Evolution of Activity Monitoring Through Various Projects

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Abstract. The paper presents the evolution of activity monitoring utilising wearable sensors through several sequential projects running in the last decade. It covers the change and improvement towards sensor technology that is more affordable and comfortable for the users and development of additional functionalities to achieve accurate activity monitoring in terms of activity recognition. All presented systems are developed to perform on-line activity recognition.

Keywords: Activity monitoring, activity recognition, wearable sensors, smart-phone, real-time location system, inertial sensors, optical motion capture

1 Introduction

Activity monitoring has been a popular research domain over the last decade. Recognition of the person’s activity and the intensity of the activity are key pre-processing steps in various health related applications in the pervasive and ubiquitous computing field. When the person’s health status or supplement/drug intake depends on the amount of physical activity, e.g., in treating diabetes, the patient and health professional can utilise the information about the level of physical activity to provide better care. The activity monitoring is also very important in health prevention, e.g., obesity, where users can track their own physical activity and adapt diet accordingly.

To efficiently monitor the activity, the user is equipped with some sort of dedicated sensors. Accurate motion tracking is possible using cameras, however usability studies have shown that cameras are too intrusive and are therefore often not accepted by users. In addition, camera based motion tracking systems as well as ultra-wideband (UWB) real-time location systems (RTLS) can only be used in a limited space where the system is located and calibrated (usually indoors). The privacy issues and location constraints are resolved using less intrusive and restrictive wearable sensors, which are the focus of this paper.

The major drawbacks for using wearable sensors have been their cost and the fact that they were cumbersome to wear. The first wearable sensors were wired, which made them unacceptable for every day use. After the wireless sensors
became available at reasonable prices, other problems remained; the usability studies performed in various projects have shown that elderly and sick people have significant problems with correct attachment of the sensors. For example, the user is given two sensors: one to be attached on the chest and one on the thigh. The first confusion for the user is the correct placement – which sensor is for which part of the body. The second problem is the correct orientation of the sensor (e.g., inertial sensor); the acceptability of the sensor system is even lower if correct orientation is required. Furthermore, users frequently forget to wear the sensor, lose the sensor, or forget to charge the sensor battery. Even though complex algorithms achieved high accuracy of activity recognition, the measurements of this kind are of low quality and hence hardly usable for the recognition. The monitoring does not bring any benefits to the person unless the sensors are attached precisely.

The price, size, and battery consumption of the wearable sensors have decreased significantly in the last decade, which made them more acceptable for everyday use. Very cumbersome and wired sensors were priced at several tens of thousands of Euros in the past while today a single dedicated sensor costs up to several hundreds of Euros. The price and availability of sensor technology has also enriched sensing capabilities of smart-phones. As a result, today, an average smart-phone contains various sensors that are appropriate for activity monitoring. The fact that most people in western-world own and carry their smart-phones with them at all times makes them very handy for activity recognition.

![Fig. 1: Comparison of average sensor prices on a logarithmic scale.](image)

Using smart-phone sensors for activity monitoring requires solving several non-trivial tasks that are not needed if classic wearable sensors are used. Knowing where the smart-phone is placed and how it is oriented is important for accurate
activity recognition and monitoring. Documentation that comes with wearable sensors usually contain straightforward instructions about the placement and orientation of the sensors. However, this can not be applied to smartphones since they are primarily used for other purposes and people are used to carrying them freely on the body in different orientations. Therefore, methods to detect the location and orientation of a freely worn smartphone are needed to enable using them for activity monitoring.

This paper presents the evolution of activity monitoring in terms of activity recognition. We compare several activity-recognition systems utilising different wearable sensors which were available at the time of development: starting with cumbersome UWB localisation technology and ending with the latest activity monitoring systems utilising only smartphone sensors. The paper is structured as follows. Section 2 covers the chronological development of the sensor technologies used in our research, Section 3 presents the projects and evaluation of the developed activity recognition and Section 4 concludes the paper.

2 Wearable Technology

Sensors which are today used as a wearable technology have been primarily developed for the industrial purposes. These sensors were expensive and large since they were not designed for pocket use of a broader population. The size and price of the sensors decreased over time and the potential of them being used as a wearable broadened the possible application. In our activity recognition research, we used three types of sensor modalities: (i) localisation sensors, (ii) inertial sensors, and (iii) integrated heart rate and inertial sensors. Figure 1 compares prices and limitations of different sensor sets we have used in the past and will use in the future (e.g., wrist band). Each of them is discussed below.

**Smart infra-red** camera based motion tracking [1] is based on a high precision optoelectronic system, which is the most accurate technology for kinematics analysis and motion modelling in a laboratory environment. The system is composed of four or more high precision infra-red cameras (Figure 2a), usually attached to the walls, and reflective markers which are attached on the persons body. The motion is tracked with accuracy of 0.2 to 1 mm and frequency well above 100 Hz. However, there are several limitations making it inappropriate for real-life activity monitoring. First, such systems are expensive. Second, their operation is limited to a small space covered by the cameras (usually below 10 m²). Third, the markers are cumbersome to wear and have to be in line-of-sight to at least one of the infra-red cameras at all times. And finally, such systems suffer from tracking problems: the system may mix-up markers because they all look the same, therefore a human operator is required to label the markers when the system is not able to track them across consecutive images.

**Ultra-wide-band** technology (UWB) real-time locating system (RTLS) detects the location of the tag by calculating the time difference and the angle of arrival
of the radio signal sent to the sensors. In our research, Ubisense [2] (Figure 2b) RTLS was used. It is composed of four to six sensors attached on the walls of a room and up to four tags which are attached to the person's body (chest, waist, both ankles). The system can also track hundreds of tags, however the sampling frequency drops proportionally to the number of tags. Ubisense RTLS has the maximum frequency of about 9 Hz and accuracy (in a typical open environment) of about 15 cm that is achieved across 95% of the readings. However, in real-life scenarios, the accuracy occasionally drops below 200 cm and up to 1.5% of location values are missing, which represents quite a challenge for preprocessing and filtering [14]. In addition to the low accuracy, the system can be used only in the room where it is set-up. The calibration process typically takes more than an hour of work. The advantage of UWB RTLS over camera based systems is that they allow more privacy (do not record video), do not require the line-of-sight, and do not suffer from tracking problems. However, locating accuracy and frequency of UWB RTLS are much lower compared to camera based systems.

![Ubisense RTLS](image1)

![Ubisense RTLS](image2)

![Ubisense RTLS](image3)

Fig. 2: Localisation sensors used in our research on activity recognition.

**Xsens** [3] was, at the time of our research, a system composed of ten wired inertial sensor enclosures (Figure 2c) attached to the body on predefined locations using straps. The enclosures contain a 3-axis accelerometer, gyroscope and magnetometer. Wires connecting the enclosures with the waist worn hub can easily get entangled and disconnected from the system. The sensor readings are stored on the hub or transmitted to a dedicated computer over Bluetooth. Therefore on-line motion analysis can only be done if the hub is in the range of Bluetooth receiver. The ability to track ten points (usualy body joints) on human body with high precision makes Xsens system a good choice for high precision motion analysis and modelling in animation studios and laboratories. However, the limitation for use in everyday life are the high price, short battery life, and difficulty to place each enclosure on the correct location and in the correct orientation.

**Dedicated** inertial sensors, e.g., Shimmer [4] (Figure 3a), are similar to Xsens but wireless and more adaptable. Each dedicated sensor contains a 3-axis accelerometer, gyroscope and magnetometer, and stores or sends the readings over
Bluetooth to the dedicated server or hub. An expansion module — for example, electrocardiogram (ECG), electromyogram (EMG), or galvanic skin response (GSR) — can be added to the sensor. The relatively lower price, extended battery life and the absence of wires makes this technology accessible and convenient for everyday use, while the accuracy is still high enough for accurate activity recognition. Nevertheless, some limitations still remain. The sensor has to be worn on the exact location with predefined orientation and the sensor has to be in the Bluetooth range.

(a) Inertial sensor  (b) BioHarness  (c) Smart-phone  (d) Wrist band

Fig. 3: Inertial sensors and devices containing inertial sensor.

Heart-rate monitor with integrated inertial and additional physiological sensors, e.g., Zephyr BioHarness (Figure 3b), come in a form of a chest strap, t-shirt or even a sensor attachable to skin. Zephyr uses a traditional chest strap ECG sensor technology with three electrodes from which the heart rate is calculated. The skin temperature is measured with a temperature sensor and the breathing rate is extracted from the strap’s stretch value. The chest strap is convenient for use since it is not expensive and the correct placement of the sensor is very straightforward. The main drawback are its price and the fact that it is a dedicated sensor and needs a central hub (usually a smart-phone) for real-time processing of data. Because of the direct contact of the sensor with the skin, it is uncomfortable (but not intolerable) to wear it for extended period of time.

Smart-phones are currently one of the most popular pieces of technology (Figure 3c). The need for mobility made smart-phone an indispensable piece of everyday equipment for virtually everybody. An average smart-phone contains a limited set of sensors including those important for activity monitoring (e.g., inertial sensor). The fact that the smart-phone is always somewhere near or on the person makes it very convenient for activity monitoring. The popularity reflects in numerous activity monitoring apps, which recognise a limited set of activities, mostly related to sports. The drawback of smart-phone is that it is carried in different locations (e.g., trouser or chest pocket, bag) and in different orientations
and that it would be utterly user-unfriendly to set limitations on its placement. However, the placement is important for fine grain activity recognition.

Wrist band [5] or smart-watches are considered the future must have technology (Figure 3d). Earlier wrist bands contained only an inertial sensor, while latest models also add optical heart-rate monitor, skin temperature and sweat index sensors. The optical heart-rate sensor is not highly accurate; however, the research on wristbands is in full swing and we believe that in the near future this drawback will be resolved. We recently began to utilise this device for activity recognition and mental stress analysis.

All of the mentioned technologies were at some point used for activity-recognition in our work. The efficiency and accuracy of activity monitoring is discussed in the next section.

3 Evolution of Activity Monitoring

The activity-recognition evolved from limited set of activities detected with expensive localisation sensors to recognising all relevant activities of everyday life using only sensors which are embedded in an average smart-phone, which can be worn freely on the body. The results for each approach are presented in Table 1.

<table>
<thead>
<tr>
<th>Project</th>
<th>Recognised activities</th>
<th>Recall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDR (UWB)</td>
<td>Sitting, Lying, Standing, Moving</td>
<td>92%</td>
</tr>
<tr>
<td>Confidence (Infra-red)</td>
<td>Sitting, Lying, Standing, Falling,</td>
<td>96%</td>
</tr>
<tr>
<td></td>
<td>Sitting on the ground, Going up, Standing up, On all fours</td>
<td></td>
</tr>
<tr>
<td>Confidence (UWB)</td>
<td>Sitting, Lying, Standing, Falling,</td>
<td>86%</td>
</tr>
<tr>
<td></td>
<td>Sitting on the ground, Going up, Standing up, On all fours</td>
<td></td>
</tr>
<tr>
<td>EvAAL (inertial)</td>
<td>Sitting, Lying, Standing, Falling,</td>
<td>99%</td>
</tr>
<tr>
<td></td>
<td>Falling, Bending, Walking, Cycling</td>
<td></td>
</tr>
<tr>
<td>Chiron (inertial)</td>
<td>Sitting, Lying, Standing, Bending, On all fours, Kneeling, Transition, Walking, Running, Cycling</td>
<td>93%</td>
</tr>
<tr>
<td>Commodity12 (smart-phone)</td>
<td>Sitting, Lying, Standing, Walking, Running, Cycling</td>
<td>91%</td>
</tr>
</tbody>
</table>

Table 1: Recalls of the discussed activity recognition systems.

3.1 Activity-recognition Using Localisation Sensor Systems

We first analysed human motion in 2008 within the PDR project [6] using Ubisense UWB RTLS. PDR is an intelligent system for surveillance of personnel and equipment movement in high security indoor environment. It learns
a model of the usual behaviour and compares it with the current motion to detect abnormalities. The goal is to alarm the commander about unusual and forbidden activities and enable centralised overview of the monitored environment.

After filtering the raw location data [14] the system performs simple activity recognition. First, the pose of a person wearing a tag at their chest is recognised using a threshold based algorithm [6]. The thresholds that distinguish standing, sitting and lying were obtained using machine learning and are dynamically adjusted to prevent misclassification during transitions between the poses.

Second, motion and stationary activity are distinguished [7]. The classification algorithm computes a set of attributes from time windows of location data. Movement detection classifier is trained using a machine-learning algorithm. The attributes of the classifier are: average velocity, standard deviation of velocity, average difference of consecutive velocities, approximate length of travelled path, standard deviation of velocity direction, and average change of direction within the time window. The recall of motion detection is above 96%.

The main challenge for both activity recognition algorithms is the low accuracy of UWB RTLS, which is compensated for by the measurement frequency. Such basic activity recognition is computationally efficient, reliable, and enables motion analysis required by the project. The promising initial results provided motivation for improving the activity recognition in the following projects.

In the Confidence system [8] (2010) we advanced form security to health domain. The system analyses movement of an elderly who lives alone and wears four tags: on chest, waist and both ankles. The short term motion analysis detects falls while the long term motion analysis detects deviations in motion patterns and habits which often correspond to changes in person’s health. To detect the deviations, we developed an improved activity-recognition algorithm, which is able to recognise an extended set of activities using the UWB RTLS. To define the set of activities to be recognised using only four tags, we used the more accurate smart infra-red technology. After preprocessing and filtering [14] the raw data, a set of attributes are computed [15]. Machine-learning is used for activity classification. The classification recall using high precision smart infra-red camera technology was up to 96%. Next, a less expensive technology was used for the same task. Preprocessing and filtering procedures as well as the machine-learning approach remained unchanged, while UWB RTLS was used for sensing. The recall decreased to 86%, which was higher than recall of the competing approaches using similar technology at that time.

3.2 Activity-recognition Using Dedicated Inertial Sensor Systems

The initial activity-recognition research with inertial sensors was already done in the Confidence project using the Xsens system. Since the quality of inertial sensors did not influence the accuracy of the activity recognition, we switched to a less expensive dedicated inertial sensors (Shimmer). Within the Chiron project (2012) we developed activity recognition system using one inertial sensor attached to the person’s thigh and the second on the chest. The chest inertial sensor was integrated with a heart-rate monitor. This sensor combination was also
used for the estimation of human energy expenditure. The activity-recognition procedure was similar as before: after preprocessing and computing a set of features, a machine-learning algorithm recognized the activities. For more details the reader is referred to [12]. The achieved classification recall was 93%. The user interface of the application is shown in Figure 4a.

![Chiron system and Commodity12 smart-phone application](image)

Fig. 4: User interfaces of two presented activity-recognition systems. The Chiron system (which was a bit altered for the EvAAL competition) and Commodity12 smart-phone application.

In parallel, we also developed an activity recognition system utilising two dedicated inertial sensors: one on the thigh and second on the persons chest. It was presented in the benchmark EvAAL competition (2013). The system outperformed other competing systems in free-living conditions achieving 99% recall. Validation of the activity recognition classifier was difficult, therefore we developed a method that provides a good trade-off between classifier comprehensibility and accuracy [10, 11]. The result was a classification tree hybrid with 72% comprehensibility and 84% accuracy using a single accelerometer.

### 3.3 Activity-recognition Using Smart-phone and Optional Heart-rate Monitor

We have already achieved high recognition accuracy using dedicated fixed inertial sensors and were keen to experiment with the smart-phone which can be worn freely on the body and can receive data from optional heart-rate monitor. To successfully achieve that, two obstacles had to be solved before performing the traditional machine-learning approach. These obstacles were the presence of...
the devices (smart-phone or heart-rate monitor), orientation and the location of the smart-phone. The research and development was done as a part of the Commodity12 project (2015).

The presence of the smart-phone was detected with simple heuristics utilising proximity sensor and a calculated attribute which differentiate between movement of the smart-phone and stillness (e.g., laying on the table). The heart-rate monitor reports its presence by itself. In case the smart-phone is present, the orientation normalisation is triggered. When the system detects ten seconds of walking, the rotation matrix is utilised together with the average walking vector to normalise the orientation for all readings of the smart-phone’s inertial sensor until the next ten seconds of walking occur.

After normalisation, a set of attributes is computed and the attribute vector is fed into the machine-learning model to detect the location of the smart-phone (e.g., trouser pocket, breast pocket or bag). The location serves as a context for selection of the appropriate activity-recognition and human energy expenditure estimation models. The reader is referred to [13] for more details. This approach resulted in recall of 91% on average. The best recall is achieved 96% when both smart-phone and heart-rate monitor are present and the location of the smart-phone is the trousers pocket. The user interface of the application is shown in Figure 4b.

<table>
<thead>
<tr>
<th>Project</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDR (UWB)</td>
<td>Line-of-sight not required</td>
<td>Indoor only, limited to 6x6 m area, high price</td>
</tr>
<tr>
<td>Confidence (Infra-red)</td>
<td>High accuracy</td>
<td>Limited to 6x6 m area, line-of-sight, high price</td>
</tr>
<tr>
<td>Confidence (UWB)</td>
<td>Wireless tags</td>
<td>Limited to the room where UWB is installed</td>
</tr>
<tr>
<td>EVAAL (inertial)</td>
<td>Wirelesses tags, accuracy</td>
<td>Correct placement and orientation of the sensors</td>
</tr>
<tr>
<td>Chiron (inertial)</td>
<td>Wirelesses tags, accuracy</td>
<td>Correct placement and orientation of the sensors</td>
</tr>
<tr>
<td>Commodity12 (smart-phone)</td>
<td>Accuracy, freedom of orientation</td>
<td>Presence of smart-phone on the body</td>
</tr>
</tbody>
</table>

Table 2: Advantages and disadvantages of each sensing technology and activity-recognition approach.

4 Conclusion

In this paper, we present the evolution of activity-recognition systems throughout the last decade. We begin with a cumbersome and expensive technology for
simple detection of movement and limited set of sedentary activities. Later, we
switched to more affordable technology and expand the set of recognised ac-
tivities, finishing with affordable and convenient activity monitoring using an
average smart-phone. The advantages and disadvantages of used wearable tech-
nology is presented in Table 2. All our systems achieve high activity-recognition
call and were deployed and tested in free-living conditions as a part of the
project. We discuss the suitability of different wearable technology for the task
of activity-recognition through aspects of price, cumbersomeness and ease of use.
Our future work will be focused on using even more appropriate technology such
as wrist bands, which are becoming increasingly more popular.

References

1. BTS Smart-Dx, http://www.btsbioengineering.com/products/kinematics/
bts-smart-dx/
5. FitBit wristband, https://www.fitbit.com
6. Piltaver, R., Dovgan, R., Gams, M.: An intelligent indoor surveillance system. In-
7. Piltaver, R.: Strojno učenje pri načrtovanju algoritmov za razpoznavanje tipov
gibanja. In: Proceedings of 11th International multiconference Information Society,
8. Koluža, B., Cvetković, B., Dovgan, E., Gjoreski, H., Gams, M., Luštrek, M.,
Mirchevski, V.: A Multi-Agent Care System to Support Independent Living. In-
ternational Journal on Artificial Intelligence Tools. 23(1) (2014)
and Fall Detection Using Accelerometers. In: Evaluating AAL Systems Through
Competitive Benchmarking, pp. 13–23 (2013)
and Comprehensible Classifiers — a Case Study. In: Proceedings of 7th European
Learning of Hybrid Classifiers. In: Proceedings of European Conference on Artificial
Intelligence (2014).
Combining Domain Knowledge and Meta-classification. Journal of Medical and Bi-
14. Piltaver, R., Cvetkovic, B., Koluža B.: Denoising Human-Motion Trajectories Cap-
15. Luštrek, M., and Koluža, B.: Fall detection and activity recognition with machine