

Human Activity Recognition in Smart Environments

Edited by

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Abstract

This report documents the program and the outcomes of Dagstuhl Seminar 12492 “Human Activity Recognition in Smart Environments”. We established the basis for a scientific community surrounding “activity recognition” by involving researchers from a broad range of related research fields. 30 academic and industry researchers from US, Europe and Asia participated from diverse fields including pervasive computing, over network analysis and computer vision to human computer interaction. The major results of this Seminar are the creation of a activity recognition repository to share information, code, publications and the start of an activity recognition book aimed to serve as a scientific introduction to the field. In the following, we go into more detail about the structure of the seminar, discuss the major outcomes and give an overview about discussions and talks given during the seminar.

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1 Executive Summary

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Today, commercial systems have become popular that utilize a broad range of sensors to facilitate gesture and motion-based interaction. Examples range from multi-touch surfaces, through tilt control common in mobile phone applications, and complex motion-based games controllers, e.g. Nintendo Wii and Microsoft Kinect. While these systems are mainstream, the next basic research challenge is activity-driven, implicit interaction. Two key differences to existing systems are:

1. the interpretation of complex human activities, and
2. the extension of interaction from periods where a user consciously performs control gestures to permanent monitoring of user activity.



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Editors: James L. Crowley, Kai Kunze, Paul Lukowicz, and Albrecht Schmidt



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Conceptually, activity-driven interaction builds on the vision of context awareness developed since the 1990 [1, 2, 3]. Applications range from sports, through mobile gaming, information retrieval, personal healthcare to industrial work support [4, 5, 6]. For example, monitoring certain activities can support therapy in areas ranging from cardiovascular diseases to psychiatric disorders and cognitive disabilities. Activity based support (automatically showing correct manual pages, pointing out mistakes) can speed up industrial maintenance tasks by up to 30%.

Despite demonstrated potential, currently only very simple activity based applications such as physical activity monitoring have managed to go beyond early stage lab demonstrations. From the scientific point of view the question is how to map information available from unreliable, often simple sources onto complex human activities. The main challenges stem from the combination of three factors:

- In every day situations sensor choice, placement and configuration is often dictated by practicability, usability, and user acceptance constraints rather by the requirements of the recognition system. In addition, the system configuration may dynamically change [7, 8].
- The diversity of human behavior. Even the simplest activities can be performed in a multitude of ways differing not only between people, but also between individual execution instances of a single person. (e.g. using different arms, different hand positions, or even the hip to close a drawer)
- The complexity of human behavior. Relevant human actions are seldom atomic and independent. Instead, a complex hierarchy of actions that may be executed in parallel, overlap and interleave is to be considered by the recognition system.

Beyond the technological challenges involved in the recognition system, there are additional unsolved problems including application design, usability, user acceptance, and business models for commercialization.

The field lacks also definitions for many commonly used terms including “action,” “sensor,” “evidence,” and even “activity” itself, leading to ambiguity in scientific discourse. The conceptual grounding provided by Nardi and Kaptelinin’s definition of Activity Theory are perfectly understandable to a human [9]. Yet, they are not easily codified into machine programmable constructs. The theory recognizes that elements of “activity” such as goal and motive are socially constructed, depending on the perspectives of the actors in the system. Despite the complexities of “activity” at the human cognitive level, researchers demonstrated that some notions of activity can be utilized in computer systems, but meanings of terms differ among the various research groups. Currently, many different communities are involved in research related to activity recognition, including the core ubicomp community, human computer interaction, computer vision, cognitive science and artificial intelligence.

Privacy concerns are a critical barrier to adoption of activity-based technologies [10]. These concerns range from risk of criminal activities(e.g., stalking and identity theft), to social issues of managing personal relationships. Technological approaches to addressing the concerns must also be based on deep understanding of the psychological, sociological and political constraints under which people will operate activity-based systems.

The top level objective of the workshop was to define and establish the scientific community and associated research questions/methodologies related to the broad area of activity recognition. The major tangible outcomes are the start of the creation of an activity recognition repository accessible under <http://activity-recognition.github.com> and the plan of writing a standard book about activity recognition.

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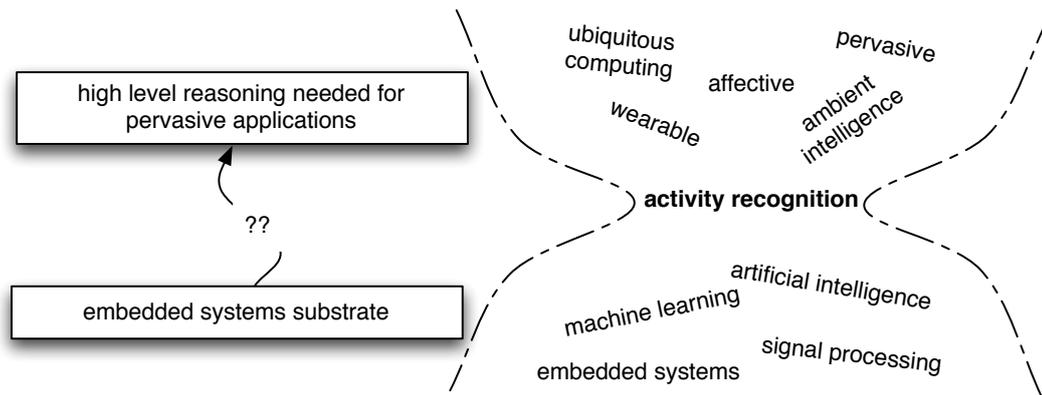
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■ **Figure 1** Activity recognition – the link between our sensor rich environments and high level reasoning.

3 Outcomes

There was broad agreement that activity recognition is the link between our sensor rich environments and high level reasoning about a user’s actions (see Fig. 1). However, the definitions for “activity”, “action”, “sensor” and “activity recognition” depend highly on the research direction. Based on the presentations and discussions during the seminar we can abstract 5 major research directions each with different relations towards activity recognition. They are listed subsequently:

- Sensing – researchers explore novel sensing modalities to detect specific types of activities [2]. Here the focus is on novel sensors for activity recognition, building new hardware prototypes. The activities recognized are usually relatively simple (no complex time series etc.) to emphasize the usefulness of the sensors. The research itself is very practical and evidence based, with an emphasis on elaborate experimental setups. Therefore it’s often difficult to reproduce the results, since building identical sensors involve significant effort and many papers do not contain sufficient details on the hardware.
- Systems – Building activity recognition systems, usually focused on a specific application scenario (e.g. health care, maintenance etc.). This field is very similar to sensing, as it emphasizes the usefulness of a system to a particular application field, also empirical and difficult to reproduce as the systems use often prototype hardware and are fine tuned for a specific environment.
- Machine Learning – researchers work on novel machine learning algorithms and see the field of activity recognition as a suitable application field for the novel algorithms [1]. Although the inference is based on sensors, the hardware itself is secondary. The emphasis of the research is on the type of algorithms and the improvements they bring over other inference approaches. The research focuses is often more theoretical. As long as the datasets and algorithms the research is based on are available, it’s easier to reproduce.
- Middleware – researchers combine different isolated sensing, systems and machine learning solutions to build integrated systems [3]. This field is more on the theoretical side as it tries to build standards to use for exchanging activity recognition information.
- High Level Modeling – to apply higher level reasoning towards lower level activity inference [4]. This research direction deals mainly with applying artificial intelligence reasoning techniques to activity recognition problems. It also looks to cognitive science

for models of how complex activities can be composed of simple actions. Work is often theory focused and can be reproduced more easily, as long as algorithms and datasets are open.

Depending on the research direction, the general understanding of the term “activity” might differ and the interests are very diverse. However, there are two major agreements:

1. Every researcher utilizes a recognition chain for their work (ranging from sensor inputs towards the higher level activity recognition), although the actual implementations and components differ widely.
2. Some sort of hierarchical structure exists for activities in nearly all scenarios (atomic motions/actions towards compositions).

To consolidate the different view points towards activity recognition and facilitate a more closely integrated research community, we decided to work on two distinct projects, which are the major outcomes of the seminar:

1. The creation of a activity recognition repository to enable a single access point for anybody who wants to learn about activity recognition and to provide an ongoing exchange about research methods, code, datasets and other types of information.
2. Planning of an “Activity Recognition” book to introduce interested Master-level students and researcher from other fields to activity recognition.

3.1 Activity Recognition Book

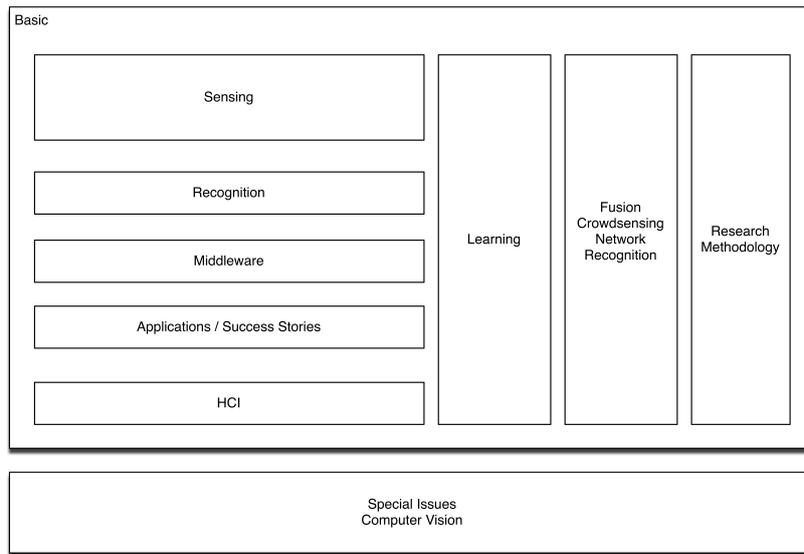
To build the foundation for a new research community around activity recognition, we started with a book project. The goal of the book is to provide a broad introduction into the field of activity recognition. The tentative audience is advanced Bachelor or Master students with some background in Computer Science. The topics brainstormed that should be included are shown in Fig. 2.

During the seminar we succeeded to come up with a general outline (Fig. 3), starting with a introduction that describes the vision of the field and gives the reader already some hands-on applications (to illustrate the usefulness and power of activity recognition). The foundations chapter gives general definitions and an overview about the recognition architectures and the focuses of the different research directions discussed beforehand. The Tools and Systems Chapter is a more practical part, providing the reader with essential background in the recognition chains used. Finally, information sources touches the sensing part of activity recognition, discussing a broad variety of sensors. The problem types mention the issues one can tackle with activity recognition techniques. Finally, the Applications Chapter explains how the new methods learned can be applied using again detailed examples. As activity recognition lives from detailed, extensive experimental setups and empirical evaluations a Research Methodology Chapter is also crucial (as some readers might have a more theoretical Computer Science background).

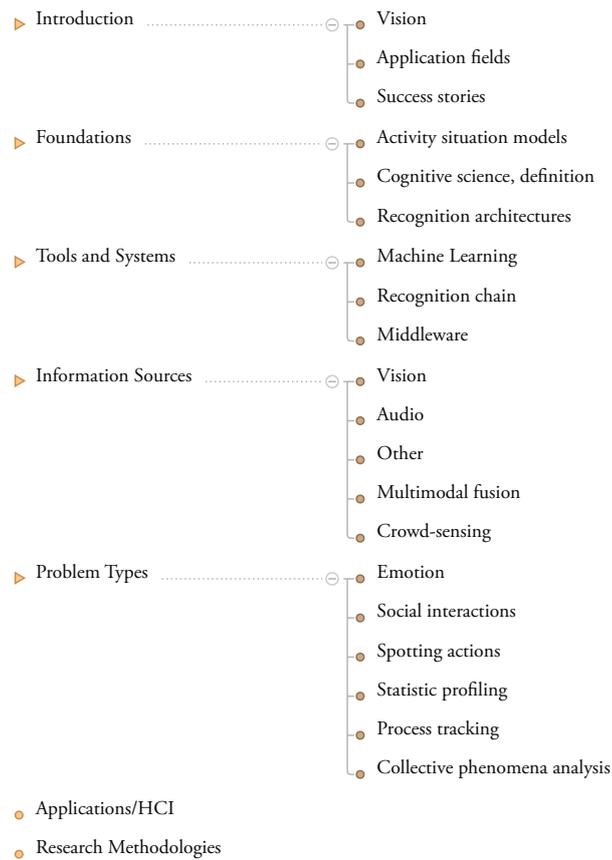
3.2 Activity Recognition Repository

During the workshop we have setup a public repository about information, code and datasets related to activity recognition.

So far, information about activity recognition was distributed among the different research groups and most definitions and explanations focused on a particular type of activity



■ **Figure 2** Topic brainstorming results for the activity recognition book.



■ **Figure 3** Tentative outline of the activity recognition book.



■ **Figure 4** Tentative outline of the activity repository.

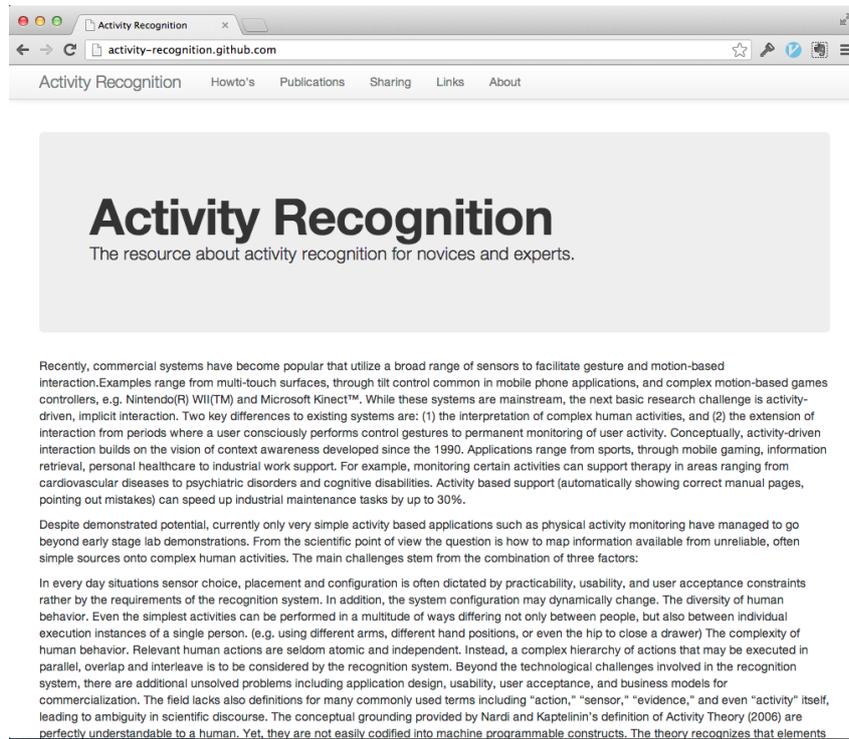
recognition. To overcome this problem we decided to create a central repository where we can gather all types of information about the topic. A first version of the repository website, as seen in Fig. 5 is available under: <http://activity-recognition.github.com> The tentative outline of the repository as concluded during the seminar is shown in Fig. 4. The home page starts with an introduction to the field and the definitions. It contains also a information page with lectures, tutorials and talks centering around activity recognition. The publications page holds all relevant papers and articles. In the sharing section, links to datasets, codes and schematics are included. Followed by information about research groups and publication venues.

The repository is hosted at github, see Fig. 6 (all the source-code is available under a free license), this is done so it's independent from any individual research institution contributing and give people easy access to all information contained on the repository.

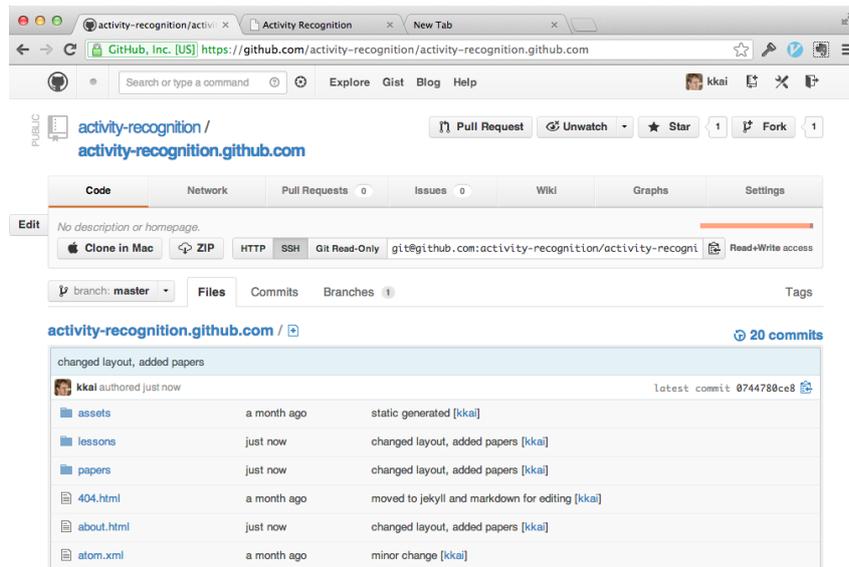
Some only partially resolved issues center around how to make the datasets accessible and how to best use social media. The sections should not be too broad at the beginning to gather enough meaningful data and not have a sparsely-populated site, that might not be helpful.

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■ **Figure 5** Initial version of the activity repository is already online under <http://activity-recognition.github.com>.



■ **Figure 6** Github interface to manage the repository.

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4 Open Problems

In the following we discuss some open problems which could not be completely resolved and need to be tackled in turn by the community and the two projects – repository and book.

4.1 What is an activity?

Although we were able to exchange the definitions used by the different research directions related activity recognition, we did not succeed in defining all terms dealing with this novel research field. In particular, the question of an adequate hierarchical representation and of a taxonomy of relevant activities remained open.

4.2 Reproducibility

Given the nature of activity recognition, some research is hard to reproduce, as it centers around specific hardware (mostly prototype systems) etc. We need a community effort to create a research environment that enables better reproducibility (sharing of schematics, usage of rapid prototyping AR platforms etc.). The same holds for datasets and algorithms. Given there are invite types of “activities” and a wide variety of sensor modalities, we really lack datasets. We really need an openCV for activity recognition to move the filed forward. One of the bigger questions here, was how can we give incentives as a community to ensure reproducibility etc.

5 Keynote Talks

The seminar began with a series of keynote talks as a starting point and to provide common ground for later discussions.

5.1 Wearable and Pervasive Sensor-based Activity Recognition

Paul Lukowicz (DFKI Kaiserslautern, DE)

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Activity Recognition in Smart Environments can be defined as the ability to extract high level information about human actions and complex real world situations from heterogeneous ensembles of often very simple, unreliable sensors. The talk started by discussing the foundations of such systems as well as issues related to sensing and empirical evaluation in complex real life applications. Such applications range from industrial process support

through personal health care, sports and entertainment to the optimization of energy usage at home. Examples were given from divers EU and national project in which I currently participate.

The core of current work on context aware systems involves small groups of devices interacting with a single user or a small groups of users in system configurations specifically designed for often narrowly defined applications. On the other hand, smart phones, home automation devices, robots and other intelligent systems are becoming ubiquitous and are increasingly equipped with flexible networking capabilities. Thus, looking at the future of context aware systems we need to consider large collectives of such devices dynamically forming, cooperating, and interacting with large user populations over a broad range of spatial and temporal scales.

5.2 Analysis of human interactions through complex networks theory

Katharina A. Zweig (TU Kaiserslautern, DE)

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Network analysis provides the uniform framework to analyze big data sets from disciplines as far apart as medicine, sociology, human complex problem solving, cancer biology, and archaeology. Once the problem is represented as a network, various centrality measures, clustering algorithms, and statistical models can be applied to find the most central nodes, the densest subgraphs, or the strongest motifs [1]. Most of us have heard sentences like this for so long, that we do not even question them anymore. In this talk has shown that while all methods are in principle applicable, they come with their own modeling assumptions that might yield their results useless for a specific network. To prove the talk looked at airports with a low degree and a high betweenness centrality are not necessarily anomalous in an economic sense. It also solved the riddle why market basket analysis assumes that Pretty Woman is a good recommendation for somebody who loves Star Wars V. Understanding when to use which method is what I call “network analysis literacy”. To make us all more literate, I finally advocate for a more transparent description of network analytic methods and their implicit modeling assumptions to enable an informed choice of the best measure for a given network analytic question.

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5.3 Socio-inspired ICT

Alois Ferscha (Universität Linz, AT)

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A yet underexplored impact of modern ICT (like e.g. pervasive and ubiquitous computing) relates to services exploiting the “social context” of individuals towards the provision of quality-of-life technologies that aim at the wellbeing of individuals and the welfare of societies”. This talk therefore is concerned with the intersection of social behavior and modern ICT, creating or recreating social conventions and social contexts through the use of

pervasive, omnipresent and participative technologies. An explosive growth of social computing applications such as blogs, email, instant messaging, social networking (Facebook, MySpace, Twitter, LinkedIn etc.), wikis and social bookmarking is observed, profoundly impacting social behavior and life style of human beings while at the same time pushing the boundaries of ICT simultaneously. We aim to investigate interface technologies for one important phenomenon in humans, namely that of “social awareness”. We aim at providing human environment interfaces, which allow individuals and groups to sense, explore and understand their social context.

5.4 Visual Perception of Activities

James L. Crowley (INRIA Rhône-Alpes, FR)

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This talk focuses on vision based activity recognition. Computer vision is a mature research field that had to face similar problems as activity recognition does today (with the limitation of just using one sensor). The talk introduces different problems in computer vision related to activities, from tracking over situation models.

5.5 Recognizing Reading Activities

Koichi Kise (Osaka Prefecture University, JP)

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Today more and more people monitor their daily physical activities, from jogging, over step counting to sleeping to improve the quality of their physical life. We want to achieve the same for reading activities. As reading is fundamental to knowledge acquisition, we would be able to improve the quality of our knowledge life. We use reading, defined as the process of assigning meaning to characters, words and sentences, as a primary information source, recognizing and monitoring reading activities in unconstrained, natural settings is still largely unexplored. We propose reading activity recognition to analyze the whole process of human reading activity and knowledge acquisition [1]. So far, the activity recognition community focused mainly on detecting an activity, yet especially for reading activities it is important to look at the quality of the activity (how instead of what).

References

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6 Overview of Talks

In addition to the keynote talks, a number of additional presentations were given to stimulate discussions and broaden the understanding about interesting topics at hand.

6.1 Bringing Social Computing to Smart Environments: Synergies and Challenges

Elisabeth André (Universität Augsburg, DE)

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Societal challenges create a high demand for technology able to emulate human-style interaction modes. Currently, most human-machine interfaces focus on input that is explicitly issued by human users. However, often it is the myriad of unconsciously conveyed social and psychological signals that will determine whether an interaction with a machine is successful or not. The talk demonstrated how progress made in the areas of social computing and ambient environments can contribute to a deeper symbiosis in human-machine interaction by collecting subtle behavioral cues under naturalistic conditions and linking them to higher-level intentional states. However, on the way to this goal, a number of challenges need to be solved: Users show a great deal of individuality in their behaviors, and there is no clear mapping between behavioral cues and intentional states. This is in particular true for real-life settings where users are exposed to a more diverse set of stimuli than under laboratory conditions. Furthermore, it isn't obvious how to acquire ground truth data against which to evaluate the performance of system components that map unconsciously conveyed behavioral cues onto intentional states. Finally, we need to cope with limited resources when recording social and psychological cues in a mobile context and responding to them in real-time. Apart from technological challenges, psychological, societal and privacy issues need to be taken into account. Based on an analysis of recent activities in the areas of social computing and ambient environments, the talk outlined a road map for future research [1].

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- 1 Johannes Wagner, Jonghwa Kim, and Elisabeth André. From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification. In *Multimedia and Expo, 2005. ICME 2005. IEEE Int'l Conf. on*, pp. 940–943. IEEE, 2005.

6.2 Eye-based activity and context recognition

Andreas Bulling (University of Cambridge, GB)

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The talk discusses the feasibility and potential of eye-based activity recognition, including an assessment of eye tracking techniques, specifically of optical methods that track features on the eye, and of electrooculography (EOG) measuring eye movement with skin electrodes placed near the eyes. Insights into what eye movement reveals about everyday activity

a methods for extraction of features from eye movement patterns that may be useful for activity and context recognition are presented [1].

References

- 1 Andreas Bulling, Jamie A. Ward, Hans Gellersen, and Gerhard Tröster. Robust recognition of reading activity in transit using wearable electrooculography. In *Proc. of Pervasive '08*, pp. 19–37, 2008.

6.3 Where Activity Recognition supports User Interface Plasticity

Joelle Coutaz (Université de Grenoble, FR)

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This short talk presents my background and my interest for Activity Recognition. In short, I do not do “Activity Recognition”, but I need solutions from Activity Recognition to build User Interfaces (UI) that are truly plastic.

UI plasticity is the capacity of a UI to adapt to the context of use while preserving human values. In this “context”, context of use denotes an information space that describes the humans using the system, the physical and social environment where the interaction takes place, and the physical platform (interaction resources) available in this space.

6.4 Interacting with Machine Learning

James Fogarty (University of Washington – Seattle, US)

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This talk provided an overview of the sensing On Shared Datasets and Validation. A concrete example given related to what sensors might predict interruptibility and verifying that implemented sensors are effective, looking more closely at programmer task engagement, demonstrating signal in audio-based water sensing, demonstrating signal in pressure-based water sensing and relating WiFi activity to coffee shop seat availability.

6.5 Social Situations and Co-Activity Detection

Georg Groh, Alexander Lehmann, and Daniel Bader (TU München, DE)

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We introduce our current projects and research directions, our interest in activity recognition, our point of view towards datasets and evaluation and the main research questions in are that are relevant in connection with our research.

The main conceptual axis is social contexts on all temporal scales: From Social Situation models as short term social context to long term social context such as topics of social relations, employing machine learning techniques to detect these contexts. An interesting aspect

are agent models for combining social contexts on various levels of abstraction, ranging from exchanging raw data to collaborative symbolic reasoning on these contexts. Furthermore, we also investigate various applications of social context, such as social recommender systems, privacy for social networking, social information retrieval etc. One specific project is the detection of co-activities, which neglects the actual activity classification and concentrates on identifying common activities among people [1].

References

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6.6 A generalized computational model for complex systems

Jochen Kerdels (FernUniversität in Hagen, DE)

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The use of computer models and simulation is a widely adopted approach to study complex systems. To this end a diverse set of computational models like Cellular Automata, Artificial Neural Networks, or Agent-based simulation is being used. As a common denominator virtually all of these approaches favor different variations of complex systems and are tailored to support the description of systems that fit the corresponding variation well. Although this form of specialization has its benefits like ease of modeling with respect to the particular subset of complex systems, the drawbacks of this specialization are a lack of comparability between structurally different systems and a diminished expressiveness with respect to systems that do not fit any particular subset of complex systems favored by existing, specialized models. In this talk a generalized computational model for complex systems is proposed which allows for the description of most types of systems with a single model. Furthermore, the proposed model provides a high degree of encapsulation and reduces the amount of shared knowledge needed among the constituents of the system. The talk closes with a set of example applications of the proposed model to further illustrate the involved concepts and to provide an intuition on how this model may be used [1].

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6.7 Discovery of Everyday Languages

Daniel Kohlsdorf (Georgia Institute of Technology, US)

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This talk introduces the concept of simultaneously learning patterns and grammar for activity recognition tasks guided by evaluation [1]. We have to find the atomic patterns (Discovery), define their interactions (Grammar) and finally evaluate to see how well our model fits to the real world.

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6.8 Real Life Activity Recognition

Kai Kunze (Osaka Prefecture University, JP)

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This talk investigates how placement variations of electronic devices influence the possibility of using sensors integrated in those devices for activity recognition [1]. The vast majority of activity recognition research assumes well defined, fixed sensor locations. Although this might be acceptable for some application domains (e.g. in an industrial setting), users, in general, will have a hard time coping with these limitations. If one needs to remember to carry dedicated sensors and to adjust their orientation from time to time, the activity recognition system is more distracting than helpful. How can we deal with device location and orientation changes to make activity sensing mainstream?

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- 1 Kai Kunze and Paul Lukowicz. Dealing with sensor displacement in motion-based onbody activity recognition systems. In *Proc. of the 10th Int'l Conf. on Ubiquitous Computing*, pp. 20-29, ACM, 2008.

6.9 Computational Behaviour Analysis

Thomas Plötz (Newcastle University, GB)

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This talk centers around computational (that is statistical) models that describe and will help in assessing human behaviour. The basis for this is the analysis of behavioural data that is captured in a pretty opportunistic way utilising a variety of sensing modalities, most notably pervasive/ubiquitous sensors (e.g., accelerometers, RFID, environmental sensors), cameras, or microphones. The modelling itself is agnostic in terms of the actual choice of sensing modalities as long as the relevant information for behaviour analysis is captured. Behaviour data are sequential by definition. Consequently, related modelling techniques are focused on sequential models (for example of Markovian type). I am especially interested in quantitative assessments of human behaviour, which is of value for, for example, skill assessment. My day-to-day work can probably best be summarised as applied machine learning for activity recognition.

6.10 Multimodal Activity Recognition using Wearable Sensors and Computer Vision

Bernt Schiele (MPI für Informatik – Saarbrücken, DE)

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Understanding sensor information is a fundamental problem in computer science. Scientific challenges cover the entire pipeline from single-sensor processing, over spatial and temporal fusion of multiple and divergent sensor modalities to the complete description of large-scale multimodal sensor streams. At the same time we observe a tremendous increase in both the quantity as well as the diversity of sensor information due to the increasing number of sensors (such as cameras, GPS, or inertial sensors) embedded in a wide variety of digital devices and environments as well as due to the increasing storage of multimodal sensor data (such as surveillance data, personal storage of digital information, multimedia databases, or simply the Internet). While storing and indexing large amounts of sensor data has made tremendous progress, understanding of this multimodal sensor data still lacks far behind. Therefore the long-term goal of our research is to make progress on how to process, structure, access and truly understand multi-sensory data both for online use as well as for large-scale databases.

6.11 Sensitivity for environment-induced RF-channel fluctuation

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We consider the detection of activities from non-cooperating individuals with features obtained on the Radio Frequency channel [1]. Since environmental changes impact the transmission channel between devices, the detection of this alteration can be used to classify environmental situations. We identify relevant features to detect activities of non-actively transmitting subjects. In particular, we distinguish with high accuracy an empty environment or a walking, lying, crawling or standing person, in case-studies of an active, device-free activity recognition system with software defined radios. We distinguish between two cases in which the transmitter is either under the control of the system or ambient. For activity detection the application of one-stage and two-stage classifiers is considered. Apart from the discrimination of the above activities, we can show that a detected activity can also be localised simultaneously within an area of less than 1 meter radius.

References

- 1 Markus Reschke, Sebastian Schwarzl, Johannes Starosta, Stephan Sigg, and Michael Beigl. Context awareness through the rf-channel. *ARCS 2011*, 2011.

6.12 Short Introduction Talks

Additionally, all participants gave short introduction talks about their background split into the sessions depicted in Fig. 7.

Topic	Participants
Interaction I	Elisabeth André (Universität Augsburg, DE) Nora Broy (BMW Group Forschung und Technik GmbH - München, DE) Elizabeth F. Churchill (ACM SIGCHI, US) Joelle Coutaz (Université de Grenoble, FR)
Sensing	Andreas Bulling (University of Cambridge, GB) Jingyuan Cheng (Universität Passau, DE) Gerald Pirkl (DFKI - Kaiserslautern, DE) Kristof Van Laerhoven (TU Darmstadt, DE)
Interaction II	James Fogarty (University of Washington - Seattle, US) Niels Henze (Universität Stuttgart, DE) Jochen Kerdels (FernUniversität in Hagen, DE) Alireza Sahami (Universität Stuttgart, DE)
Real Life AR	Gernot Bahle (DFKI - Kaiserslautern, DE) Ulf Blanke (ETH Zürich, CH) Daniel Kohlsdorf (Georgia Institute of Technology, US) Kai Kunze (Osaka Prefecture University, JP)
Modelling	Mehul Bhatt (Universität Bremen, DE) Diana Nowacka (Newcastle University, GB) Thomas Plötz (Newcastle University, GB) Bernhard Sick (Universität Kassel, DE)
Mobile + Social	Oliver Brdiczka (PARC - Palo Alto, US) Thomas Phan (Samsung Research, US) Georg Groh (TU München, DE) Alexander Lehmann (TU München, DE)
Systems I	Hedda R. Schmidtke (Carnegie Mellon University - Moffet Field, US) Stephan Sigg (NII - Tokyo, JP)
Systems II	Michael Beigl (KIT - Karlsruhe Institute of Technology, DE) Dawud Gordon (KIT - Karlsruhe Institute of Technology, DE) Bernt Schiele (MPI für Informatik - Saarbrücken, DE) Hideyuki Tokuda (Keio University, JP)

■ **Figure 7** Introduction talks of the participants divided into topic groups.

Participants

- Elisabeth André
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- Gernot Bahle
DFKI – Kaiserslautern, DE
- Michael Beigl
KIT – Karlsruhe Institute of
Technology, DE
- Mehul Bhatt
Universität Bremen, DE
- Ulf Blanke
ETH Zürich, CH
- Oliver Brdiczka
PARC – Palo Alto, US
- Nora Broy
BMW Group Forschung und
Technik GmbH – München, DE
- Andreas Bulling
University of Cambridge, GB
- Jingyuan Cheng
DFKI – Kaiserslautern, DE
- Joelle Coutaz
Universite de Grenoble, FR
- James L. Crowley
INRIA, FR
- Alois Ferscha
Universität Linz, AT
- James Fogarty
University of Washington –
Seattle, US
- Dawud Gordon
KIT – Karlsruhe Institute of
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- Georg Groh
TU München, DE
- Niels Henze
Universität Stuttgart, DE
- Jochen Kerdels
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- Koichi Kise
Osaka Prefecture University, JP
- Daniel Kohlsdorf
Georgia Inst. of Technology, US
- Kai Kunze
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- Alexander Lehmann
TU München, DE
- Paul Lukowicz
DFKI – Kaiserslautern, DE
- Diana Nowacka
Newcastle University, GB
- Thomas Phan
Samsung Research, US
- Gerald Pirkel
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