Multi-Sensory Environment Analysis and Human Activity Recognition via Wearable Technologies

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Abstract: The sensing of human activities and user surrounding environments is an essential topic in computer science. Application domains include the Ambient Assisted Living (AAL), healthcare, sports gear and military use cases. Especially mobile or wearable technologies made significant progress in the past years. The current development of Smartwatches and Smartphones which include a variety of sensors is a good example for this progress. With the increasing sensor density in unobtrusive wearable designs, new ways for complex Human Activity Recognition (HAR) and environmental sensing (ES) are opened. This paper focuses on the current state of the art in wearable sensor technologies and gives a short overview of present techniques for HAR and ES. Therefore, a classification of sensors by use case and body position is made. Furthermore, the principal challenges and issues are discussed and known solutions will be referenced. Finally, existing problems that should be addressed are pointed out.

1 Introduction

The past and ongoing development processes in the area of mobile devices and wearable technologies led to a high miniaturization and sensor density. While the computational power of mobile devices is increasing, lower costs make devices more affordable and the energy consumption decreases. As a result of this, a broad variety of use cases and research areas like the AAL movement, healthcare topics, security topics, or military applications has evolved. Hence, areas like the Ubiquitous Sensing or the Pervasive Sensing gain more and more interest. In particular, the sensing of human activities and user surrounding environments are interesting subjects. To address these topics, different sensing strategies are applied. These sensing strategies can be differentiated by their utilized technologies. A primary, coarse grained separation of vision-based and sensor-based technologies is a common way to proceed. Vision-based sensing describes the usage of cameras to externally detect activities and actions. The gathered visual data can then be analyzed in a manual or automatic manner. The variety of examples for vision-based approaches has been addressed in many survey papers [MHK06], [Po10], [WRB11]. Due to the focus in this paper, vision-based sensing will not be addressed in more detail.

Furthermore, strategies concerning sensor-based recognition can be divided into on-body (or wearable sensing) on the one hand and environmental (or dense sensing) on the other hand. In some cases, a combination of both is possible to gain even better results. Examples for environmental or dense sensing are the so called Smart-Environments, e.g. Smart-Homes [Web1], [Web2], [Web3]. In these cases, an intelligent environment detects activities or actions via distributed sensors. Another example for dense sensing is the solitary distribution of RFID-Tags for object recognition [SLS08], [BRP+09]. In their work, Stiefmeier et al. applied RFID-Tags to identify used tools (like a cordless screwdriver) in car assembly lines [SRT+08]. The finest granularity of a wearable sensing classification is reached by the partitioning of sensing positions by body parts (single-point or multi-point) and locally used sensor types.

This paper gives an overview on current sensor technologies in a wearable context. The classification is therefore done by body position and sensor technology. Therefore, existing problems and issues are discussed and a future outlook is given.

2 Classification scheme

This work introduces a taxonomy for a classification of papers concerning wearable sensors. The taxonomy is shown in figure 1. It divides wearable sensing technologies in either homogeneous or heterogeneous systems. Additionally, a differentiation between single- or multi-point systems is done.

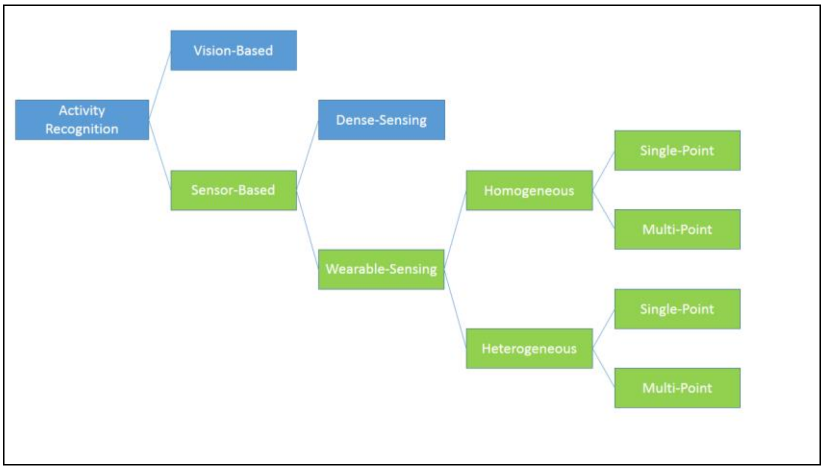

Figure 1: Taxonomy for wearable sensing classification

3 Simple activity recognition

Most papers about Human Activity Recognition (HAR) topics address simple activities like walking, running, climbing stairs, cycling, sitting, lying and others) [MS10], [BGC09], [BVU09], [BMT+01], [YC08], [HSA+10], [NCL+11], [AB10], [MHS01]. Mannini et al. explored seven different activities (walking, running, climbing stairs, cycling, sitting, lying, standing) by using four tri-axial accelerometers. They reported classification accuracies (varying by classifier) from 92.2% (Gaussian Mixture Model – GMM) up to 98.5% (Nearest Mean – NM) [MS10]. The work of Brezmes et al. describes the recognition of six activities (walking, climbing stairs up, go down stairs, sit down, stand up, falling) via a conventional mobile phone. The reported classification accuracies were fluctuating (depending on measured activity) between 70% and 90% [BGC09]. Bieber et al. also used a common mobile phone for detecting simple activities (resting, walking, running, cycling, car driving, being active). Like Brezmes et al. they used the tri-axial accelerometer built into the mobile phone. According to Bieber et al. the proof-of-concept prototype reached a recognition rate >95% for the activities resting, walking, running, cycling and car driving (carrying position of the mobile phone was the trousers pocket) [BVU09]. A commonly addressed topic in papers concerning the recognition of simple activities is located in the labelling of recorded activity data. Many datasets of afore mentioned papers have been recorded and annotated under laboratory conditions. Therefore, the data suffers from multiple problems when used in field tests. For example, the recognition rates reached in field tests do not correlate with those achieved under laboratory conditions. Bao et al. present a method that allows users to annotate data that has been recorded by themselves in their own homes. Therefore, the reported overall recognition rate of 84.26% shows a better stability and comparability in field tests. Bao et al. also evaluated simple activities like walking, running, climbing stairs, standing up, sitting down or lying down by varying the sensor complexity. The measurement was done by using five bi-axial accelerometers (positioned at: right hip, dominant wrist, non-dominant upper arm, dominant ankle, non-dominant thigh). Referring to Bao et al., the sensor setup consisting of either thigh and wrist or hip and wrist achieved similar results (deviation of 5%) like the complete sensor setup (consisting of all five measurement points) [BI04].

4 Complex activity recognition

The recognition of complex activities is a topic that addresses activities which are composed by a variety of easy partial activities. Thereby, partial activities can overlap or occur concurrently. Additionally, complex activities can be interrupted and they can later be resumed. Therefore, complex activities are mostly stretched over long timeframes. Another example for complex activities are activities that involve no reoccurring patterns. A commonly investigated class of complex activities are the Activities of Daily Living (ADL). These activities been addressed by many researchers [SLS08], [BRP+09], [SRT+08], [ZLS07], [BI04], [MYK+10], [PBB12], [GWT+09], [KHS+09], [LWJ+04], [OKL07], [SCC10]. Zinnen et al., for example, used inertial sensors located at the wrist, to measure short, non-reoccurring activities (open hood, close hood, open oil container, close oil container, open sun shield, close sun shield, pulling handbrake, releasing handbrake, heating on, heating off). According to Zinnen et al., the activities had to be extracted from continuous activity data streams. The reported overall recognition rate was estimated with 88% [ZLS07]. Maekawa et al. presented a wristband with three integrated sensors (USB-

Camera, microphone, 3-axis accelerometer). With this wristband they evaluated the detection of ADLs. The described ADLs contained brushing teeth, cooking noodles, cooking rice, feed fish, listen to music, making cocoa, making coffee, making tea, making green tea, vacuuming, washing the dishes, and others. By using the USB-Camera, data like color information (characteristic colors for each ADL) could be recorded. Because of the low camera resolution, the low bandwidth and for privacy reasons, the authors only extract color information as a feature from the camera data. Referring to Maekawa et al., an accuracy of about 75% is achieved if only camera data is taken into account. The accuracy for exclusive accelerometer usage is 48% according to the authors. According to Maekawa et al., the main reasons for this rather bad accuracy rate are similar patterns for different ADLs. For example, the activities making tea and making green tea include the same arm movements. By using the C4.5 decision tree and a Hidden Markov Model (HMM), Maekawa et al. achieved a precision of 87.3% at a recall rate of 84.7% [MYK+10]. Grosse-Puppendahl et al. extend the recognition by accelerometer via a capacitive proximity sensor (in loading mode). Both sensors are combined in a wristband for activity recognition purposes. The capacitive proximity sensor is shielded against the body of the wearer by a shield electrode, which has the same potential as the sensing electrode. If the sensing electrode approaches or touches a grounded object, the capacitance changes (increases) and as a result, the approximation can be detected. Grosse-Puppendahl et al. showed that by applying an additional sensor, the recognition rate could be increased by up to 10.7%. Detected ADLs included making a sandwich, eating or getting things [PBB12]. Stikic et al., Stiefmeier et al., and Buettner et al. applied RFID-Tags to objects of daily use (hand brush, bucket, flat iron, cordless screwdriver etc.) to recognize ADLs [SLS08], [BRP+09], [SRT+08]. Stikic et al. combine the RFID-Technology with an accelerometer (both attached to the wrist). The detected accelerations helped to identify the performed activity. The detected ADLs included vacuuming, ironing, wiping, cleaning the windows, watering the plants, and others. The reported recognition rate of 70% is, according to Stikic et al., caused by a varying execution of the activities by different users (training and testing was done with different users). Additionally, only one accelerometer was applied (only at the wrist) [SLS08]. Stiefmeier et al. used an inertial sensor on the back of the wrist to detect movements of the dominant arm. Additionally, via a wrist worn RFID-Reader, objects (e.g. a cordless screwdriver) can be detected. Force sensitive resistors (applied to the lower arm) detect acting forces (e.g. vibrations). The test environment, according to Stiefmeier et al., simulates a car assembly line production. The car which is worked on is also equipped with force sensitive resistors which detect interactions with the car. Additionally, magnetic switches are attached to detect the current assembly progress (headlight assembly). With the help of distributed sensors and wearable sensors, the complex activity of mounting a headlight can be recognized [SRT+08]. Gu et al. use a wrist worn device including a variety of sensors (accelerometer, temperature sensor, humidity sensor, ambient light sensor). Additionally, a RFID-Reader is installed at the wrist. Gu et al. evaluate the recognition of sequential, concurrent and overlapping activities in their work. The evaluated activities include making coffee, applying make-up, washing hands and others. Gu et al. report an overall accuracy of 90.96% for sequential activities, 87.98% for overlapping activities and 78.58% for concurrent activities (accuracy total 88.11%) [GWT+09].

Heterogeneous single-point	**Heterogeneous multi-point**	**Homogeneous single-point**	**Homogeneous multi-point**
[ZLS07], [MYK+10], [PBB12], [YC08], [HSA+10], [KHS+09]	[SRT+08], [LWJ+04], [NCL+11], [AB10]	[BGC09], [BVU09], [OKL07], [SCC10]	[SRT+08], [MS10], [BMT+01], [BI04], [MHS01]

Table 1: Papers categorized by taxonomy

5 Summary and outlook

Activity recognition by wearable body-worn sensors is a topic of scientific interest. Especially the recognition of complex activities is in the focus of researchers. Many scientific works deal with solutions and problems concerning this area. The segmentation of continuous sensor data is an example for current research topics. In this area, partial or non-reoccurring activities have to be extracted out of continuous data streams. Zinnen et al. achieved a segmentation of continuous data by defining start and end postures. These postures were defined by a short pausing of movement and a characteristic orientation of the arm. In consequence, the postures build a frame around the actual activity of interest (non-reoccurring movement) [ZLS07]. In addition to the segmentation of data, another topic of interest is the complexity and type of used sensors (important issues: unobtrusiveness, energy consumption etc.). Papers concerning complex activities often applied multiple sensors [SRT+08], [BI04], [MYK+10]. Nevertheless, the increasing number of sensors is accompanied by possible sources of error (e.g. overfitting). Another subject of interest is machine-learning, specifically semi-supervised and unsupervised-learning. Wyatt et al.

describe a method for unsupervised activity recognition. They use RFID-Tags to identify objects (e.g. a toothbrush and toothpaste) that are involved in an activity (brushing teeth). The used objects result in a probabilistic activity (e.g. brushing teeth) which is searched for in the web. The websites (describing the activity) are then searched for utilities that are involved. Via the described routine, the sensor data of performed activities can be labelled automatically [WPC05].

In future research, the recognition of complex ADLs or complex activities (in general) will still be an important topic. The adaption of learning of activity data based on a membership to a specific group (elderly, kids, disabled people etc.) is also a topic of interest. To reduce the effort of labelling data, the unsupervised-learning needs to develop. Additionally, an extensive standardization in the area of activity recognition is needed.
Furthermore topics like intend or goal recognition, abnormal activity recognition or crowd human activity recognition are of huge significance and scientific interest.

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