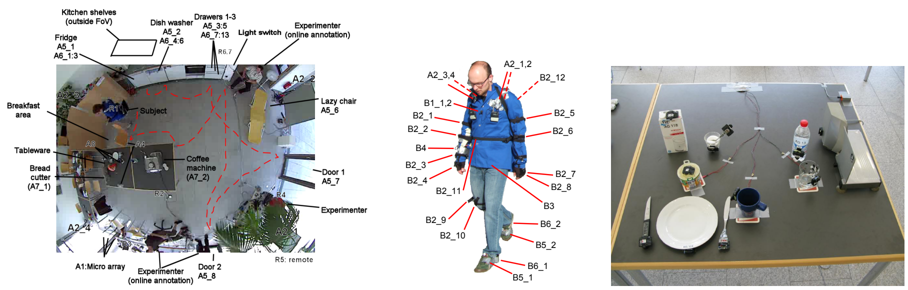
There are a few public datasets. The more known include: the PlaceLab dataset, focusing on ambient and object sensing [2]; Van Kasteren's dataset [3] with particularly long recordings (month-long) but with fewer sensors, and the Darmstadt routine dataset used for unsupervised activity pattern discovery [4], that is a long recording from body activity collected by the Porcupine system [5]. The TUM Kitchen data set is a recent dataset for video-based activity recognition [6]. It also contains RFID and reed switch data, but it does not include on-body sensors. Most of the existing datasets are however not sufficiently rich to investigate opportunistic activity recognition.

3 The OPPORTUNITY dataset

We designed the activity recognition environment and scenario to generate many activity primitives, yet in a realistic manner. Subjects operated in a room simulating a studio flat with a lazy chair, a kitchen, doors giving access to the outside, a coffee machine, a table and a chair (figure 1(a)).

Each subject performed 5 times an activity of daily living (ADL) 'run', and one 'drill run'. The ADL run (15-25 minutes) consists of temporally unfolding situations (from getting up to preparing a coffee, preparing a sandwich, cleaning up, etc). In each situation (e.g. *preparing sandwich*), composite activities (e.g. *cutting bread*) occur as well as atomic activities (e.g. *reach* for bread, *move* to bread cutter, *operate* cutter). An instructor followed the subject in the first run to indicate him the sequence of situations. The subject behaved alone in the following runs. We instructed subjects to follow the high level sequence but to behave naturally. Users were allowed to interleave their actions (e.g. start the sandwich preparation while still taking sips from the coffee cup). The drill run

(20-35 minutes) is designed to generate a large number of activity instances by going through a scripted sequence of interactions with the environment. Still, we encouraged users to behave naturally (e.g. we told subjects not to hesitate to use different hands when interacting).



(a) View of the room from top. Dashed line: typical user trajectory in the drill run. In the ADL runs subjects behaved freely.

(b) Placement of body-worn sensors.

(c) Objects are instrumented with an acceleration and rate of turn sensor node.

Fig. 1. Sensor setup

ID	Sensor system	Location and observation
B1	Commercial wireless microphones	Chest and dominant wrist. Senses user activity
B2	Custom wireless Bluetooth acceleration sensors	12 locations on the body. Senses limb movement
B3	Custom motion jacket	Jacket including 5 commercial RS485-networked XSense inertial measurement units
B4	Custom magnetic relative positioning sensor	Emitter on shoulder, receiver on dominant wrist. Senses distance of hand to body
B5	Commercial Sun SPOT acceleration sensors	One per foot, right below the outer ankle. Senses modes of locomotion
B6	Commercial InertiaCube3 inertial sensor system	One per foot, on the shoe toe box. Senses modes of locomotion
O1	Custom wireless Bluetooth acceleration and rate of turn sensors	On 12 objects used in the scenario. Senses object use
A1	Commercial wired microphone array	4 at one room side. Senses ambient sound
A2	Commercial Ubisense localization system	Corners of the room. Senses user location
A3	Axis network cameras	3 locations, for localization, documentation and visual annotation
A4	XSense inertial sensor	On the table and chair. Senses vibration and use
A5	USB networked acceleration sensors	8, on doors, drawers, shelves and lazy chair. Sense usage
A6	Reed switches	13, on doors, drawers, shelves. Sense usage, provides ground truth
A7	Custom power sensors	Connected to coffee machine and bread cutter. Senses usage
A8	Custom pressure sensos	3 on the table, user placed plates and cups on them. Senses usage

Table 1. Sensor systems deployed in the experimental setup.

We deployed 15 networked sensor systems with 72 sensors of 10 modalities on body (fig. 1(b)), on objects (fig. 1(c)) and in the environment (fig. 1(a)), including motion sensors (inertial and accelerometers), localization, microphone; see table 1 for details.

We synchronized data to annotate them from video footage using a custom software developed by the University of Passau. The annotations are done on four tracks. On track contains modes of locomotion (sitting, standing, walking). Another two tracks indicate the actions of the left and right hand (e.g. reach, grasp, release), with an attribute indicating to which object it applies (e.g. milk, switch, door). The fourth track indicates the high level activities (e.g. prepare sandwich). Twelve subjects executed activities of daily living in this environment (2h per subject). In total 25 hours of data were recorded. Currently 9 out of 60 ADL runs and 1 out of 12 drill runs are annotated. Extrapolating from this, over 11000 interactions with objects and 17000 interactions with the environment may have been recorded. This leads to approximately 57 hours of labels. For more details see [7].

4 Conclusion

A key characteristic of this dataset is to have high number of activity instances (composite and primitives), and especially to include a large number of sensors of different modalities, and potentially even redudent modalities (e.g. motion sensor of different manufacturers at identical locations). This richness is key to realistically simulate opportunistic sensor configurations. This activity dataset is also well suited for other activity recognition purposes. We invite members of the community to contact the OPPORTUNITY consortium to discuss an early access to the dataset.

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References

1. Roggen, D., Förster, K., Calatroni, A., Holleczek, T., Fang, Y., Tröster, G., Lukowicz, P., Pirkl, G., Bannach, D., Kunze, K., Ferscha, A., Holzmann, C., Riener, A., Chavarriaga, R., del R. Millán, J.: Opportunity: Towards opportunistic activity and context recognition systems. In: Proc. 3rd IEEE WoWMoM Workshop on Autononomic and Opportunistic Communications. (2009)
2. Intille, S., Larson, K., Tapia, E., Beaudin, J., Kaushik, P., Nawyn, J., Rockinson, R.: Using a live-in laboratory for ubiquitous computing research. In: Proc. Int. Conf. on Pervasive Computing. (2006) 349–365
3. van Kasteren, T., Noulas, A., Englebienne, G., Kröse, B.: Accurate activity recognition in a home setting. In: Proceedings of the 10th international conference on Ubiquitous computing, ACM Press (2008) 1–9
4. Huynh, T., Fritz, M., Schiele, B.: Discovery of activity patterns using topic models. In: Proceedings of the 10th international conference on Ubiquitous computing, ACM New York, NY, USA (2008) 10–19
5. Van Laerhoven, K., Gellersen, H., Malliaris, Y.: Long-term activity monitoring with a wearable sensor node. In: BSN Workshop. (2006)
6. Tenorth, M., Bandouch, J., Beetz, M.: The TUM kitchen data set of everyday manipulation activities for motion tracking and action recognition. In: IEEE Int. Workshop on Tracking Humans for the Evaluation of their Motion in Image Sequences (THEMIS) at ICCV. (2009)
7. Lukowicz, P., et al.: Recording a complex, multi modal activity data set for context recognition. In: Workshop on Context-Systems Design, Evaluation and Optimisation, 23rd Int. Conf. on Architecture of Computing Systems. (2010)