Towards Dynamically Configurable Context Recognition Systems

Kai Kunze
Graduate School of Engineering
Osaka Prefecture University
1-1 Gakuencho, Osaka, Japan
firstname.lastname@gmail.com

David Bannach
Embedded Systems Lab
University Passau
Innstr. 43, Passau, Germany
firstname.lastname@uni-passau.de

Abstract

General representation, abstraction and exchange definitions are crucial for dynamically configurable context recognition. However, to evaluate potential definitions, suitable standard datasets are needed. This paper presents our effort to create and maintain large scale, multimodal standard datasets for context recognition research. We ourselves used these datasets in previous research to deal with placement effects and presented low-level sensor abstractions in motion based on-body sensing.

Researchers, conducting novel data collections, can rely on the toolchain and the the low-level sensor abstractions summarized in this paper. Additionally, they can draw from our experiences developing and conducting context recognition experiments.

Our toolchain is already a valuable rapid prototyping tool. Still, we plan to extend it to crowd-based sensing, enabling the general public to gather context data, learn more about their lives and contribute to context recognition research.

Applying higher level context reasoning on the gathered context data is a obvious extension to our work.

Motivation

As of today, Context recognition systems, the core enablers of pervasive computing, are still handcrafted for specific application scenarios. To find the right sensors, features and classifiers to recognize non-trivial activities, is sadly more an art than science. Suitable context abstraction and representation formats for context would help for better re-use and self-configuration. Yet, they are missing. To develop and evaluate these formats, there's the need for standardized, multimodal context data collections and corresponding software tools to manage them.

As a basis for discussions about context representation formats, we present the following in this paper:

- a description and pointers to several multimodal context datasets recorded with our toolchain for rapid prototyping.
- a short overview of our toolchain for recording, handling and using large context data sets.
- a placement categorization and low level sensor abstraction for motion based, on-body context recognition (evaluated on the datasets introduced).
- the proposal towards a crowd-sourced context data collection.

All tools introduced are open-sourced. The datasets are in the process of being published.

Sensor-rich context data collection

Compared to the computer vision or speech recognition fields, context recognition still lacks standardized datasets. This makes it very difficult to compare recognition systems, algorithms, models and the usefulness of higher level abstractions. However, compared to other research disciplines recording context recognition datasets proves to be difficult due to the following:

Diverse Sensing Modalities – Often a multitude of different sensors needs to be managed. One needs to deal with the differing physical properties, sampling rate and other peculiarities. .If the application area is relatively unexplored, it is difficult to determine which sensing modality will work best.

User/Environment Augmentation – From a research perspective, the more and the diverse the sensors are that are used in a setup the better. On the other hand, the more sensors the more complex the recordings and the more burden is on the user.

Synchronization – Of course, the sensor streams also need to be synchronized. Activity class assignments get especially tricky if the sensing devices do not supply a steady sampling rate.

Broad Application Scenarios – The user's "Context" a system is to recognize depends highly on a given application scenario. As there are wide application areas for pervasive computing technology, it is not feasible to provide a dataset for every use case.

To tackle a part of these problems and manage the complexity of the recordings better, we developed an integrated toolchain for development, testing and deployment of context recognition systems.

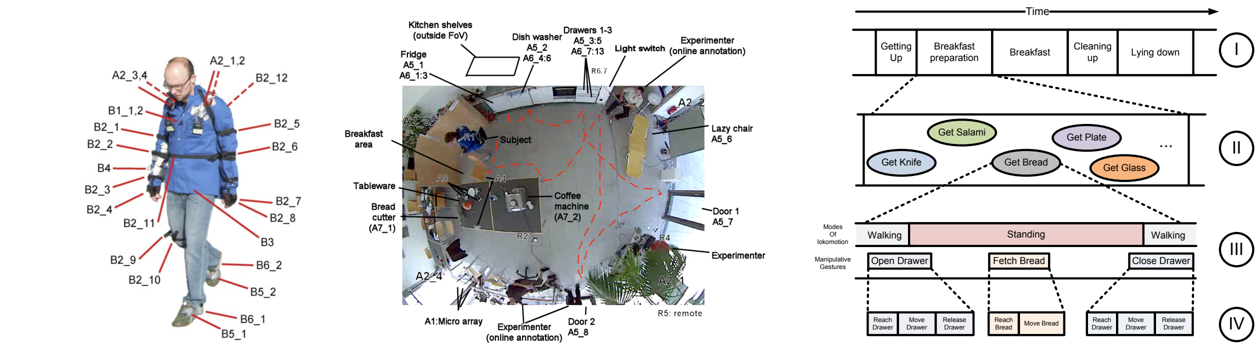

Figure 1: Experimental Setup for the "Everyday living" dataset. On the left, the on-body sensing setup is shown. The picture in the middle depicts the sensors in the environment. On the right, you see a part of the hierarchical activities performed by the test subjects. The experiments were recorded for the Opportunity EU Project. (Roggen, Calatroni, and Rossi 2010)

Toolchain for recording, post-processing and online classification

The toolchain is composed of three parts, as depicted in fig. 3. The first part deals with data collection. We can monitor all sensors, detect failures and signal degradation during this part. After collection, the datasets are stored in a database (an Apache CouchDB in our case). In the data management and annotation step, sensor signals can be plotted, labelled and arranged (channel synchronizations can be adjusted using offsets etc.). Training data traces can be generated in this step. These traces are then used to train machine learning classifiers and enable online context classification in the last step of our toolchain (Bannach and Lukowicz 2011). Core components are explained subsequently:

Context Recognition Network Toolbox (CRNT) – The CRN Toolbox allows for a fast implementation of context recognition systems. It can be also used for synchronized recordings of data streams. It comes with software components provinding a broad range of online signal processing filters and machine learning algorithm. It supports a broad range of mobile and wearable devices.

MASS (Monitoring Application for Sensor Systems) – MASS helps to monitor experiments. It features graphical and tabular views for visualizing sensor up-times and dynamic plots of live sensor signals for quick checking of signal quality.

Labelling Tool– This tool enables us to review and synchronize different sensor streams. We can also assign labels to given sensor signal regions and export data for training classifiers.

Fig. 2 shows some of the software tools used during the three part process.

Available datasets

Even though we developed this context recognition software stack, recording a dataset is still a lot of work. With presenting some of the datasets we recorded we show the usefulness of our software stack and give other researchers the possibility to utilize our already recorded data for their hypotheses. In the following, we introduce four larger datasets recorded by collaborating researchers and our group utilizing our integrated toolchain:

Everyday living – This is by far the largest data set. It was recorded as part of the Opportunity EU Project. The activities are from everyday living and include "making a sandwich", "pouring coffee", "eating" etc. 12 users repeated the setup 5 times each with a total of 72 sensors (in the environment, on the body and on objects), 10 modalities and 25 hours of data (Roggen, Calatroni, and Rossi 2010). Part of the data is already published under http://www.opportunity-project.eu/challenge/.

Drink and Work –This data set contains mostly sitting activities, working on a computer and taking in food and drinks. In total it includes 6 subjects with 4 reparations each; one experimental run is around 30-40 min. The sensor setup includes motion, capacitive and force resistive sensors on the body of the user (Cheng, Amft, and Lukowicz 2010).

Bicycle Repair – The experimental setup includes repair activities on a bike (attaching a tire, opening screws etc.) with 6 test subjects. Again motion sensors and ultrasonic sensors on the body and in the environment were used (see (Stiefmeier, Ogris, and Junker 2006)).

Car Maintenance – This dataset contains car maintenance activities. 5 subjects are recorded with motion, force resistive sensors, an ultra wide band positioning system and RFID tags (Stiefmeier et al. 2008).

We are currently post-processing these datasets and are preparing them for a public release. Interested researchers can also contact us directly to gain early access to them.

Towards self-configuration and abstraction

Leveraging the multimodal experiments described, we could develop a set of categorizations and low level sensor abstractions, focusing on motion based on-body sensing.

Dealing with on-body placement effects

The vast majority of context recognition research assumes well defined, fixed sensor locations. In every day situations

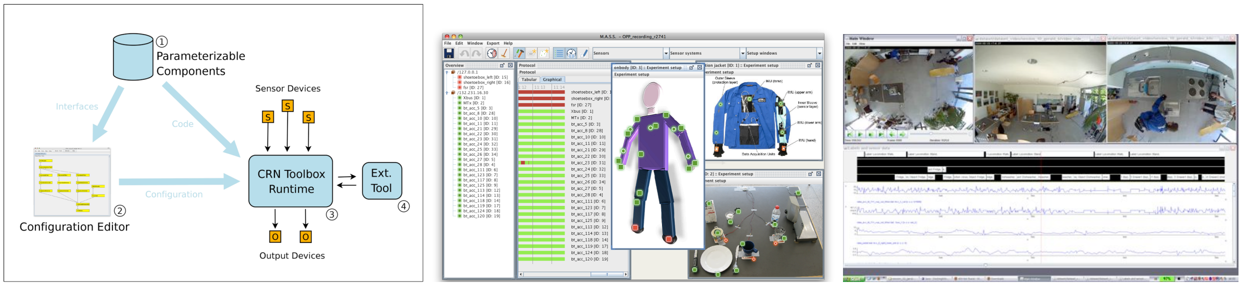

Figure 2: The Context Recognition Network toolbox concept on the left shows a repository of combinable components. The monitoring tool in the middle helps to keep track of sensor failures etc. during recordings. The labeling tool on the right helps to assign context labels and readjust sensor data in post-processing. All software is made available as open source (Bannach and Lukowicz 2011).

sensor placement is often dictated by practicability, usability, and user acceptance constraints rather by the requirements of the recognition system. On-body device placement may also change during deployment. To make context recognition more self-configurable, we developed the following methods (Kunze 2011):

- to detect if a device is carried on the body or placed at a specific location in the environment (on a wooden table, in a closed metal compartment etc.),
- to infer the coarse on-body location (on the wrist, on the torso, ...) of a device, solely based on rotation and acceleration signals of the device.
- to utilize heuristics that significantly increase the robustness of motion sensor-based activity recognition with respect to sensor displacement.
- to detect the orientation of a device related to the users body.

All methods have been empirically evaluated on the elaborate, realistic experimental setups presented above. These inference methods can be used as a starting point for a context categorization of on-body devices. After detecting its on-body placement and orientation, a device is able to decide which type of contextual inference it can provide. For example, a device on the wrist is able to recognize specific arm movements, whereas a device in the trousers pocket is better to infer modes of locomotion.

Sensor abstractions

We also started to investigate low level encapsulations of sensors based on the large scale experimental setups. For example, angular velocity information derived from magnetic field sensors can approximate and replace gyroscope signals (Kunze et al. 2010; Bahle, Kunze, and Lukowicz 2010). We showed to which extend magnetic field sensors and gyroscopes are interchangeable for getting angular velocity (see fig. 5 for a signal example). This is a crucial first step towards dealing with changing sensor configurations and failures.

Although abstractions on the signal level are already valuable, common abstractions on higher levels are crucial for a broader adoption of context recognition. Take the concept of location on mobile devices. The software development kits from Android and iPhone encapsulate the complexity for the developers. The developer does not need to choose if he wants to use cell-tower triangulation, wifi or GPS for localization. The modality is chosen by the SDK depending on the developer's needs. The developer just receives location coordinates.

We need similar encapsulations for other sensing modalities. For example, a straight forward abstraction to introduce for human motion would be a "modes of locomotion" sensor, that can recognize walking, standing etc. If this inference is achieved over a ball switch, gyro, accelerometer or magnetic field sensor should be handled transparently.

Low level primitives, like modes of locomotion, should be straight forward to define given the sensing modalities. However, higher level abstraction primitives will be more difficult, as they might depend on the application scenario, the current circumstances or even the cultural background of the user.

Crowdsourcing context data

In an attempt to get an idea what these higher level primitives might be and to streamline context data recording, we started to develop a version of our toolchain for non-expert use. As a next step, we are remodeling parts of our recoding and labeling tools. We provide a sensor logger for the Android and iOS platforms available in the corresponding application stores for everybody to download. Smartphones today come with a multitude of sensors very similar in quality to the dedicated devices used in research. A prototype, stripped-down version of our labeling tool already runs in a browser (based on html and javascript) and can access the data from the phone loggers.

Of course, we cannot hope that the toolchain, as it is now, will directly be used by ordinary people. Although there might be some very interested users, especially in the quantified-self community, the average user might feel overwhelmed and alienated by raw sensor signals. Therefore, there are some obvious issues to discuss:

- To engage regular people to collect sensor data, we need to provide additional value to them. This can be done in

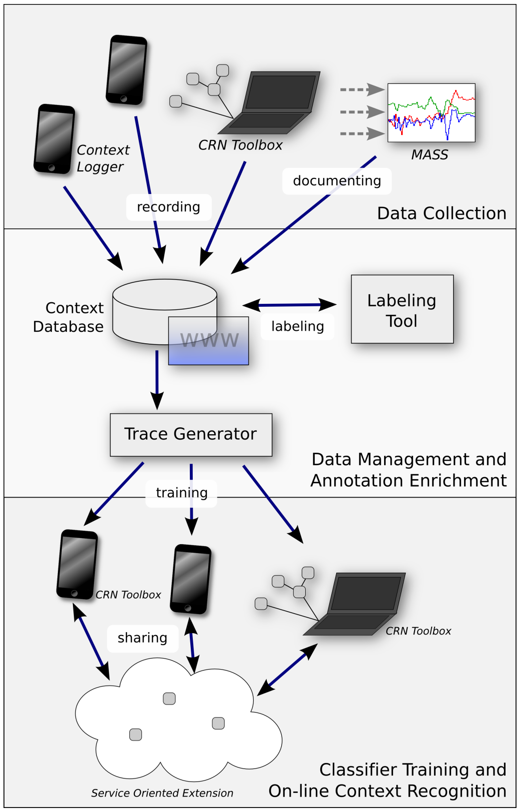

Figure 3: Overview of the three step process of our integrated toolchain (Bannach and Lukowicz 2011)

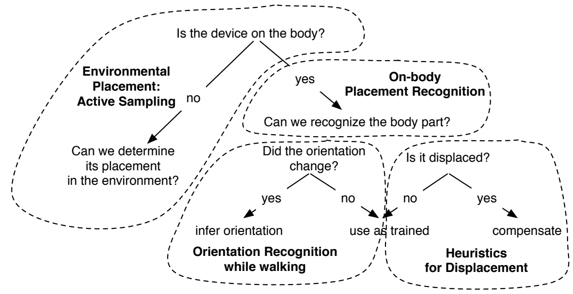

Figure 4: Categorization and contributions dealing with on-body placement effects of single sensing devices (Kunze 2011).

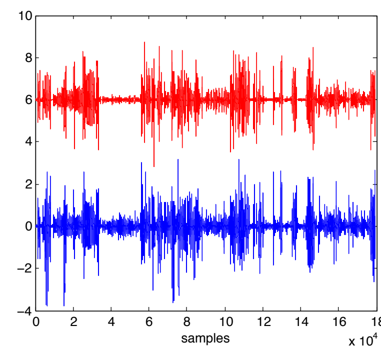

Figure 5: Signal level estimation of angular velocity using the magnetic field sensor vs. the gyroscope. To magnetic field sensor estimation is shifted by six units to make it easier to compare the two signals.

giving the users access to self-tracking information and some rudimentary inference on their collected data.

- Some self-configuration and abstraction primitives need to be introduced, to make handling of the tools easy and enable usable data collections.
- The user interfaces right now are geared towards expert users and require a steep learning curve.
- A lot of users will just have smart phones. Is it possible to provide the complete toolchain on smart phone like devices?
- We cannot expect the same precision and quality in sensor data and labeling from the crowd-sourced collections. On the other hand, there is a plentitude of additional data sources on the phone to tap into (e.g. a lot of people use twitter on their mobiles).

Summary

In this paper we presented our efforts towards creating standardized datasets (and tools to record them) for developing context representations and abstractions. Extensions to our work would include:

- The evaluation of high level context representations on the datasets provided (e.g. testing ontology based context models).
- The use of our tools and expertise to design experiments for evaluation of context representations.
- Collaborations to setup and maintain a crowdsourced context sensing architecture and tools.

Acknowledgements

This work is partially supported by the EU-funded OPPORTUNITY project (http://www.opportunity- project.eu) and the WearIT@Work project (http://www.wearitatwork.com).

References

Bahle, G.; Kunze, K.; and Lukowicz, P. 2010. On the use of magnetic field disturbances as features for activity recognition with on body sensors. In *EuroSSC'10: Proceedings of the 5th European conference on Smart sensing and context*. Passau, Germany: Springer-Verlag.

Bannach, D., and Lukowicz, P. 2011. Integrated Tool Chain for Recording, Handling, and Utilizing Large, Multimodal Context Data Sets for Context Recognition Systems. *Proceedings of the 2nd Workshop on Context-Systems Design, Evaluation and Optimisation.*

Cheng, J.; Amft, O.; and Lukowicz, P. 2010. Active capacitive sensing: Exploring a new wearable sensing modality for activity recognition. *Pervasive Computing*.

Kunze, K.; Bahle, G.; Lukowicz, P.; and Partridge, K. 2010. Can magnetic field sensors replace gyroscopes in wearable sensing applications? In *ISWC '10: Proceedings of the 2010 11th IEEE International Symposium on Wearable Computers*. Seoul, South Korea: IEEE.

Kunze, K. 2011. *Compensating for On-Body Placement Effects in Activity Recognition*. Ph.D. Dissertation, University Passau.

Roggen, D.; Calatroni, A.; and Rossi, M. 2010. Walkthrough the OPPORTUNITY dataset for activity recognition in sensor rich environments. *Adjunct Proceedings of the Eighth International Conference on Pervasive Computing*.

Stiefmeier, T.; Roggen, D.; Ogris, G.; Lukowicz, P.; and Troster, G. 2008. Wearable Activity Tracking in Car Manufacturing. *IEEE Pervasive Computing* 7(2).

Stiefmeier, T.; Ogris, G.; and Junker, H. 2006. Combining motion sensors and ultrasonic hands tracking for continuous activity recognition in a maintenance scenario. *Proceedings of the 2006 IEEE International Symposium on Wearable Computers*.

1