

A Practical Platform for Combining Sensor-measurement from Body Sensor Networks with Flexible Human-provided Tagging

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Abstract—Recent developments in wearable sensor technologies allow for collecting various information about the person in different conditions. This data is often of limited use without proper interpretation provided by human experts. We propose a practical platform that collects long-term data from multiple body and ambient sensors along with human-provided tagging in practical and mobile conditions. We address the platform requirements of security, privacy, and trustworthiness. Our approach will be tested in a case study focused on stress monitoring at work.

Keywords—*body sensor networks; practical platform; mobile application; data collection; tagging; trustworthiness*

I. INTRODUCTION

Advantages of using multiple sensors for monitoring physiological and emotional reactions of people, their activities and environmental conditions in order to improve their health or life style are clear: sensor-fusion, holistic knowledge, increased accuracy and reliability. However, despite technical possibilities, the raw data collected from sensors might be of limited use without proper tagging. Tagging provided by human experts or derived automatically can serve as a ground truth for correct interpretation and training of classification algorithms. In addition, sensor measurements usually need to be collected for long periods of time in order to achieve decent classification accuracy in practical conditions. This poses a number of practical challenges, calling for a platform solution that: 1) flexibly integrates multiple unobtrusive sensors, 2) is scalable, reconfigurable and self-monitoring 3) enables collecting relevant tagging for data interpretation from human experts or automatically derived from context, 4) allows for long-term data collection in practical settings and 5) provides security, privacy, trustworthiness.

To exemplify the need for a reconfigurable and self-monitoring platform, consider a number of practical examples that we encountered in the studies performed in the Stress@Work project [5]. In our specialized solution, unplanned, extended use of the sensors by the study participants led to increased battery drain and affected the long-term data collection. Using a generic platform instead, admits monitoring and detecting such problems and even remedy them in the field by e.g. reducing the sampling frequency or switching the sensor from wireless transmission to local storage. These types of re-configurations are performed dynamically by the platform itself or via a

downloadable application. Using the infra-structure of mobile phones as a central element in the platform improves the scalability of the system as one can rely on the existing infra-structure of downloading apps, which can also be used for updating attached sensor firmware. The capabilities of the mobile phone make tagging easier. A downside is that this re-configurability and downloadable software concept increases the risk of affecting the privacy and the trustworthiness of the system.

As another example, the data from the sensor might be incorrect or misleading due to improper mounting (e.g., lack of skin contact for GSR (Galvanic Skin Response) as described in [6]). These abnormal readings should be detected as close as possible to the source of the problem rather than being detected only in the backend when the data is analyzed. A reconfigurable platform allows adding self-monitoring features to systems in the field by adding a component to evaluate the quality of the data and giving direct feedback to users.

In the remainder of the paper we describe the system we use as solution, along with an application to show the utility.

II. SYSTEM ARCHITECTURE

The system we use is developed as the VITRUVIUS body sensor platform [1], which has the following features. 1) The basic platform can be installed on an Android mobile phone as a regular app. This mobile phone is referred to as the body hub. 2) New sensors are attached by downloading a driver indicated by a QR code on the sensor; 3) new services (like quality control) that operate on collected data are added as apps as well; 4) applications, that connect to the environment are also apps. The system components and downloaded apps rely on a shared ontology. In this way we integrate commonly available wearable, unobtrusive sensors like the DTI-2 wristband [2], Mio Alpha [3], and Shimmer [4]. The phone allows us to connect to backend systems and to obtain tagging information from the user and obtain context data (see Figure 1). We specifically design an easy-to-use interface that allows for defining tags relevant for specific purposes. An important extra-functional goal of the platform is to manage privacy and data ownership by providing data access control and protecting data communication. A particular part of the platform is therefore dedicated to managing security, trust and ownership e.g. to decide whether a third-party is able to

access certain stored data or whether a new application is given access. The Body Area Sensor Network (BASN) platform such provides a better privacy protection by not sending the whole data to the backend.

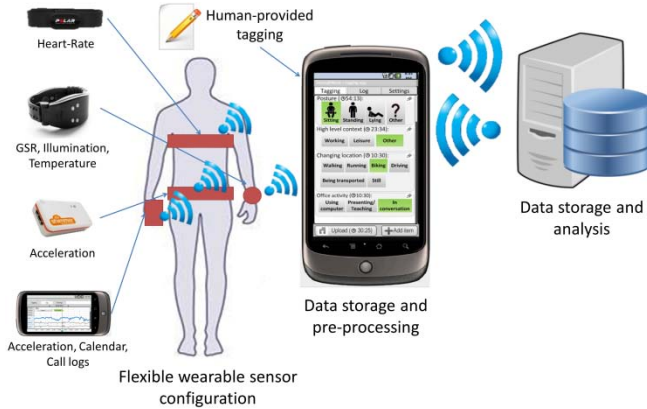


Figure 1 - The system overview: flexible sensor setting along with the mobile phone for data storage and preprocessing.

The ultimate purpose of any data collection platform is to make practical use of the collected data. The fact that the platform is capable of long-term storing from many sensors, and of adding context information easily in a similar fashion leads to more advanced strategies applied in situ (as opposed to intelligence being only available at the backend). In our application we use a variation of semi-supervised learning to improve the tagging (see Figure 2) in a number of stages: Stage 1 entails supervised training where the platform collects enough human-tagged sensor measurements to train the classification algorithm. Once sufficient data is collected, the system gradually switches to Stage 2, the semi-supervised training stage, in which the human-provided tagging is requested only when the classification accuracy falls below a certain threshold. Finally, in Stage 3 the operational stage, no further human-provided tagging is required, and the system is able to make reliable interpretations based only on automatically derived information. In practice, we expect the system to be able to switch from Stage 3 to Stage 2 when encountering unknown or conflicting sensor measurements.

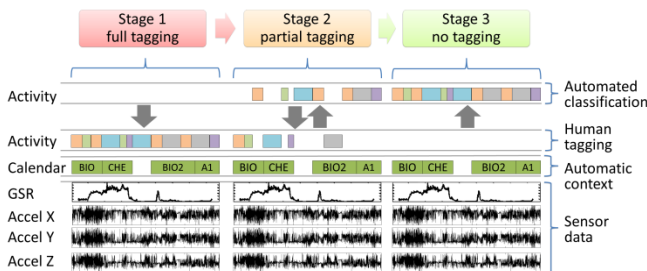


Figure 2 - Stages of the system to gradually decrease the need for human-provided tagging.

Furthermore, in order to make the system invariant to the type of sensor data used and to particular tagging categories,

we use automated feature generation. We extract a set of basic features from the data (e.g., mean, median, and standard deviation) and create new features as combinations of the basic features, hence generating a large feature space. In the end, however, we want to use only the features relevant for automated classification of the tagging categories provided. To limit the features space and avoid a dimensionality explosion, we perform automated feature selection and apply Principal Component Analysis (PCA) to reduce feature space dimensionality and prevent overtraining.

III. ONGOING WORK

We are testing our approach in a case study focused on stress monitoring at work continuing our previous work described in [5]. We want to obtain the context in which the stress is experienced by automatically recognizing physical activities of a person. In this setup we combine information from multiple sources: 1) skin-conductance, 2) heart-rate, 3) accelerometers, 4) skin temperature, 5) ambient illumination, 6) ambient temperature, all measured by 3 different wearable sensors: 1) chest-belt, 2) wristband and 3) mobile phone. Sensors are worn simultaneously and unobtrusively on different locations on the body: 1) chest, 2) wrist and 3) pocket (mobile phone). We combine the sensor data and the context obtained from a digital calendar with user-provided tagging of physical activities and emotional state.

In this practical setting we want to be able to perform fully automated classification of the sensor data based on the initial user-provided tagging about physical activity, in principal entirely local on the BASN based on downloaded apps. In addition, we study the concerns of privacy and trustworthiness, which will become more apparent in the fully functional system. From the user perspective, we will verify the usefulness and unobtrusiveness, and provide a meaningful visualization of the collected data.

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