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Signal processing technologies for activity-aware smart textiles

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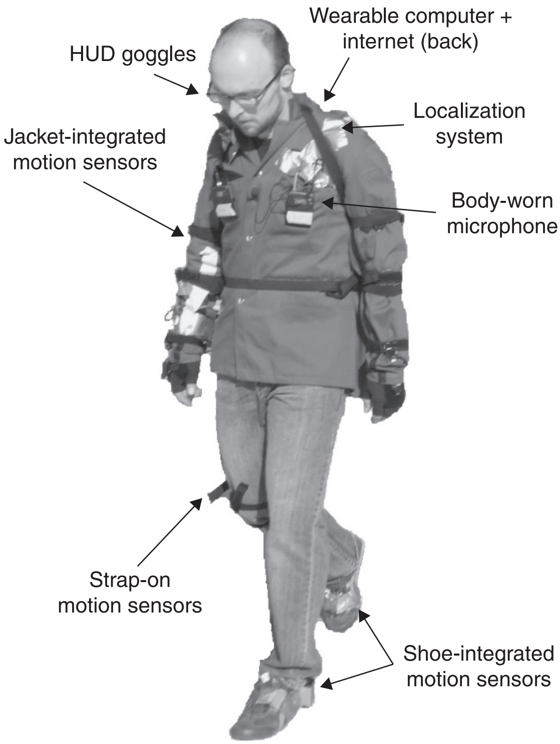
Abstract: Garments made of smart textiles have an enormous potential for embedding sensors in close proximity to the body in an unobtrusive and comfortable manner. Combined with signal processing and pattern recognition technologies, complex high-level information about human behaviors or situations can be inferred from the sensor data. The goal of this chapter is to introduce the reader to the design of activity-aware systems that use body-worn sensors, such as those that can be made available through smart textiles. We start this chapter by emphasizing recent trends towards 'wearable' sensing and computing and we present several examples of activity-aware applications. Then we outline the role that smart textiles can play in activity-aware applications, but also the challenges that they pose. We conclude by discussing the design process followed to devise activity-aware systems: the choice of sensors, the available data processing methods, and the evaluation techniques. We discuss recent data processing methods that address the challenges resulting from the use of smart textiles.

Key words: wearable sensing, signal processing, activity recognition, context recognition.

12.1 Introduction: from on-body sensing to smart assistants

Sensors integrated into textiles open up the way to new kinds of functionalities, built right into our everyday clothing. As an example, a heart rate belt – a gadget commonly used by sports enthusiasts – may be realized in a shirt with conductive fibers serving as electrodes (Pola and Vanhala, 2007). Thus, the gadget's functionality becomes inherent to the clothing and available anytime and anywhere. This is the view promoted in wearable computing, as originally presented by Mann in 1996, which emphasized a shift in computing paradigm. Computing would no longer be separate from the user but would become an unobtrusive extension of our very bodies, providing us with additional ubiquitous sensing, feedback and computational capabilities (Fig. 12.1). In the figure, a number of sensors are integrated in the jacket, within the shoes, or inside other accessories. In a mature product, the integration is supposed to be unobtrusive. A see-through head display in the goggles provides the user with contextual information. With an internet connection, the on-body computer and sensors can infer the user's context, such as his activities or location, and his needs.



12.1 Representation of a prototype of a typical ‘wearable computing’ system.

In particular, Mann (1998) and Starner *et al.* 1998) were among the first to show that complex contextual information can be obtained by interpreting the data from sensors placed on the body. They underlined that this would lead to novel adaptive applications. These so-called ‘context-aware’ applications are capable of adapting their behavior, providing information right when needed, or delivering other forms of assistance when specific needs are detected. Context-awareness has been defined as ‘any information that can be used to characterize the situation of a person, place, or object that is considered relevant to the interaction between a user and an application’ (Dey, 2001). The ‘context’ of a user collectively refers to the user’s activities (activity awareness) (Davies *et al.*, 2008; Lukowicz *et al.*, 2010), his emotional and cognitive states (cognitive-affective awareness) (Picard, 1997; Bulling *et al.*, 2010), his social surroundings and inter-personal interactions (social awareness) (Lazer *et al.*, 2009), or the physical surrounding (environmental awareness).

Pattern recognition techniques are used to infer these elements of context from sensor data. In many cases, a close proximity of the sensors to the body is required.

This is especially the case for activity awareness, where sensors must measure limb movement (Davies *et al.*, 2008; Lukowicz *et al.*, 2010), for physiological sensing, and for cognitive-affective awareness that also requires physiological measurements (Picard, 1997; Bulling *et al.*, 2010). Smart textiles offer such close proximity to the body and represent an ideal substrate for sensing technology to disappear into. Thus *smart-textile sensing* is a key enabling technology for a wide range of novel applications.

The goal of this chapter is to introduce the reader to the design of activity-aware systems, as they can benefit from smart-textiles sensing. We discuss the choice of sensors, the selection of data-processing techniques, and the evaluation methodologies. We also discuss data processing options to address the specific challenges posed by smart textiles.

In Section 12.2, we illustrate the breadth of activity-aware systems being investigated, by presenting a few examples from the literature. Many sensors have been considered in past work. Some of these sensors can readily be integrated into smart textiles, while others may be integrated in the future. Nevertheless, researchers are exploring the scope of possibilities enabled by a wide range of sensor kinds. In Section 12.3, we emphasize the benefits brought about by smart textiles for on-body sensing, and give an overview of commonly used sensors. We also mention the challenges posed to data-processing techniques resulting from smart-textile sensing. In Section 12.4, we introduce the basic principles of activity recognition and some common terminology. In Section 12.5, we explain how signal processing and machine learning techniques can be applied to sensor signals to infer activities or context. We discuss recent methods that address some of the challenges of smart-textile sensing and capitalize on their properties. The experimental aspects, such as the acquisition of datasets, their annotation, the evaluation of recognition methods, and the means available to prototype activity-recognition systems are covered in Section 12.6. In Section 12.7, we identify future trends, and provide sources of further information on the topic.

12.2 Activity-aware applications

Some of the most active application domains for activity-recognition technologies using body-worn sensing include healthcare and assisted-living, sports, industrial worker assistance, entertainment, or human-computer interfaces (HCI). We present a few recent works drawn from various fields, to illustrate the rich diversity of activity-aware systems.

Stiefmeier *et al.* (2008) present methods to recognize complex manipulative gestures performed by industrial workers in the car manufacturing industry. The authors show that it is possible for a jacket with built-in sensors to recognize activities such as checking the hood latch mechanism, checking the seat sliding mechanism, or checking the spacing between doors and car body. The authors present this system as an aid to workers who perform quality assurance tasks, as the system may automatically log all the checked parts without the need for an additional interface (e.g. mobile device operated with buttons, or paper checklists). Activity recognition in industry may also be used to improve the safety of workers in hazardous areas, such as detecting unsafe movements towards running machinery.

Dunne *et al.* (2008) present a garment that can measure seated posture. The authors motivate their work by the need to prevent musculoskeletal disorders, which may arise from an inadequate seated posture over extended periods of time. They argue that a garment-integrated system has the advantage to be always available to the user, and thus may offer reminders if the user is at risk. In Bächlin *et al.* (2010), the authors present a system capable of detecting the freezing of the gait of patients suffering from Parkinson's disease, as a way to provide bio-feedback to support these patients. The system is ideally integrated in trousers, belts or shoes. These are but a few examples of activity recognition in health-related domains (Park *et al.*, 2003; Pentland, 2004; Sixsmith *et al.*, 2007).

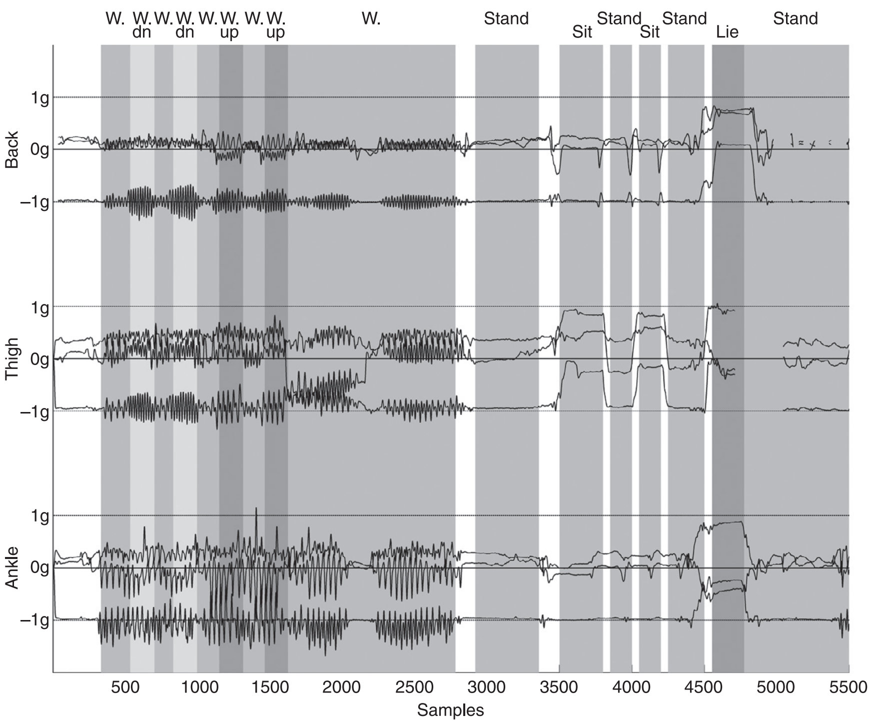
Gestural interfaces for HCI have been envisioned for many years (Myers *et al.*, 1996). Body-worn sensors provide gestural interfaces anywhere the user goes. For instance, Kallio *et al.* (2006) presented a way to interact with ambient devices by means of natural hand gestures with a sensor placed on the wrist. Nowadays, a wide range of motion-based interaction patterns exist for entertainment, for instance with the Nintendo Wii game console and Microsoft Kinect.

Other fields that benefit from activity recognition with body-worn sensing include, for example, sports (Bächlin *et al.*, 2009; Gravenhorst *et al.*, 2011; Strohrmann *et al.*, 2011), human-robot interaction (Martin *et al.*, 2010), or even crowd management (Roggen *et al.*, 2011). Mobile phones also offer a wide range of sensors suited for activity recognition and can complement smart textiles (Campbell *et al.*, 2010). In Section 12.7, we discuss future trends and point to conferences and journals where further application-oriented research outcomes can be found.

12.3 Sensing principles for activity recognition

A *sensor* is a device that converts one physical quantity (e.g. acceleration) into another physical quantity (e.g. voltage), which can be acquired by a computer. Typically, the sensor data will be acquired (or *sampled*) by the computer at a regular interval (the *sampling interval* and its inverse, the *sample rate*). A *sample* is the digital representation of the sensor signal. It refers to a value at a point in time. The *resolution* is the smallest incremental change in the physical quantity that leads to a change in sample value. It is limited by the acquisition electronics (usually an analog-to-digital converter) that uses a limited number of bits to represent a sample. Sensors are typically continuously sampled and provide a continuous stream of sensor data. The *data rate* indicates the number of bits of data acquired per unit time. It is the product of the sample rate by the number of bits used to represent samples. With a *calibration* formula, the value of the physical quantity can be computed from the sample. This formula may be a simple linear transformation, where the relation between the physical quantity and the sample is defined by a slope (the sensor *sensitivity*) and an *offset*. However, the relation may also be non-linear or time-dependent (e.g. *hysteresis*).

In Fig. 12.2, we illustrate the signal obtained from an acceleration sensor with a sample rate of 32 Hz and a resolution of 10 mG. The data is from a recording that is 170 s long at 32 Hz sample rate. The periodicity related to the user's gait is clearly visible. Finer distinctions can be made, such as between walking on a flat surface and walking up a staircase. This is particularly visible on the back sensor. Sitting, standing and lying also have distinctive signal patterns. The thigh sensor helps distinguish between sitting and standing. Lying is no different than sitting for the thigh sensor, but together with the back or ankle sensor, this posture can be distinguished. The signal values remain mostly constant, while the user retains the posture. Note that some data loss occurred around sample 5000 for the thigh and back sensors. The thigh sensor suffered from inadvertent rotation around sample



12.2 On-body accelerometer signals measured on the back, thigh and ankle for some modes of locomotion (indicated by W., W. dn, and W. up for walk, walk downstairs, and walk upstairs, respectively) and body postures.

2000. These issues are common with textile integrated sensors and wireless sensor nodes and the data-processing techniques must be robust to these situations.

12.3.1 Sensing requirements

The design of a recognition system starts by selection of a set of sensors based on the activities to be recognized. The sensors are selected according to a trade-off between information content, usability and power:

- *Characteristic signal patterns*: Activity recognition is based on the assumption that sensors placed on the body provide characteristic signal patterns when an activity is executed by the user. Thus, the selected sensors must measure signals that are characteristic of the activities that must be recognized. This influences the choice of the sensor modality and of its placement on the body.
- *Usability*: Since the sensors are on-body, they must meet usability requirements. A garment equipped with sensors should be comfortable, and in no way differ from a 'normal' garment. Consequently, the sensors must be small, unobtrusive and invisible. They must not hamper the user's freedom of motion, and must be wearable for extended periods of time without adverse effects.
- *Power*: Higher energy use calls for batteries of larger capacity and size, which adversely affect comfort. Thus, sensors must be chosen taking into account the energy use. This includes the energy use of the sensor, and also the energy required to communicate the data (e.g. to a wearable computer), and to run data processing algorithms. For instance, cameras are currently only rarely used in wearable computing, and even though they do not use much power by themselves, the computational requirements for video analysis are significant. Thus, sensor modalities that allow lightweight computations are preferred.

A major focus of the wearable computing community has been to look for sensor modalities that fit these requirements, and research in smart textiles has a key role to play.

12.3.2 Benefits of smart textiles for activity awareness

Hereafter, we use '*smart-textile sensing*' to refer to several approaches by which sensors are integrated within smart textiles. The ideal deployment vector for on-body sensors is to integrate the sensing element directly into the fiber with which the garment is woven (Tognetti *et al.*, 2006; Mattmann *et al.*, 2007). Another approach consists of using fiber-like substrates on which the sensors are deposited, and then to inter-weave this substrate between textile fibers (Kinkeldei *et al.*, 2011(a)). Highly miniaturized conventional sensing electronics can also be encapsulated into the garments (Harms *et al.*, 2009). Wireless communication or conductive fibers embedded within textiles can be used to interconnect the miniaturized electronics (Locher *et al.*, 2004).

Smart-textile sensing offers many benefits. A few of them include:

- *Close proximity to the skin*: This makes the smart-textile approach ideal to sense skin temperature, electric fields for electromyography (EMG), or electrocardiography (ECG). This is also a benefit to sense body movements, as the sensors can measure precisely the movements at any time, unlike camera systems that often suffer from image occlusion and limited field of view.
- *Integration of many multimodal sensors*: Smart textiles can integrate a large number of sensors of various modalities for a given context-aware application on a unique substrate (fiber, textile or garment). This simplifies deployment, as a single entity needs to be managed rather than a multitude of individual sensor nodes. Consequently, it also reduces the risk that a sensor is forgotten, swapped or placed at an inappropriate position during deployment.
- *Convenience and comfort*: Smart textiles allow for clothing that offers context-aware functionality and that is convenient and comfortable to wear.
- *Long-term use*: A consequence of convenience and comfort is to enable sensing applications on long timescales (weeks, months, or more). This is especially important in fields such as rehabilitation or assisted living, where trends must be assessed over long periods of time, or continuous assistance may be required day in and day out.
- *User acceptance and privacy*: Smart-textile sensing makes the sensors invisible to the outside. This enhances user acceptance: it preserves the user's privacy and does not draw the attention of others to the fact that one wears an assistive system.

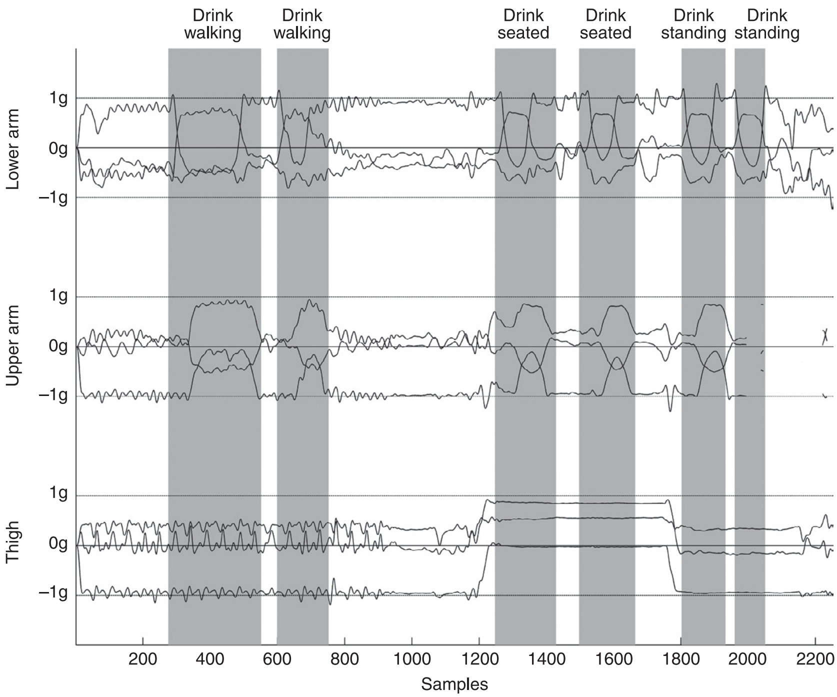
However, capitalizing on these strengths is challenging, as Section 12.3.3 shows.

12.3.3 Challenges of textile sensing

There are several challenges to smart-textile sensing. Challenges cover technological aspects such as manufacturing, as smart textiles are still an active area of research. For activity awareness, we are especially concerned with data processing challenges. A few of those include:

- *Variability of sensor characteristics*: Variability in the production process can lead to different sensor sensitivity, offset or hysteresis. This can have adverse effects on subsequent data processing and must be compensated for, e.g. through a calibration process.
- *Deterioration of sensor characteristics*: Over long periods of time, sensor characteristics may be less stable with smart textiles than with conventional sensor nodes. This is due to the harsh conditions to which they are exposed, such as bending or washing (Schwarz *et al.*, 2011). This may lead to changing sensor characteristics after the initial calibration.

- *Sensor failure*: Sensors may fail altogether, e.g. due to cracks occurring in conductive materials (Kinkeldei *et al.*, 2011(b)). This requires the data processing methods to detect the faults, and ideally select replacement sensors at run-time.
- *Motion artifacts*: Motion artifacts occur when the user's own movements affect the placement of the sensor or its contact pressure to the skin. This can corrupt the sensor signal. Motion artifacts can affect, e.g. ECG measurements (changing skin-sensor impedance) or movement measurements (changing relative placement or orientation of a clothing-integrated sensor with respect to the body). Figure 12.3 shows an example of a motion artifact in the 'drink' gesture. As the user walks, we can see small oscillations in the 'drink' signal, which do not appear when the 'drink' gesture is executed when standing still. These oscillations are artifacts from the user's walking. The data processing methods must either be able to detect or compensate such motion artifacts. This is challenging, as the artifacts are usually difficult to model. The data was obtained from a recording 70 s long at 32 Hz sample rate. The drinking movement is a sporadic gesture, which must be identified in the continuous data stream. It is visible in the upper and lower arm sensors as a smooth



12.3 On-body accelerometer signals measured on the thigh, the upper arm and lower arm while the user drinks from a cup.

change in the acceleration readings. These reflect change in inclination of the arm as the user brings the cup to his mouth. The gesture is recorded while the user walks, is seated or stands. Periodic patterns due to the gait are superimposed on the readings of the arm sensors when the user walks. The readings of the sensors are smoother when the user is seated or standing still. The embedding of activities (drinking) within others (walking) must be taken into consideration when devising the recognition methods.

In Section 12.5, we present methods that can be used to address these challenges.

12.3.4 Typical sensor modalities

Developing sensors within fibers calls for significant investment in fundamental research, but has the potential to deliver ground-breaking functionalities. However, by using conventional electronics, researchers can tap into a large pool of well characterized and understood sensor modalities, some of which may not yet be available for integration into fibers. Researchers are investigating how to use existing as well as upcoming sensor modalities for activity-aware systems. A few typical sensor modalities used for activity recognition are indicated in Table 12.1, together with the possible means to deploy them on-body. Other sensor modalities are listed in Roggen *et al.* (2010(a)). We comment on a few common modalities below.

One of the most common modalities for activity recognition is the acceleration sensor. Accelerometers realized in MEMS technology are extremely small and low-power, and can measure the acceleration around three axes. They can easily be included into conventional but highly-miniaturized circuits and included in garments (Harms *et al.*, 2009). Many low-cost commercial solutions are available. When attached to a limb, accelerometers measure a static and a dynamic acceleration. The static acceleration stems from the Earth's gravity when the sensor is not moving. This can be used to determine the inclination of the sensor and thus the inclination of the limb with respect to the vertical plane (Ermes *et al.*, 2008; Randell, 2000; Harms *et al.*, 2009), to measure static body postures. The dynamic acceleration is due to the movement of the limb to which the sensor is attached. This can be used to recognize HCI gestures (Förster *et al.*, 2010) or modes of locomotion (Figo *et al.*, 2010; Randell, 2000). Inertial measurement units (IMUs) contain accelerometers, magnetometers and gyroscopes and sense the orientation of the device with respect to an Earth coordinated system. They are typically placed on each body segment and create a stick figure representing the user.

They can also be integrated into garments (Stiefmeier *et al.*, 2008) and are used when relative position and orientation of the limbs is relevant (e.g. the position of the hands with respect to the torso). Usually activity recognition performed on limb positions outperform the recognition performed on simpler sensors such as accelerometers (Zinnen *et al.*, 2009). Others have demonstrated that various

Table 12.1 Common sensor modalities for activity recognition from body-worn sensors, and the deployment possibilities for smart-textile sensing

Sensor	Observation	Smart-textile deployment
Microphone	Social interaction recognition, speaker identification, localization by ambient sounds, activity detection	No smart-textile equivalent, but commonly available on-body through mobile phones (Campbell, 2010)
Accelerometer, magnetometer, gyroscope, or inertial measurement unit	Movement patterns, orientation, or rotation of the body or limbs	No smart-textile equivalent, but flexible substrates, which can be woven into garments and on which bare-die sensors can be bound (Zysset, 2010), highly miniaturized conventional electronics encapsulated into garments (Harms, 2009)
Pressure	Pressure of clothing against the body, muscle activity, weight distribution, posture characterization	Textile pressure sensor used for muscle activity detection (Meyer, 2006) or posture recognition (Meyer, 2010)
Temperature	Health state (e.g. fever)	Textile integrated temperature sensor presented in Kinkeldei (2011)
Humidity	Sweat, physical activity	Textile integrated pressure sensor presented in Kinkeldei (2011)
Strain	Breathing (respiration belt), movement (elongation sensor in clothes)	Textile strain sensors for posture measurement in clothing (Mattmann, 2007; Giorgino, 2006; Tognetti, 2006), clothing-integrated strain measurement by optic fiber (Dunne, 2008)
ECG, EMG, EOG	Physical activity and health state (ECG), muscle (EMG) and eye (EOG) activation	Textile electrodes (Pola, 2007), dry electrodes (Lamparth, 2009; Bulling, 2009)

combinations of accelerometers, gyroscopes or magnetometers can in some cases be substituted for each other (Kunze *et al.*, 2010).

Sensorized textile fibers allow for truly unobtrusive garment-integrated on-body sensing. Mattmann *et al.* (2007) proposed the use of conductive elastic fibers as stretch sensors and showed that body postures can be detected based on the elongation of the fiber. Lukowicz *et al.* (2006) showed that pressure sensors can be used to measure muscle activity from which modes of locomotion can be inferred, or fatigue during sports exercise. They argue that the sensor is well suited for integration in garments, as force sensors can be realized as thin foils or even as textiles (Meyer *et al.*, 2006).

Smart textiles open the way to the development of new sensor modalities, which is pursued chiefly for two reasons: to further increase the usability of an existing system, or to enable the recognition of activities for which current modalities are not sufficient. Thus, new sensors are usually characterized in terms of the improvements they bring in usability and activity recognition performance. For instance, detecting swallowing without using implanted sensors is difficult. To address this, Cheng *et al.* (2010) developed a novel capacitive sensor, which may be integrated in close proximity to the neck in a shirt. This sensor can be used to detect drinking and eating from the movement of the throat during swallowing. As part of the evaluation procedure, the parameters of the sensor are characterized, its comfort evaluated, and the influence of body movements on the detection accuracy is quantified (Cheng *et al.*, 2010).

In order to enhance sensing capabilities, smart-textiles sensing can be combined with sensors that are readily available in commonly used gadgets. For instance, the user's location (e.g. using GPS or cellular network signals) is an important modality for context awareness. It does not lend itself well to be integrated into fibers but it is available in mobile phones. On-body microphones are also successfully used for activity recognition, as many human activities generate characteristic sounds (e.g. using a coffee machine, brushing teeth), and microphones are also available in mobile phones (Ward *et al.*, 2006). Mobile phones have a large number of other sensors to complement smart-textile sensing (Campbell *et al.*, 2010). Furthermore, they can be used as a computer to process the data from the smart-textile sensors and can realize the desired assistive function by providing user feedback (Want, 2009).

12.4 Principles of activity recognition

The purpose of activity recognition methods is to identify the patterns characteristic of an activity within the signals delivered by one or more sensors. The identification of a pattern indicates that the corresponding activity is likely to have been executed by the user. In this section we introduce the terminology commonly used in the field of activity recognition to distinguish different kinds of human activities and different kinds of recognition approaches.

12.4.1 Human activities

A wide range of different limb movements are commonly termed as 'activities', depending on their complexity or duration. Often, the terms 'action primitives' (or actions) and 'activities' are distinguished (Turaga *et al.*, 2008). Action primitives refer to simpler gestures (e.g. reaching for an object, raising a cup to the mouth to drink, toggling a switch), while activities are made up of a succession, interleaving or simultaneous execution of several action primitives spanning a longer duration. For instance, eating consists of using cutlery, bringing food to the mouth, chewing, swallowing, etc. To simplify, we will use 'activity' to refer to both action primitives and more complex sequences of primitives, unless the distinction is required.

Nevertheless, a precise definition of activity is elusive, as it involves perceptual aspects that are still being investigated (Blake and Shiffrar, 2007). These may lead observers of the same scene to describe it in different ways. Therefore activity-based computing usually defines activities from an application perspective: activities are sequences of body limb movements that – if they can be detected – can trigger useful behaviors in an application. Following this pragmatic approach, there is usually an agreement on the following broad categories of activities:

- *Body postures*: The subjects take a posture, which is static over a defined time period. Although static, the recognition of such postures is comprised in the broader umbrella of activity recognition. Examples of body postures are standing, lying or sitting (Randell, 2000; Ermes *et al.*, 2008) (Fig. 12.2). Also, finer distinctions in these postures can be made, such as seated and leaning forward or backward. Body postures may include particular limb configurations, such as when performing rehabilitation exercises (Mattmann *et al.*, 2007).
- *Modes of locomotion*: These activities relate to how the user moves around, e.g. by walking or running. Finer distinctions can also be made, such as walking upstairs or downstairs, or even jumping (Randell, 2000; Lester *et al.*, 2006; Figo *et al.*, 2010) (Fig. 12.2). Bicycling or driving may also be considered as modes of locomotion (Berchtold *et al.*, 2010).
- *Gestures*: The user performs a short gesture, such as toggling a light switch or bringing a cup to the mouth to drink. These gestures may be 'isolated' in the sense that the user returns to a rest position or marks a pause after the gesture is completed. This tends to be the case, e.g. in human-computer interaction scenarios with pointing gestures used to control a device (Martin *et al.*, 2010). Gestures may also be embedded among other user's activities. In this case, recognition tends to be harder, as the system has to disambiguate the gesture from other movements (Fig. 12.3).

Since activities are generally sensed with movement sensors (e.g. accelerometers), we can distinguish activities in terms of the nature of the resulting sensor signals:

- *Periodic nature*: This includes activities that exhibit periodicity (Fig. 12.2). Modes of locomotion usually exhibit such periodicity (e.g. walking, running, bicycling), but also some sports (e.g. step exercises, weight lifting). Such activities lend themselves to be detected in the frequency domain.
- *Static nature*: The activities are characterized by a signal that is relatively stable over time. This is typically the case with postures. These activities lend themselves to be detected by an analysis in the time domain (Fig. 12.2).

- *Sporadic nature*: The activities or gestures occur sporadically, interspersed with other activities or gestures. The detection of such activities usually requires a preliminary process of segmentation, which isolates the subset of data containing the activity, before doing a time or frequency analysis (Fig. 12.3).

In Fig. 12.2 and Fig. 12.3, we illustrate the sensor signals delivered by accelerometers placed on the body for the different activity categories introduced above. On longer timescales (e.g. days, weeks), human activities usually comprise a repetitive structure, where roughly similar activities are executed day after day. Such 'daily routines' are usually composed of a complex interleaving of lower-level activities (Blanke and Schiele, 2009). Thus, recognizing high-level activities builds upon the recognition of lower-level action primitives in a hierarchical manner (Hong *et al.*, 2009; Manzoor *et al.*, 2010).

12.4.2 Recognition system

Further distinctions can be made in the way that the machine recognition of activities operates. Activity recognition is done 'offline' when the system records the sensor data first, and the recognition is performed afterwards. Offline activity recognition is typically used for non-interactive or logging applications. For instance, the data can be collected over the day, and at night is uploaded to a server for analysis. Activity recognition is done 'online' when the system acquires sensor data and processes it on-the-fly. This is typically used for activity-based computing and interactive applications, where an immediate action must be carried out upon the detection of a specific activity.

Since sensors deliver continuous streams of data, the recognition system must identify at any time those parts of the data stream that are likely to correspond to the execution of an activity. This is referred to as 'continuous activity recognition'. When an activity is identified in the data sensor stream, it is said to be 'recognized' or 'spotted'.

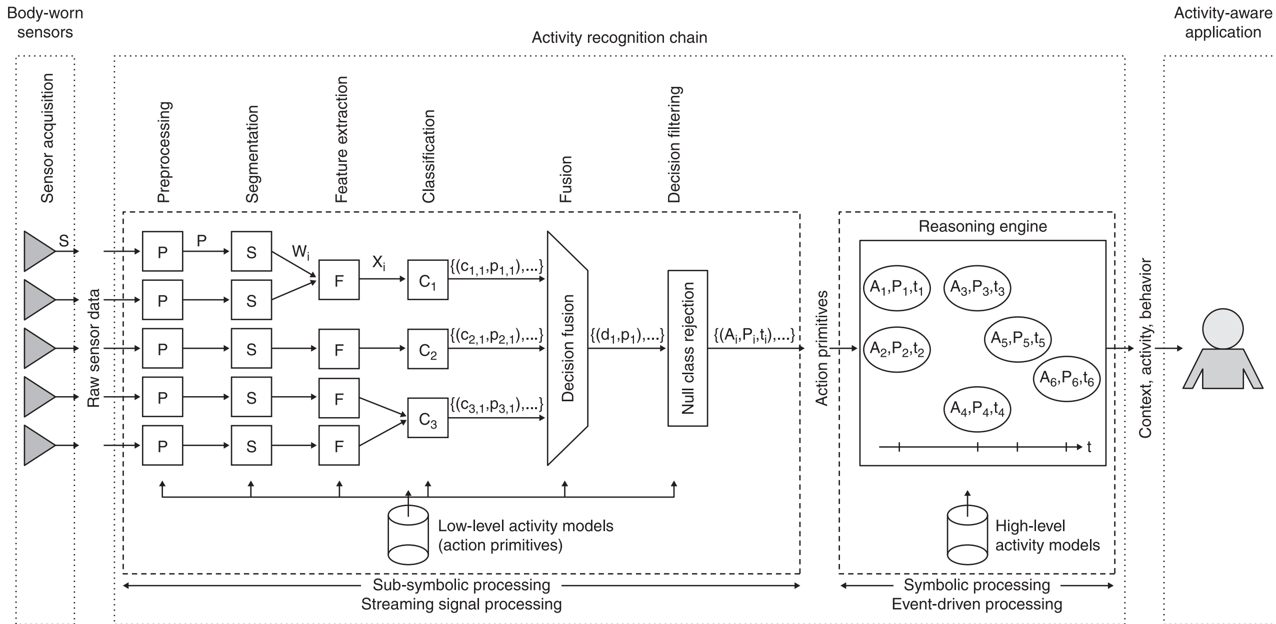
Alternatively, in 'isolated activity recognition', the sensor data stream is 'segmented' at the start and end of each activity. In other words, the system gets to process only chunks of data that were acquired while the user performed exactly one activity, but the nature of the activity is unknown and must be determined. Thus, the system must 'classify' the sensor data into one of several predefined activity classes. The segmentation can be done by the experimenter when assessing classification performance during design phases. When the system is deployed, the segmentation can be done by an external system (e.g. cross-modality segmentation, where one sensor modality is used to segment the data stream of another sensor), or by a 'segmentation' algorithm. Continuous activity recognition combines the challenges of data segmentation with that of activity classification. Isolated activity recognition only deals with the problem of classification, and it is thus usually easier to address.

12.5 Signal processing and pattern analysis

The machine recognition of human activities consists in finding, in a stream of continuous sensor data, those points where the sensor signals are likely to be the result of the execution of an activity. Thus activity recognition is a problem of matching known patterns in large streams of data. To a large extent, the same principles also apply to the recognition of other elements of context, such as cognitive-affective states (e.g. detection of emotions (Picard, 1997) or of memory recall (Bulling *et al.*, 2010)), although the sensors used would be different. Despite the wide variety of sensors and activities, most of the methods used in the works mentioned previously can be cast into a common data processing architecture. We refer to it as the 'activity recognition chain' or ARC (Roggen *et al.*, 2011(b)) (Fig. 12.4). It is a roughly common processing structure that has emerged across most published work in activity recognition. It is based on streaming signal processing, machine learning and reasoning techniques (Bao and Intille, 2004; Ward *et al.*, 2006; Bettini *et al.*, 2010; Figo *et al.*, 2010). The raw sensor data is mapped to the occurrence of action primitive (events) with signal processing and machine-learning techniques. Here five sensors deliver data. Data fusion is illustrated at the feature, classifier and decision level. Optionally, symbolic processing can be used to infer higher-level activities from the occurrence of action primitives, usually with reasoning or statistical approaches.

The specific parameters and methods within the ARC are selected using a 'learning by demonstration' approach. In this approach, the user is instrumented with the selected sensors and put into a situation where he performs the activities of interest at design time. The sensor data is acquired with ground-truth annotations describing what the user performs or experiences. The resulting dataset is used to train the recognition system and test its performance. The training process consists of identifying the prototypical signal patterns corresponding to the user's activities, and then to select the methods and their parameters that best allows identification of these patterns in the sensor data stream. At run-time, the ARC essentially 'compares' the streaming sensor signals to prototypical activities. These prototypical activities are also called activity models (Section 12.6.1). The ARC identifies sensor patterns to match sufficiently the activity models to indicate that an activity has been 'spotted'.

The ARC illustrated in Fig. 12.4 shows the typical data processing steps from the input, which is the raw sensor signals, to the output, which is a series of events indicating the occurrence of an activity. First, sub-symbolic processing maps the raw sensor data (e.g. body-limb acceleration) to semantically meaningful action primitives (e.g. grasp). This is realized by streaming signal processing and machine-learning techniques. The outcomes of the sub-symbolic processing are events indicating the occurrence of action primitives.



12.4 Processing steps used to infer activities from on-body sensors.

The ARC terminates at this stage when the activities of interest consist of simple gestures, for instance used for gestural interfaces (Kallio *et al.*, 2006). When more complex activities must be detected, symbolic reasoning can be used in a second stage to infer higher level activities. However, this is outside of the scope of this article.

Sub-symbolic processing ought to be robust to the large observed variability in sensor-signal to activity-class mapping resulting from variability in human behaviors. It must also be robust to variability in sensor characteristics and to deployment variability (e.g. displacement along limbs every time a garment is worn). This is especially important in a smart-textile approach to sensing, where the variability in sensor characteristics may be larger than for conventional sensor nodes, and may change over time due to the harsh conditions of use. In any case, the ARC (i.e. the specific methods that are applied and their parameters) is usually co-optimized with the sensors that are used, to maximize comfort, as well as to recognition performance.

The sub-symbolic processing stages are described below.

12.5.1 Sensor data acquisition

A time series corresponding to the sensor data is obtained. Since sensors can provide multiple values (e.g. an acceleration sensor provides a three-dimensional (3-D) vectorial acceleration), multiple sensors are jointly sampled and vector notation is used:

$$S = \{\vec{s}_0, \vec{s}_1, \vec{s}_2, \ldots\}. \qquad [12.1]$$

12.5.2 Signal pre-processing

Basic signal pre-processing is applied to the sensor data. The objective is to increase the signal-to-noise ratio. Typical pre-processing include calibration or normalization of sensor values, and various signal processing operations such as de-noising, bandpass filtering, discriminant analysis, etc. Sensor-specific processing can be performed. For instance, the l^2-norm of the values delivered by an accelerometer can be computed when the direction of the acceleration is not relevant. Other forms of pre-processing involve the conversion of the sensor values to other physical units. For instance, IMUs generally deliver quaternions indicating the sensor orientation. When several IMUs are placed on multiple limbs, it becomes possible to map the orientation of the IMUs to the spatial coordinate of the limb based on a body model (Zinnen *et al.*, 2009). This is a form of sensor fusion occurring at the signal level.

The outcome is pre-processed time series P:

$$P = \{\vec{p}_0, \vec{p}_1, \vec{p}_2, \ldots\}. \qquad [12.2]$$

12.5.3 Segmentation

The data stream is segmented into sections that are likely to contain an activity. Segment i is delimited by its start time t_i^s and end time t_i^e within the time series, yielding a segmented time series W_i:

$$W_i = \{\vec{p}_{t_i^s}, \ldots, \vec{p}_{t_i^e}\}. \quad [12.3]$$

A common type of segmentation technique is the sliding window. In that case, the window has a fixed size w and we have $t_i^s = t_i^e - w$. The sliding window segmentation is typically used when the sensor signals are best analyzed in the frequency domain. This is the case for many periodic movements (e.g. walking, running, biking, rowing). A sliding window can also be used with static movements. In that case, it is used to increase the robustness of the subsequent feature extraction, in comparison to a sample by sample processing. In particular, it allows increased robustness to noise (e.g. by smoothing outliers resulting from communication errors or motion artifacts). Other segmentation methods include energy-based or rest-position based segmentation, when the user performs isolated gestures or returns to a rest position between gestures (Roggen *et al.*, 2010(b)). Other segmentation methods have been proposed in the context of time series analysis (Keogh *et al.*, 2001; Armstrong and Oates, 2007), online learning schemes (Kulic *et al.*, 2009) and hybrid segmentation-classification schemes (Deng and Tsui, 2000; Stiefmeier *et al.*, 2008).

12.5.4 Feature extraction

Features are computed on the identified segments. This is done to reduce data dimensionality, and to better discriminate activities of interest. The result is a feature vector $\vec{X}_i$, often represented as a point in a feature space:

$$\vec{X}_i = \Psi(W_i) \quad [12.4]$$

A large set of features can be computed from the sensor signal. Knowing which must be computed is an explorative process. It benefits from past experience, 'educated guesses' supported by visual inspection of the data, or computational approaches (Guyon *et al.*, 2006). Evolutionary algorithms can also be used to explore a greater set of features than what is humanly possible to envision (Förster *et al.*, 2009(a)). A taxonomy of features commonly used with acceleration sensors has been proposed in Figo *et al.* (2010). It applies to a large extent to other sensor data (e.g. data from gyroscopes, magnetic field sensors, stretch sensors). Usually feature extraction attempts to generate an exhaustive set of candidate features. This set is then pruned to include only the most relevant features using feature selection heuristics (Guyon and Elisseeff, 2003).

12.5.5 Classification

The feature vector $\vec{X}_i$ is mapped into one output class (i.e. the user activity) c_i, using pattern classification or machine-learning methods (Duda *et al.*, 2000):

$$\vec{X}_i \to c_i, p_i \qquad [12.5]$$

Usually, classification also yields an indication as to the confidence in the classifier output. This is often a probability p_i with Bayesian approaches. Other classifiers may be calibrated to provide probabilistic outputs (Cohen and Goldszmidt, 2004).

12.5.6 Decision fusion

Decision fusion is one form of data fusion that combines the decisions of multiple classifiers into a common decision about the activity that occurred. Multiple classifiers are typically used with multi-modal sensors, when it is difficult to combine the sensor's data in the same feature vector (Sharma, 1998). In that case, the activities are first spotted in each sensor modality individually, then these individual decisions are combined. Generally multiple sensors are improving the recognition of complex real-world activities (Stiefmeier *et al.*, 2007). A detailed introduction to classifier fusion is found in Polikar (2006).

12.5.7 Null-class rejection

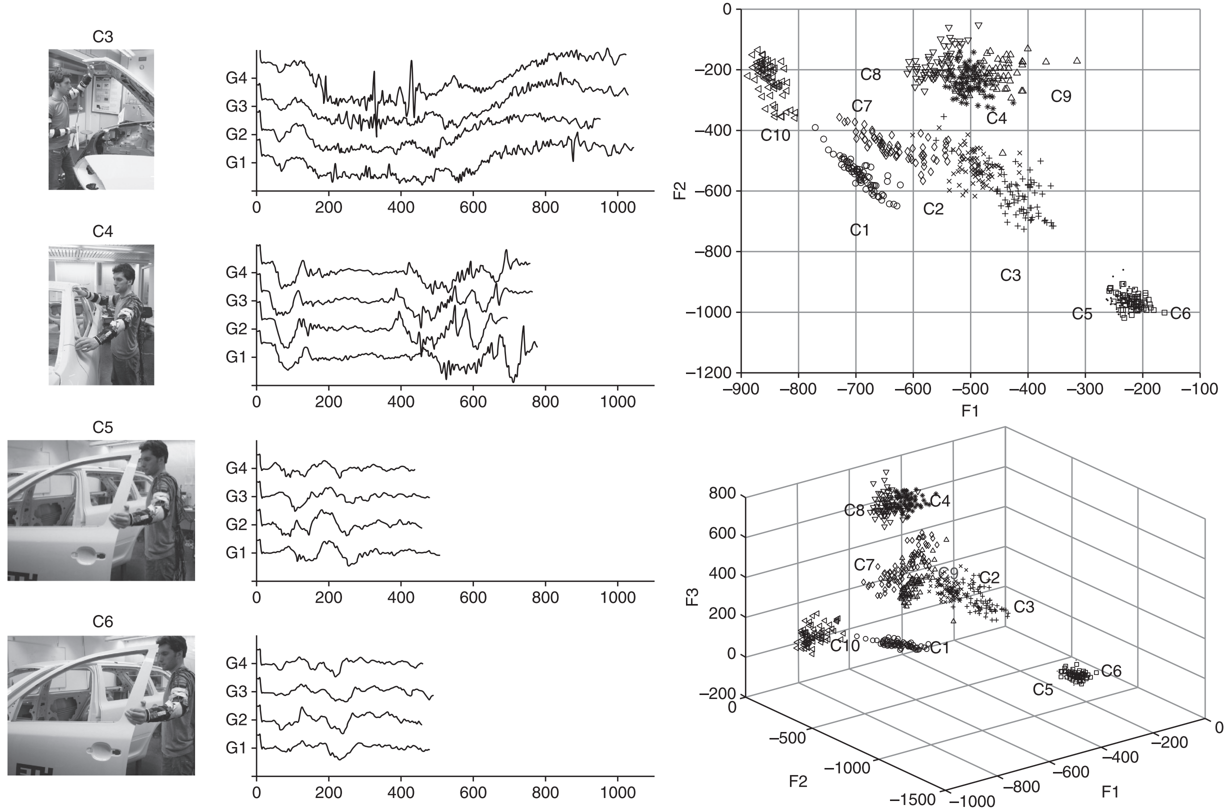
In principle, the segmentation stage should identify sections of the signal corresponding to an activity. In practice, segmentation may be inaccurate. For example, a data segment may cover a time span where 'no activity' took place. This is the case if a sliding window approach is used with sporadic activities such as short gestures. Null-class rejection attempts to discard these segments by assessing how likely it is that the data corresponds to an activity described by the classifier models. Thus, in cases where the confidence in the classification result is too low, the system may discard the classified activity i based on p_i, in the simplest case by comparison to a threshold (Lee and Kim, 1999; Sagha *et al.*, 2011). At this stage, the outcome is the detection of an activity A_i with likelihood p_i at time t_i.

12.5.8 Method and parameter selection

The specific methods for each of the elements outlined above and their parameters are defined at design time through an interactive or automated optimization process. The parameters subject to optimization include, for example, the window sizes, the thresholds to segment activities or reject the null class, the signal normalization parameters, the set of features to compute, and the classifier models. The objective of this optimization is usually to reach high activity recognition accuracy. This typically translates to increasing the separation and thus reducing the overlap between the distribution of the activity classes in the feature space. Power, computational requirements, and user comfort must also be taken into account when devising wearable activity recognition systems. Usually heuristics are available to find these parameters. Many methods exist for feature selection (Guyon and Elisseeff, 2003) and classifiers usually have a corresponding 'training' heuristic (Duda *et al.*, 2000).

For activities that are of periodic nature (e.g. walking, running, bicycling, rowing, hammering) a sliding window segmentation is generally used. The features that are used are then selected to capture the repetitive nature of the activity (e.g. zero or mean crossing rate, power spectrum, dominant frequency (Figo *et al.*, 2010)). With static postures, a sliding window approach is also commonly used with time-domain or statistical features (e.g. limb angle or angle between several limbs, means of acceleration). For periodic activities and static postures, the classifiers typically used include Support Vector Machines (Qian *et al.*, 2010; Bulling *et al.*, 2011(a,b)), decision trees, k-Nearest Neighbor or Naive Bayes classifiers (Randell, 2000). When the activities are sporadic (i.e. they are short and occur interleaved with other activities, which the system does not need to recognize) a sliding window of appropriate size (commensurate with the length of the activity), together with a null-class rejection, can be used (Sagha *et al.*, 2011). Alternatively, segmentation and classification techniques that take the temporal dynamics of the sensor signal into account can be used. These techniques include, for example, hidden Markov models (HMMs) (Starner *et al.* 1998; Deng and Tsui, 2000), dynamic time warping (Ko *et al.*, 2005; Stiefmeier *et al.*, 2008), methods based on feature similarities (Keogh *et al.*, 2001) or neural networks (Bailador *et al.*, 2007; Yang *et al.*, 2008). Further methods are mentioned in Figo *et al.* (2010).

In Fig. 12.5, we illustrate a set of activities carried out by an industrial worker during the quality assurance check of the car manufacturing process (Stiefmeier *et al.*, 2008). The data of an acceleration sensor integrated into the garment at the right wrist is depicted. We can note the variability in the gesture execution length and signal shape. Related activities, such as opening and closing the door (C5 and C6), show sensor signals with subtle differences. Unrelated activities, such as opening a door (C5) and checking the engine hood (C3), show markedly different signals. With simple statistical features, the sensor signals can be projected in a feature space where the activities form clusters suitable for classification. Here two possible feature spaces are represented. The features are the average value of the accelerometer reading on two or three axes of the sensor (this is an approximation of the average angle of the user's right lower arm). This yields a two-dimensional (2-D) and a 3-D feature space. Some activities are well separated, leading to accurate classification (e.g. C10 and C1 in the 3-D feature space), while others overlap as they are more similar (e.g. C5 and C6). In this example, the increase of the dimension of the feature space allows to better separate classes



12.5 Four activities of a car assembly scenario are shown on the left: checking the engine hood (C3), the gap spacing between doors and car body (C4), the opening of the front door (C5), and the closing of the front door (C6). In the middle, the data of an acceleration sensor attached to the garment at the right wrist is shown for four repetitions (G1–G4) of the activity. After feature extraction, the sensor signals are projected into a feature space for pattern recognition. Here the projection in a two-dimensional (right up) and three-dimensional (right down) feature space is represented (sensor data from Zappi, 2008).

C1 and C7, which overlap in the 2-D feature space, but are well separated in the 3-D feature space. During the training of the recognition chain, the method and parameter selection aims at increasing the separation between the activity classes.

12.5.9 Addressing the challenges of smart textiles

In Section 12.3.3, we outlined a few of the challenges arising from the use of smart textiles for sensing, such as variability and deterioration of sensor characteristics, sensor failure and motion artifacts. Without precautions, these issues can adversely affect recognition performance once a system is deployed. We outline here a few approaches that can be employed to mitigate these effects. These approaches are also applicable when conventional sensor nodes are used.

Variability in sensor parameters is a result of the tolerances of the manufacturing process. One way to address this variability is to perform a *calibration* of the sensor (typically at production time) by characterizing and then compensating for differing sensitivity, offset and hysteresis prior to using it for activity recognition (Mattmann *et al.*, 2008; Meyer *et al.*, 2010). Sensor calibration may also be performed at the same time as user calibration (the process by which a generic recognition system is tuned for a specific user). Some recent user calibration methods were proposed in Ohmura *et al.* (2009) and Maekawall *et al.* (2011).

The variation of parameters over time may lead to a drift of activity classes in the feature space (concept drift). Addressing this needs a form of *online self-adaptation*. Self-adaptation methods were proposed for activity recognition in Förster *et al.* (2009(b)) and Bayati *et al.* (2011), to cope with sensor placement variability. These methods are related to expectation maximization and are also envisioned for adaptation to other forms of concept drift. Such methods must achieve an equilibrium between stability (the capacity to retain the current activity model) and plasticity (the capacity to adapt the model) by matching the speed of adaptation to the characteristics of the concept drift. These adaptation parameters can be found at design time from the characterization of the long-term properties of batches of sensors. Further details on an extension to the ARC to make it adaptive are found in Roggen *et al.* (2011(b)).

There is a thin line between a sensor whose parameters have significantly degraded, and a sensor which has failed. Since fiber-integrated sensors are often passive analog sensors (e.g. using resistive or capacitive sensing principles), they are not able to report whether they have failed, except obvious cases where sensing a high impedance indicates a loss of connectivity (e.g. when cracks form in a conductive material) (Kinkeldei *et al.*, 2011(b)). For activity recognition, it is important to estimate whether the data delivered by the sensor may come from a functional sensor, or whether the sensor is damaged and delivers data that should be discarded. The fields of *fault detection* and *anomaly detection* have investigated a wide range of methods, which can be used to assess whether the data delivered by a sensor are plausible for the given sensor. Many of these methods are reviewed in Betta and Pietrosanto (2000), Chandola *et al.* (2009) and Gage and Murphy (2010). Problematic sensors can be also identified when activities are recognized, by fusing the decisions taken by multiple ARCs operating on individual nodes (Sagha *et al.*, 2011(b,c)).

Motion artifacts are noise sources indirectly resulting from user movement. As the user moves, the pressure of the sensor against the skin may vary around a nominal value. Changing contact pressure against the skin is a common source of noise when measuring ECG or EMG from electrodes due to the variations in impedance induced by the movement. These motion artifacts can be identified using fault and anomaly detection methods, as mentioned above. As smart textiles can host a large variety of sensors unobtrusively, another approach is to use an additional motion sensor to perform *signal quality appraisal* (Schumm *et al.*, 2011).

Motion artifacts also affect movement sensors. A motion sensor may be displaced or become subject to rotations around its nominal position and orientation. This can occur when motion sensors are integrated into loose-fitting clothes. In that case, the orientation of a sensor may not reflect the orientation of the limb, but that of wrinkles of the clothing. This may be compensated by modeling techniques (Harms *et al.*, 2010(a)). Sensor displacement can also be compensated by a combination of multiple sensor modalities and a body model (Kunze and Lukowicz, 2008).

When the fibers themselves are functionalized, a large number of sensors may become available. The large amount of data may be challenging to process. *Feature and sensor selection techniques* can be used to reduce the amount of information that is subsequently processed. This is used, for instance, in Meyer *et al.* (2010) to select appropriate textile pressure sensing elements to monitor sitting behavior.

While having a large number of sensors can lead to increased computational requirements, it is also a unique characteristic of smart textiles that can be exploited. In order to do this, a typical practice followed with conventional sensor nodes must be overturned. With conventional nodes, the designer attempts to maximize user comfort by using only the minimal set of sensors sufficient to recognize the activities of interest. With smart textiles, the data processing paradigm rather shifts towards making the best use of a large amount of sensors readily available. This is achieved by relying on data fusion techniques. This in turn can address some of the challenges discussed above.

Setz *et al.* (2009) present a system to recognize emotions based on modalities, which could be integrated into textiles: ECG, EMG, EOG, galvanic skin response and respiration rate. Due to motion artifacts, these sensors deliver sporadically-corrupted data. By relying on the fusion of decisions taken by classifiers operating on each sensor modality individually, the authors could significantly improve the performance of the system, despite the motion artifacts. This approach can be chiefly generalized to other context recognition problems and other sensor modalities.

Zappi *et al.* (2007) showed that by fusing the decision of individual classifiers, the activity recognition performance can be significantly improved. They showed that the effect of unexpected sensor rotation, such as those that might occur if there are wrinkles in the clothing, can also be addressed. Finally, data fusion also improves the robustness to sensor failures. This work was extended to show that the sensor fusion approach can be dynamically adapted at run-time to achieve desired power-performance tradeoffs. This allows achieving a desired target performance while minimizing energy use (Zappi *et al.*, 2008). Furthermore, the system is able to replace at run-time faulty sensors by others to maintain the desired power-performance trade-off. Information theoretical principles can also be used to form optimal combinations of sensors for activity recognition (Chavarriaga *et al.*, 2011). Other examples of distributed fault-tolerant classification can be found in Wang *et al.* (2005).

In summary, one main drawback of smart textiles, compared to dedicated sensor nodes, is the higher variability in sensor characteristics due to manufacturing aspects, usage patterns and textile-embedding conditions. A promising way to handle these challenges is to capitalize on the characteristic of smart textiles: their capacity to embed a large number of sensors with high comfort. This requires shifting the activity and context recognition paradigm to a more prevalent use of data fusion techniques, rather than the traditional attempt to minimize the sets of sensors used. In this way, the variability issues can be compensated for by capitalizing on the large number of available sensors.

12.6 Experimental aspects

12.6.1 Data recording and ground truth annotation

A reference dataset comprising annotated activities (i.e. their start and end point is identified) is required to train and optimize the ARC, and to evaluate the recognition performance. Reference datasets can be recorded in a continuum from laboratory environments to daily life situations.

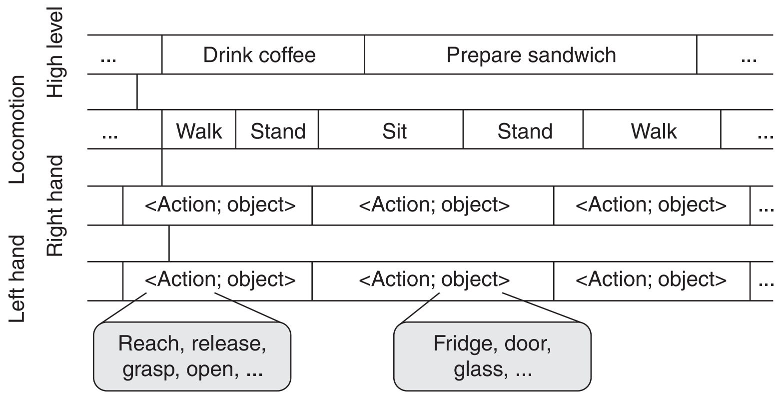
Recordings in the laboratory are typically done to ensure reproducible execution of activities without external influences. Laboratory set-ups are well suited to acquire annotations, as an experimenter can observe the scene and video footages can be made without privacy issues. Reference datasets can also be collected in daily life. This ensures a realistic execution of activities, which usually show a higher variability than in laboratory set-ups. Such recordings are more challenging to conduct. Experimenters must take care of technical issues (e.g. sensors that might be displaced while worn, or that run out of energy) and user aspects, in particular privacy issues. Annotation in daily life is also more challenging as video footage is often inappropriate (e.g. when recording data at the subject's home, or in the streets where other persons may appear in the footage). An intermediate approach is recordings in naturalistic environments. Such an environment is a laboratory environment designed to allow a set of highly realistic activities (Roggen *et al.*, 2010(a)).

Reference datasets need to capture the activity variability likely to be encountered when the system is deployed to ensure reliable training of activity models. The types of variability that must be captured include, among others, the inter-user and intra-user activity variability, and the sensor placement variability. Thus, ideally, datasets must include activities from multiple users, captured over multiple days or multiple deployments of the on-body sensors. The size of the reference dataset (number of repetitions of each activity) is a function of the expected variability, which can be assessed in a preliminary small-scale recording.

If multiple sensors are used but are not synchronized at the hardware level, offline synchronization is performed. Video footage assists greatly in this task. The subject is often asked to perform specific movement patterns at the start and end of the recording, such as clapping the hands (Bannach *et al.*, 2009; Roggen *et al.*, 2010(a)). This results in sound, a characteristic movement pattern visible in acceleration signals measured on body, and a clear visual identification of the moment of the clap (Roggen *et al.*, 2010(a)).

Annotation consists of identifying the starting and ending time of the activities of interest in the sensor data stream (see Fig. 12.2 and Fig. 12.3, for examples of annotated data streams). Data annotation can be done in real time by an expert observing the situation. However, this is difficult. Thus, annotation is preferably done offline using video footage documenting the data acquisition and synchronized with the sensor data recording. Short activities and transitions between activities are difficult to precisely identify, as human activities tend to be highly interleaved, and are also subject to different semantic interpretation. Labeling consistency is important. Thus, when possible, multiple experts should annotate the video footage. It allows quality control on the resulting annotations. When multiple persons share the work of labeling a dataset, it is recommended to arrange classroom sessions where it is explained to all persons how to perform the task.

We developed the concept of label tracks (Roggen *et al.*, 2010(a)) to represent a wide range of activities in a structured manner (Fig. 12.6). Hand activities are annotated by a pair of action tags and an object tag. An action tag indicates primitive activities, such as ‘reach’, ‘open’, ‘move’, ‘grasp’. An object tag indicates the object that the action applies to. Another label track represents the modes of locomotion: ‘walk’, ‘stand’, ‘sit’, etc. Since the label tracks are independent of each other, new label tracks can be seamlessly added. In daily-life recordings, the annotations may be provided by the subject himself. This may occur in real time, *a posteriori* with a time diary (Van Laerhoven *et al.*, 2008), or by using ‘experience sampling’, which consists in asking the subject at regular intervals to annotate his activities (Froehlich *et al.*, 2007). Tools such as Anvil[1]



12.6 Activity labeling approach composed of multiple 'tracks', which indicate at each time step the ongoing activity of the user. This approach based on tracks allows independent labeling of different aspects of the user's activities in a scalable manner. Here we show a high-level activity track, modes of locomotion track, and two tracks for the action of the left or right hand.

can be used for annotation. Some groups are developing customized tools for data acquisition[2] and annotation (Bannach *et al.*, 2010).

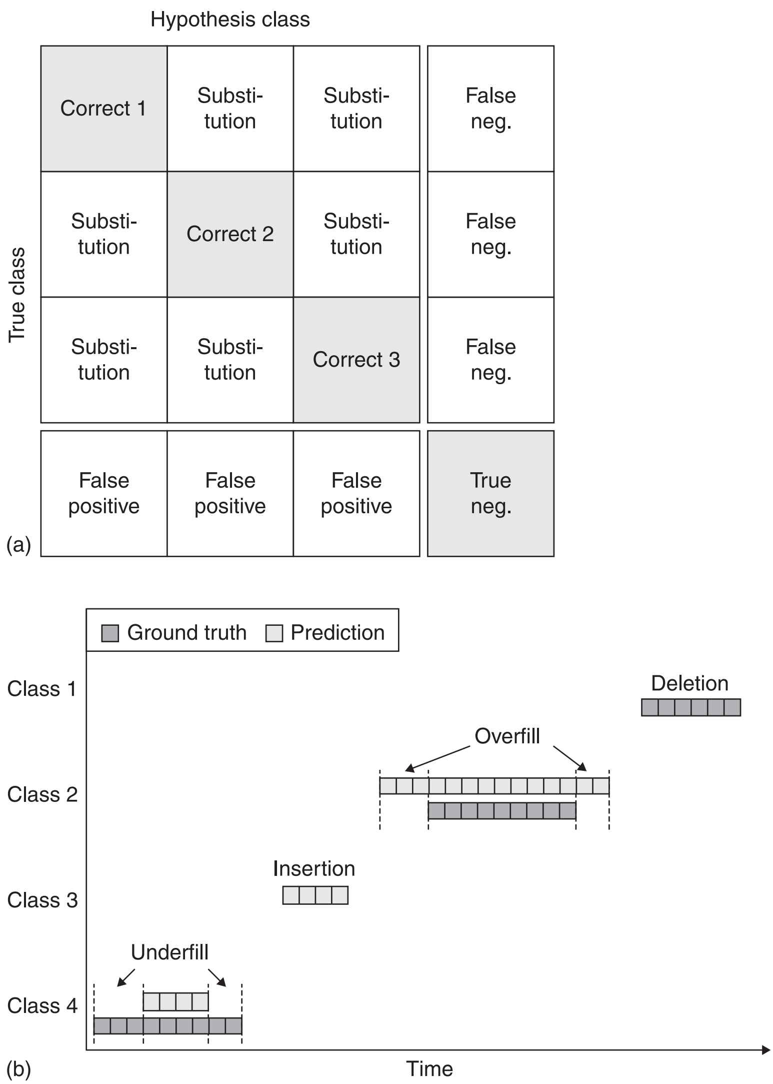
In Roggen *et al.* (2010(a)) we describe a rich dataset of activities conducted in a kitchen environment. This dataset is annotated and available for use by the community. It has been used to organize an 'activity recognition challenge' within the System, Man, and Cybernetics conference in 2011, where several research groups took up the challenge of comparing their respective recognition methods (Sagha *et al.*, 2011(a)).

12.6.2 Performance evaluation

The evaluation of activity recognition systems is done along user aspects and objective performance and cost metrics, based on a reference dataset with ground truth annotations.

User aspects include user acceptance, comfort, etc. These subjective elements are assessed in user studies by means of questionnaires and expert interview (Gemperle *et al.*, 1998; Bächlin *et al.*, 2010; Franke *et al.*, 2011).

Depending on whether the activity recognition is continuous or isolated, different sets of performance metrics are used. For isolated activity recognition (i.e. when the sensor data streams are pre-segmented) the performance metrics are those used in machine learning (Duda *et al.*, 2000). The accuracy is commonly used to describe the performance. It indicates the number of correctly recognized activity instances divided by the total number of activity instances. The confusion matrix indicates for each activity class the distribution of the predictions made by the recognition system (Fig. 12.7(a)). The diagonal of the matrix contains the



12.7 Performance metrics of activity recognition. (a) Confusion matrix. (b) Continuous recognition performance.

proportion of correctly recognized activity instances, while the off-diagonal elements denote the proportion of activity instances that have been confused with another activity. The off-diagonal elements can be summed up along the recognized activities column to obtain the false positives and along the true class row to obtain the false negatives.

In continuous activity recognition, the activities are interspersed by periods where no relevant activity occurs (null class). In that case, 'recognition accuracy', as defined above, is meaningless and metrics suited for continuous activity recognition must be used. From the confusion matrix, the following metrics can be derived: precision (true positives divided by positives), recall or sensitivity (true positives divided by true positives and false negatives) and specificity (true negatives divided by true negatives and false positives). Ward *et al.* (2011) introduced a *de facto* standard set of performance metrics specifically for continuous activity recognition (Fig. 12.7(b)). These metrics include 'insertions': activities that have been recognized but have not happened in reality; 'deletions': activities that happened in reality but have not been recognized; 'merges': when multiple activity instances are recognized as only one; 'fragmentations': when single activity instances is recognized as several instances. Finally, 'overfill' and 'underfill' describe how well the duration of an activity instance has been recognized.

The recognition latency is another important performance criterion, typically in gesture-based HFCs. Since power consumption affects battery size, the system evaluation should also include the energy required for activity recognition. Minimizing the number of recharges is especially important for continuous and long-term (week to month) activity monitoring (Van Laerhoven *et al.*, 2008). Additional ways in which recognition systems can be evaluated along 'cost and quality' metrics are presented in Villalonga *et al.* (2009).

Evaluation is typically conducted using cross-validation techniques to assess how the recognition system generalizes to a new situation. First, the reference dataset is partitioned into multiple folds. In a 'leave-one-X-out' cross-validation, all folds except one are used to train the recognition system. The left-out fold is used for testing. The process is repeated rotating the left-out fold until all folds have been used once for testing. Datasets may include recordings of multiple persons, on multiple days, and of multiple 'runs' containing repetitions of a set of activities. Folds are built differently to assess different aspects of generalization. Leave-one-person-out is used to assess generalization to an unseen user. This is done when designing a user-independent recognition system. Leave-one-run-out is used to assess a user-specific system. Since the way activities are executed may change over time, leave-one-day-out could be used to assess the robustness of the system over time.

12.6.3 Technical implementation, networking and prototyping

The technical implementation of activity recognition comprises elements such as databases for the storage of a dataset, the technical realization of networked sensing, and the implementation and optimization of the recognition algorithms.

Sharing datasets is identified as a key issue in the community to ensure reproducible machine-learning research (Sagha *et al.*, 2011(a)). This requires storing multimodal sensor data (including audio and video) in a standardized, synchronized and easy to retrieve manner, together with activity annotations. A set of open tools for data annotation, visual inspection and sharing of the dataset has been recently proposed to stimulate reproducible research (Bannach *et al.*, 2009).

Usually, there is no attempt to embed the context recognition processing in smart textiles. The dominant paradigm consists in using a mobile phone on the body as a 'wearable computer', which is running the recognition algorithms. Thus sensors are interfaced to the mobile device over a wireless gateway (Mattmann *et al.*, 2007). Prior to the gateway, multiple body worn sensors are interconnected by wires or wirelessly on the body. Wired connection may be employed to reduce the risks of data loss. This is possible in garments by hiding the wiring between textile layers (Harms *et al.*, 2009). Some textiles also offer built-in conductive wires (Locher *et al.*, 2004) and flexible substrate hosting sensors may also serve as interconnects (Zysset *et al.*, 2010). For greater flexibility, wireless interconnects can be used (Benini *et al.*, 2006). Usually the wireless sensors are directly connected to the wearable computer within one hop in a star network (Want, 2009). The typical wireless interconnections used include Bluetooth[3] (Roggen *et al.*, 2010(b)), Zigbee[4] (Calatroni *et al.*, 2009) or Ant[5] (Harms *et al.*, 2010(b)), all operating in the ISM band. Special care must be taken with wireless sensors to ensure the desired quality of data (Roggen *et al.*, 2010(a)). Several designs have been proposed for planar patch antennas based on textile materials (Locher *et al.*, 2006; Hertleer *et al.*, 2007). This allows the realization of sensing and communication with smart textiles.

Finally, software frameworks support the implementation of activity recognition algorithms and reduce the complexity of devising new algorithms. Frameworks focusing on the sub-symbolic network-oriented data processing include the CRN Toolbox[6] (Bannach *et al.*, 2008), TITAN[7] (Roggen *et al.*, 2011(c)) or SPINE[8] (Fortino *et al.*, 2009). Machine learning toolboxes, such as WEKA[9] or MOA[10], can be used to assist in the process of selecting features, training classifiers and assessing the system's classification performance. They also facilitate the comparative analysis of different methods.

12.7 Future trends

One major area of research is to devise systems that are portable across domains. For instance, rather than devising a recognition system for a specific garment, it should be able to generalize to any garment. The challenges result from the likely different sets of sensors and their placement offered in garments of different origins. Methods that are robust to this variability are investigated, among others, within the EU project OPPORTUNITY (Roggen *et al.*, 2009) and recent approaches are reviewed in Roggen *et al.* (2011(d)).

In past work, multimodal sensing was shown to increase activity recognition performance (Stiefmeier *et al.*, 2008). Smart garments have the capacity to hold a wide range of multimodal sensors in close contact to the skin. Thus, multi-modal data fusion for activity recognition is an important area of ongoing research.

The monitoring of human activities over a long period of time is extremely promising as a motivational tool to support persons that want to change their lifestyle. It is also relevant to quantify the progress of a rehabilitation procedure, or to assess health trends in the elderly. This requires sensors permanently on-body. Smart garments are ideally suited to fulfill this role. Translating laboratory prototypes of smart textiles to robust garments, which can be deployed to end-users, is key to pursuing this line of research.

Finally, smart textiles offer new possibilities for ambient intelligence, in particular for sensing on a large scale. Cheap industrial manufacturing means that many textiles found in our daily environments may be functionalized. A few examples illustrate the breadth of possible applications. Chair and seat coverings are made of textiles, which could sense human activities or physiological parameters at home, at work, in a car or in an airplane (Schumm *et al.*, 2011). Curtains are made of textile and could sense the amount of ambient and sun light, radiations, temperature and humidity for HVAC control. Carpets are found in many buildings and could offer user localization (Ueoka *et al.*, 2009) or gait pattern analysis to assess risk of falls in the elderly (Aud *et al.*, 2010). Power is less of an issue in ambient intelligence, as the sensing systems are deployed in a fixed environment. Thus, the aspects of miniaturization, computational limitations or comfort that we discussed previously, are less relevant or do not apply altogether. Besides this, the data processing methods that we introduced can be translated to context awareness in ambient intelligence environments with little differences, and the methodology to design and assess a context-aware system is essentially similar between ambient intelligence or on-body sensing.

12.8 Sources of further information and advice

We invite the interested readers to look for further information on activity-aware and context-aware systems in wearable computing and ambient intelligence in the following conference proceedings: *International Symposium on Wearable Computers; International Conference on Pervasive Computing*; and *International Conference on Ubiquitous Computing*. The following journals also cover the topic: IEEE *Pervasive Computing* Magazine; *Personal and Ubiquitous Computing* (Springer); and *Pervasive and Mobile Computing* (Elsevier).

There are a number of miniaturized sensors that can be used to prototype activity-aware smart garments. Sparkfun[11] and Phidgets[12] offer components for prototyping. The LilyPad[13] is a particularly interesting platform that offers components on a textile substrate, which is meant to be integrated into clothing. Commercial high-quality motion sensors include those from Xsens[14], Intersense,[15] MotionNode[16] or APDM.[17] Some hardware is also open source [18,19](Roggen *et al.*, 2010(b)).

A number of activity datasets have been made public and can be used to prototype recognition systems. A few well-known datasets include Intille *et al.* (2006), van Kasteren *et al.* (2008), Huynh *et al.* (2008), Tenorth *et al.* (2009) and Kawaguchi *et al.* (2011). Within the EU project, OPPORTUNITY, we collected a sensor-rich and activity-rich dataset comprising daily morning activities. This dataset has been used by multiple groups to benchmark activity recognition methods and can be obtained (Roggen *et al.*, 2010(a); Sagha *et al.*, 2011(b)).

12.9 Acknowledgments

We acknowledge the financial support of the Seventh Framework Programme for Research of the European Commission, under the project OPPORTUNITY with grant number 225938.

12.10 Notes

1 http://www.anvil-software.de/
2 http://wiki.esl.fim.uni-passau.de/index.php/Context_Logger_for_iPhone_OS
3 http://www.bluetooth.com
4 http://www.zigbee.org/
5 http://www.thisisant.com/
6 http://crnt.sourceforge.net
7 http://code.google.com/p/titan/
8 http://spine.tilab.com/
9 http://www.cs.waikato.ac.nz/ml/weka
10 http://moa.cs.waikato.ac.nz
11 http://www.sparkfun.com
12 http://www.phidgets.com
13 http://web.media.mit.edu/~leah/LilyPad
14 http://www.xsens.com
15 http://www.intersense.com
16 http://www.motionnode.com
17 http://apdm.com
18 https://sites.google.com/a/mis.tu-darmstadt.de/porcupine
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