PROJECT FINAL REPORT

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Name of the scientific representative of the project's co-ordinator[1], Title and Organisation:

Dr. Daniel Roggen

ETH Zürich

Institut für Elektronik

ETZ H 93

Gloriastrasse 35

CH-8092 Zürich

Switzerland

Tel: +41 44 632 2993

Fax: +41 44 632 1210

E-mail: droggen@ife.ee.ethz.ch

Project website[Error! Bookmark not defined.] address: www.opportunity-project.eu

[1] Usually the contact person of the coordinator as specified in Art. 8.1. of the Grant Agreement.

4.1 Final publishable summary report

4.1.1 Executive summary

OPPORTUNITY picks up on the very essential methodological underpinnings of any Ambient Intelligence (AmI) scenario: recognizing (and understanding) human context and activities. Methodologies are missing to design context-aware systems that work over long periods of time despite changes in sensing infrastructure (failures, degradation), that provide the freedom to change wearable device placement, and that can be deployed without user-specific training.

We develop opportunistic systems that recognize activities/contexts despite the absence of assumptions about sensor availability and characteristics. We develop: (1) intermediate features that reduce the impact of sensor parameter variability and isolate the recognition chain from sensor specificities; (2) classifier and classifier fusion methods suited for opportunistic systems, capable of incorporating new knowledge online, monitoring their own performance, and dynamically selecting most appropriate information sources; (3) unsupervised dynamic adaptation and autonomous evolution principles to cope with short term changes and long term trends in sensor infrastructure, (4) goal-oriented cooperative sensor ensembles that spontaneously and autonomously arise and self-organize to achieve the recognition task. The methods are demonstrated in activity recognition scenarios, and on robust EEG-based BCI systems.

We collected a reference activity dataset (the OPPORTUNITY dataset) to assess opportunistic activity recognition methods. We released it publicly and organized activity recognition challenges to evaluate systematically competing approaches to activity recognition

We developed many building blocks of opportunistic recognition techniques (opportunistic algorithms) that fit within the overall opportunistic recognition architecture. In particular, we devised unsupervised methods to exploit novel, unknown sensors, for activity recognition - a key element to create open-ended ambient intelligence environments. Furthermore, we developed information-theoretical approaches to select and combine optimally at any point in time available resources into sensing ensembles. This allows to reconfigure a recognition system at run-time according to the sensor nodes available at any point in time.

Complementing these building blocks, we developed a software framework - the OPPORTUNITY framework - that is a runtime engine discovering and organizing the sensors into a goal-oriented sensing mission. Conforming sensors deliver self-description metadata to the framework. According to the self-descriptions and a domain specific activity ontology, the specified recognition goal is translated by the framework into a dynamically instantiated recognition chain. A key characteristic of the framework and opportunistic methods is that have been co-designed to enhance each other. For instance, when opportunistic algorithms discover new relations between sensors, this knowledge is stored and can be re-used by the framework to substitute sensors at run-time.

4.1.2 Summary description of the project

*We envision **opportunistic activity recognition systems.** They are **goal-oriented sensor assemblies** that **spontaneously arise** and **self-organize** to achieve a **common goal**, here **activity and context recognition.***

*The objective of OPPORTUNITY is to develop **generic principles, algorithms and system architectures** to reliably **recognize complex activities** and contexts despite the **absence of static assumptions about sensor availability and characteristics** in opportunistic systems.*

The objective of this project is to develop **mobile systems** to **recognize human activity** and **user context** with **dynamically varying sensor setups,** using **goal oriented, cooperative sensing**. We refer to such systems as **opportunistic**, since they take advantage of sensing modalities that just happen to be available, rather than forcing the user to deploy specific, application dependent sensor systems.

This project is grounded in wearable computing and pervasive/ubiquitous computing, collectively named hereafter **Ambient Intelligence (AmI)**. The vision of AmI is that of pervasive but transparent technology, always on, always present, that provides the appropriate information, assistance and support to users at appropriate moments, proactively and in a natural way. The key mechanism to achieve this is to recognize the user's activities and the user's context from body-worn and ambient sensor-enabled devices, in order to infer automatically when, how, and by which modality to support the user.

OPPORTUNITY aims to develop **a novel paradigm for context and activity recognition that will remove the up-to-now static constraints placed on sensor availability, placement and characteristics.** This is in contrast to most state of the art approaches that assume fixed, narrowly defined sensor configurations dedicated to often equally narrowly defined recognition tasks. Thus, currently, for each application, the user needs to place specific sensors at certain well-defined locations in the environment and on his body. For a widespread use of context awareness and activity recognition this approach is not realistic. As the user moves around, he is at times in highly instrumented environments, where a lot of information is available. At other times he stays in places with little or no sensor infrastructure. Concerning on-body sensing, the best one can realistically expect is that at any given point in time the user carries a more or less random collection of sensor enabled devices. Such devices include mobile phones (today often equipped with GPS, and a variety of sensors), watches (today also available with a wide range of sensors), headsets, or intelligent garments (shoe worn motion sensors are already commercially available). As the user leaves devices behind, picks up new ones and changes his outfit, the sensor configuration changes dynamically. In addition the on-body location of the sensors may also change. For example, a mobile phone can be placed in the trousers pocket, in a hip holder, in the backpack or in the users hand. Finally, large scale sensor systems deployed in real life environments over long time periods are bound to experience failures, again leading to dynamically varying sensor setups.

In summary, considering realistic settings, **no static assumptions can be made about the availability, placement, and characteristics of sensors** (sensors and other information sources become dynamically available/unavailable at unpredictable points in time).

OPPORTUNITY addresses this challenge by developing generic principles, algorithms and system architecture to reliably recognize complex activities and contexts despite the absence of static assumptions about sensor configurations.

The overall objectives of OPPORTUNITY are broken down by specific objectives yielding advances beyond the state of the art in specific areas.

Self-* capabilities of sensors and sensor ensembles.

Self description: We will investigate metadata formats for sensor self-descriptions, i.e. investigate markup languages suitable for metadata description of sensor typology and interoperability, develop (XML) parsing technologies for very small and tiny execution platforms (i.e. small form factors, low memory footprint, etc.), develop metadata similarity analysis and semantic interoperability of sensor systems, and develop a sensor ontology particularly addressing scenarios of opportunistic sensing.

Dynamic sensor self-characterisation: We develop methods that allow sensors to automatically characterize themselves. In particular we want sensor to be able to automatically detect when their performance degrades. The detection ability should work for degradation caused by internal factors (e.g. drift) as well as environment related degradation (occlusion, displacement). The specific measures that we intend to develop are

- Degradation detection based on sudden events followed by long term change in the statistical properties of the signal. Thus for example we might detect a sudden drop in the intensity of the sound detected through a mobile phone microphone followed by all the statistical properties except the intensity being unchanged. This would indicate that the phone was placed in a pocket damping the sound intensity.
- Using information about user activity and context to re-calibrate the sensors. In previous work we have demonstrated how the knowledge that the user is walking can be used to determine the on body placement of an acceleration sensor. We intend to develop similar methods for other sensors and variation types.

Self Managed interaction and configuration. We will develop methods and algorithms to allow for a self-managed interaction among sensors in spontaneous sensor ensemble configurations. We will:

- Address scalability and protocols for large sensing ensembles, i.e. investigate algorithms and protocols for redundant and fail safe sensing within cooperative ensembles involving many sensors, develop models for fault tolerant and fail safe sensing systems involving multiple, multimodal sensor nodes, and develop utility models for sensor ensembles relating the resource effort (number of sensors, energy and powering, deployment strategy) to the quality of sensing.
- Develop inconsistency and uncertainty protocols for sensing ensembles, i.e. develop models to cope with faulty, stale, unavailable sensor nodes involved in cooperative sensing missions, and develop utility based reliability and dependability mechanisms able to guarantee cooperative sensing and at least a certain levels of quality of service

Creating and Coordinating ad-hoc goal-oriented sensor ensembles.

Goal oriented behavior: Individual sensing activities in spontaneous sensor ensembles need to be aligned according to the information demands coming from the application. To this end, OPPORTUNITY will:

- Develop goal representations and strategies for goal processing, i.e. identify knowledge and goal representation techniques and metadata formats, together with mechanisms for storing and retrieving, implement a goal generation, goal processing, goal distribution and resource configuration engine able to steer cooperative sensing in dynamic ensembles, and implement a goal extraction and sensor data capture kernel able to physically collect data according to the goal/utility.
- Develop solutions for cooperative sensing mission management by first studying methods to extract goals from application request and encode them in the respective goal representation, then develop protocols for the identification, execution and harmonious adjustment of individual sensing efforts towards the accomplishment of a sensing mission goal, and finally develop a framework for the formation of sensing missions involving sensors able to contribute to the ensemble sensing goals, respecting utility, resource effort and quality of service.

Ensemble coordination architectures: A coordination architecture steering the individual sensing efforts towards a sensing goal will be developed (and exhibited in application scenarios). OPPORTUNITY will:

- Design and develop a sensor ensemble management system supporting the dynamic participation (join, leave, re-join) of individual sensor nodes, while sustaining the ensemble sensing mission.
- Develop protocols for the identification, execution and harmonious adjustment of individual sensing efforts towards the accomplishment of an ad-hoc ensemble sensing goal.
- Develop protocols and mechanisms for distributed sensor querying based on the sensor markup developed before. These query mechanisms, for scalability reasons, will go beyond traditional flooding type protocols.
- Designing an overall spontaneous interaction coordination architecture, and integrate the protocols for distributed querying with the scalability, inconsistency, and uncertainty protocols into a consistent protocol architecture and software framework.
- Develop and implement the components towards an infrastructure-free cooperative sensing system.

Variations tolerant Signal Processing and Feature Extraction

Variability tolerant signal conditioning. The signal processing methods used by an opportunistic system should not only lead to optimal class separation under one specific set of parameters, but be as insensitive as possible to parameter variations. Thus, even considerable variations in the sensor parameters should lead to only small changes in the probability density distributions of the involved classes and the optimal separation surfaces. To this end we will investigate the following:

- Typical variations to be expected in different classes of activity recognition problem and ways to modify the usual features used in this problems to be less sensitive to such variations.
- Features based on combinations of different sensors in which one sensor can compensate degradation caused to the other by typical changes in environmental parameters. In previous work we have for example shown how signals from and accelerometer and a gyroscope can be combined in such a way that the resulting feature is insensitive to shifts of the sensor within a body part [**Error! Reference source not found.**].

Abstract, sensor independent features. Different physical quantities can provide the same abstract information about an activity. Thus, for example, on-body inertial sensors, clothing-integrated textile elongation sensors, and visual tracking, all give information about body parts trajectories. If the classifiers are trained on such trajectories rather than on raw sensor signals, then the classification system will be able to easily tolerate sensor modality changes. With respect to such abstract features we intend to:

- Define abstract feature sets for the most common activity recognition problems
- Show how such features can be computed from different sensor configuration. In particular demonstrate how dynamic changes in the sensor configuration can be handled. We will apply and adapt different variability tolerant signal conditioning methods to the computation of the abstract features (see previous sub-objective)
- Show how differences in the levels of detail, reliability and accuracy that different types of sensors will provide for a certain abstract feature can be handled. Consistent methods are needed to specify how such differences propagate to the features and how the following stages of the recognition chain can be made aware of such changes.

Machine learning algorithms optimized for opportunistic networks

Opportunistic classifiers: we will use machine learning techniques to develop improved classification algorithms for activity recognition. In order to be suitable for dynamically changing sensor networks OPPORTUNITY algorithms should exhibit the following properties:

- Graceful performance degradation with respect to changes in the quality of the input signal
- Provide a measure of the reliability of their decisions, taking into account the (estimated or reported) uncertainty of available inputs
- Allow for fast training, and online adaptation incorporating supervisory information provided either by the user or by an external system (c.f. WP3 on dynamic adaptation and autonomous evolution)
- Achieve signal segmentation and classification respecting application-specific constraints of pervasive and wearable computing (e.g. real-time operation, computational cost)

<u>Success Criteria.</u> The success criterion is the comparison of the opportunistic classifiers to state of the art dedicated classifiers on a set of realistic problems. We aim at a recognition rate comparable to the dedicated classifiers (not more than 10% to 20% below). We will do a systematic performance evaluation of the developed classifiers with respect to <u>sensitivity to signal noise</u>, <u>training requirements</u>, and their <u>suitability for online implementations</u>

Opportunistic Classifier Fusion: Develop and adapt classifier fusion methods able to cope with changes in the availability, type, and characteristics of their input classifiers/sensors. To this end we will:

- Make a comparative assessment of classifier fusion methods with emphasis on the specific characteristics of opportunistic sensor setups, such as scalability and robustness.
- Develop methods for dynamic selection and fusion of sensing modalities with respect to application-defined requirements.

- Develop fault-recovery mechanisms based on the addition or removal of input channels based on the reliability of available sensors.

Unsupervised dynamic adaptation

System modelling of context recognition systems: we will develop, based on information theoretical models and empirical approaches:

- Models linking system configuration to multiparametric performance metrics focusing on the specific properties of opportunistic systems
- Methods to quantify the benefit resulting from including specific additional sensors and features based on the information provided in the sensor meta description, as well as runtime evaluation of channel's information content.

Dynamic adaptation of context recognition systems: we develop dynamic adaptation methods to cope with rapid changes in sensor configurations (e.g. change in desired performance, or re-occuring changes in number of Self-* sensor). To this end we:

- Develop heuristics, based on system models, for the optimal dynamic adaptation of an opportunistic system in a given situation. The adaptivity dimensions are defined by the system performance models and include as a minimum the linkage between sensor number and performance goal.

Autonomous evolution

Runtime supervision. We will develop methods to monitor the performance of the activity recognition system with respect to long term changes in sensor configurations. These methods will:

- Provide a confidence assessment of classifier outputs w.r.t. to possible signal degradation (due to e.g. sensor degradation, slow change in placement/orientation, or long term changes in user action-limb trajectories) in order to trigger a system retraining
- Provide an indication of correlation between sensors (at the signal, feature, and class output level) in order to support self-supervised learning
- Investigate the use of error-related EEG correlates (brain signal patterns occurring when a system deviates from expected behavior) as an endogenous, automatically detected, measure of system performance.

Autonomous evolution. We will develop methods for long-term gradual adaptation of the system to a new sensor configuration. These methods are:

- Self-supervised learning techniques to train classifiers of sensor devices (not yet capable of Self-*) entering the system.
- Self-supervised learning techniques to re-train classifiers of sensors when long term sensor degradation is observed.
- Performance metrics characterizing online adaptation. This includes traditional machine learning performance metrics (precision/recall, ROC curves) and novel metrics suited for autonomous evolution that will indicate adaptation speed, system robustness and stability, evolution of activity class signal templates and attractors.

Interactive minimally supervised adaptation: In some cases it may be more valuable to rely on interactive user feedback to supervise system adaptation. These method will:

- Evaluate the gain obtained by one time interactive supervision w.r.t. self-supervised learning, on the basis of confidence values and information content in the system parameters and sensors.
- Decide when user input shall be queried to minimize user disturbance while maximizing information gain.
- Rely on error-related EEG correlates and include them as a self-supervisory feedback to support autonomous evolution.

Empirical validation

The approach is validated in tasks of increasing complexity, starting with recognition of modes of locomotion and then addressing complex manipulative gesture recognition and higher level composite activities. A benchmark dataset collected in the project is used for that purpose.

4.1.3 Description of the main S&T results/foregrounds

The key foregrounds are:

- A dataset of human activities for the benchmark of traditional and opportunistic recognition techniques. This OPPORTUNITY dataset is open-sourced and accessible on the UCI machine learning repository: http://archive.ics.uci.edu/ml/datasets/OPPORTUNITY+Activity+Recognition and on web-based browser interface developed in the project: http://www.contextdb.org

- The establishment of this dataset as a benchmark dataset through an activity recognition challenge

- Management tools for the opportunity dataset, see http://www.contextdb.org

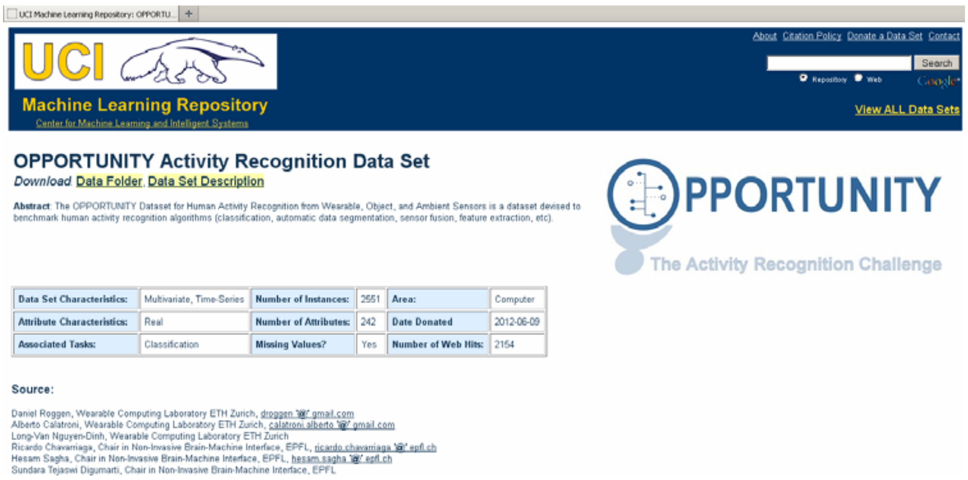
- The opportunistic machine learning methods, published in scientific papers. It is a combination of "building blocks" that are combined to fulfil an opportunistic recognition goal. We present them here individually, and in a last section show their interplay.

- The OPPORTUNITY framework, that orchestrates sensors and methods to fulfil recognition goals. This is as well published in scientific papers.

The OPPORTUNITY dataset and toolchain

We collected a reference dataset in 2009, hereafter called the OPPORTUNITY dataset, to assess opportunistic activity recognition methods against a common dataset of naturalistic complex activities and gestures. The dataset is based on a breakfast scenario, rich in terms of different activity types. The setup consisted of 72 sensors of 10 modalities distributed in 15 networked sensors systems. The recording contains around 25 hours of data from 12 subjects. On the low level there are around 30'000 individual actions (e.g. picking up a knife, opening a drawer). On the highest level (getting up, breakfast preparation) we have around 200 context instances. While the number of high level contexts is not unusual for this type of experiment, the number of annotated low level actions is far beyond what is available in other data sets.

We completed the annotation of the quality part of the OPPORTUNITY dataset. We released publicly this dataset in early 2011. It is available on the UCI ML repository at:
http://archive.ics.uci.edu/ml/datasets/OPPORTUNITY+Activity+Recognition



The OPPORTUNITY dataset on the UCI ML repository

The UCI Machine Learning repository is a dataset hosting initiative from University of California Irvine which has become the de-facto source of datasets for the machine learning community. The released dataset comprises:

- Body-worn sensors: 7 inertial measurement units, 12 3D acceleration sensors, 4 3D localization information
- Object sensors: 12 objects with 3D acceleration and 2D rate of turn
- Ambient sensors: 13 switches and 8 3D acceleration sensors
- Recordings: 4 users, 6 runs per users. Of these, 5 are Activity of Daily Living runs characterized by a natural execution of daily activities. The 6th run is a "drill" run, where users execute a scripted sequence of activities.
- Annotations/classes: the activities of the user in the scenario are annotated on different levels: "modes of locomotion" classes; low-level actions relating 13 actions to 23 objects; 17 mid-level gesture classes; and 5 high-level activity classes

The benefits of presence on the UCI ML repository ensures:

- A high visibility in the machine learning community. The dataset is the first dataset on the UCI repository for activity recognition.
- Longevity of the data and benchmarks, even after the project team disperses
- Simple access to the widest audience, as no registration or special programs are required
- Continued visibility of the project name and the EU as funding agency: the license requires to cite a paper describing the dataset that itself acknowledges the funding from the EU.

Current statistics indicate that the dataset page is visited >40 times a day.

We have developed an integrated tool chain to support the above process (data acquisition, storage, annotation, retrieval) and make it more efficient. The tool chain comprises (1) a data base system based on Apache CouchDB in order to allow sensor data, annotations and accompanying videos to be stored and accessed in an organized way, (2) a GUI based labelling tool for the inspection, annotation, and manual resynchronization of context data stored in the above data base, (3) a trace generation tool that allows combinations of signals from a subset of sensors referring to certain ground truth events to be easily retrieved from the data base and streamed for system training, testing or demonstration. The software is open source, available at http://www.contextdb.org.

The OPPORTUNITY activity recognition challenge

We organized an "activity recognition challenge" based on the OPPORTUNITY dataset. We received 18 submissions from 9 teams. We invited participants to a workshop at the Systems, Man, and Cybernetics conference on October 9th 2011, where participants presented their results and top performers received awards. This event established and promoted the use of the OPPORTUNITY dataset for benchmarking activity recognition techniques. A publication in Pattern Recognition Letters, a top machine learning journal, sustain the effort of establishing the OPPORTUNITY dataset as a reference dataset.

Opportunistic activity recognition chain

We introduced multiple methods that address a specific aspect of the activity recognition system, in the form of building blocks that can be combined, towards a rich set of methods for opportunistic activity recognition.

Architecture

As the number of sensors available for activity recognition can change according to the user's surrounding infrastructure. The opportunistic recognition chain architecture is based on a classifier fusion core (ensemble classifiers). Besides passively allowing for change in sensor numbers, this allows to implement active mechanisms to select - among available sensors - which are those that effectively contribute to the recognition chain. We illustrate this by an example where a dynamic sensor selection mechanism minimizes overall sensor network power use while maintaining an application-defined performance.

Baselining

We started by comparing several classification and fusion techniques for activity recognition systems within that architecture. In particular, we assessed the performance degradation in the case of changes in the sensor network. This provides a measure of how existing techniques can cope with the requirements of Opportunistic systems and provides a baseline measure to evaluate the performance of newly developed methods.

Opportunistic building blocks

These building blocks provide functions in the following categories:

- Independence to sensor variation or sensor self-characterization
- Sensor abstraction and substitution methods
- Dynamic adaptation and autonomous evolution methods

We introduced methods to infer the placement and orientation of mobile device carried in a pocket from acceleration and sound signals sensed on the device. This self-determination is key to filter out the effect of placement variations. Finally we improved the self-characterization of on-body sensor placement by including particle filtering and performing systematic evaluations on several datasets.

Along signal processing and feature abstraction, we demonstrated how magnetic field sensors and gyroscopes can substitute each other. We showed that magnetic disturbance can be used for activity recognition. Thus additional information can be obtained from existing sensors through more advanced processing techniques.

We introduced an online unsupervised classifier self-calibration algorithm. Upon re-occurring context occurrences, the self-calibration algorithm adjusts the decision boundaries through online learning. The method can be applied to reduce the effect of changes in on-body sensor placements, and is especially suited to address unpredictable - but small in magnitude - variations in sensor signal templates.

Along signal processing and feature abstraction, we demonstrated how to autonomously discover whether two sensor nodes are measuring the same thing, and hence can be used to perform sensor substitutions in case of failures. We enhanced past methods to autonomously detect anomalies in an opportunistic sensor network with adaptive fusion. Hence, the detection of an anomaly can lead to a re-training of the system or an adaptation of the fusion weight.

A robust activity and context-recognition system must be capable of operating over a long period of time, and evolving in an autonomous manner, coping with changes in the number and type of available sensors. In order to take advantage of new sensors discovered in the environment, it is necessary to autonomously find how to exploit the information they provide. We present two contributions to that end. Within a single sensor node, we show how a C4.5 classifier can be extended to exploit information from an additional sensor without manual training. Across multiple sensor nodes, we show basic principles for lifelong adaptation in simulated ContextCells. They are sensor nodes with classifiers running on them, capable of sending and receiving activity labels upon detection, and of on-line learning according to received labels. Through information exchange, a newly deployed ContextCell can automatically learn to recognize activities by imitating the behaviour of previously deployed ContextCells.

We proposed and evaluated methods using opportunistic user feedback to adjust online a hand gesture recognition system from wearable motion sensors. We demonstrate these using as feedback the error related potentials (ErrP) recognized from electroencephalography (EEG) signals. Thus, besides showing that an adaptive method using minimalist feedback, we also show a first convergence towards BCI foreseen in the project.

Along classifier and classifier fusion, we presented a method to autonomously detect anomalies in an opportunistic sensor network. Extending this, we presented a method to handle missing sensor data by imputation. Finally we presented a robust fusion method based on a polynomial rule.

Along dynamic adaptation, we showed how anomaly detection can trigger a reconfiguration of the opportunistic recognition system, which outperforms a system that does not react on unreliable data. We proposed a heuristic predictor which enables to estimate the accuracy of a classifier ensemble. This is a step towards autonomously reshaping an ensemble configuration according to resource availability. Along autonomous evolution, we showed how to use unknown new resources for activity recognition. We showed that a new initially untrained sensor, which joins a pre-existing ecology of sensor systems capable of activity recognition, can be autonomously trained without involving labelling from the user. We showed that a new sensor providing unlabelled data can be automatically exploited to improve the classification accuracy of a pre-existing sensor system operating. We showed that many sensors not foreseen for activity recognition can be repurposed for activity recognition by capitalizing on assumptions about human behaviour. Finally, in any wearable computing scenario the user is necessarily in close interaction with the wearable system. Thus, an activity recognition system should be able to capitalize on the presence of the user to improve its own behaviour. We presented a system which allows minimalistic user feedback to guide the adaptation of an activity recognition system. We analyzed the resulting user and system co-adaptation dynamics.

We showed how to efficiently rank sensor nodes which may be candidate for transfer learning methods developed previously. We also enhanced past transfer learning approaches with a new method based on system-identification techniques. While it uses more network bandwidth, transfer is more rapid than the previous approach of supervised training. We introduced information-theoretic based approaches to create and reconfigure ensemble of sensors for activity recognition. We also combine multiple opportunistic approaches. In particular we showed the benefits of combining anomaly detection and classifier retraining. Finally, we extended the method to use a novel sensor to disambiguate classification results of a pre-existing sensor by evaluating robust heuristic indicating when the method is likely to be beneficial and thus should be activated.

These methods are all documented in more details in papers. The take home message is that we have identified and developed a basic set of opportunistic methods that allow for solutions to recognition problems in a wide range of situations of opportunistic sensing.

Opportunity framework

Towards the ad-hoc cooperative sensing required to sense information relevant to the contexts of interests, we reviewed self-description markup language, self-aggregation and self-composition algorithms. Based on SensorML - which is an approved standard for describing sensor systems - we provide a sensor self-description language which can be further used to enable the self-managed, opportunistic ad-hoc sensing. We outlined an early description of the ensemble coordination architecture (the OPPORTUNITY framework). together with first ideas and considerations of the development.

A reference implementation of the OPPORTUNITY Framework was developed. It is implemented in Java with the OSGi framework. It includes the runtimes to enable various different network nodes to communicate, share, cooperate, and coordinate. The ability to execute on a variety of tiny hardware platforms having small memory footprint was considered. The framework included development of:

Sensor Self-Description Segmentation and Application: The sensors self-descriptions are split into a fixed and technical part, which holds the physical properties and working characteristics of the sensor, and a dynamic and changeable part. This dynamic self-description holds the information to which recognition goal a sensor can contribute and to what extent by providing *Trust Indicator (TI)* and *Degree of Fulfillment (DoF)* metrics. Both self-descriptions follow the standardized SensorML specification.

Sensor Abstractions: As different sensing devices exist, which measure different environmental quantities, and which are accessible in different ways, we introduced the concept of sensor abstractions. The concept of “sensor abstractions” makes use of physical as well as immaterial sensors (physical, logical and virtual) transparent from any technical sensor properties. “Sensors” include physical sensors as well as online and software resources.

Goal-Oriented Sensor Configurations: To enable the dynamic configuration of sensing ensembles according to a recognition goal at runtime, we introduced the concept of *ExperienceItems* in the sensor self-descriptions which enable the dynamic instantiations of *Recognition Chains* (consisting of (i) an *Unpacker* to separate the required channel from the sensor-datastream, (ii) a *Feature Extraction* method, (iii) a *Classifier* method, and optionally (iv) a *Fusion* method which combines multiple sensor devices) in the OPPORTUNITY Framework. Based on the ExperienceItems, which enable the dynamic instantiation of chains, the quantification of the senor ensembles capabilities based on the DoF and the TI, and the ability to formulate and process a recognition goal at runtime, a first functioning prototype that enables goal-oriented sensing and activity and context recognition has been implemented.

Eventually, in a prototypical scenario involving the recognition of activities of daily living we related about 200 low-level activities to 15 to high-level activities. In the self-description, sensors advertise the activities that they can recognize and the parameters of the recognition chain. Upon execution, the planner attempts to match the recognition goal with the capabilities of the sensors. Goal reasoning and sensor substitutions are used to find a configuration solving the recognition problem. The framework has been tightly co-designed to take advantage of, and to support, the methods devised for opportunistic activity recognition.

The framework is implemented with Java and the OSGi module system and can be deployed to various platforms (e.g. embedded ARM boards with capabilities identical current smartphones). Each sensor abstraction and processing element is encapsulated by an OSGi bundle. New ones can be included by providing additional abstraction bundles. The framework supports centralized or decentralized execution of the recognition chain. Sensors in the Internet of Things are accessed over TCP/IP.

A showcase scenario was developed at JKU allows to include different types of sensors together with their abstractions to execute a recognition goal in an opportunistic way. The preliminary findings of the framework evaluation prove all the software architecture design choices valid and practically promising. The preliminary assessment suggest for a distribution model at the software components level.

The overall OPPORTUNITY system

Hereafter, we describe the overarching functioning and take-home lessons of the project.

> ***Achieving true ambient intelligence calls for a new opportunistic activity recognition paradigm in which, instead of deploying information sources for a specific goal, the recognition methods themselves dynamically adapt to available sensor data.***

More than 20 years ago, Xerox PARC's Mark Weiser laid out a vision in which highly miniaturized wireless sensor nodes and computers, so small that they would disappear in the background, would assist us in all facets of our lives.[1] By being ubiquitous, they would know what we need at all times and deliver support proactively.

This vision of *ambient intelligence* continues to drive researchers. The Internet of Things (IoT) now provides the necessary infrastructure to transparently access sensors, processors, and actuators using standardized protocols regardless of hardware, operating systems, or location.[2] For example, the IPv6 protocol forms the IoT's backbone.

To realize ambient intelligence, these "things" must understand the user's context,[3] including the location, activities (gestures, body posture, modes of locomotion), cognitive/affective states, and social interactions as well as the environment's state. Knowing this information makes it possible to provide unprecedented types of user support. Consider, for example, a person with dementia who forgets to pour water into a container on a hot plate in the kitchen. Activity recognition could help a pervasive monitoring system identify this situation and then either inform the user or turn off the hot plate. Many other high-risk or potentially dangerous scenarios at home, in the workplace, and other locations would likewise benefit from this capability.

However, current context-recognition approaches are restricted to domains with dedicated sensors. Achieving true ambient intelligence calls for a new *opportunistic activity recognition* paradigm. Instead of deploying information sources for a specific recognition goal, the methods themselves must adapt to the data available at any time. We present novel techniques that allow for opportunistic activity recognition in dynamic sensor configurations.

A NEW PARADIGM

The IoT provides access to many sensors "for free" as a by-product of other applications. On-body sensors are found in smartphones, wristwatches and other wearable or portable gadgets, as well as in smart clothing and shoes. Homes and offices include a rich array of sensors for lighting and climate control, appliance usage (oven and refrigerator door sensors), electricity usage metering, security (motion-activated lights and surveillance cameras, door/window position sensors for intrusion detection), and entertainment (motion-sensing game consoles like Microsoft Kinect for Xbox 360 and the Wii U). The number of sensors in our environments is likely to increase in the future. As users change locations, pick up or leave behind devices, change smart clothing, or interact with smart objects, they will encounter various sensor configurations in their surroundings.

Despite this potential for widespread sensing, however, ambient intelligence is still far from ubiquitous. Indeed, as the "Classic Activity Recognition Paradigm" sidebar explains, researchers derive the probabilistic models that current signal processing and machine learning techniques use to identify activities in sensor data streams from datasets collected at design time with predefined and optimal sensor configurations. However, collecting datasets for all possible sensor configurations is clearly not feasible. A new opportunistic activity recognition paradigm is thus required to realize ambient intelligence with readily available resources.

BRIDGING THE ABSTRACTION GAP

Service-oriented architectures (SOAs) have become a common abstraction for building context-aware applications.[4] In the IOT, smart things advertise their services, such as recognizing a contextual element—for example, presence in a room. SOAs can include autonomic properties[5] and adapt to changing resources,[6] which makes it possible to substitute service providers and compose services to address complex problems. At the core of the approach lies a semantic description of application goals, service capabilities, and their interrelations, enabling semantic reasoning. Many context-aware middleware systems support SOAs in dynamic environments.[7]

SOAs require that sensor nodes provide contextual data. This is relatively straightforward with RFID, presence, or temperature sensors. An SOA can apply reasoning on single sensor readings and easily substitute semantically identical sensors, such as one temperature sensor for another in the same room. However, these sensors cannot understand complex manipulative gestures, body postures, or modes of locomotion.

Opportunistic activity recognition requires the ability to detect meaningful patterns hidden in noisy time series spread across multiple on-body and environmental sensors. Advanced signal processing and machine learning techniques are needed to recognize these patterns. In addition, identical types of sensors cannot be substituted naively for one another, as a sensor's location, orientation, and field of view influence its readings—for example, a smartphone's motion sensor delivers very different signals when its orientation changes, or if it is placed in a shirt versus a trousers pocket. Opportunistic activity recognition must account for this highly variable input.

OPPORTUNISTIC ACTIVITY RECOGNITION

We envision ambient intelligence as an autonomous system, in the AI sense, with the capacity to solve new problems, adapt online, analyze its own behavior, and learn from past experience. The novelty of our approach is that it adapts the data-processing steps alongside the sets of sensors used. A combination of advanced streaming signal processing and machine learning techniques with sensor self-descriptions and a management framework make it possible to solve recognition problems in a wide range of situations with opportunistic sensing.

Only a few situations change the opportunistic configuration of sensor nodes:

- *Sensor appearance*. The user enters a sensor's range, resulting in the appearance of one or more signal channels. The sensor is known if it was expected at design time or has already been detected. It is unknown if it was unforeseen or has been detected for the first time and no metadata exist to immediately use it—this could be the case for legacy devices introduced in the IoT.
- *Sensor disappearance*. The user leaves a sensor's range or the sensor is powered down, resulting in the loss of signals.
- *Change in sensor characteristics*. Various conditions can change sensor signal patterns. For example, power-management adjustments to the signal sampling rate, displacement of an on-body sensor along a limb, or sensor degradation due to harsh conditions could cause a moderate change, while displacement of an on-body sensor to a completely different body location, an alteration of the field of view of ambient sensors, or sensor failure could produce a major change.

In these situations, an opportunistic activity recognition system must efficiently use the available resources and keep working when the sensor configuration changes; ideally, it should be capable of improving throughout these changes.

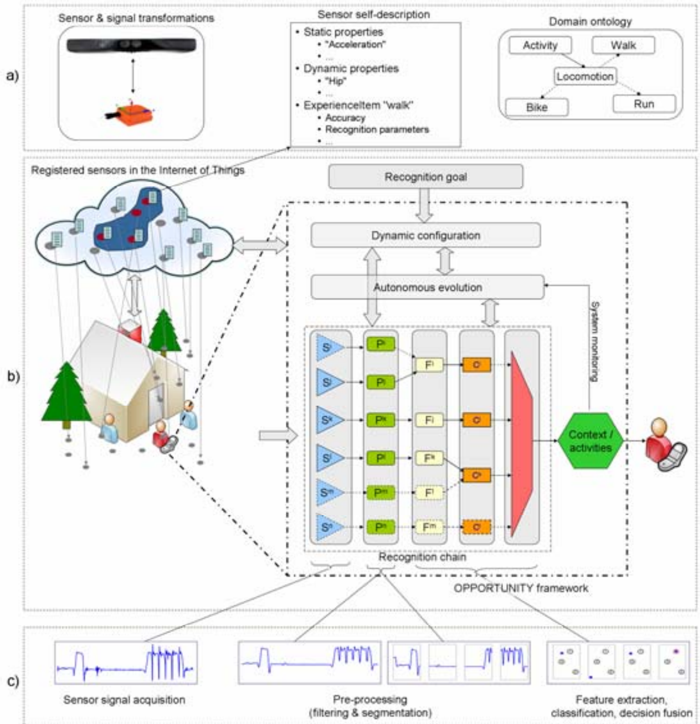


Figure 1. Opportunistic activity recognition system architecture. (a) The system leverages domain knowledge including sensor self-descriptions, signal and sensor transformation rules, and an activity ontology. (b) The system dynamically configures an activity recognition chain based on the recognition goal, the available sensors, and the domain knowledge. It continuously analyzes relations between sensors and activities to expand the domain knowledge, thus realizing autonomous evolution. (c) The recognition chain maps sensor signals (S) to activity or context classes by applying preprocessing (P), feature extraction (F), classification (C), and decision fusion methods. The arrows indicate streaming dataflows, while dashed arrows indicate sensors that might appear or disappear. The signal example is acceleration data measured at the wrist. The second half of the signal corresponds to the activity "cleaning table," characterized by periodic hand movements.

As Figure 1 shows, our system achieves this with a sensing and context framework that manages an adaptive *recognition chain*. The "Opportunity Framework" sidebar describes the framework in detail. The recognition chain constitutes interconnected streaming signal processing and machine learning elements that map the raw sensor signals to activity primitives. To capitalize on the vast number of multimodal sensor nodes in the IoT, the recognition chain uses dynamic classifier ensembles in which each node has a dedicated pipeline for signal preprocessing, feature extraction, and classification. The opportunity activity recognition system then fuses the decisions of the node-specific classifiers into a global decision by, for example, majority voting. This architecture allows local processing on the nodes and is well suited to handle node addition and removal.

The system generates solutions to a recognition problem on the fly using domain knowledge, dynamic configuration, and autonomous evolution.

Domain knowledge

Just as the availability of domain knowledge enables an AI system to exhibit more advanced behaviors, our opportunistic activity recognition system relies on rich domain knowledge to identify solutions to recognition goals.

Sensor nodes store part of this knowledge as self-descriptions. The system caches this information upon node discovery, obtaining an overview of the capabilities of nodes in the user's surrounding. A sensor self-description contains static parameters, such as the physical quantity that the node measures. It also contains ExperienceItems, each of which indicates a goal toward which the node can contribute (for example, "walk"), when this is possible (for example, "body placement" is required for "walk"), the parameters of the recognition chain required to achieve that goal (for example—features, classifier), and the recognition accuracy.

We provide an initial set of ExperienceItems at design time, and train these in the same way as is done with the classic paradigm. For instance, "walk" could be derived from a gait dataset and indicate that the energy in a 1- to 3-Hz frequency band for a foot-mounted accelerometer is a feature suited to a decision tree classifer.

An ontology relates activity concepts to support goal reasoning, and known sensor transformations indicate how sensors can be combined to emulate others. We provide the system with basic transformations for typical modalities. For example, the system can process signals from a compass to emulate a gyroscope. This allows rich capabilities for substituting sensors.

Dynamic configuration

As in SOAs, our approach favors dynamic configurations. We specify what the system is to recognize, but not how. At runtime, the system searches for a configuration that satisfies the recognition goal. It uses goal reasoning to restate the goal according to the nodes' capabilities. Because some required sensors might not be available, the system also attempts to match available and required sensors through sensor transformations.

Autonomous evolution

As with AI learning agents, our system can adapt and expand its domain knowledge as new situations arise at runtime. This autonomous process combines self-monitoring, self-adaptation, and self-learning.

Nodes can self-monitor and describe dynamic parameters, such as their current orientation, and then update dynamic entries in their self-description. The system can autonomously adapt ExperienceItems or create new ones when it discovers new solutions to a recognition goal. It also can store new sensor transformations as it discovers them.

Over time, the system evolves to operate in unforeseen situations beyond the initially provided domain knowledge.

SYSTEM OPERATION

Following a user as he moves about his house illustrates how the opportunistic activity recognition system operates. Figure 2 focuses on five typical situations: coming home, relaxing, cooking, gaming, and going jogging.

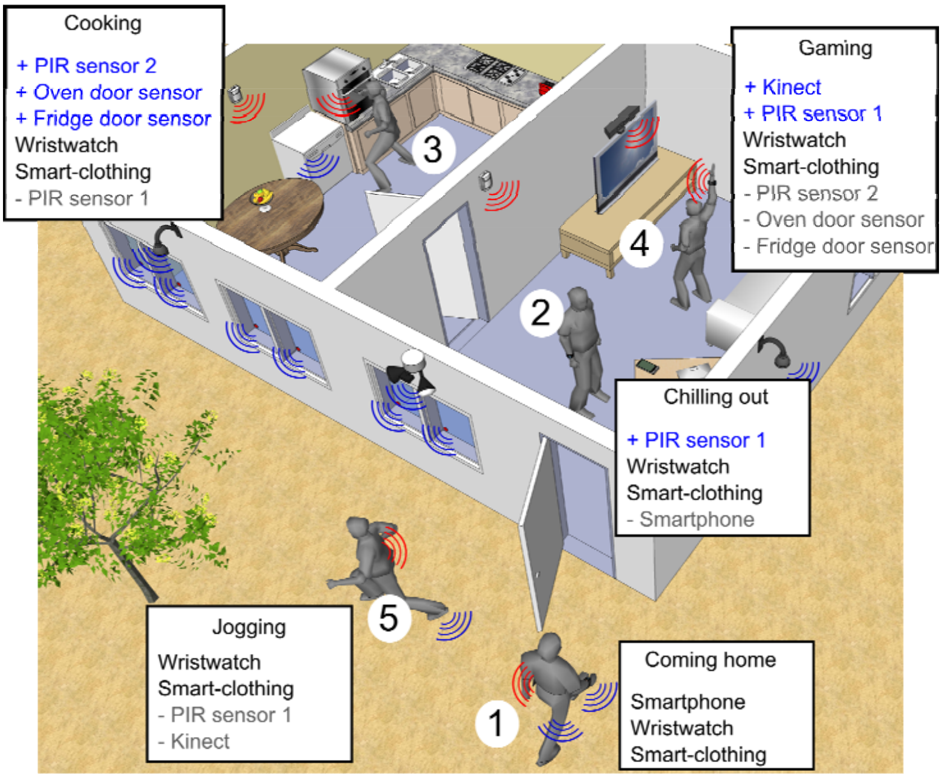


Figure 2. The opportunistic activity recognition system leverages a wide range of sensors available in the user's surroundings. As the user moves around, he enters and leaves the sensing range of these devices. This scenario includes five typical situations: (1) coming home, (2) relaxing, (3) cooking, (4) gaming, and (5) going jogging.

Setting up the recognition goal

The scenario begins with the user returning home (1). To quantify his physical activity, we set the recognition goal to "locomotion." There are accelerometers in the user's smartphone, wristwatch, and smart clothing, but none of the nodes' ExperienceItems recognize this activity. After goal reasoning, the system determines that "walk" and "run" are aspects of locomotion.

The smartphone indicates that it can recognize these activities when placed in a hip holster or trousers pocket, with the node's ExperienceItems specifying different recognition chain parameters for these locations. We found that a device can autonomously identify the body location at which it is being carried by analyzing its movement patterns.[8] The system thus can instantiate a recognition chain for locomotion according to the phone's position. If the phone changes location, the system updates the node's self-description and reconfigures itself.

Substituting sensors

The user enters his home and heads to the living room to relax, leaving his smartphone on a table (2). Although the system can no longer use the phone to perform activity recognition, the user is within range of a passive infrared (PIR) motion sensor for lighting control. The PIR sensor recognizes "movement," and the system uses goal reasoning to determine that this constitutes locomotion in the house. The recognition chain instantiated using the PIR sensor does not need complex features or classifiers: movement simply means locomotion.

Exploiting unknown sensors with transfer learning

Unknown new sensors will appear in the IoT with infrastructure upgrades, or when the user buys new gadgets. These sensors might not self-describe if they are legacy devices. Nevertheless, being able to use an unknown sensor automatically would reduce system maintenance and programming costs. Our approach thus uses an autonomous process that "spreads" recognition capabilities to new nodes, much like AI agents teaching each other tasks.

Transfer learning consists of translating the knowledge available to solve a problem in one domain to a different but related domain. We devised a lightweight implementation of transfer learning to translate the ability to recognize activities from one node to another.

As Figure 3a shows, when a preexisting node detects an activity, it triggers an incremental supervised learning process for task recognition on a new node. The system estimates the new node's performance by comparing its decisions to those of the preexisting node. If transfer learning is successful, a new ExperienceItem is created on the new node, which can now help fulfill the recognition goal. We have used this approach to transfer recognition tasks for locomotion and body postures (stand, sit, walk, lie) to eight different on-body accelerometers.[9]

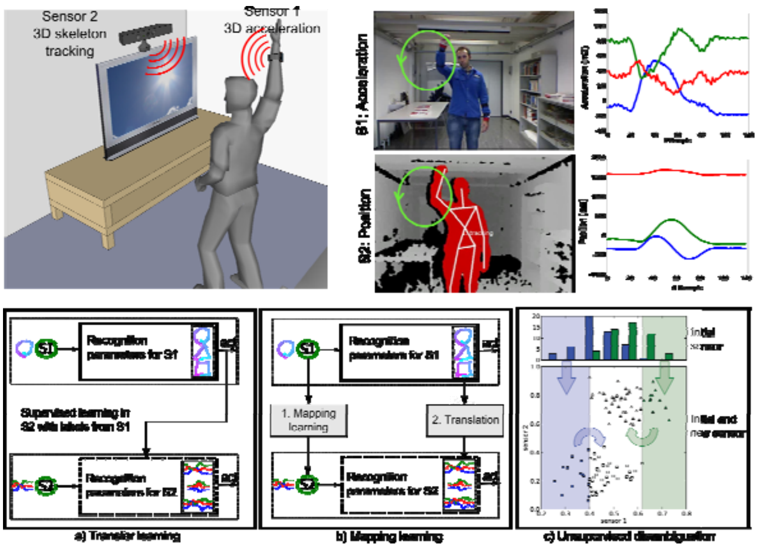


Figure 3. Using an unknown new sensor node (wristwatch accelerometer) that coexists for some time with a preexisting node (Microsoft Kinect for Xbox 360 motion-capture device) for opportunistic activity recognition. (a) The preexisting node supervises incremental learning of the new node when it detects an activity or context. (b) System identification makes it possible to map the two nodes' signals. The mapping function translates the first node's recognition chain for use by the second node. In both (a) and (b), the new node learns to recognize the same events as the preexisting node, which can disappear. (c) Activities that are confused in the feature space spanned by one sensor (top) can be disambiguated by expanding the feature space with the second sensor's dimensions (bottom). The two nodes must coexist.

Continuing with our scenario, the user enters the kitchen to prepare lunch (3). His wristwatch can sense arm movements with an acceleration sensor, but this node has no relevant ExperienceItems to identify these movements as locomotion. However, people also typically move their arms when walking or running. In this case, a PIR sensor in the kitchen detects the user's arm movements and then teaches this recognition task to the user's wristwatch.

Exploiting behavioral assumption

Some consumer appliances, such as clothes driers and ovens, have sensors indicating that the door is open to stop operation. These sensors can also provide information about a user's activities when combined with assumptions about human behavior. For example, when the appliance detects the door opening or closing, it can indicate an "open" or "close" gesture by the user and provide a new ExperienceItem to the wristwatch.[9]

Behavioral assumptions can also be applied to locomotion: a user is likely to "stand" when opening a door and afterwards will "walk" away. The Opportunity framework applies numerous behavioral assumptions using the large annotated dataset of activities in the UCI Machine Learning Repository (http://archive.ics.uci.edu/ml).

Exploiting unknown sensors through system identification

After lunch, the user returns to the living room to play a game using his Microsoft Kinect system (4). The Kinect is a depth camera with motion-tracking as well as facial- and voice-recognition capabilities: it delivers 3D coordinates of the user's joints to the Xbox 360 console, enabling him to simply move his body to control an on-screen avatar.

The opportunistic activity recognition system can relate this data to that of other unknown sensors, including the user's wristwatch accelerometer, using various system identification techniques. As Figure 3b shows, the system finds this mapping automatically at runtime, translating the Kinect's recognition chain for use by the wristwatch sensor. Using system identification, we have successfully translated the capacity to recognize five hand gestures between the Kinect and body-worn accelerometers with performance degradation of less than 4 percent in as short a time as 3 seconds.[10] Many other sensor transformations could be achieved in this way.

Exploiting unknown sensors for unsupervised disambiguation

We have developed a method, inspired by semisupervised learning techniques, to use a newly discovered sensor without ExperienceItems to improve a known sensor's accuracy. The top part of Figure 3c shows two activities that overlap in a feature space spanned by one sensor and thus cannot be recognized without errors. As the bottom part of Figure 3c shows, expanding the feature space with the new sensor's dimensions helps disambiguate the two activities, which now form distinct clusters. A systematic analysis of three sets of data from thousands of pairs of sensors showed that it is possible to enable this method only when disambiguation is likely to be beneficial.[11] Once it discovers this information, a sensor can store it in its ExperienceItems for future use.

Self-adaptation

Our scenario concludes with the user, outfitted in smart clothing, going jogging (5). As Figure 4 shows, intense physical activity can lead to sensor displacement, which in turn causes the sensor signal patterns to change. To address this problem, we developed an expectation-maximization method using a nearest class-center classifier that enables the opportunistic activity recognition system to dynamically self-adapt to the variable statistics of sensor signals.[9,12] This technique improved performance when sensors were displaced along a limb. Related methods are applicable to other moderate changes, such as sensor rotation or sensitivity change.

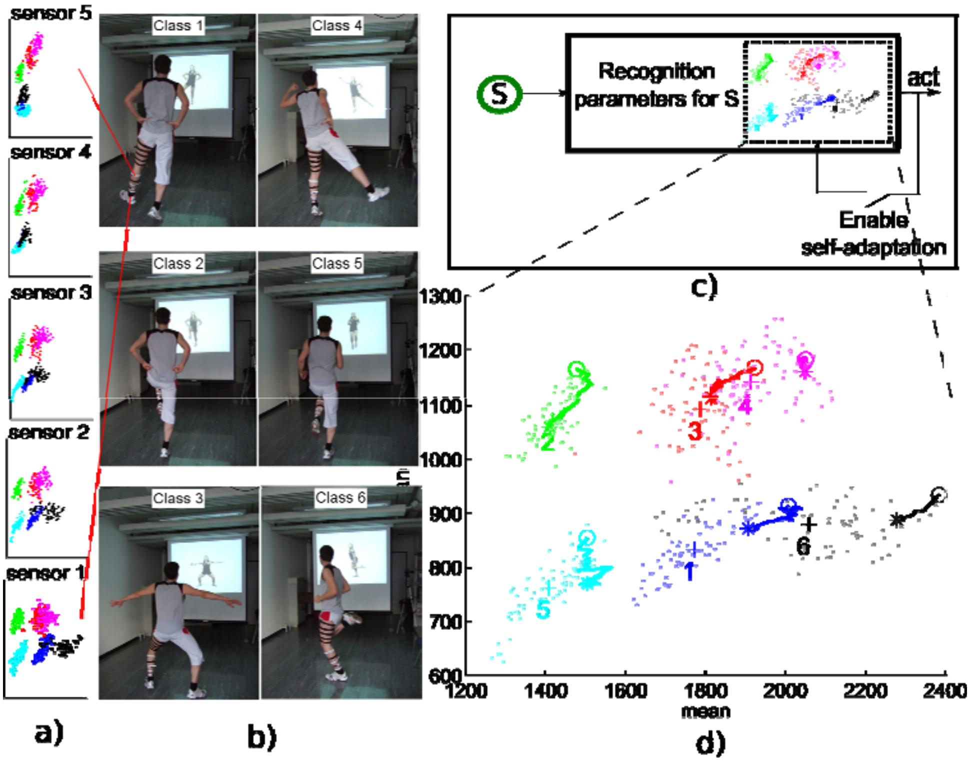


Figure 4. Self-adaptation. (a) Sensor placement affects the mapping between activity classes and features derived from sensors, in this case for six fitness activities. (b) Self-adaptation makes it possible to incrementally adjust the activity models to follow the distributions of the classes in the feature space. (d) Adaptation dynamics of a nearest class-center classifier trained on one sensor position and deployed on another position.

Exploiting ensembles to assess performance

An autonomous system must assess its own performance. It usually accomplishes this via a "critic"—a module that estimates performance from signals available within the system. The node ensembles that the IoT makes available offer a promising way for an opportunistic activity recognition system to utilize multiple critics. Because ensembles work toward the same goal, they can assess others' performance or control their adaptations as long as most of the nodes fulfill their mission. We have developed several methods to exploit this capability.

Harsh environments or strenuous activities can damage sensors—for example, fibers in smart clothing can rupture while the user is exercising. A critic can detect anomalous sensors in a node ensemble by looking at the statistical agreement between the nodes over time. Significant changes in the agreement patterns indicate an anomaly. Upon detecting such an anomaly, the system either adapts the dynamic ensemble to avoid the faulty node or it includes additional nodes.

There is, however, no way to estimate the performance of a fused set of nodes based solely on the accuracy parameters in their ExperienceItems. Indeed, this requires a pairwise measure of their complementarity, known as diversity,[12] and precomputing diversity is not appropriate in an opportunistic setting. For this reason, the system uses another critic to estimate diversity at runtime by observing the decision agreement between individual classifiers and the fused decision. It then uses an information-theoretic approach to build classifier ensembles based on the diversity estimated by the critic and the accuracy reported in the nodes' ExperienceItems. Experimental results showed that this approach leads to high-performance ensembles.[12]

LESSONS LEARNED

The opportunistic activity recognition paradigm is ideally matched to the big data that the IoT makes available and could help fulfill the promise of ambient intelligence anywhere, anytime, using a plethora of readily deployed sensor nodes.

Our work addresses the gap between low-level activity recognition methods, which require training data from predefined sensor configurations, and higher-level contextual abstractions, which assume the existence of services that can be semantically replaced or combined. Functionally, our approach is complementary to SOAs and can be used to create reliable applications despite changing sensor availability. The opportunistic principles can be included as part of the firmware of smart things or within an overarching IoT framework. As IoT-enabled “things” becomes more common, an opportunistic activity recognition system becomes more capable as it can exploit larger node ensembles and discover more elaborate solutions to a recognition problem. Most methods are equally applicable to ambient, object, or wearable sensors.

Our approach tightly integrates signal processing and machine learning techniques to identify data patterns across multiple noisy sensors with a contextual framework to handle goals, sensor capabilities, and sensor transformations and to reason about complex activities. For instance, the system will instantiate an opportunistic method to carry out transfer learning between specific sensor modalities only in appropriate situations. In addition, the system includes runtime capabilities that are important to discovering new solutions to the recognition problem and to operating in open-ended environments. This integration of low- and high-level approaches enables us to translate AI-based principles of autonomous operation into a practical ambient intelligence system.

If opportunistic activity recognition is to become a mainstream technology, commercial vendors and researchers must work together to create adequate sensor self-descriptions and activity ontologies for future smart things. In addition, there is a need for standardized methodological evaluations and performance benchmarks for recognition systems. We must also assess the stability-plasticity tradeoff to avoid catastrophic failures in long-term deployments. This poses new design and validation challenges that might be addressed using control theory.

In the near term, opportunistic activity recognition brings immediate benefits to the IoT:

- the reuse of readily deployed sensors will reduce system costs;
- the ability to roam around our surroundings and seamlessly substitute various sensors will improve user acceptance;
- reconfiguring systems to mitigate sensor losses will increase robustness; and
- systems will autonomously expand to include newly deployed resources, simplifying scale-up.

Decoupling pervasive application design from sensor deployment could create a market that is as hot as the current smartphone apps market. The decreased reliance on dedicated infrastructure will make the IoT accessible to enthusiasts as well as established players, leading to the creative exploration of many novel concepts in ambient intelligence.

Looking farther down the road, ambient intelligence systems could learn to discover autonomously when and how to use actuators accessed through the IoT to maximize user satisfaction. Achieving this next level of intelligence will require more human-like machine learning techniques[13] and implicit understanding of users’ needs.[14]

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Classic Activity Recognition Paradigm

An activity recognition system exploits the fact that sensors—whether ambient, object, or wearable—deliver characteristic raw signal patterns when a user carries out an activity or encounters a specific situation.

System designers first define the activities the deployed sensors are intended to recognize—for example, opening a door, cooking, or eating. A common on-body sensor is the accelerometer, which is cheap, small, and delivers rich information. Typically placed on the wrist, it provides unique signals for gestures as diverse as drinking, turning a knob, or pulling a drawer. More complex activities require combinations of sensors.[1]

Designers then devise a recognition chain to detect the characteristic signal patterns. To support robustness and computational complexity, the system first uses signal processing and machine learning techniques.[2,3] It then applies preprocessing to remove noise from the signals and segment them. Next, the system extracts signal features to enhance the characteristics unique to each activity and to reduce data dimensionality, then it uses classifiers to map these features to discrete activity or context classes. If the system uses many sensors, it can fuse the decisions of several classifiers operating on individual sensors. The system often performs individual classification on the nodes to reduce network load, performing decision fusion centrally. At this stage, the system calculates class occurrence probabilities to recognize more complex activities through probabilistic reasoning.

The system obtains recognition chain parameters—cutoff frequencies, kinds of features, classifier properties, and so on—by training on an annotated dataset of sensor readings recorded as users execute the activities of interest. Larger datasets capture greater variability in activity execution and sensor characteristics.

Although classic activity recognition uses probabilistic approaches, it is optimized to the selected sensors. Changing the sensors requires redesigning the system.

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The Opportunity Framework

Opportunity is a reference framework for an opportunistic activity recognition system designed around a planner.[1] The system autonomously executes a recognition chain in the form of a directed dataflow graph of sensor data, relying primarily on signal processing and machine learning techniques to detect different activities or contexts.

The framework includes a set of descriptors and tools to generate recognition chain configurations on the fly. This includes an activity-related ontology, self-descriptions in markup language derived from SensorML that the sensor nodes must deliver once they register with the system, and sensor and signal transformations.

Self-descriptions can be updated dynamically to reflect new node properties discovered by opportunistic methods. In a prototypical scenario involving the recognition of daily activities, we related about 200 low-level activities to 15 high-level activities. Self-descriptions advertise the activities that the sensors can recognize and the recognition chain parameters. Upon execution of the recognition chain, the system attempts to match the recognition goal with the sensors' capabilities. It uses goal reasoning and sensor substitutions to find a configuration solving the recognition problem.

The framework is implemented using Java and OSGi modules and can be deployed on various platforms, including embedded ARM boards with capabilities identical to those of current smartphones. An OSGi module encapsulates each sensor abstraction and processing element. The framework supports centralized or decentralized execution of the recognition chain. The system accesses sensors in the Internet of Things over TCP/IP.

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4.1.4 Potential impact

Summary

Opportunistic activity and context recognition could be the missing link to fulfill the promise of ambient intelligence everywhere, by using a plethora of readily deployed sensor nodes accessible, for instance, through the Internet of Things. The methods developed in OPPORTUNITY bring immediate benefits for ambient intelligence:

- Costs can be reduced by reusing readily deployed sensors.
- User acceptance can be improved by letting users roam around, substitute or displace on-body
- gadgetry at will.
- Robustness can be increased by reconfiguring to mitigate sensor losses.
- Scaling up is simplified by letting the system autonomously expand to newly deployed resources.

Essentially, the ideal opportunistic system allows to human activity/context recognition anytime and anywhere with top performance, and high user acceptance. The methods in OPPORTUNITY go a long way towards this. The technical advantages enabled by opportunistic methods translate into a number of broader societal advantages described below.

Assuming activity recognition capabilities (modes of locomotion and location) enabled by OPPORTUNITY - anytime and anywhere at home -, we quantified the energy benefit of managing appliances in an implicit, way. The results gathered from a field study show that implicit energy management can lead to energy saving of up to 17%.

The methods developed in OPPORTUNITY focused on the recognition of activities of daily living. These are key activities that need to be recognized in smart home scenarios designed to support elderly or persons with special needs. Seamlessly activity-awareness anytime and anywhere can lead to costs saving within the context of smarter healthcare. As an example, falls in elderly occur for 1 in 3 person above 65 each year. It costs the UK's NHS 4.6m£ a day. Participating in exercise programmes designed to increase strength and balance can reduce falls by 55%, however 20% of the elderly do not remember the last time they exercised. Fall detection and supporting at-home physical exercises through activity recognition thus has huge potential to save costs. Assuming that the "anytime and anywhere" characteristics of opportunistic activity recognition allows to remind the forgetful 20% of elderly to exercise regularly, we estimate there could be cost savings of the order of 400k£ per day in the UK, from which saving across the European Union can be extrapolated.

Wider societal implications

The technical advantages of opportunistic methods translate into a number of broader societal advantages described below.

Smarter energy management

In deliverable D5.3 chapter 5 and deliverable D4.3 chapter 6 we detail the application of OPPORTUNITY methods to implicit energy management.

Assuming activity recognition capabilities (modes of locomotion and location) enabled by OPPORTUNITY - anytime and anywhere at home -, we quantified the energy benefit of managing appliances in an implicit, way. The results gathered from the field study show that implicit energy management reaching an average energy saving over all 15 households of about 21,5 Watt per hour, respectively 17%, for a home including appliances such as TV Set, PC Set, DVD Player, Floor lamp, Indirect light, HiFi tuner, Microwave oven, Laptop power adapter, and Coffee machine. The highest potentials of saving energy can be identified in consumer electronics and in electric lightning, where it frequently reaches a 50% reduction of energy loss.

Further scenarios that benefit from activity recognition include optimizing urban mobility patterns, where predictive activity recognition can be used to reduce energy and pollution resulting from traffic congestion, and allow better scheduling of HVAC systems by predicting arrival times on city scales.

These results highlight the strong societal benefits of activity recognition technologies to support a more efficient use of energy and decrease in pollution.

Improved ambient assisted living

The methods developed in OPPORTUNITY focused on the recognition of activities of daily living such as those in the OPPORTUNITY dataset. These are key activities that need to be recognized in smart-home scenarios designed to support elderly or persons with special needs.

The benefits of OPPORTUNITY are of 3 kinds: increased user acceptance, larger spatial coverage of AmI, and reduced deployment and maintenance costs of AmI thanks to many methods enabling open-ended AmI.

Increased user acceptance and larger spatial coverage of AmI means that activity recognition becomes seamlessly possible anytime and anywhere. We focus on a single number to demonstrate the benefits of robust activity recognition anytime and anywhere. Falls in elderly occur for 1 in 3 person above 65 each year. It costs the UK's NHS 4.6m£ a day. Participating in exercise programes designed to increase strength and balance can reduce falls by 55%, however 20% of the elderly do not remember the last time they exercised (http://www.bbc.co.uk/news/10353642).

Fall detection and supporting at-home physical exercises through activity recognition thus has huge potential to save costs. Assuming that the "anytime and anywhere" characteristics of opportunistic activity recognition allows to remind the forgetful 20% of elderly to exercise regularly, we estimate there could be cost savings of the order of 400k£ per day in the UK, from which saving across the European Union can be extrapolated.

Mainstreaming of activity/context awareness

What will happen if activity and context awareness is suddenly made easy and possible anywhere? The decreased reliance on dedicated infrastructure will make it accessible to enthusiasts alongside established players. We believe this "trickling down" of the competences of designing context-aware system from experts to enthusiasts will lead to a creative exploration of many new and unforeseen concepts in ambient intelligence. This may lead to a next revolution. It could create a market for "PervasiveApps": activity- and context-aware applications that enrich our daily life through implicit interaction. This market may become as hot as the current smartphone "apps" market.

Generalized opportunistic information processing

The extension of OPPORTUNITY methods to the BCI scenario showed that the methods devised in OPPORTUNITY are quite generic. Methods such as information-theoretical fusion, adaptation and anomaly detection are likely applicable to many “big data” problem domains, such as the interpretation of data coming from millions of smartphone in urban sensing or environment monitoring, but also the interpretation of inherently noisy physiological signals (e.g. galvanic skin response, electromyography) used for cognitive-affective state recognition.

Continued spreading of the “OPPORTUNITY DNA”

Necessarily the research initiated by a project such as OPPORTUNITY does not end here. Many new initiatives and projects involving the consortium partners contributing to further spreading the “OPPORTUNITY DNA”.

The swiss-funded project Smart-Days (funding by Hasler Foundation, 2011-2014) extends opportunistic activity recognition from a single person to a population by using crowd-sourcing techniques to acquire, share, adapt and instantiate a generic cloud-based recognition algorithm onto the specific sets of sensor opportunistically available to a given person.

The upcoming INSERTIO proposal (INtegrating SEnsors and Robotic Technology Into everyday Objects to provide smart care and support, Swiss “Nano-Tera” funding programme, submission 18th of September, 2012) will extend opportunistic sensing in home environment with opportunistic feedback through robotic objects "that happen to be available" to inform or assist users.

The upcoming CrowdFluence (Sinergia, Swiss National Science Foundation, submission 15th of January 2013) will look at sensing and influencing crowd behaviors in dense crowds building on opportunistic communication and activity recognition to sense critical situations and influence behavior for better management of large public events and more efficient response to emergencies.

OPPORTUNITY showed the applicability of methods of opportunistic information processing to BCI scenarios. This paves the way to upcoming hybrid BCI, that combines EMG, EEG and eventually accelerometers for neuroprosthetics applications.

JKU has decided to establish a "niche" research initiative in the otherwise broad energy research domain. For the first time in research and education, the electrical power generation, transformation, delivery and consumption loop is addressed as single, but closed complex control system. The inspiration for this initiative has been delivered through the OPPORTUNITY "everything-is-a-sensor" understanding, suggesting every activity at the level of society to define the control circuit of future energy eco-systems. Convincing demonstrations of the OPPORTUNITY framework in the context of implicit energy management has lead to promising research cooperation with Austria's largest power grid operators, ENERGIE AG, at JKU. In a first joint research project started in 2011 (PowerIT), JKU is developing a sensor ensemble management system involving dedicated but also spontaneously available energy consumption sensors in homes and offices. Abstract feature sets for home/office context and activity recognition are defined, a knowledge driven rule engine will be deployed to control home and office electronics with the ultimate goal to prevent from standby losses and consumption inefficiencies.

The OPPORTUNITY recognition chain optimizations have fertilized an ad-hoc, very large scale, low energy sensor system, comprising a wearable recognition platform (sports community token) and a low power relay station to the WWW. Classifying locomotion (together with authentication, timing, data exchange to first responders, etc.) has been successfully demonstrated at one of Europ's largest sports events (Vienna City

Marathon 2012). Public safety and security stakeholders have assessed the token platform as a potentially effective means for event security management beyond smart-phone based sensing systems.

The OPPORTUNITY "everything-is-a-sensor" understanding has been inspirational to the design of information ecosystems in public places (FP7 FET project SAPERE, partner JKU), in that ICT primarily designed to deliver information (public displays, smart light displays, digital signage, digital billboards) can at the same time serve as a sensor capturing impressions on how society perceives information. The OPPORTUNITY framework here convincingly explained how to implement highly distributed service eco-systems, and has even generated a public displays architecture project (SensorDisplays) funded by one of the most "high flying" media companies worldwide (Red Bull Media House).

Aside the mentioned ICT underpinnings OPPORTUNITY was able to create, the project has also been successful in addressing very fundamental concerns of next generation ICT research. Thinking OPPORTUNITY radically, at the largest possible scale, has lead to what the FET flagship FuturICT initiative calls the "planetary nervous systems", a goal oriented, opportunistic configuration of more than 10^{10} abstract and physical sensors dispersed across the whole planet, capturing, filtering, correlating and possibly classifying data at rates of about Petabits per second, or mining Zettabyte data collections.

One of the rationals underlying FuturICT is to enhance individuals with novel a ICT providing an additional artificial social sense, e.g. to help gather, explore and understand social context, to represent, store, retrieve and reason about social experience, or to provide new, socially inspired access opportunities via participative technologies. Aiming for the development of computational models of how humans collect social experience, particularly the aspect of perception (via all senses) of social impressions, the aspect of remembering and recalling social experiences, as well as the aspect of retrieving actionable social knowledge and its use in interactions with ICT, FuturICT apparently inherits the "genetic structure" of OPPORTUNITY.

Where	When	What	Partner
Lago Maggiore, IT	2-7.9.2011	Sensing in a world of big data	JKU
Frankfurt, DE	21.10.2011	Planetary Nervous System	JKU
Frankfurt, DE	4.11.2011	Global Participatory Platform	JKU
Torino, IT	17.11.2011	Socially Inspired ICT	JKU
Warsaw, PL	25.11.2011	FET Flagship Midtime Performance Checkpoint	JKU
Zurich, CH	6.12.2011	For opportunistic FuturICT	JKU

Talks where the OPPORTUNITY fundamentals are delivered to the FuturICT Flagship Vision

Opportunistic sensing and information processing concepts were also injected within the Flagship GuardianAngels (http://www.ga-project.eu/) to play a key role in supporting zero power electronics.

Within the Human Computer Confluence VISIONS workshop (http://www.pervasive.jku.at/hccvisions/) organized by JKU, three of the OPPORTUNITY consortium members contributed with 7 other top researchers in ubiquitous computing to build a shared vision of the future research. We expect this to influence the “Horizon 2020” funding programme.

Concepts developed within OPPORTUNITY are now recognized as fundamental building blocks in ubiquitous and wearable computing, leading to dedicated call for papers on “opportunistic activity recognition” within the top conferences in the field, such as in the Int Symposium on Wearable Computers 2013 (http://www.iswc.net/iswc13/calls/papers.html).

The project contributed through dissemination through the following most important events:

This list does include invited talks and events. It does not include participation at conferences which can be found in the list of publications.

Occasion	**Where**	**When**	**What**	**Partner**
Neuroimaging Research Laboratory seminar	University Hospital of Lausanne (CHUV), Switzerland	March 2011	Cognitive brain machine interfaces	EPFL
IEEE CAS-FEST Forum on Emerging and Selected Topics	Rio de Janeiro, Brazil	May, 2011	Current challenges in non-invasive brain-machine interfaces	EPFL
Pervasive Computing System Development Lecture at University Linz	Linz, Austria	17-18.05.2011	Lecture: "Wearable Computing and Activity Recognition" & "Brain computer interfaces"	ETHZ, EPFL
Festvortrag beim grenzüberschreitenden Innovationstag mit Cross Border Award Verleihung	Passau, DE	May, 2011	Vom Verschwinden des Computers und dem Aufkommen eingebetteter Assistenzlösungen	JKU
User Heaven or Techno Hell: Where are intelligent, adaptive technologies leading us	London, UK	May, 2011	User Heaven or Techno Hell: Where are intelligent, adaptive technologies leading us	JKU
Qualcomm Context Awareness Symposium	San Diego, USA	9-10.09.2011	Future directions in mobile activity recognition: "Smartphones in need of open-ended context awareness"	ETHZ, UNI PASSAU
XVI Simposio de Tratamiento de Señales, Imágenes y Visión Artificial STSIVA 2011	Pontificia Universidad Javeriana, Cali, Colombia	September 2011	Signal processing techniques for brain-machine interfaces	EPFL
Systems, Man, Cybernetics 2012i	Anchorage, USA	9-12.10.2011	Robust Machine Learning Techniques for Human Activity Recognition using Body-Worn Sensors	EPFL, UNI PASSAU

Workshop "Future Tools & Topics" (MACH Dedication)	Linz, AT	October, 2011	Very Large Scale Agent Based Simulation: Cognitive Decision Making	JKU
Unilever Physiological Monitoring Workshop	Port Sunlight, UK	7-8.11.2011	Wearable sensors and activity recognition	ETHZ
Bio-Robotics Network in Zurich seminar	ETHZ	11.11.2011	Wearable sensing and human activity recognition	ETHZ
XI Jornadas Castellano-Manchegas de Fisioterapia	Toledo, SP	November 2011	Brain-machine interfaces and neuroprosthesis	EPFL
EDV-Tag der oö. Versicherungsmakler	Linz, AT	November, 2011	Future ICT: Eintrittswahrscheinlichkeit mal Ereignisschwere	JKU
World Summit Youth Award	Graz, AT	November, 2011	An Idea is worth nothing - innovation needs a plan!	JKU
Awareness Inter-Project Day	Bologna, IT	January, 2012	From awareness to adaptation: large scale recognition and opportunistic configuration	JKU
Guardian Angels Workshop: Sensors, Interfaces and Systems	Paris, FR	February 2012	Current and future challenges for Brain Computer Interfacing	EPFL
Media&Lifestyle Summit	AT	March, 2012	The Web may be dead, but Internet is everywhere!	JKU
COSI-ICT Workshop	Brussels, BE	March, 2012	ASSYST	JKU
IBIT seminar: activity recognition in motion-aware gaming	Foundation Balearic Islands For The Technological Innovation (ibit) Mallorca, Spain	09.03.2012	Wearable sensing and human activity recognition: a crash course	ETHZ
KIT seminar	Pervasive Computing Systems, Karlsruhe Institute of Technology Karlsruhe, Germany	19.04.2012	Activity recognition: opportunistic, collective, crowd-sourced	ETHZ
Long night of research	Linz, AT	April, 2012	Lassen Sie abschalten?	JKU
HC2 visions: human computer confluence research challenges	Vienna, AT	May 2012	Better interaction through cognitive prostheses	EPFL
HC2 visions: human computer confluence research challenges	Vienna, AT	May 2012	From Individual to Collective Attention - Models and Dynamics	JKU
NextBerlin	Berlin, DE	May, 2012	Spectacles – personal displays for	JKU

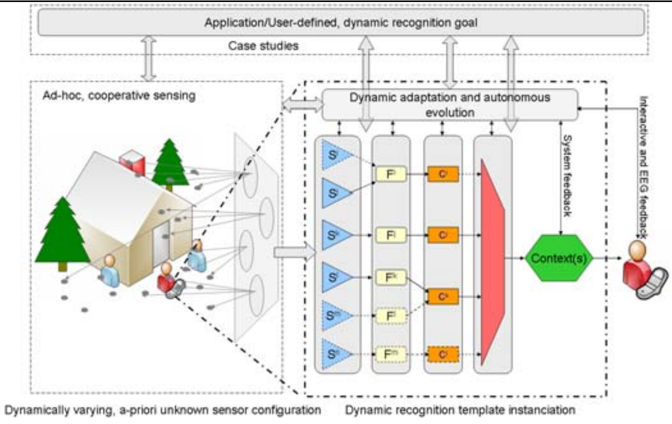
			everyone	
HC2 summer school	Milan, IT	July 2012	Human computer confluence	JKU

Invited talks and public presentations having carried the most important outcomes of the project

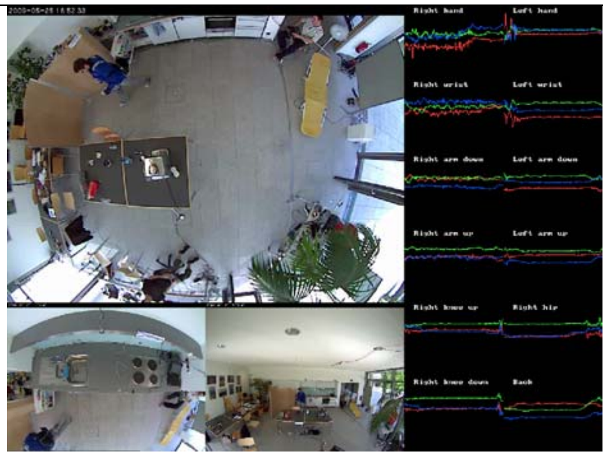
4.1.5 Address of the project public website

- www.opportunity-project.eu
- Dr. Daniel Roggen, droggen@gmail.com

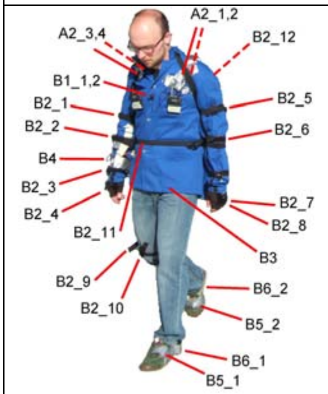
4.1.6 Photographs and contact



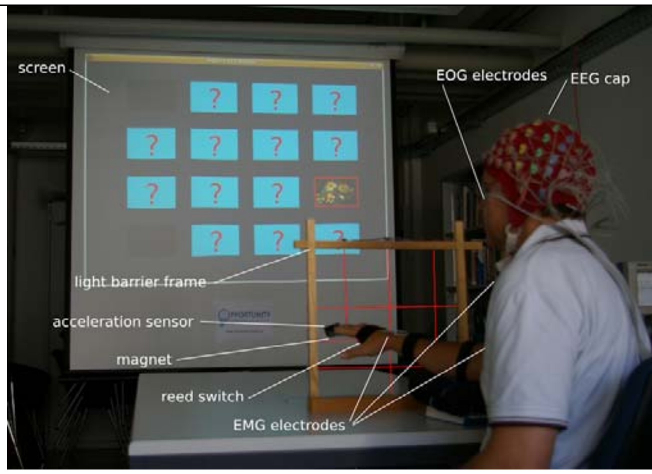
The OPPORTUNITY system



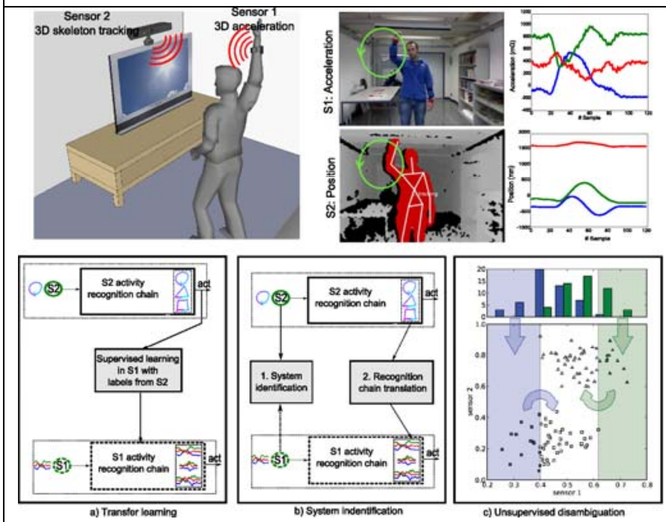
The OPPORTUNITY reference dataset for complex activity recognition in sensor rich environments.

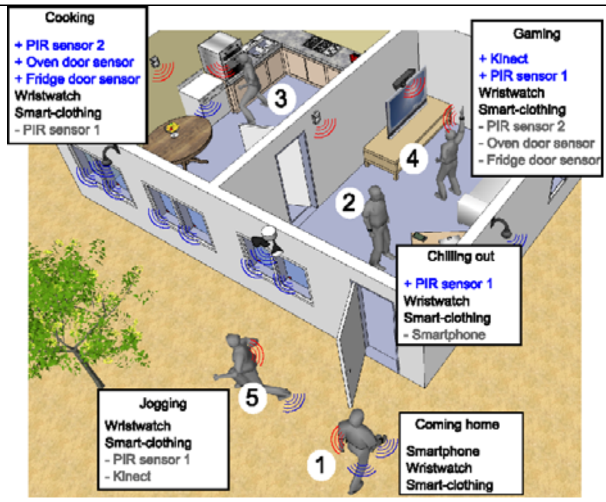


The OPPORTUNITY reference dataset: a rich set of sensors were deployed for on-body activity recognition.



An OPPORTUNITY testbed: guiding the adaptation of a movement-based HCI system by exploiting brain signals

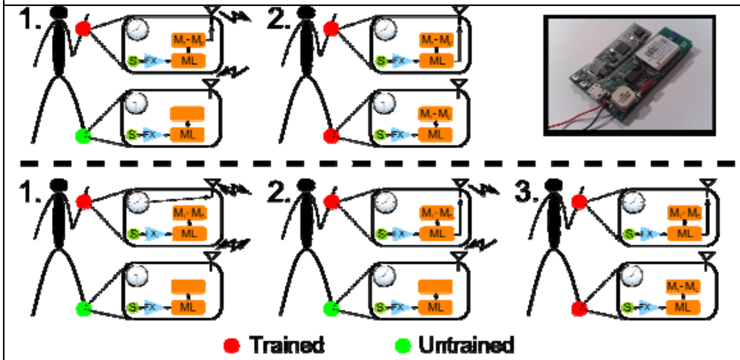




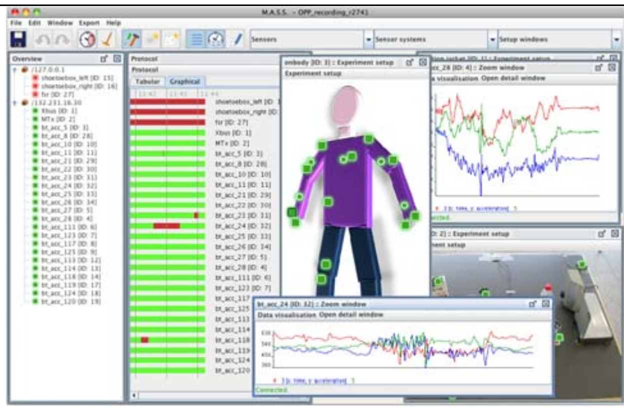
The Internet of Things gives access to a wide range of

Thanks to OPPORTUNITY, activity recognition is possible even with an unknown sensor (e.g. a wristwatch), assuming that it coexists for some time with a pre-existing sensor (e.g. a camera). a) The pre-existing node supervises the incremental learning of the new node when it detects an activity or context. b) A transfer function between the signals of two sensor nodes is obtained by system identification. c) Activities that are confused in the feature space spanned by the first sensor (top) are disambiguated by including the second sensor (bottom).

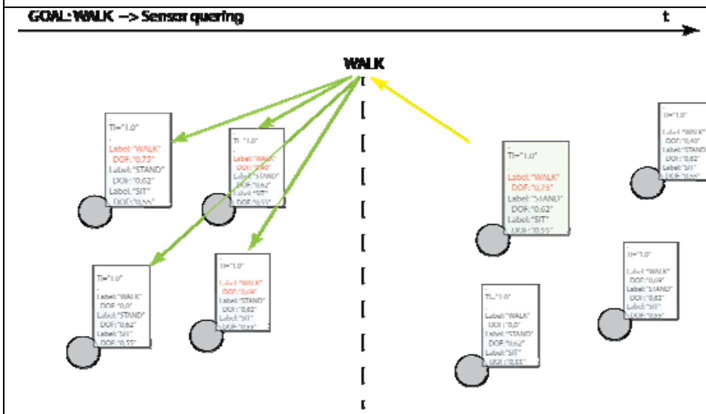
sensors readily available in our surroundings. We illustrate here some scenarios where OPPORTUNITY enables to seamlessly provide activity recognition by dynamically selecting and combining resources discovered in the user's surroundings.



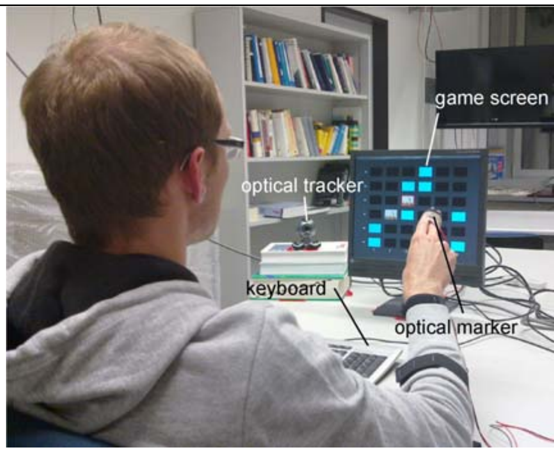
Principle of self- learning or transfer learning by which unknown new sensors can learn to recognize activities by imitating the behaviour of a pre-existing ecology of sensors already capable of activity recognition.



The monitoring application MASS to analyse sensor data quality for opportunistic sensing.



The selection of the sensors according to the recognition goal and the sensor self-description in the OPPORTUNITY framework.



An OPPORTUNITY testbed: investigating the co-adaptation dynamics of an adaptive activity recognition system and the user.

Project Coordinator ETHZ, Wearable computing laboratory	University of Passau, Embedded Systems Laboratory Prof. Paul Lukowicz

<table>
<tr>
<td>Dr. Daniel Roggen
Wearable Computer Laboratory
Gloriastrasse 35
ETH Zentrum, ETZ H 93
CH-8092 Zürich, Switzerland
Tel: +41 44 632 2993
Fax: +41 44 632 1210
@: daniel.roggen@ife.ee.ethz.ch</td>
<td>Universität Passau
Lehrstuhl für Informatik - Schwerpunkt Eingebettete Systeme
Innstr. 43
D-94032 Passau, Germany
Tel: +49 851 509 3080
Fax: +49 851 509 3082
@: paul.lukowicz@uni-passau.de</td>
</tr>
<tr>
<td>Johannes Kepler Universität Linz, Institut für Pervasive Computing

Prof. Alois Ferscha
JKU Linz
Institut für Pervasive Computing
Altenberger Straße 69
A-4040 Linz, Austria

Tel: +43 732 2468 8556
Fax: +43 732 2468 8426
@: ferscha@pervasive.jku.at</td>
<td>Defitech Foundation Chair in Non-Invasive Brain-Machine Interface

Dr Ricardo Chavarriaga
Ecole Polytechnique Fédérale de Lausanne
EPFL STI STI-DEC PPPS
ELB 140 (Bâtiment ELB)
Station 11
CH-1015 Lausanne, Switzerland
Tel: +41 21 693 69 68
Fax: +41 21 693 53 07
@: ricardo.chavarriaga@epfl.ch</td>
</tr>
</table>

4.2 Use and dissemination of foreground

Section A (public)

TEMPLATE A1: LIST OF SCIENTIFIC (PEER REVIEWED) PUBLICATIONS, STARTING WITH THE MOST IMPORTANT ONES										
NO.	Title	Main author	Title of the periodical or the series	Number, date or frequency	Publisher	Place of publication	Year of publication	Relevant pages	Permanent identifiers[2] (if available)	Is/Will open access[3] provided to this publication?
1	Opportunistic Human Activity and Context Recognitiond'	D. Roggen	IEEE Computer Magazine	To appear, 46(2),	IEEE	New York	2013	To appear		No
2	The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition	R. Chavarriaga	Pattern Recognition Letters	To Appear	Elsevier	NA	2013	To appear		No
3	Wearable Computing: Designing and Sharing Activity-Recognition Systems Across Platforms	D. Roggen	IEEE Robotics and Automation Magazine	18(2)	IEEE	New York	2011	83-95	10.1109/MRA.2011.940992	No
4	Activity recognition in opportunistic sensor environments	D. Roggen	Procedia Computer Science	Vol 7	Elsevier	NA	2011	173-174	10.1016/j.procs.2011.09.003	No
5	20 Years Past Weiser: What's Next?	A. Ferscha	IEEE Pervasive Computing Magazine	11(1)	IEEE	New York	2012	52-61		No
6	From context awareness to socially aware computing	P. Lukowicz	IEEE Pervasive Computing Magazine	11(1)	IEEE	New York	2012	32-41		No
7	The opportunity framework and data processing ecosystem for opportunistic activity and context recognition	M. Kurz	International Journal of Sensors,Wireless	June	Bentham Science	NA	2011	NA		Yes

[2] A permanent identifier should be a persistent link to the published version full text if open access or abstract if article is pay per view) or to the final manuscript accepted for publication (link to article in repository).
[3] Open Access is defined as free of charge access for anyone via Internet. Please answer "yes" if the open access to the publication is already established and also if the embargo period for open access is not yet over but you intend to establish open access afterwards.

			Communications and Control							
8	A hybrid BCI based on the fusion of EEG and EMG activities	R. Leeb	Journal of Neural Engineering	8(2)	IOP Publishing	NA	2011	NA	doi:10.1088/1741-2560/8/2/025011	No
9	The adARC pattern analysis architecture for adaptive human activity recognition systems	D. Roggen	Journal of Ambient Intelligence and Humanized Computing	August	Springer	Berlin	2011	NA	10.1007/s12652-011-0064-0	Yes
10	Network-level power-performance trade-off in wearable activity recognition: a dynamic sensor selection approach	P. Zappi	ACM Transactions on Embedded Computing Systems	11(3)	ACM	NA	2012	NA		No
11	Unsupervised adaptation for acceleration-based activity recognition: robustness to sensor displacement and rotation	R. Chavarriaga	Personal and Ubiquitous Computing	December	Springer	Berlin	2011	NA		No
12	Evidence Accumulation in Asynchronous BCI	S. Perdikis	International Journal of Bioelectromagnetism	13(3)	International Society for Bioelectromagnetism	NA	2011	131-132		No
13	A Framework for Utilizing Qualitative Spatial Relations between Networked Embedded Systems	C. Holzmann	Pervasive and Mobile Computing	6(3)	Elsevier	NA	2010	362-381		No
14	Titan: An enabling framework for activity-aware “PervasiveApps” in opportunistic personal area networks	D. Roggen	EURASIP Journal on Wireless Communications and Networking	2011:172831	EURASIP	NA	2011	NA		No
15	Context-aware brain-computer interfaces	R. Chavarriaga	PerAda Magazine	NA	for the 'Awareness: Self-Awareness in Autonomic Systems' Future and Emerging Technologies Proactive Initiative, funded by the European Commission under FP7.	NA	2010	NA		No
16	Kinect=IMU? Learning MIMO Signal Mappings to Automatically Translate Activity Recognition Systems across Sensor Modalities	O. Banos	Proc. 16th Int Symp on Wearable Computers	Yearly	IEEE Press	New York	2012	92-99		No

17	Locomotion@ Location: When the rubber hits the road	G. Hölzl	9th International Conference on Autonomic Computing	Yearly	ACM Press	NA	2012	73-77		No
18	Goal oriented opportunistic recognition of high-level composed activities using dynamically configured hidden markov models	G. Hölzl	3rd International Conference on Ambient Systems, Networks and Technologies	Yearly	Elsevier	NA	2012	308-315		No
19	Goal-Oriented Opportunistic Sensor Clouds	M. Kurz	2nd International Symposium on Secure Virtual Infrastructures	Yearly	Springer	Berlin	2012	NA		Np
20	Dynamic adaptation of opportunistic sensor configurations for continuous and accurate activity recognition	M. Kurz	Fourth International Conference on Adaptive and Self-Adaptive Systems and Applications	Yearly	IARIA	NA	2012	13-18		No
21	Unsupervised adaptation to on-body sensor displacement in acceleration-based activity recognition	H. Bayati	IEEE International Symposium on Wearable Computers	Yearly	IEEE	New York	2011	C1	10.1109/ISWC.2011.38	No
22	Collection and curation of a large reference dataset for activity recognition	A. Calatroni	IEEE International Conference on Systems, Man, and Cybernetics	Yearly	IEEE	New York	2011	30-35		No
23	Automatic transfer of activity recognition capabilities between body-worn motion sensors: Training newcomers to recognize locomotion	A. Calatroni	8th International Conference on Networked Sensing Systems	Yearly	IEEE	New York	2011	NA		No
24	Ensemble creation and reconfiguration for activity recognition: An information theoretic approach	R. Chavarriaga	IEEE Int Conf Systems, Man, and Cybernetics	Yearly	IEEE	New York	2011	2761-2766		No
25	Dynamic quantification of activity recognition capabilities in opportunistic systems	M. Kurz	Vehicular Technology Conference	Yearly	IEEE	New York	2011	1-5		No
26	Real-time transfer and evaluation of activity recognition capabilities in an opportunistic system	M. Kurz	3rd International Conference on Adaptive and Self-Adaptive Systems and Applications	Yearly	IARIA	NA	2011	73-78		No
27	Benchmarking classification techniques using the Opportunity human activity dataset	H. Sagha	IEEE International Conference on Systems, Man, and Cybernetics	Yearly	IEEE	New York	2011	36-40		No
28	VIDEO: A Framework for Opportunistic Context and Activity	G. Hölzl	9th International	Yearly	NA	NA	2011	NA		No

	Recognition		Conference on Pervasive Computing							
29	Detecting and rectifying anomalies in opportunistic sensor networks	H. Sagha	International Conference on Body Sensor Networks	Yearly	IEE	New York	2011	162 - 167		No
30	Shaping Sensor Node Ensemble according to their Recognition Performance within a a Planning-based Context Framework	C. Villalonga	Proc. 8th Int Conf on Networked Sensing Systems	Yearly	IEEE	New York	2011	NA		No
31	Design of an Ecology of Activity-Aware Cells in Ambient Intelligence Environments	A. Calatroni	10th IFAC Symposium on Robot Control	3 years	IFAC	NA	2012	NA	10.3182/20120905-3-HR-2030.00181	No
32	Sensor Abstractions for opportunistic Activity and Context Recognition Systems	M. Kurz	5th European Conference on Smart Sensing and Context	Yearly	Springer	Berlin	2010	135-148		No
33	DarSens: A Framework for Distributed Activity Recognition from Body-Worn Sensors	M. Haslgrübler	Fifth International Conference on Body Area Networks	Yearly	ICST	NA	2012	NA		No
34	On the use of magnetic field disturbances as features for activity recognition with on body sensors	G. Bahle	Proc. Smart Sensing and Context	Yearly	Springer	Berlin	2010	71-81		No
35	Integrated tool chain for recording, handling, and utilizing large, multimodal context data sets for context recognition systems	D. Bannach	Proceedings of the 2nd Workshop on Context-Systems Design, Evaluation and Optimisation	Yearly	TeCo	Karlsruhe	2011	NA		No
36	Identifying Important Action Primitives for High Level Activity Recognition	A. Manzoor	5th European Conference on Smart Sensing and Context	Yearly	Springer	Berlin	2010	149-162		No
37	Adaptation of Hybrid Human-Computer Interaction Systems using EEG Error- Related Potentials	R. Chavarriaga	32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society	Yearly	EMBC society	NA	2010	NA		No
38	Incremental knn classifier exploiting correct - error teacher for activity recognition	K. Förster	Proc. The Ninth International Conference on Machine Learning and Applications	Yearly	IEEE Press	New York	2010	445-450		No
39	Can magnetic field sensors replace gyroscopes in wearable	K. Kunze	International	Yearly	IEEE Press	New	2010	1-4		No

	sensing applications?		Symposium on Wearable Computers			York				
40	Multimodal fusion of muscle and brain signals for a hybrid-BCI	R. Leeb	32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society	Yearly	EBMC society	NA	2010	Na		No
41	Collecting complex activity data sets in highly rich networked sensor environments	D. Roggen	Proc. Seventh International Conference on Networked Sensing Systems	Yearly	IEEE Press	New York	2010	233-240	10.1109/INSS.2010.5573462	No
42	Detecting anomalies to improve classification performance in an opportunistic sensor network	H. Sagha	7th IEEE International Workshop on Sensor Networks and Systems for Pervasive Computing	Yearly	IEEE Press	New York	2011	154-159		No
43	On the use of brain decoded signals for online user adaptive gesture recognition systems	K. Förster	Proceedings of the Eighth International Conference on Pervasive Computing	Yearly	Springer	Berlin	2010	427-444		No
44	Which way am i facing: Inferring horizontal device orientation from an accelerometer signal	K. Kunze	Proc. of Int. Symp. on Wearable Computers	Yearly	IEEE Press	New York	2010	149-150		No
45	Context Cells: Towards Lifelong Learning in Activity Recognition Systems	A. Calatroni	4th European Conference on Smart Sensing and Context	Yearly	Springer	Berlin	2009	121-134		No
46	Evolving discriminative features robust to sensor displacement for activity recognition in body area sensor networks	K. Förster	5th Int. Conf. on Intelligent Sensors, Sensor Networks, and Information Processing	Yearly	IEEE Press	New York	2009	NA	10.1109/ISSNIP.2009.5416810	No
47	LifeBelt: Silent Directional Guidance for Crowd Evacuation	A. Ferscha	Proc Int Symp Wearable Comptuers	Yearly	IEEE Press	New York	2009	NA		No
48	Variability in foot-worn sensor placement for activity recognition	J. Doppler	Symp Wearable Comptuers	Yearly	IEEE Press	New York	2009	NA		No
49	Unsupervised Classifier Self-Calibration through Repeated Context Occurences: Is there Robustness against Sensor Displacement to Gain?	K. Förster	Int. Symp. Wearable Computers	Yearly	IEEE Press	New York	2009	77-84	10.1109/ISWC.2009.12	No

50	OPPORTUNITY: Towards opportunistic activity and context recognition systems	D. Roggen	Third IEEE WoWMoM Workshop on Autonomic and Opportunistic Communications	Yearly	IEEE Press	New York	2009	1-6		No
51	Pervasive Adaptation in Car Crowds	A. Ferscha	First International Workshop on User-Centric Pervasive Adaptation at MOBILWARE	Yearly	Springer	Berlin	2009	111-117	10.1007/978-3-642-03569-2_12	No

TEMPLATE A2: LIST OF DISSEMINATION ACTIVITIES

NO.	Type of activities[4]	Main leader	Title	Date/Period	Place	Type of audience[5]	Size of audience	Countries addressed
1	*Workshops*	*P. Lukowicz*	NSF/EU Workshop on Future Directions on Pervasive Computing and Social Networking for Emerging Applications. OPPORTUNITY dataset presentation	*29 March 2010*	*Mannheim, DE*	*Policy Makers*	*30*	Germany, USA
2	Workshops	P. Lukowicz	First IEEE PerCom Workshop on Pervasive Healthcare. Keynote on activity recognition	March, 2010	Mannheim Germany	Scientific Community	50	Germany

[4] A drop down list allows choosing the dissemination activity: publications, conferences, workshops, web, press releases, flyers, articles published in the popular press, videos, media briefings, presentations, exhibitions, thesis, interviews, films, TV clips, posters, Other.

[5] A drop down list allows choosing the type of public: Scientific Community (higher education, Research), Industry, Civil Society, Policy makers, Medias, Other ('multiple choices' is possible).

3	Workshops	A. Fersha	Talk at automotive.2010 conference. OPPORTUNITY methods for recognition of in-car driver activities	5 May 2010	Steyrermühl, Austria	Industry	50	Austria
4	Workshops	D. Roggen	Workshop on Best practices in activity recognition, Pervasive 2010. Best-practices learned from OPPORTUNITY	17 May 2010	Helsinki, Finland	Scientific Community	20	World
5	Video	D. Roggen	Video presentation of OPPORTUNITY at Pervasive 2010	19 May 2010	Helsinki, Finland	Scientific Community	200	World
6	Workshops	R. Chavarriaga	Fourth International BCI Meeting. Presentation on the use of Opportunistic principles applied to BCI) Talk: Multimodal fusion of muscle and brain activity for a hybrid BCI	1 June 2010	Asilomar, USA	Scientific Community	50	World
7	Workshops	R. Chavarriaga	Fraunhofer Institute for Computer Architecture and Software Technology FIRST, PerAda author's workshop. Context-aware Brain-Computer Interaction	June, 2010	Berlin, Germany	Scientific community	50	Europe
8	Conference	D. Roggen	KAIST, Semiconductor Systems Lab (Prof Hoi-Jun Yoo Prof. Kyoung-Soo Park) and ISWC TPC members.	3 July 2010	Daedeok, KR	Scientific community	20	US, KR, DE
9	Workshops	A. Ferscha	Talk at ESRC Complexity Research Seminar	8 July 2010	Schumacher	Scientific Community	20	UK, EU

			SOCIONICAL/OPPORTUNITY implementation issues for large scale AmI Environments		College, UK			
10	Presentations	D. Roggen	Culture Lab, Newcastle University, Prof. Patrick Olivier's group. OPPORTUNITY so far.	19 July 2010	Newcastle, UK	Scientific Community	30	UK
11	Workshops	R. Chavarriaga	Workshop: “Advancing Brain-Computer Interface” at the International Computational Neuroscience Meeting. Principles for efficient non-invasive neuroprosthetics: Machine learning, shared control and cognitive states	27 July 2010	San Antonio, Texas	Scientific Community	30	World
12	Conferences	D. Roggen, P. Lukowicz	Chinese-German Advanced Workshop on Wearable Computing	26 August 2010	Chengdu, CN	Scientific Community	50	DE, CN
13	Conferences	A. Ferscha	Presentation at PERADA Summerschool. Opportunistic sensing to track implicit user interactions	20 September 2010	Budapest	Scientific Community	25	EU
14	Workshops	D. Roggen	Context awareness and information processing in opportunistic ubiquitous systems Workshop at Ubicomp 2010	26 September 2010	Copenhagen, DK	Scientific Community	15	World
15	Presentations	A. Ferscha	Keynote-Talk at CISIM2010 Pervasive Computing: What Next?	10 October 2010	Krakow, Poland	Scientific Community	50	World

16	Presentations	A. Ferscha	Keynote-Talk at iiWAS 2010 conference Pervasive computing in the large	8 November 2010	France, Paris	Scientific Community	40	World
17	Presentations	A. Ferscha	Keynote-Talk at AmI-2010 conference Implicit Interaction	11 November 2010	Malaga, Spain	Scientific Community	80	World
18	Presentations	A. Ferscha	Invited Talk at PerAda Workshop in Security, Trust and Privacy Modelling trust in socio-technical systems	22. November 2010	Rome. Italy	Scientific Communtiy	30	EU
19	Workshops	R. Chavarriaga	Workshop on Translational Issues in BCI Development: User Needs, Ethics, and Technology Transfer. (Presentation on the use of Opportunistic principles applied to BCI) Talk: Evidence accumulation in asynchronous BCI	December 2-3, 2010	Rome, Italy	Scientific Community	20	EU
20	Workshops	R. Chavarriaga	Workshop on Machine Learning for Assistive Technologies, NIPS 2010 Talk: Robust activity recognition for assistive technologies: Benchmarking machine learning techniques	December 10, 2010	Whistler, CA	Scientific Community	20	World
21	Presentations	P. Lukowicz	NSF Workshop on Pervasive Computing at Scale (PeCS) Presentation of	January 27th-29th, 2011	Seattle, USA	Policy Makers	50	US

			Opportunistic sensing concepts as key future direction of pervasive computing					
22	Presentations	P. Lukowicz	DFG Joint German Japanese Symposium on Interaction with Smart Artefacts Large scale, context aware socio-technical systems	08 March 2011	Tokyo, JP	Scientific Community	30	DE, JP
23	Presentations	R. Chavarriaga	University Hospital of Lausanne (CHUV), Switzerland ,Neuroimaging Research Laboratory seminar Cognitive brain machine interfaces	March 2011	Lausanne, CH	Scientific Community	20	CH
24	Presentations	R. Chavarriaga	IEEE CAS-FEST Forum on Emerging and Selected Topics Current challenges in non-invasive brain-machine interfaces	May, 2011	Rio de Janeiro, Brazil	Scientific Community	40	Brazil
25	Presentations	D. Roggen R. Chavarriaga	Pervasive Computing System Development Lecture at University Linz Lecture: "Wearable Computing and Activity Recognition" & "Brain computer interfaces"	17-18.05.2011	Linz, Austria	Scientific Community	25	AT
26	Presentations	A. Ferscha	Festvortrag beim grenzüberschreitenden Innovationstag mit Cross Border Award Verleihung Vom Verschwinden des Computers	May, 2011	Passau, DE	Civil Society	25	DE

			und dem Aufkommen eingebetteter Assistenzlösungen					
27	Presentations	A. Ferscha	User Heaven or Techno Hell: Where are intelligent, adaptive technologies leading us	May, 2011	London, UK	Civil Society	50	UK
28	Presentations	D. Roggen	Qualcomm Context Awareness Symposium	9-10.09.2011	San Diego, CA	Industry	50	US
29	Presentations	R. Chavarriaga	XVI Simposio de Tratamiento de Señales, Imágenes y Visión Artificial STSIVA 2011. Signal processing techniques for brain-machine interfaces	September 2011	Pontificia Universidad Javeriana, Cali, Colombia	Scientific Community	30	Colombia
30	Workshops	R. Chavarriaga	Systems, Man, Cybernetics 2012 Robust Machine Learning Techniques for Human Activity Recognition using Body-Worn Sensors	9-12.10.2011	Anchorage, USA	Scientific Community	30	World
31	Presentations	A. Ferscha	Workshop "Future Tools & Topics" (MACH Dedication) Very Large Scale Agent Based Simulation: Cognitive Decision Making	October, 2011	Linz, AT	Scientific Community	40	AT
32	Workshops	D. Roggen	Unilever Physiological Monitoring Workshop Wearable sensors and activity recognition	7-8.11.2011	Port Sunlight, UK	Industry	30	UK
33	Presentations	D. Roggen	Bio-Robotics Network in Zurich seminar	11.11.2011	Zurich, CH	Scientific Community	40	CH

			Wearable sensing and human activity recognition					
34	Presentations	R. Chavarriaga	XI Jornadas Castellano-Manchegas de Fisioterapia Brain-machine interfaces and neuroprosthesis	November 2011	Toledo, SP	Scientific Community	50	ES
35	Presentations	A. Ferscha	EDV-Tag der oö. Versicherungsmakler Future ICT: Eintrittswahrscheinlichkeit mal Ereignisschwere	November, 2011	Linz, AT	Civil Society	40	AT
36	Presentations	A. Ferscha	World Summit Youth Award An Idea is worth nothing - innovation needs a plan!	November, 2011	Graz, AT	Civil Society	30	World
27	Presentations	A. Ferscha	Awareness Inter-Project Day From awareness to adaptation: large scale recognition and opportunistic configuration	January, 2012	Bologna, IT	Scientific Community	40	EU
28	Presentations	R. Chavarriaga	Guardian Angels Workshop: Sensors, Interfaces and Systems Current and future challenges for Brain Computer Interfacing	February 2012	Paris, FR	Scientific Community	30	EU
29	Presentations	A. Ferscha	COSI-ICT Workshop	March, 2012	Brussels, BE	Scientific Community	20	EU
30	Presentations	D. Roggen	IBIT seminar: activity recognition in motion-aware gaming Wearable sensing and human	09.03.2012	Mallorca, Spain	Industry	10	ES

			activity recognition: a crash course					
31	Presentations	D. Roggen	Pervasive Computing Systems, Karlsruhe Institute of Technology Activity recognition: opportunistic, collective, crowd-sourced	19.04.2012	Karlsruhe, Germany	Scientific Community	10	DE
32	Presentations	A. Ferscha	Long night of research Lassen Sie abschalten?	April, 2012	Linz, AT	Civil Society	300	AT
33	Presentations	R. Chavarriaga A. Ferscha	HC2 visions: human computer confluence research challenges Better interaction through cognitive prostheses, From Individual to Collective Attention - Models and Dynamics	May 2012	Vienna, AT	Scientific Community	40	EU
34	Presentations	A. Ferscha	NextBerlin Spectacles – personal displays for everyone	May, 2012	Berlin, DE	Civil Society	50	DE
35	Presentations	A. Ferscha	HC2 summer school Human computer confluence	July 2012	Milan, IT	Scientific Community	40	EU
36	Video	M. Kurz	OPPORTUNITY Framework video http://vimeo.com/46696294	June, 2011	San Francisco, US	Scientific Communtiy	20	World

Section B (Confidential[6] or public: confidential information to be marked clearly)
Part B1

TEMPLATE B1: LIST OF APPLICATIONS FOR PATENTS, TRADEMARKS, REGISTERED DESIGNS, ETC.					
Type of IP Rights[7]:	Confidential Click on YES/NO	Foreseen embargo date dd/mm/yyyy	Application reference(s) (e.g. EP123456)	Subject or title of application	Applicant (s) (as on the application)
NO PATENT APPLICATIONS					

[6] Note to be confused with the "EU CONFIDENTIAL" classification for some security research projects.

[7] A drop down list allows choosing the type of IP rights: Patents, Trademarks, Registered designs, Utility models, Others.

Part B2

Type of Exploitable Foreground[8]	Description of exploitable foreground	Confidential Click on YES/NO	Foreseen embargo date dd/mm/yyyy	Exploitable product(s) or measure(s)	Sector(s) of application[9]	Timetable, commercial or any other use	Patents or other IPR exploitation (licences)	Owner & Other Beneficiary(s) involved
General advancement of knowledge	Opportunistic Activity Recognition	No	Not applicable	Not applicable	Computational behaviour science, Human-computer interaction	2013	None	Consortium
Exploitation of R&D via standards	OPPORTUNITY dataset of human activities	NO	Not applicable	Not applicable	Computational behaviour science, Human-computer interaction	2013	None	Public domain

The OPPORTUNITY dataset is public domain, available on the UCI Machine Learning Repository. It asks for acknowledgement to the EU project OPPORTUNITY by citing a key OPPORTUNITY publication. It's purpose is to establish a baseline and standard for the evaluation of activity recognition techniques. Impact will be showing that an EU project provided a benchmark used worldwide in the scientific community.

[19] A drop down list allows choosing the type of foreground: General advancement of knowledge, Commercial exploitation of R&D results, Exploitation of R&D results via standards, exploitation of results through EU policies, exploitation of results through (social) innovation.

[9] A drop down list allows choosing the type sector (NACE nomenclature) : http://ec.europa.eu/competition/mergers/cases/index/nace_all.html

4.3 Report on societal implications

Replies to the following questions will assist the Commission to obtain statistics and indicators on societal and socio-economic issues addressed by projects. The questions are arranged in a number of key themes. As well as producing certain statistics, the replies will also help identify those projects that have shown a real engagement with wider societal issues, and thereby identify interesting approaches to these issues and best practices. The replies for individual projects will not be made public.

A General Information *(completed automatically when **Grant Agreement number** is entered.*	
Grant Agreement Number:	225938
Title of Project:	Activity and Context Recognition with Opportunistic Sensor
Name and Title of Coordinator:	Dr. Daniel Roggen

B Ethics	
1. Did your project undergo an Ethics Review (and/or Screening)? • If Yes: have you described the progress of compliance with the relevant Ethics Review/Screening Requirements in the frame of the periodic/final project reports? Special Reminder: the progress of compliance with the Ethics Review/Screening Requirements should be described in the Period/Final Project Reports under the Section 3.2.2 *'Work Progress and Achievements'*	***0Yes XNo***
2. Please indicate whether your project involved any of the following issues (tick box) :	***YES***
RESEARCH ON HUMANS	
• Did the project involve children?	
• Did the project involve patients?	
• Did the project involve persons not able to give consent?	
• Did the project involve adult healthy volunteers?	X
• Did the project involve Human genetic material?	
• Did the project involve Human biological samples?	
• Did the project involve Human data collection?	
RESEARCH ON HUMAN EMBRYO/FOETUS	
• Did the project involve Human Embryos?	
• Did the project involve Human Foetal Tissue / Cells?	
• Did the project involve Human Embryonic Stem Cells (hESCs)?	
• Did the project on human Embryonic Stem Cells involve cells in culture?	
• Did the project on human Embryonic Stem Cells involve the derivation of cells from Embryos?	
PRIVACY	
• Did the project involve processing of genetic information or personal data (eg. health, sexual lifestyle, ethnicity, political opinion, religious or philosophical conviction)?	
• Did the project involve tracking the location or observation of people?	
RESEARCH ON ANIMALS	
• Did the project involve research on animals?	
• Were those animals transgenic small laboratory animals?	
• Were those animals transgenic farm animals?	

• Were those animals cloned farm animals?	
• Were those animals non-human primates?	
RESEARCH INVOLVING DEVELOPING COUNTRIES	
• Did the project involve the use of local resources (genetic, animal, plant etc)?	
• Was the project of benefit to local community (capacity building, access to healthcare, education etc)?	
DUAL USE	
• Research having direct military use	0 Yes X No
• Research having the potential for terrorist abuse	0 Yes X No

C Workforce Statistics

3. Workforce statistics for the project: Please indicate in the table below the number of people who worked on the project (on a headcount basis).

Type of Position	Number of Women	Number of Men
Scientific Coordinator	0	1
Work package leaders	0	4
Experienced researchers (i.e. PhD holders)	0	0
PhD Students	0	8
Other	1	0

4. How many additional researchers (in companies and universities) were recruited specifically for this project?	**6**
Of which, indicate the number of men:	6

D Gender Aspects

5. Did you carry out specific Gender Equality Actions under the project?	X ○	Yes No

6. Which of the following actions did you carry out and how effective were they?

		Not at all effective				Very effective
X	Design and implement an equal opportunity policy	X	○	○	○	○
X	Set targets to achieve a gender balance in the workforce	X	○	○	○	○
❑	Organise conferences and workshops on gender	○	○	○	○	○
X	Actions to improve work-life balance	X	○	○	○	○
○	Other:					

7. Was there a gender dimension associated with the research content – i.e. wherever people were the focus of the research as, for example, consumers, users, patients or in trials, was the issue of gender considered and addressed?

○ Yes- please specify

X No

E Synergies with Science Education

8. Did your project involve working with students and/or school pupils (e.g. open days, participation in science festivals and events, prizes/competitions or joint projects)?

X Students of universities, University open days, “night of science”

○ No

9. Did the project generate any science education material (e.g. kits, websites, explanatory booklets, DVDs)?

X The OPPORTUNITY dataset for activity recognition makes it easy for bachelor students to test applied machine learning techniques.

○ No

F Interdisciplinarity

10. Which disciplines (see list below) are involved in your project?

X 1.1

X 2.2

○ Associated discipline[Error! Bookmark not defined.]:

G Engaging with Civil society and policy makers

11a Did your project engage with societal actors beyond the research community? *(if 'No', go to Question 14)*	○ X	Yes No

11b If yes, did you engage with citizens (citizens' panels / juries) or organised civil society (NGOs, patients' groups etc.)?

X No

○ Yes- in determining what research should be performed

○ Yes - in implementing the research

○ Yes, in communicating /disseminating / using the results of the project

11c In doing so, did your project involve actors whose role is mainly to organise the dialogue with citizens and organised civil society (e.g. professional mediator; communication company, science museums)?	○ X	Yes No

12. Did you engage with government / public bodies or policy makers (including international organisations)

- X No
- ○ Yes- in framing the research agenda
- ○ Yes - in implementing the research agenda
- ○ Yes, in communicating /disseminating / using the results of the project

13a Will the project generate outputs (expertise or scientific advice) which could be used by policy makers?

- ○ Yes – as a **primary** objective (please indicate areas below- multiple answers possible)
- ○ Yes – as a **secondary** objective (please indicate areas below - multiple answer possible)
- X No

13b If Yes, in which fields?

Agriculture Audiovisual and Media Budget Competition Consumers Culture Customs Development Economic and Monetary Affairs Education, Training, Youth Employment and Social Affairs		Energy Enlargement Enterprise Environment External Relations External Trade Fisheries and Maritime Affairs Food Safety Foreign and Security Policy Fraud Humanitarian aid		Human rights Information Society Institutional affairs Internal Market Justice, freedom and security Public Health Regional Policy Research and Innovation Space Taxation Transport	

13c If Yes, at which level? ○ Local / regional levels ○ National level ○ European level ○ International level	

H Use and dissemination

14. How many Articles were published/accepted for publication in peer-reviewed journals?		**14**
To how many of these is open access[10] provided?		**1**
How many of these are published in open access journals?		**1**
How many of these are published in open repositories?		**0**
To how many of these is open access not provided?		**13**
Please check all applicable reasons for not providing open access:		
X publisher's licensing agreement would not permit publishing in a repository ❑ no suitable repository available X no suitable open access journal available X no funds available to publish in an open access journal ❑ lack of time and resources ❑ lack of information on open access ❑ other[11]: ……………		
15. How many new patent applications ('priority filings') have been made? *("Technologically unique": multiple applications for the same invention in different jurisdictions should be counted as just one application of grant).*		**0**
16. Indicate how many of the following Intellectual Property Rights were applied for (give number in each box).	Trademark	**0**
	Registered design	**0**
	Other	**0**
17. How many spin-off companies were created / are planned as a direct result of the project?		**0**
Indicate the approximate number of additional jobs in these companies:		**0**

18. Please indicate whether your project has a potential impact on employment, in comparison with the situation before your project:			
X	Increase in employment, or	X	In small & medium-sized enterprises
X	Safeguard employment, or	❑	In large companies
❑	Decrease in employment,	❑	None of the above / not relevant to the project
❑	Difficult to estimate / not possible to quantify		

19. For your project partnership please estimate the employment effect resulting directly from your participation in Full Time Equivalent (*FTE = one person working fulltime for a year*) jobs:	*Indicate figure:* *6*

[10] Open Access is defined as free of charge access for anyone via Internet.
[11] For instance: classification for security project.

Difficult to estimate / not possible to quantify	❑

I Media and Communication to the general public

20. As part of the project, were any of the beneficiaries professionals in communication or media relations?

○ Yes X No

21. As part of the project, have any beneficiaries received professional media / communication training / advice to improve communication with the general public?

○ Yes x No

22 Which of the following have been used to communicate information about your project to the general public, or have resulted from your project?

❑	Press Release	X	Coverage in specialist press
❑	Media briefing	X	Coverage in general (non-specialist) press
❑	TV coverage / report	❑	Coverage in national press
❑	Radio coverage / report	❑	Coverage in international press
❑	Brochures /posters / flyers	X	Website for the general public / internet
X	DVD /Film /Multimedia	X	Event targeting general public (festival, conference, exhibition, science café)

23 In which languages are the information products for the general public produced?

❑	Language of the coordinator	X	English
❑	Other language(s)		

***Question F-10*:** Classification of Scientific Disciplines according to the Frascati Manual 2002 (Proposed Standard Practice for Surveys on Research and Experimental Development, OECD 2002):

FIELDS OF SCIENCE AND TECHNOLOGY

1. NATURAL SCIENCES

1.1 Mathematics and computer sciences [mathematics and other allied fields: computer sciences and other allied subjects (software development only; hardware development should be classified in the engineering fields)]

1.2 Physical sciences (astronomy and space sciences, physics and other allied subjects)

1.3 Chemical sciences (chemistry, other allied subjects)

1.4 Earth and related environmental sciences (geology, geophysics, mineralogy, physical geography and other geosciences, meteorology and other atmospheric sciences including climatic research, oceanography, vulcanology, palaeoecology, other allied sciences)

1.5 Biological sciences (biology, botany, bacteriology, microbiology, zoology, entomology, genetics, biochemistry, biophysics, other allied sciences, excluding clinical and veterinary sciences)

2 ENGINEERING AND TECHNOLOGY

2.1 Civil engineering (architecture engineering, building science and engineering, construction engineering, municipal and structural engineering and other allied subjects)

2.2 Electrical engineering, electronics [electrical engineering, electronics, communication engineering and systems, computer engineering (hardware only) and other allied subjects]

2.3. Other engineering sciences (such as chemical, aeronautical and space, mechanical, metallurgical and materials engineering, and their specialised subdivisions; forest products; applied sciences such as geodesy, industrial chemistry, etc.; the science and technology of food production; specialised technologies of interdisciplinary fields, e.g. systems analysis, metallurgy, mining, textile technology and other applied subjects)

3. MEDICAL SCIENCES

3.1 Basic medicine (anatomy, cytology, physiology, genetics, pharmacy, pharmacology, toxicology, immunology and immunohaematology, clinical chemistry, clinical microbiology, pathology)

3.2 Clinical medicine (anaesthesiology, paediatrics, obstetrics and gynaecology, internal medicine, surgery, dentistry, neurology, psychiatry, radiology, therapeutics, otorhinolaryngology, ophthalmology)

3.3 Health sciences (public health services, social medicine, hygiene, nursing, epidemiology)

4. AGRICULTURAL SCIENCES

4.1 Agriculture, forestry, fisheries and allied sciences (agronomy, animal husbandry, fisheries, forestry, horticulture, other allied subjects)

4.2 Veterinary medicine

5. SOCIAL SCIENCES

5.1 Psychology

5.2 Economics

5.3 Educational sciences (education and training and other allied subjects)

5.4 Other social sciences [anthropology (social and cultural) and ethnology, demography, geography (human, economic and social), town and country planning, management, law, linguistics, political sciences, sociology, organisation and methods, miscellaneous social sciences and interdisciplinary , methodological and historical S1T activities relating to subjects in this group. Physical anthropology, physical geography and psychophysiology should normally be classified with the natural sciences].

6. HUMANITIES

6.1 History (history, prehistory and history, together with auxiliary historical disciplines such as archaeology, numismatics, palaeography, genealogy, etc.)

6.2 Languages and literature (ancient and modern)

6.3 Other humanities [philosophy (including the history of science and technology) arts, history of art, art criticism, painting, sculpture, musicology, dramatic art excluding artistic "research" of any kind, religion, theology, other fields and subjects pertaining to the humanities, methodological, historical and other S1T activities relating to the subjects in this group]

2. FINAL REPORT ON THE DISTRIBUTION OF THE EUROPEAN UNION FINANCIAL CONTRIBUTION

This report shall be submitted to the Commission within 30 days after receipt of the final payment of the European Union financial contribution.

Note from the coordinator: the final contribution has not been received yet.

Report on the distribution of the European Union financial contribution between beneficiaries

Name of beneficiary	Final amount of EU contribution per beneficiary in Euros
1.	
2.	
n	
Total	