Goal-Oriented Opportunistic Sensor Clouds

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Abstract. Activity- and context-aware systems, as they are known, established, and well evaluated in small-scale laboratory settings for years and decades, suffer from the fact, that they are limited concerning the underlying data delivering entities. The sensor systems are usually attached on the body, on objects, or in the environment, directly surrounding persons or groups whose activities or contextual information has to be detected. For sensors that are exploited in this kind of systems, it is essential that their modalities, positions and technical details are initially defined to ensure a stable and accurate system execution. In contrast to that, opportunistic sensing allows for selecting and utilizing sensors, as they happen to be accessible according to their spontaneous availability, without presumably defining the input modalities, on a goal-oriented principle. One major benefit thereby is the capability of utilizing sensors of different kinds and modalities, even immaterial sources of information like webservices, by abstracting low-level access details. This emerges the need to roll out the data federating entity as decentralized collecting point. Cloud-based technologies enable space- and time-free utilization of a vast amount of heterogeneous sensor devices reaching from simple physical devices (e.g., GPS, accelerometers, as they are conventionally included on today's smart phones) to social media sensors, like Facebook, Twitter, or LinkedIn. This paper presents an opportunistic, cloud-based approach for large-scale activity- and context-recognition.

1 Introduction and Motivation

Activity and more generally the context of persons are important fragments of information in different kinds of ubiquitous applications. The sensor-based recognition of human activities by applying different machine learning technologies has been subject to research over the last years and decades and is thus very well evaluated, at least in laboratory surroundings [3,26,32,34]. By utilizing the so-called *Activity Recognition Chain* (in the following abbreviated as *ARC*) [22,27,28], which is a staged processing principle for mapping the sensor signals into a set of activity classes, it is possible to recognize human activities from sources of information (i.e., sensors) of different kinds and modalities that can be mounted in the environment, on objects, or on the body of persons. Usually, the ARC consists of stages for (i) signal preprocessing and data segmentation,

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(ii) feature extraction to reduce the sensor signal dimensionality and to yield a vector of significant features, (iii) activity classification to map the sensor signal (or rather the feature vector) into a set of activity classes, (iv) null class rejection in case the sensor signal cannot be assigned to a known activity class, and (v) sensor fusion for combination of multiple ARCs to increase the recognition accuracy. This sensor signal processing and mapping into a predefined set of activity classes works reasonably well [35], if specific conditions for the sensing infrastructure and the activity recognition application are fulfilled: (i) the sensors, their modalities and physical operating characteristics together with their exact positions and orientation have to be initially defined at design time of the system (i.e., the sensing infrastructure) to be able to accurately map the sensor signals into a predefined set of output classes, and (ii) the sensing infrastructure has to be static and stable during system's execution.

These prerequisites and characteristics might be sufficient and acceptable for applications that are executed in stable laboratory settings, but limit the feasibility of real-world deployments in sensor rich environments. Nowadays, sensor systems are massively integrated into things of every day life [1], in the environment (e.g., electronic appliances), and on the body of persons (e.g., smart phones, sensor-rich garments, etc.) [29]. This means, the underlying sensing infrastructure is of dynamic nature, thus changes over time. The sensors spontaneous availability (even during execution of an activity recognition task) opens a new approach and paradigm of human activity recognition: *opportunistic sensing* [21,30]. By considering a dynamically changing sensing infrastructure, a system that executes activity recognition tasks in an opportunistic way, it is possible to (i) operate in a real-world environment, without forcing the users to artificially deploy specific sensors at specific locations (thus being unobtrusive), (ii) ensure a continuous and stable execution of the recognition task [19], and (iii) provide an extensible open-ended environment in terms of inclusion of unforeseen sensor devices. The OPPORTUNITY Framework [21] is a reference implementation of such a system that autonomously configures orchestrated sensor ensembles according to a recognition goal that is stated to the system (by users or other applications) at runtime [13]. This "goal-oriented behavior" is the second novelty (besides the aforementioned dynamic sensing infrastructure) compared to established activity recognition systems, where the activities of interest have to be announced and configured at system's design time.

The flexibility in the sensing infrastructure according to the sensors characteristics of being of heterogeneous nature and being spontaneously available and unavailable [19] opens new challenges to systems in terms of handling devices of different kinds, modalities, and even physical availability. As we have already learned in [18] and [21], utilizing sensors of different kinds is not a trivial task. The concept of *Sensor Abstractions* allows to access material as well as immaterial sensors in a common way, by abstracting low-level access details. This approach is sufficient and efficient for a locally operating system. Nevertheless, for large scale applications (or multiple applications that are fed upon the same sensor pool), that also make use of social media networks (where information from platforms like Facebook or Twitter is aggregated, further referred to as *SocialSensor*), and that operate in a highly distributed environment, a new level of handling sensors is needed: the concept of *sensor-clouds*. Processing sensor data of different kinds can be totally decoupled and decentralized from a goal-oriented activity recognition application by utilizing sensor clouds, where environmental and personal information is aggregated and processed for further use in a specific application. This paper presents the concept of goal-oriented sensor clouds, where cloud-based technology enables the decentralized, time-, and space-free processing, aggregating, and storing of sensor data from devices of different kinds.

The remaining paper is structured as follows. Section 2 discusses related work on the activity recognition side with respect to the opportunistic aspect and in terms of processing sensor signal acquisition and utilization for activity recognition in a cloud-based surrounding. Section 3 presents the vision of opportunistic activity recognition and presents needs and characteristics for such systems that share sensor signals over cloud technologies. Section 4 discusses the proposed concept of utilizing cloud-based technologies for sensor data processing in activity recognition systems in detail. This is followed by Section 5 where the approach is presented and illustrated on a large scale setting and use case (i.e., the 29^{th} Vienna City Marathon 2012 (VCM2012)[1]). The last Section 6 closes the paper with a conclusion and an outlook to future work.

2 Related Work

Related work that is relevant to the scope of this paper can be identified in three different scientific areas: (i) *human activity recognition* (that tackles the basic processing principles and novel application domains), (ii) *opportunistic sensing and activity recognition* (as new paradigm and next generation of activity-aware computing), and (iii) *cloud-based pervasive applications* (as concept of bringing sensors into the cloud). The following three paragraphs discuss recent related work on these research areas.

The basic characteristics, concepts, and contributions to the field of sensor-based activity recognition (i.e., static and presumably defined sensing infrastructure [3,26,32,34], and the activity recognition chain as staged processing principle [22,27,28]) have already been discussed in the introductory Section. Recent advancements in this area have to do with long-term evaluations for achieving higher performances and recognition rates [24], in specific application domains (e.g., elderly care [15], or smart home settings [16], etc.). Furthermore, activity recognition by utilizing sensor modalities that are initially integrated on off-the-shelf mobile platforms (e.g., smart phones) is lately being investigated (see [11] and [23] for recent examples).

Opportunistic sensing and activity recognition is a rather new research area, that operates in open-ended (sensing) environments with dynamically varying heterogeneous sensor settings in a goal-oriented manner [13]. In [21] and [22] a reference implementation of a system that operates in an opportunistic way is

[1] `http://www.vienna-marathon.com/`, last visited June 2012.

presented (i.e., the OPPORTUNITY Framework). By utilizing the concepts of *Sensor Abstractions* (to handle material as well as immaterial sensors of different kinds, modalities and working characteristics), *Sensor Self-Descriptions* (to preserve the sensors capabilities towards the recognition of specific activities), and qualitative metrics to dynamically estimate the sensor's or ensemble's recognition performance (i.e., *Degree of Fulfillment* and *Trust Indicator*), the system is capable of dynamically configuring and invoking ARCs upon spontaneous sensor availability and relevance to the currently active activity recognition goal (thus operates in an opportunistic way). Calatroni et al. present in [6] an approach that allows an opportunistic system to autonomously extend the activity recognition capabilities of available sensor systems. The concept of *transfer learning* allows one sensor to gather knowledge concerning the recognition of activities by monitoring another, already trained sensor and learning the sensor signal mapping to activities at runtime. This approach is evaluated and discussed in a real-time setting with physical sensors utilizing the OPPORTUNITY Framework in [20]. Sensor displacement or rotation is another known problem in activity recognition systems, therefore Chavarriaga et al. have investigated in methods to be robust against these anomalies by autonomously adapting the system and underlying machine learning technologies [8]. The same authors present in [7] an approach to configure ensembles, based on the pairwise mutual information between two sensor nodes, for specific activity classes.

Cloud computing [2,36] and integrating or supporting pervasive and ubiquitous applications with cloud services constitute the final block of related work. Interesting in the scope of this paper is especially the combination of sensors and sensor networks in the cloud, subsequent security aspects and concrete application domains. Kurschl and Beer present a model in [17], which combines wireless sensor networks with the cloud computing paradigm, since clouds usually provide massive processing power, which can be beneficial for long term operations and observations with sensor networks. Similar work is presented by Dash et al. [10], where the concept of *sensor clouds* is initially mentioned. Thereby, one aim is to make the sharing and analysis of real-time sensor data easier by integrating wireless sensor networks within cloud computing technologies. The authors propose a framework that addresses this integration, whereas a broad spectrum of numerous application areas are mentioned (e.g., weather forecasting, health-care, military services, etc.). In [12], Hassan et al. propose also a framework for connecting sensors and cloud services for utilization in "next-generation community-centric" applications. Furthermore, to deliver sensor data to cloud application users, an event matching algorithm is presented and evaluated on a health-care scenario. Corredor et al. [9] present a middleware architecture for embedded networks, which aims at integrating pervasive system components into the future service cloud to achieve high performance within the *Internet of Things* paradigm. The authors argue that traditional service-oriented architecture approaches are unsuitable for resource-limited sensors devices since they are usually too complex. Combining technology of different areas of research (in our case cloud computing and sensor technology) emerges the need to discuss specific requirements to security and trust. This is done in [25], where different security aspects are presented (e.g., identity and access management, data privacy, trust in data aggregation, etc.). Furthermore, specific security aspects (i.e., interface encryption, possible threats, etc.) for smart phone based sensor networks and the integration into cloud technology are discussed in [14]. Finally, specific application domains and use cases for combining sensor network and cloud computing technologies are presented in [5] and [31], where on the one hand a platform that utilizes cloud services for pervasive positioning is presented, and on the other hand an approach to collect, aggregate, and process patient vital-data in hospitals.

3 The Vision of Opportunistic Sensing

Over the past decades, activity recognition has followed the same general principles: deploy sensors application-specific, build the activity recognition system and use it with the defined setup. With the emerging plethora of sensing devices that are already deployed in the environment, the task of defining a sensor setup for a recognition system is outdated. Nowadays, sensors are already embedded and integrated on objects, in the environment, or also on the body of persons. Due to technological advancements, sensor systems are becoming smaller and smaller and due to their vast heterogeneity and to the (wireless) communication capabilities, devices that measure different environmental quantities can be embedded and integrated in different kinds of electronic appliances [4]. Thus, future environments (and partially also current environments) will see an ever larger availability of readily deployed sensors. The newest generation of smartphones, for example, can be seen as a multi-sensor platform, as most of them are equipped with position sensors (GPS), acceleration, orientation, light, noise and temperature detection. Digital cameras, with their capabilities of automatically tagging photographs with their global position, can be easily utilized as positioning sensors. Sensors are also available in toys, in building automation systems (e.g., to detect door/windows being opened or closed), in furniture, and even in some garments [33] and sport shoes. Even social networking services, like Facebook, Twitter, or LinkedIn, can be seen as sensor (i.e., *SocialSensor*), since these platforms could also provide valuable information to an activity recogniton system for a specific user. This massive amount of already deployed sensor devices reverses the activity and context recognition architecture in a way that the workflow in activity recognition beginning with the explicit deployment of sensors is gratuitous. The challenge altered from the deployment of sensors to the utilization of already available heterogeneous devices by enabling activity and context recognition systems to operate with dynamically varying sensor settings in an opportunistic way by not considering a closed world but open world assumption.

As already mentioned, opportunistic activity and context recognition as specialized discipline offers (implicit) human computer interaction based on recognition of activities by taking an open world assumption concerning the recognition goals as well as the involved sensor systems and technologies for signal processing, machine learning and pattern classification. Since the sensing infrastructure in an opportunistic activity and context recognition system is not fixed, predefined, or constrained to specific sensor types with specific modalities, the accessory methods to gather environmental sensor data have to be unified on an abstract software-level. Recent technological advancements allow for the production of low-cost sensor devices of different kinds, which can nowadays be integrated in artifacts of everyday life (e.g., toys, garments, electronic appliances, smart phones, etc.). Even immaterial entities (e.g., online available webservices, or social network services) can be valuable sources of important information to an activity recognition system. Everything that delivers environmental information should be considered as beneficial source of data and thus has to be made available in an opportunistic system (i.e., *everything is a sensor*).

Taking these definitions and attributes of an opportunistic system, the following list presents major requirements and key characteristics for such a system:

(i) *Temporal Availability of Sensors*: The sensing infrastructure in an opportunistic system is not meant to be fixed over a certain amount of time. Thus, sensors can spontaneously connect or (temporarily) disconnect, which has to be handled by the system by either reconfiguring the ensembles or finding other sensors that can be utilized to execute a recognition goal.

(ii) *Reduced Sensor Quality*: Another crucial aspect is the fact that sensors could unintentionally be moved, rotated, or interfered by another jamming signal. This results in a reduced quality of the delivered environmental sensor data, which has to be handled by the opportunistic system.

(iii) *Self-Adaptiveness*: As sensor configurations are not defined at design time of the system, the capability of self-adapting and extending the sensor's capabilities is another major characteristic. Sensors are meant to learn from their past contributions to recognition goals, but also from contributions from other sensors to gather knowledge and further capabilities for future goals (i.e., *transfer learning* [6,20]).

(iv) *Self-Management and Cooperative Behavior*: One major aspect in an opportunistic activity and context recognition is the configuration of sets of sensors that are best suited to execute a recognition goal (the ensemble). To be able to operate in a dynamic environment as ensemble, this presumes self-management capabilities in terms of configuring and adapting ensembles, and cooperative sensing capabilities in order to operate in a sensing ensemble.

As discussed in the previous paragraphs, the following list summarizes the important aspects that discriminate the opportunistic from the traditional activity and context recognition approach. These benefits can be seen as motivation to investigate in opportunistic sensing for activity and context recognition. As it will be shown later, by utilizing cloud technologies, the realization of these aspects can be supported by considering a decentralized, time-, and space-free sensor data processing methodology.

(i) *Utilization of Unforeseen Sensor*: The utilization of sensor systems that have not been considered in the initial system definition enables the integration of sensing devices of different kinds and modalities as they spontaneously appear in the sensing infrastructure.
(ii) *Improved Robustness and Flexibility*: As an opportunistic system dynamically reacts and adapts to changes in the sensing infrastructure, this aspect improves the robustness and flexibility of an opportunistic activity and context recognition system in contrast to traditional applications.
(iii) *Improved Unobtrusiveness*: As an opportunistic system does not rely on a fixed sensing infrastructure and the fact that it dynamically reacts on changes in the sensing infrastructure, such systems improve the unobtrusiveness especially in wearable and smart home applications, as persons do not have to be considerate of the sensor systems and the artificial deployment.
(iv) *Implicit Sensor Deployment*: The explicit sensor deployment becomes gratuitous in an opportunistic system. The sensing infrastructure does not have to be initially defined, the system utilizes sensor systems as they happen to be available in a way, that the best set of sensors is configured according to a recognition goal.
(v) *Utilization of Inconvenient Sensor*: The utilization of systems as sensors that have not been considered as being a sensor (e.g., smart phone as sensor for crowd sensing, or a social network as social sensor), together with the aforementioned benefits, enables the development of next generation flexible and robust activity and context recognition systems, that dynamically adapt to the current situation with respect to the available heterogeneous sensing infrastructure and the recognition goal that has to be executed.

The approach so far to access sensors of different physical characteristics and different modalities was defined as abstracting them into a generalized accessing interface (i.e., *Sensor Abstractions*) [18,21]. Figure 1 illustrates this concept, whereas three different sensor abstractions ((i) *PhysicalSensor*, (ii) *PlaybackSensor*, and (iii) *HarvestSensor*) as defined in [18,21] are presented. Abstracting sensors to make them accessible in a common way might be sufficient for a stand-alone system or application that locally hosts security aspects, synchronization and timing issues in case multiple sensors are utilized, and if the data aggregation and processing is done locally. For a more flexible environment, a cloud-based service, were sensor data is collected, processed and provided in a decentralized, time-, and space-free way for different kinds of applications, could bring the paradigm of computing human activity recognition in an opportunistic manner to a new level.

Accessing and utilizing sensors in a common way by providing sensor abstractions is important but yet does not provide any information of the sensor's technical details, nor about its capabilities regarding activity recognition for the execution of a specific recognition goal. The concept of sensor abstractions enables the system to easily access the sensor datastream, but there is still some further information missing, i.e. the technical characteristics of the sensor, and

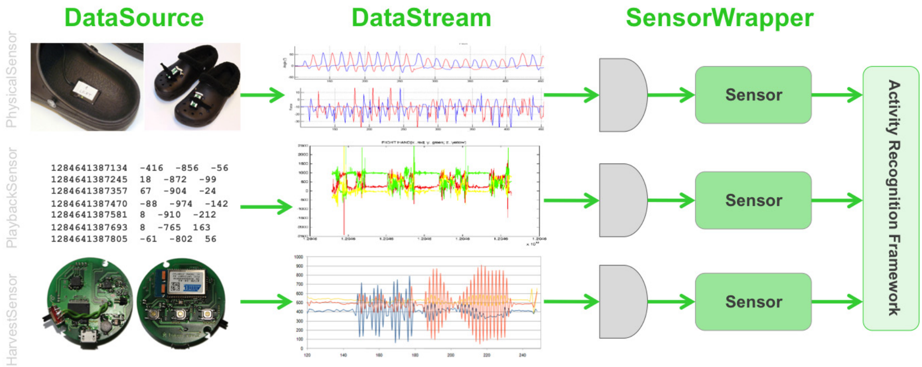

Fig. 1. The concept of *Sensor Abstractions* in the OPPORTUNITY Framework to access and utilize heterogeneous sensors [18,21]

what the system can do with it and its delivered data. Therefore, the second building block that is inevitable in an opportunistic system is another concept on the single-sensor level, which equips the sensors with semantic meta-information, concerning its technical details, its recognition capabilities, its sensor data quality, and its spatial, locational, and positional details. The semantic description of resources of valuable information has already been introduced in [20,21,22]: *Sensor Self-Descriptions*. On the syntactic level, this dynamic information is organized in two parts. A first block retains a value for what is called Trust Indicator (TI). This quality-of-service metric is a number in the range of [0, 1] indicating how trustworthy the sensor data is at a precise moment. If for example the sensor data is reduced in its quality because of sensor displacements, or because the device runs out of power, this decreasing quality is manifested in the TI value. The Trust Indicator value of a healthy sensor, that delivers high-quality data, is set to the maximum (i.e., 1). The TI value of a sensor that delivers quality-reduced data is reduced accordingly. A second block in the dynamic sensor self-description is formed by the so-called *ExperienceItems*. Each ExperienceItem acts as snapshot to memorize the sensor capabilities in form of recognizable activities. Along each activity label, every ExperienceItem features a corresponding Degree of Fulfillment (DoF), which is a quality-of-service metric in the range of [0, 1], which expresses how well a certain activity is recognized. The ExperienceItem is used by the framework to configure an available sensor with the required machine learning algorithms and the correct training data (i.e., the complete activity recognition chain) to recognize a certain set of activities. ExperienceItems memorize gathered "experience" from single sensors or sensor ensembles according to recognition goals. Each item contains every method and configuration detail to build an activity recognition chain or even a multi-sensor ensemble for a specific recognition goal. By utilizing the concept of ExperienceItems, a complete recognition chain can be dynamically configured at runtime of the system. This allows operating the system in a dynamic sensing environment without presumably defining the sensing infrastructure at design time of the system, and thus perfectly meets the requirements of an opportunistic activity and context recognition system as defined above.

The two concepts of *Sensor Abstractions* and *Sensor Self-Descriptions* can be decoupled from an opportunistic activity and context recognition system by letting a cloud-based service (i.e., *sensor-cloud*) take care of the sensor data acquisition, handling, aggregation and provision. The next Section 4 presents a concept and an approach how the OPPORTUNITY Framework can be operated in a highly distributed, time-, and space-free manner by orchestrating the sensor services via the concept of sensor-clouds.

4 Sensor Clouds

Sensor abstractions as methodology to access different sensors are sufficient for locally operated human activity recognition applications and systems. The OPPORTUNITY Framework [21] as reference implementation of an opportunistic activity and context recognition system so far was meant to be processed as centralized unit. Therefore, having a limited number of physical material sensors (all of course being spontaneously available and unavailable and dynamically varying their positions and locations), and immaterial sensors, like webservices, enable a continuous, stable and highly accurate human activity recognition. If the system has to be distributed, or multiple applications have to be deployed, that utilize sensor data from one sensor pool for different purposes, the handling and data procession effort will get increasingly massive in terms of handling sensors for multiple applications, aggregating, synchronizing and preserving sensor data, or simply provide real-time access via different sensor abstractions or different hard-, and software interfaces. Take the synchronization effort as example - as we have learned recently in [29] - when utilizing different physical sensors. Getting sensor data aligned and synchronous according to a global master-timer (which is inevitable for activity recognition purposes) is not a trivial task and needs manual reviewing and processing of all considered data streams. Another example that arises subsequently from the data synchronization is how the data can be consistently preserved for future evaluations. This has to be done locally or needs at least heavy effort and manual procession. Thus, abstracting sensors from their physical properties at it was described in the previous Section is important but this has to be further decoupled from the system to enable the development of large-scale and decentralized activity recognition applications that opportunistically coordinate and embed the available sensor data-streams.

This is where the concept of sensor-clouds is the next logical step and buidling block towards a unified, distributed, time-, and space-free sensor data handling and processing. Figure 2 illustrates where the sensor cloud comes into play. Sensors (respectively the corresponding abstractions) that are available in the environment deliver the tagged sensor measurements into the cloud over a standardized connection with corresponding protocols (e.g., TCP/IP). Figure 2 illustrates three different kinds of sensors ((i) *SocialSensors*, like Facebook and Twitter, (ii)

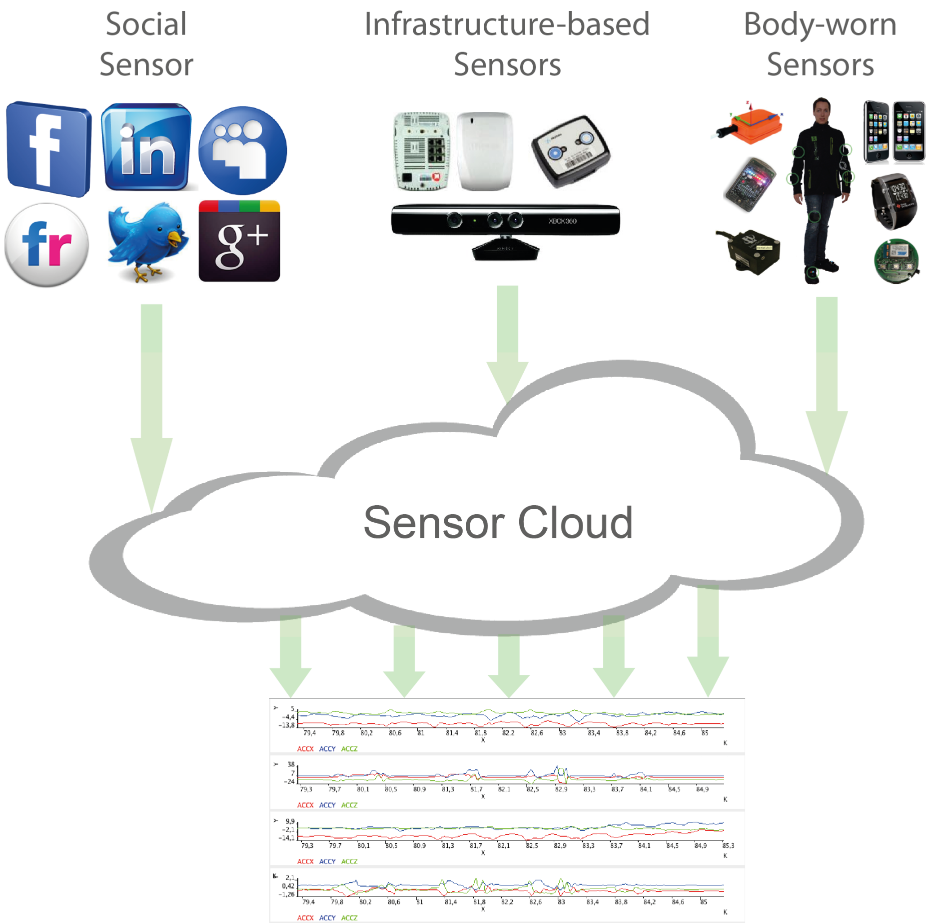

Fig. 2. The concept of sensor clouds for autonomous, decentralized, and distributed handling, processing, and aggregation of sensor data

Infrastructure-based Sensors, like Microsoft's Kinect and the Ubisense Localizations system, and (iii) *Body-Worn Sensors*, like smart phones and the XSens 3D MotionTracking system MTx) that announce and deliver their data into the cloud. An application (at the bottom of Figure 2) requests certain sensor data streams in a goal-oriented manner [13], and gets the processed, aggregated, and aligned data at real-time from those sensors that are able to contribute to the execution of this very recognition goal.

This concept of sensor clouds allows a decentralized and massively distributed execution of multiple goal-oriented human activity recognition applications in an opportunistic way. By collecting and aggregating sensor data in the sensor-cloud, the multiple access to sensor data-streams is possible without bothering about race conditions, privacy concerns or other efforts towards a secure sensor data organization. The pure real-time utilization of sensor data without any overhead by requesting sensor data from the cloud according to a recognition goal, is possible. In detail, the following characteristics and benefits when using the sensor-cloud based approach compared to "traditional" sensor application can be identified.

Comfortable *accessibility* of sensors of different kinds over the sensor-clouds is one major benefit. Traditionally, each application has to provide access to sensors that have to be included for activity recognition. Sensor abstractions are a first step towards a common usage, nevertheless, the underlying accessory mechanism have to be developed. This is not always an easy task, since different sensors are accessed over very different interface and protocols. The sensor-cloud enables an application to receive real-time sensor data without concerning about sensor access, since standardized data connection protocols (e.g., TCP/IP) can be used for network transportation. Of course, the access to the sensor has to be done on one local machine, which streams the data into the cloud, but other distributed units can simply request sensor data without concerning about accessibility.

Real-Time utilization to a (theoretically) infinite number of sensors is possible. Traditional local sensor utilization suffers from the fact that one machine can only host a very limited number of (physical) devices, due to a limited amount of available ports. The sensor-cloud enables decentralized, distributed, time-, and space-free utilization of sensors, without suffering from machine-given restrictions. This enables the utilization of an amount of sensors that exceeds the number of sensors that would be possible to host locally.

Security, trust and privacy is always an issue when using different devices. In traditional systems, due to proprietary software, open-source software, opaque software for system access, that has to be installed locally on an actual machine hosting the sensor devices, security and trust cannot be guaranteed. The sensor-cloud can be equipped with security mechanisms that only trustworthy sensor data is processed and sent to the requesting entities. This means that the effort of securing the access to the sensor data can be outsourced into the cloud.

Global synchronization and data alignment is a big problem and non-trivial task. Different (physical) sensors can have different sampling rates, and can be accessed by different machines, which themselves have different timing mechanisms and local timestamps. In traditional systems, whether they operate in an opportunistic manner or not, data has to be perfectly aligned, for training an activity recognition chain (i.e., learning the mapping from sensor signals to activity classes), as well as for real-time activity recognition. This task is often associated with massive effort in signal preprocessing and data segmentation, since high accuracies and recognition performance is only possible with clean, aligned, and synchronized data. The sensor-cloud allows for the unique synchronization of delivered sensor data-streams, by equipping the signals with globally valid and comparable time-stamps. Once an application requests specific (aggregated) sensor data, the pre-processing and alignment phase has already been done in the cloud, which avoids heavy effort.

Data preservation is a nice side-effect of the concept of sensor-clouds. Once sensor data is available in the cloud, it can be preserved for future usage (e.g., for utilization in simulation scenarios, or for evaluation purposes), similar to the sensor abstraction concept of a *PlaybackSensor*, as presented in [18,21]. Nevertheless, if no cloud-based technology is available for this data preservation and re-utilization task, this has to be individually realized for each application that wants to include this feature. Again, this could be avoided by simply requesting ancient and already available data from the cloud. This enables the development of re-usable simulation scenarios without the overhead of developing mechanism to simulate or replay sensor data locally.

Especially when it comes to *multiple-, or large-scale applications* a sensor cloud does not suffer from performance problems, limits in the sensor device access or scalability problems. By utilizing the concept of sensor-clouds, multiple and/or large-scale systems have concurrent and easy access to the available sensors in the cloud.

Limited *computational power* is often a problem in "traditional" systems. Methods on different stages of the ARC exist that are very complex in terms of computational- and runtime-complexity, even already at the aforementioned data synchronization and data alignment phases. This aspect can also be immensely improved by utilizing sensor-clouds, since clouds usually provide massive processing power [17].

The following Table 1 summarizes these findings and points out the benefits of utilizing cloud technologies for sensor data acquisition, aggregation, procession, and provision in contrast to traditional, centralized and locally executed sensor data handling.

The following Section 5 illustrates the concept of *sensor-clouds* for goal-oriented opportunistic activity recognition on a demonstration scenario.

5 Demonstration Scenario

To test and evaluate the concepts of bringing a vast amount of sensors of different modalities and occurrences (ranging from infrastructure-based, to body-worn, and social-sensors) into the cloud, we made a large scale data acquisition experiment during the 29^{th} Vienna City Marathon 2012 (VCM2012) with approximately 36.000 participating people. Each person was equipped with an RFID transponder submitting the crossing of predefined marks of Pentek Time Measuring Mats[2] that can be seen as an infrastructure-based sensor, every five kilometers for timing purposes. A large number of participant was further equipped with heart rate monitors to measure their physical status and a GPS tracking system to allow a realtime tracking of them. Furthermore we equipped 8 of the participants with a self-designed, so called *Sports Community Token* that consists (i) of an accelerometer to capture the body movements of the persons and (ii) of two buttons to submit a *social message* to Twitter[3] when passing

[2] `http://www.pentek-timing.at/`, last visited June 2012.
[3] `https://twitter.com/`, last visited June 2012.

Table 1. Overview of a comparison between traditional sensor applications for human activity recognition with the concept of sensor-clouds, highlighting the benefits of using a sensor-cloud

Feature	**Sensor-Cloud Application**	**Traditional Sensor Application**
Accessibility	common accessibility due to standardized protocols (e.g., TCP/IP) and interfaces	different hardware interfaces (e.g., RS232, USB, proprietary protocols) on different machines
Real-Time Utilization	time-, and space-free real-time access to vast amount of sensor data without any race conditions	limited access according to hardware properties (e.g., ports) since physical machines cannot access and host an unlimited number of devices
Security & Trust	secure, save, and trusted access provided by the cloud	access to sensors cannot always be secured due to unknown device properties (e.g., drivers, interfaces, etc.)
Global Synchronization	alignment and synchronization of large-scale sensor data due to a common global time possible	difficult alignment-, and synchronization process due to different timing mechanisms of machines and drifting physical sensor devices
Data Preservation	re-use of captured sensor data as if it currently delivered by an actual sensor. Common access as storage and protocol is defined (therefore exchangeable)	capturing and preserving data for replaying at a later point in time has to be developed for each physical device. No common and unified storage and protocol
Multiple-, and Large-Scalability	concurrent and easy access of a variety of sensor devices performing well on a large scale	limited and restricted access, possible performance bottlenecks and scalability problems
Computational Power	improved computational resources in the cloud allow for the execution of complex methods	limited resources according to the local machine

a timing station every five kilometers (i.e., feeling good, or feeling bad). These sensors can be seen as body-worn sensors that capture the physical status, but also can be utilized as social sensors when transmitting information to the social platform Twitter. During the experiment we covered the whole range of possible sensors as described in Section 4 that are seen as possible information delivering entities to the sensor cloud (i.e., infrastructure-based RFID sensors, body-worn accelerometer sensor, and twitter updates as social sensor). Impressions from the VCM2012 of selected attendees using the *Sports Community Token* as a wrist-worn, physical (accelerometer) and social (twitter) sensing platform are shown in Figure 3.

Fig. 3. Impressions from the data capturing at the VCM2012 showing selected attendees wearing our self designed *Sports Community Token* transmitting accelerometer data and social messages via twitter into the cloud

The data collected from the *Sports Community Token* was put into the cloud to show the concept of transmitting multiple sensor data into the cloud. Furthermore the data was queried from the cloud by an application to analyze it at realtime. The experiment highlighted the possibility of transmitting sensor data into a cloud and querying and aggregating it according to a stated goal for further (or even realtime) analysis. In this experiment we only utilized the data captured from the *Sports Community Token* and put it in the cloud (physical accelerometer values and the social Twitter messages). Considering the aforementioned availability of a huge amount of different sensing devices (RFID, GPS, bio-, and vital-state-sensors, body-worn accelerometers and social sensors), the capturing of the *Sports Community Token* data into the sensor cloud is understood as a proof of concept but has to be extended to use all available sources of information that can be captured decentralized, stored and processed in the cloud and being queried in a goal directed way to be used simultaneously by trusted entities to analyze it.

6 Conclusion

This paper presented the concept of *sensor-clouds* which subsequently arises from the novel paradigm of opportunistic activity and context recognition. There, in contrast to conventional applications for human activity recognition, the sensing infrastructure does not have to be initially defined at design time of the system. An opportunistic system makes best use of the (heterogeneous) sensors as they happen to be accessible upon their spontaneous availability (and unavailability) in a goal-oriented manner. Not only the heterogeneous sensing infrastructure is dynamically varying, also the recognition goal can be expressed and stated to the system at runtime. The approaches to handle heterogeneous sensors locally by an opportunistic activity recognition application in a goal-oriented way are *Sensor Abstractions* and *Sensor Self-Descriptions*, that allow to utilize sensors upon their spontaneous availability according to specific recognition goals. These concepts and methods have been implemented, presented and evaluated within a reference implementation of an opportunistic activity recognition system: *the OPPORTUNITY Framework*.

These concepts are sufficient and perform reasonably well for applications that are hosted on a local and centralized machine, with a limited number of (heterogeneous and spontaneously available) sensors, only. If multiple-, and large-scale activity recognition applications are considered, that are fed by a common, yet huge pool of sensors, enabling the sensor handling, processing, aggregation, and preservation with the help of cloud-technology is the next logical step. This paper identifies the need for the concept of *sensor-clouds*, discusses the benefits compared to "traditional" sensor data management and handling in activity recognition system in an opportunistic manner (i.e., (i) *accessibility*, (ii) *real-time utilization*, (iii) *security & trust*, (iv) *global synchronization and data alignment*, (v) *data preservation*, (vi) *multiple-, and large-scalability*, and (vii) *computational power*). An illustrating example (i.e., the 29^{th} Vienna City Marathon 2012) discusses these benefits and underpins the concept of utilizing *sensor-clouds* for massively distributed and large-scale goal-oriented and opportunistic activity recognition applications.

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