Pervasive and Mobile Computing 5 (2009) 447–464

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

journal homepage: www.elsevier.com/locate/pmc

Review

The use of pervasive sensing for behaviour profiling — a survey

Louis Atallah, Guang-Zhong Yang *

Department of Computing, Imperial College, London, United Kingdom

ARTICLE INFO

Article history:
Received 28 April 2008
Received in revised form 31 March 2009
Accepted 24 June 2009
Available online 16 July 2009

Keywords:
Behaviour
Sensor networks
Pervasive sensing
Probabilistic models

ABSTRACT

With the maturity of sensing and pervasive computing techniques, extensive research is being carried out in using different sensing techniques for understanding human behaviour. An introduction to key modalities of pervasive sensing is presented. Behaviour modelling is then highlighted with a focus on probabilistic models. The survey discusses discriminative approaches as well as relevant work on behaviour pattern clustering and variability. The influence of interacting with people and objects in the environment is also discussed. Finally, challenges and new research opportunities are highlighted.

Contents

* Corresponding author. Tel.: +44 2075940809.
E-mail addresses: latallah@doc.ic.ac.uk (L. Atallah), gzy@doc.ic.ac.uk (G.-Z. Yang).

1574-1192/$ – see front matter
doi:10.1016/j.pmcj.2009.06.009

1. Introduction

Recent advances in the semiconductor industry and wireless communications have enabled the miniaturisation and cost reduction of both sensor and computing technologies, leading to efficient tools and hardware platforms for monitoring individuals and their environment. Weiser's vision of technologies being pervasive and weaving themselves into the fabric of everyday life is now becoming a part of our environment [1]. This has made it possible to pervasively observe people's actions, activities and interactions. The challenge now, however, is no longer that of obtaining data, but that of using these vast amounts of data from different sources and recognising patterns that could give us a better understanding of human behaviour. Developing realistic models of human behaviour could have a range of useful applications. These include helping patients with dementia or memory loss, surveillance and the discovery of abnormalities in group behaviour, the study of sports for performance optimisation and 'predictive healthcare', i.e. detecting deteriorations in patients' health before major complications occur.

The study of human behaviour has been the focus of many fields of research. Behaviour is an extensively investigated problem in business process modelling, cognitive modelling, distributed artificial intelligence, computational organisational theory and educational psychology. Although research in these areas has provided interesting models of human behaviour, the validation of these models with data acquired from real subjects performing their normal activities has been a major obstacle to their use in everyday life. Pervasive sensing offers new techniques for obtaining such data without interfering with people's daily routines, thus providing a more realistic validation of these models. A person's behaviour is highly dependent on perception, context, environment, prior knowledge and interaction with others. Thus, a complete picture of the person's actions, interactions and surrounding environment is required to model behaviour.

Although ambient and wearable sensors can be used to detect activities, the main challenge is related to the modelling of complex human behaviour using realistic yet adaptable models. One of the most popular models is that of a Hidden Markov Model (HMM), which is a statistical model assuming a system to be a Markov process with unknown parameters. The HMM is composed of hidden states and observations, and aims to model a sequence or a time series by learning probable models of state transitions and observations. A drawback of using such simple temporal models is their lack of hierarchical modelling for representing human behaviour. The hierarchical nature of human behaviour was emphasised by Dawkins [2], who highlighted the role of hierarchical organisation in understanding the evolution of behaviour, building on analogies to cases in developmental and neural biology which have already been found to be hierarchical on grounds of efficiency. Hierarchical structuring has long been argued to be necessary for many acquired human skills, such as language and planning. Research in experimental psychology [3] also emphasises that people generally encode behaviour into segmented discrete actions, which are organised as goal–subgoal hierarchies for goal-directed behaviours. Advances in probabilistic models have rendered hierarchical models a very popular tool for observing human behaviour [4], and thus will be discussed in detail in this review.

Models of behaviour (both hierarchical and non-hierarchical) are effective when activities are well defined and constrained. However, in real life, the number of unusual activities can easily surpass observed or 'normal' activities, and model-based approaches can be overly complex. The number of normal and abnormal behaviours can rarely be pre-defined unless many assumptions are added. In addition, manual labelling of behaviour patterns is a laborious process that may be biased. This has led to a significant interest in unsupervised behaviour profiling which aims to address some of these problems. In this survey, approaches aimed at discovering abnormal behaviours is detailed as well as behaviour profiling with minimum or no labelling.

In real-life scenarios, activities may be concurrent and interleaving, which poses a significant challenge for machine learning techniques that assume that activity classes are consecutive (as shown in Fig. 1(a)). In the MIT PlaceLab *House_n* PLIA1 (PlaceLab Intensive Activity Test Dataset 1, collected using ambient sensors), for example, more than 30% of goals are shown to be either intermittent or concurrent [5]. Scenarios that show concurrent activities (Fig. 1(b)) could easily occur when modelling several subjects performing a range of activities in parallel, or even when analysing a subject listening to music while performing housework activities. Fig. 1(c), on the other hand focuses on sub-activities, shown in circles, that can also be interleaving and concurrent. Probabilistic models, such as dynamic Bayesian networks, can address the complex relationship between sub-activities and activities at different hierarchical levels and will be explained further in this survey.

Another important factor that can be observed in collecting data from pervasive sensors is that of behaviour variability [6], which can be divided into across subject variability and within (intra-) subject variability. Across subject variability can be due to physical or mental differences [7]. Physical differences between people include perceptual abilities, levels of fitness and health and physical skill. Mental differences could include levels of training, education, memory capacity and emotional state. Within subject variability refers to a case where an individual takes different actions at different times in effectively the same situation. Differences in behaviour can also arise from differences in mental or physical state. A better knowledge of the situation, for example, could lead to a different action of the subject, even if the same situation has been encountered before. A person's perception of a given situation can influence that person's emotional state, the effect of which can impact the physical state and finally, the person's actions. The complex relationship between cognition and emotion has been the subject of many studies and is worth a separate in-depth analysis on its own. This survey summarises approaches that aim to quantify and observe variability through a set of activities observed with pervasive sensors.

Finally, behavioural analysis is rarely complete without considering the effect of interaction with others as well as the surrounding environment. Although cognitive science places a high emphasis on explaining behaviour by studying

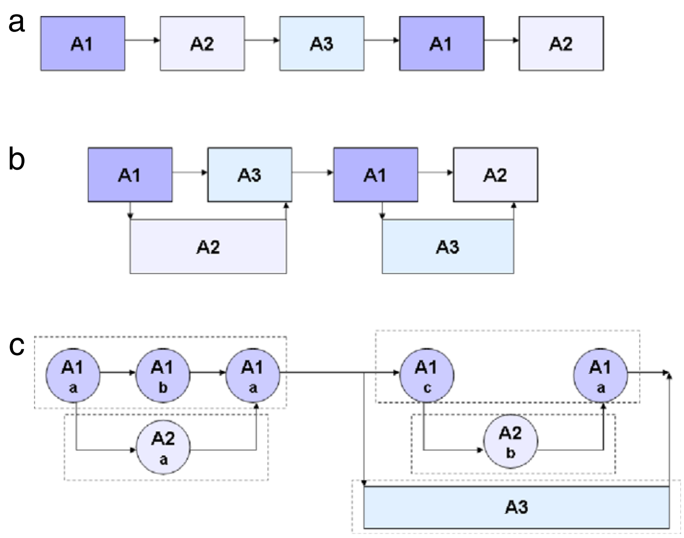

Fig. 1. Different types of behaviour patterns involving (a) a sequence of clearly defined consecutive activities (shown as rectangles A1, A2 and A3), (b) concurrent activities occurring at the same time and (c) sub-activities belonging to three activity classes occurring concurrently and interleavingly. Sub-activities are shown as circles, A1a and A1b, for example, are sub-activities of class A1. This can, for instance, represent a meeting scenario where A1 represents interactive activities, and each sub-activity shows the person interacting with a different person. A2 could be note-taking activities, that initially occur while interacting with other people (A2a) but the person needs to stop interaction in order to write on the white-board (A2b). Activity A3 could, for example, represent listening to a phone conference which can happen concurrently with other activities.

an individual as a unit of analysis, several studies in the last few years have proved that interaction between subjects is of great importance in understanding human behaviour [8,9]. Pentland [8] shows that, across several situations, 'network intelligence' can typically predict 40% or more of the variation in human behaviour. It has also been hypothesised that the majority of human behaviour is reactive and that the network of social behaviour within a group plays an important role in the group's fitness [8]. Further evidence from areas ranging from social psychology to virtual reality and game theory also highlight the importance of interaction in understanding human behaviour. Human behaviour is also heavily influenced by the environment that a person interacts with. Although earlier psychological studies regarded action and perception as two separate processes, recent investigations showed that even passive viewing of objects in the environment evokes cortical responses associated with motor processes [10]. With the same neurons involved in execution and perception, a link between action understanding and object recognition has been established [11]. The relationship between actions and perception has been investigated in [12], which proposed that when actions involving objects are perceived, spatial and functional relations provide a context in which actions are judged. Pervasive sensing can play an important role in detecting people's interaction with objects in the environment.

Fig. 2 summarises the general framework of this survey, starting from an introduction to different factors that affect human behaviour, then a description of current work in wearable and ambient sensing. Methods of behaviour modelling are detailed and key research challenges are highlighted.

2. Activity detection using pervasive sensing

Although behavioural modelling is highly dependent on activity detection, we consider the latter as a pre-processing step to obtain data and extract features for subsequent modelling. Recent work on activity recognition based on wireless sensors (both ambient and wearable) will be discussed but our focus will be on methods for modelling behaviour after activities have been detected [13–15]. A sensor network is composed of a number of sensor nodes that have the ability to acquire, store and wirelessly transmit sensor data. The reader is referred to several recent surveys on the use of wireless sensor networks [16,17] as well as books on different aspects in wireless sensor network design and implementation [18–22]. Some issues that are of great importance for wireless sensor networks include energy, scalability, security and privacy, self-configuration, dependability and quality of service [18].

2.1. Ambient sensors and smart dwellings

Thus far, several large scale projects have investigated the use of ambient sensors for providing pervasive sensing under natural living or working environments [23,24]. Many of these projects describe smart homes, where the sensors can be embedded in the environment. These systems can be used for health monitoring, assistance and in some cases information

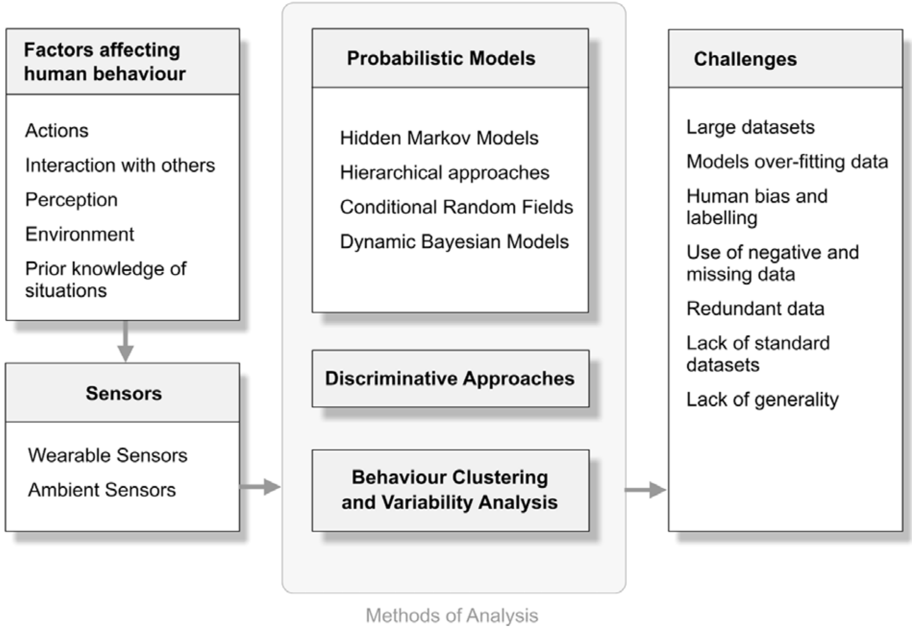

Fig. 2. Factors affecting human behaviour, sensing modalities, analysis techniques and challenges.

exchange and leisure devices [25]. Examples include MIT's PlaceLab,[1] BT's work on smart homes [26], Georgia Tech's 'Aware Home',[2] the UK Project SAPHE[3] and the Welfare Techno house in Japan [27]. In many cases, a heterogeneous set of sensors is used, combining wireless with non-wireless sensors due to different power requirements. However, a general research trend is toward wireless and self-managed nodes [18]. Example ambient sensors include miniaturised cameras, microphones, electricity and water usage detectors, pressure sensors placed on furniture, and PIR (passive infrared) and RFID (radio-frequency identification) sensors.

Among these sensors, cameras are probably the most widely used type of sensors and recently several surveys have been published on activity detection from vision. These include Moeslund and Granum [28], Poppe [29] and Wang et al. [30]. Visual recognition can be divided into the following main steps: initialisation (of the system and the model), tracking, pose estimation and recognition [28]. Initialisation involves calibration and capturing prior knowledge of a specific person which can be used to constrain tracking and pose estimation. Model initialisation normally involves instantiation of the kinematic structure, the shape and the appearance of a person. Tracking, on the other hand, generally consists of *background subtraction*, *object segmentation* and *discovering temporal correspondences* [28,30]. Pose estimation refers to estimating the configuration of the underlying kinematic or skeletal articulation structure of a person [28]. This can be performed directly from observations on a per-frame basis or considered a part of tracking as in model-based analysis-by-synthesis approaches. Novel methodologies that offer advances in pose estimation are highlighted in [28].

However, in many scenarios, cameras can be quite intrusive and a number of authors have investigated other types of sensors for activity recognition. Related work includes describing activity as a sequence of locations by using signal strength [31], using sensors such as motion detectors and RFID sensors [32–34] and GPS location sequences [35]. Other approaches for activity recognition from ambient sensors are also highlighted in two recent issues of IEEE Pervasive Computing [36,14].

2.2. Wearable sensors for activity detection

Although most of the smart homes projects mentioned in the previous section deploy a large number of ambient sensors, they do not specifically tackle certain challenges posed by human body monitoring, such as accuracy, operating frequency and bio-compatibility. The area of Body Sensor Networks (BSN) has emerged as a research subject with specific challenges such as hardware, energy scavenging and secure wireless communications [18]. Although wearable frameworks for activity detection have focused on the use of accelerometers for activity detection, other wearable sensors incorporating physiological data have also been successfully used. These include body temperature, ECG, pulse oximetry, bend and respiratory flow sensors. Table 1 lists some of the recent approaches using these sensors for activity recognition.

1 http://architecture.mit.edu/house_n/placelab.html.
2 http://awarehome.imtc.gatech.edu/.
3 http://ubimon.doc.ic.ac.uk/saphe/.

Table 1
Recent approaches using wearable sensors for activity recognition, with a summary of the sensors used and the body positions selected.

Reference	Wearable sensors used	Position
Mathie et al. [37]	Accelerometers	Several body positions (survey)
Bao et al. [38]	Accelerometers	Hip, wrist, ankle, arm and thigh
Choudhury et al. [13]	Include microphone, accelerometers, and digital compass	Waist
Krause et al. [39]	Include accelerometers and heat flux	Arm band
Morris et al. [40]	Gyroscopes, sonar and accelerometers	Shoe-mounted
Yang et al. [41]	Pulse oximetry and photoplethysmography	Ring sensors (fingers)
Van Laerhoven et al. [42]	Tilt switches and accelerometers	Ankle
Oliver et al. [43]	Pulse oximeters and heart rate	Finger/wrist
Lo et al. [44]	Accelerometers and pulse oximeters	ear-worn
Wang et al. [45]	Heart rate	Ear-worn
Ermes et al. [46]	Accelerometers and GPS	Hip and wrist
Oliver et al. [47]	ECG and accelerometers	Chest-band
Wade et al. [48]	Conductive fabric shirt	Torso
Taccini et al. [49]	Heart rate, temperature and blood pressure	Anywhere (textile sensors)
Hester et al. [50]	Accelerometers	Ankle
Subramanya et al. [51]	Include GPS, accelerometers microphones, light and temperature	Shoulder
Maurer et al. [52]	Include light, accelerometers, temperature and microphone	Wrist

2.3. Combining ambient and wearable sensors

Effective sensor fusion from both ambient and wearable sensors could combine the strengths of both modalities to provide a better means of activity recognition. Issues to be addressed by combining ambient and wearable sensors include view correspondence for extended coverage, resolution enhancement by combining both spatial and temporal tracking, and the use of prior knowledge and physical model-based approaches for better activity discrimination. McIlwraith et al. combine an ear worn sensor with visual sensors [53], whereas Zouba et al. [54] use both contact and video sensors for activity recognition. Wireless scales and wearable heart rate monitors were combined in [55] for weight management.

3. Behaviour modelling

3.1. Probabilistic models of human behaviour

The previous section detailed types of sensors that can be used to obtain signals reflecting a change in subjects or surrounding. However, developing methods that can accurately model the true nature of human behaviour remains a challenge. Probabilistic models have emerged as efficient means of representing random variables, dependence and temporal variation, making them a suitable tool for behaviour modelling. They include both temporal models such as Hidden Markov Models (HMMs) and static causal models such as Bayesian belief networks. In this section, a survey of probabilistic models that are used for behaviour modelling is presented, such as HMMs and their extension to hierarchical models, Conditional Random Fields (CRFs) and Dynamic Bayesian Networks (DBNs).

3.1.1. Hidden Markov modelling of behaviour

Due to their ability to model spatio-temporal information in a natural way, a significant amount of work in the area of behaviour recognition is based on HMMs. An HMM is a statistical model in which the system being modeled is assumed to be a Markov model. HMMs represents a finite set of hidden states, each associated with a probability distribution, where state transitions are governed by a set of probabilities and an observation can be generated for each state. Fig. 3(a) shows a left-to-right HMM whereas Fig. 3(f) shows an ergodic HMM where all possible transitions between states are allowed. In general, the use of HMMs for activity or gesture recognition [57] consists of training them on pre-defined classes, normally using the Baum–Welch algorithm, then testing them on new instances. The Baum–Welch algorithm is a generalised Expectation Maximisation algorithm that can compute maximum likelihood estimates for the parameters of an HMM given the observations as training data. HMMs have been extensively used for tracking and recognition. Examples include hand gesture, sign language recognition [57] and real-time tracking, as done in the LAFTER system [58] for facial expressions. Fig. 3 shows the structure of HMMs and their extensions, which are detailed in the next paragraphs.

A problem with the use of HMMs for activity detection is that due to the first-order Markov assumption (a state depending only on the previous one), the probability of an event state being observed for a certain interval of time declines exponentially with the length of the interval. In addition to that, the probability of there being a change in the hidden state does not depend on the amount of time that has elapsed since entry into the current state, which could be an important parameter in modelling human activities. In order to include this time dependence into the model, HMMs have been augmented to semi-HMMs [59], where the hidden process is semi-Markovian rather than Markovian. Semi-HMMs explicitly model the *a*

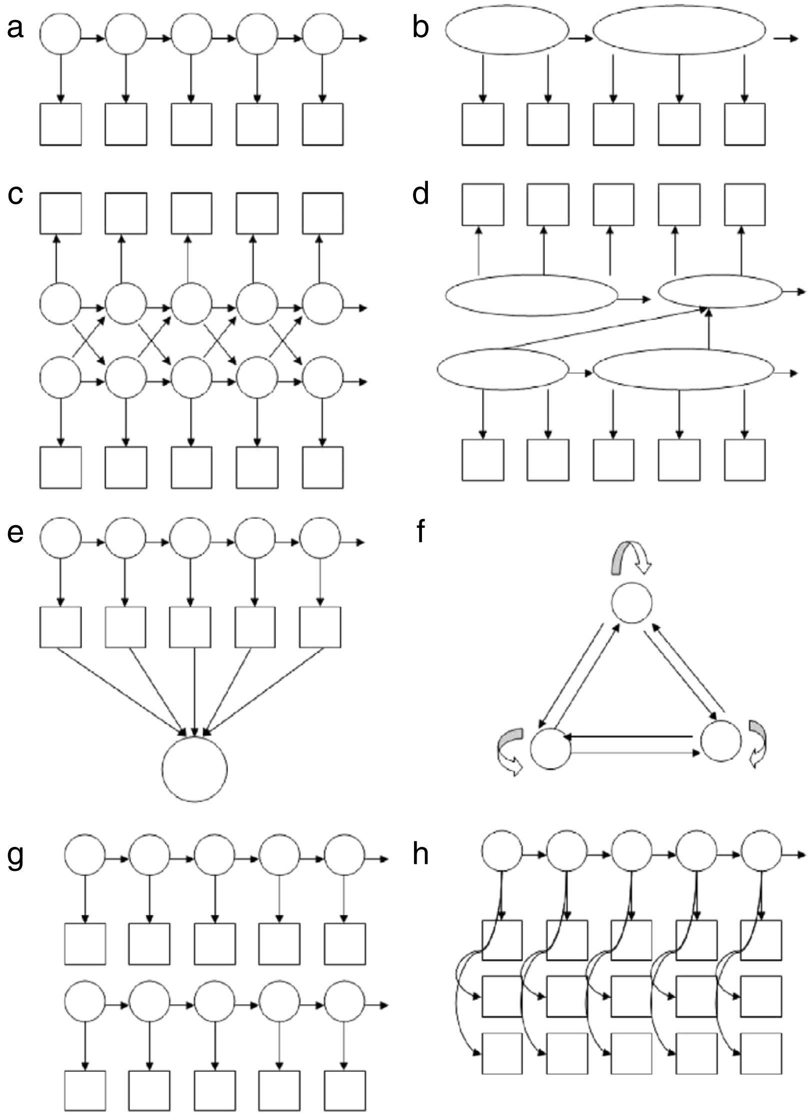

Fig. 3. HMMs for pervasive sensing. (a) The structure of a left-to-right HMM, where the observed states are squares and the hidden states are circles; (b) that of a semi-HMM; (c) that of a coupled HMM; (d) that of a coupled semi HMM; (e) that of a parametric HMM, demonstrating the dependence of the output states on the parameter θ [56]; (f) the structure of an ergodic HMM; (g) that of a parallel HMM and (h) that of a multi-observation HMM.

priori duration of the event states and can be directly incorporated into the model to better approximate visual primary and composite activities (Fig. 3(b)). A switching Hidden Semi-Markov Model is presented in [60] for activity recognition. This model is made of two layers; the bottom one represents atomic activities and their durations using semi-hidden HMMs, whereas the top layer represents a sequence of high-level activities.

Coupled HMMs have the advantage of being able to model the dynamic relationships between several signals. A coupled HMM can be considered as a collection of HMMs where the state at time t for every HMM (or channel) is conditioned by the states at time $t-1$ of all the HMMs in the collection. In coupled HMMs, each chain has its own observation sequence and is allowed to evolve independently (as shown in Fig. 3(c)). Coupled HMMs have been successfully used in activity recognition, especially when the focus was on interactive activities that require modelling more than one process at the same time [61,62]. Natarajan and Nevatia [63] extended coupled HMMs to coupled semi-HMMs where the hidden model has a compositional state in both state and time. Thus coupled semi-HMMs can be considered as multichannel HMMs where each channel, as in semi-HMMs, has states with explicitly specific duration models (shown in Fig. 3(d)).

HMMs are extended in [56] to parametric HMMs (Fig. 3(e)) to include a global parametric variation (θ) in the output probabilities of the HMM states. An Expectation Maximisation (EM) algorithm is used to train the parametric HMM, thus learning the dependence on the parameter θ. Non-linear dependences of the state outputs on θ can also be modelled using a generalisation of the parametric HMM. Advantages over an HMM include tailoring the model to specific gestures or

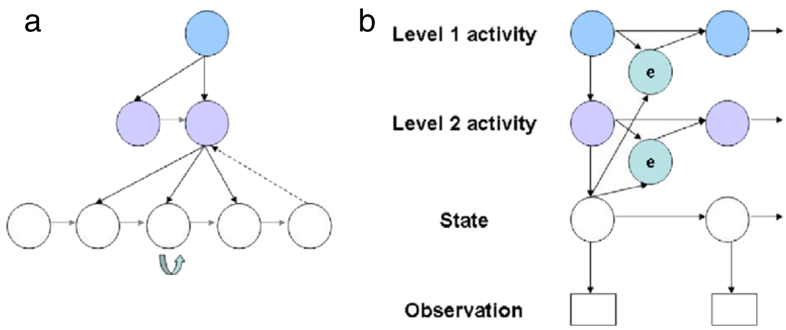

Fig. 4. Hierarchical and abstract HMMs. (a) The structure of a hierarchical HMM where the states at each level of the hierarchy are color-coded differently. The vertical transitions are given in black arrows and the horizontal transitions in grey. The dashed arrow represents the return from the last state of a certain level to the level's parent state. (b) The structure of an abstract HMM, where the bottom level is similar to a regular HMM, but abstract activity (or policy) variables are placed above the state variables in a hierarchy. The flag *e* indicates whether the current policy is to continue or terminate in the next time step.

parameters that can be general for a set of gestures (such as the gait style), or tailoring the HMMs for specific users given their activity patterns. Brand and Kettnaker [64] show that by minimising the entropy of the joint distribution of the HMM parameters, an HMM's internal state machine can be made to organise observed activity into meaningful states, which is highly relevant for activity detection and segmentation. Unlike other work that treats HMMs as a black box, this work is interesting as the model is well attuned to the data generating mechanism's dynamics, and the HMM hidden states are interpretable.

To deal with some of the problems encountered by HMMs, such as the difficulty in encoding high-order dependences, and the presence of local optima when learning HMMs with many free parameters, Galata et al. [65] suggest the use of variable-length Markov models which are able to learn model dependences on several previous states using the minimum number of parameters. Thus, they offer an advantage to using HMMs whenever sequential data presents high levels of variations such as activity detection from video and motion capture data.

Fig. 3(g) also shows parallel HMMs that aim to overcome the complexity of coupled and variable-length HMMs by modelling the different time series as independent processes that can be trained separately [66]. Parallel HMMs can be used to model independent events, such as unrelated activities of users in an environment. Fig. 3(h) shows multi-observation HMMs that can be used to model different observations generated from the same hidden states. These observations can be independent (as shown in the figure) or dependent, as hypothesised in [67]. Alternatively, the observations can be decomposed into sub-observations, as in the observation-decomposed HMM which can be used to recognise multi-agent activities [68].

3.1.2. Hierarchical probabilistic models of human behaviour using HMMs

As mentioned in Section 1, research in human psychology and biology highlights the importance of hierarchical models for observing human behaviour. Hierarchical models are able to represent activities at different time granularities and relate sub-activities which could provide richer models for behaviour representation. This section summarises recent approaches that aim to model hierarchical behaviour using HMMs and their extensions.

Layered HMMs were investigated in [69] in order to perform sensing, learning and inferencing at multiple levels of temporal granularity. In these models, each layer is connected to the next layer via its inferential results. Thus, the model is made of several cascades of HMMs that operate at different temporal granularities. According to [70], layered HMMs provide higher accuracy than HMMs in terms of recognising office activities; they are also more robust to changes in the environment.

Fine et al. [71] have extended HMMs to hierarchical HMMs which include a hierarchy of hidden states. Each of the hidden states in this model can be considered as an 'autonomous' probabilistic model on its own, i.e., each hidden state is also a hierarchical HMM. Each state generates sequences (rather than symbols) by a recursive activation of one of the sub-states of a state. The process of recursive activation ends when a special state (production state) is reached. A vertical transition in a hierarchical HMM is the activation of a sub-state by an internal state, whereas a horizontal transition refers to a state transition within the same level. Fig. 4(a) shows the structure of a hierarchical HMM in further detail. Nguyen et al. [72] use hierarchical HMMs for indoor activity recognition and prove that the use of natural hierarchical decomposition and shared semantics embedded in the movement trajectories provides an advantage over flat HMMs. The main contribution of their work lies in the development of an algorithm to estimate the parameters of the model at all levels simultaneously. Hierarchical HMMs have also been used for activity recognition by Luhr et al. [73] and Kawanaka et al. [74]. Originally, the hierarchical HMM was restricted to a tree structure, meaning that two different states cannot have the same child and cannot share common substructures. This tree structure can also lead to an exponential complexity in the depth D of the model (the depth D refers to the number of states the hidden states can transit to vertically). To deal with these problems, Bui et al. [75] investigated the extension of hierarchical HMMs to general hierarchical HMMs where the state hierarchy

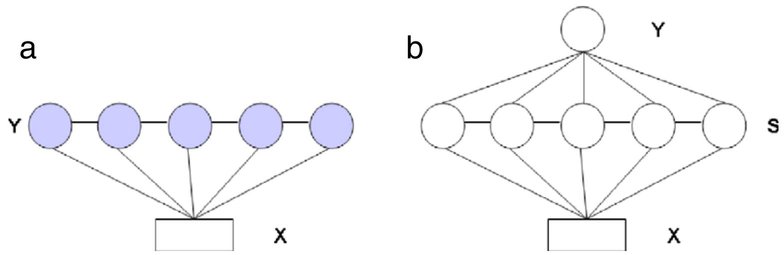

Fig. 5. (a) An example structure of a conditional random field with the relationship between the label sequence (Y) and the observations X. (b) An example of a hidden conditional random field where the hidden layer of nodes (S) is also shown.

could be a lattice allowing arbitrary sharing of substructures. Murphy and Paskin [76] converted the hierarchical HMM to a dynamic Bayesian network (explained further in Section 3.1.4) and applied general dynamic Bayesian network inferencing techniques to achieve linear complexity in time. For online filtering using a hierarchical HMM, an efficient approximate method was proposed in [77] for online recognition and classification.

Bui et al. [78] introduce the abstract HMM (shown in Fig. 4(b)) which uses a hierarchical structure for probabilistic plan recognition. The bottom part of this model consists of hidden states and observations as in a typical HMM. However, the states are linked to abstract policy (or activity) variables which are placed in a hierarchy. Flag variables are used to indicate whether the current policy or activity continues or terminates in the next time step. Abstract HMMs have been used successfully for learning hierarchical models of indoor activity and performed better than flat models [79]. They have also been used to represent and recognise complex behaviours from trajectory data [80]. The underlying problem with both abstract and layered HMMs is that the state space can be very large, augmenting the number of parameters in the transition model. This led to the introduction of the factored state abstract HMM [81] (used for activity recognition with multi-modal sensors) where the factored representation was used to partially connect the network of state transitions rather than a fully connected transition network.

Another way of extending the hidden states of an HMM is to add hidden variables which have a causal effect on the observed variables in the model. This is known as the factorial HMM [82], which has been investigated for gait recognition in [83]. Factorial HMMs can indirectly link several Markov chains through common observations. Dynamically multi-linked HMMs provide a flexible structure which consists of an optimised factorisation of the state transition matrices with fewer state connections [84]. Thus, the internal structure of the dynamically multi-linked HMM is intrinsically determined by the underlying causality and temporal order among different object events. Dynamically multi-linked HMMs have been compared to other extensions of HMMs, such as the parallel and coupled HMMs in [84], and proved to better model group activity in noisy outdoor scenes. The decomposed HMM is suggested in [85] as a solution to decomposition in both time and space, where inherent hierarchical structure and causal–temporal relations between processes can be modelled simultaneously. In decomposed HMMs, the production layer consists of several independent state channels, with several abstract layers above it. To avoid coupling these abstract layers (as in coupled HMMs), they are uncoupled by using a relation layer. Both coupled and hierarchical HMMs can be viewed as special cases of the decomposed HMM, which is a more general framework to represent long-term interacting activities [85].

3.1.3. Conditional random field modelling of activity

HMMs (as shown in Fig. 3) generally assume that all observations are independent, which could possibly miss long-term trends and complex relationships. Conditional random fields, on the other hand, are undirected graphical models that represent the conditional probability of a certain label sequence, Y, given a sequence of observations X. Thus, they model the conditional probability of the label sequence rather than the joint probability of both labels and observations, and can be regarded as a discriminative rather than a generative classifier. Conditional random fields, shown in Fig. 5, eliminate the independence assumptions between observations while maintaining the same first-order Markov assumptions over labels (as in an HMM). Conditional random fields have been compared to HMMs for gesture recognition, activity recognition and detecting unsafe driving patterns. In general, they provided better classification rates for all of these applications [86]. Inferencing with conditional random fields can be performed with the same time complexity as an HMM. Training, however, requires significantly more computation, especially if a large number of features are concerned. Several solutions have been suggested for optimising the training of conditional random fields for activity classification such as gradient tree boosting [87], which provides the training algorithm with means of performing feature selection and learning the dependence structure in conditional random fields. Regularisation methods (in particular l_1 regularisation) [88] have also been suggested as optimisation techniques for training. Conditional random fields were extended to mixture conditional random fields in [89], where a mixture node, representing domain knowledge, was added. This node can represent, for example, the identity of human subjects, which helps provide better classification rates.

Semi-conditional random fields were introduced in [90], where labels were assigned to segments of the input sequence x rather than to each individual element. The method was tested on entity recognition problems where semi-conditional random fields performed better than conditional random fields. Hidden CRFs are an extension of CRFs [91], where hidden states are incorporated to capture the underlying structure classes. In this way, no *a priori* segmentation into substructures is needed and labels at individual observations are combined to form a class conditional estimate (shown in Fig. 5(b)). Hidden conditional random fields were evaluated for gesture recognition [91], and they performed better than both conditional random fields and HMMs for such tasks.

Dynamic conditional random fields were proposed in [92] as an extension of conditional random fields with a distributed state representation similar to that of dynamic Bayesian networks. This adds to the flexibility of choosing models for different applications (factorial and hierarchical conditional random fields are examples). Since exact inference is intractable in such models, approximate inference was investigated and two types of training were suggested, mainly marginal likelihood training and cascaded training. Dynamic conditional random fields have not been yet investigated for activity recognition but they present an interesting direction to be pursued. Liao et al. [93] propose the use of conditional random fields in a hierarchical form for location-based activity recognition. The upper level of the hierarchical conditional random field (representing significant places) is generated based on the outcome of inference in the lower level (activity sequence). Joint inference is performed on the complete conditional random field once a complete model is generated.

3.1.4. Dynamic Bayesian network modelling of activity

In principle, both HMMs and conditional random fields can be interpreted as examples of dynamic Bayesian networks, which are Bayesian networks representing a sequence of variables varying over time. In this way, dynamic Bayesian networks present a more general framework for behaviour monitoring [94,15]. They also provide a generic tool for handling both uncertainty and incomplete data. Dynamic Bayesian networks are trainable, modular, encode causality and offer an interesting framework to combine previous knowledge about a domain with example data. However, the main problem they pose is that of inference, as exact probabilistic inference is intractable, in the case of loopy graphs for example. Several tractable variational algorithms exist, many of which call the Kalman filter and the forward backward algorithm as subroutines.

There are several examples of using dynamic Bayesian networks for behaviour modelling. Video surveillance activities are modelled in [95] using a hierarchical dynamic Bayesian networks, where dependences are added in order to keep the number of parameters tractable. The different levels of the dynamic Bayesian networks represent events at different granularities. Lower levels of the dynamic Bayesian network represent atomic activities, whereas higher levels represent activity. A final level is added to model the different duration of different activities. A similar hierarchical dynamic Bayesian network is used in [94], where a differentiation is made between global features (representing object motions at large scales) and local features (representing motion details). Adding the duration as part of the dynamic Bayesian network in both papers tackles the problem of exponential distribution of duration, which is a common problem of HMMs. Dynamic Bayesian networks are used in [35] to model the motion of a traveller. This model depended on lower level sensor information (GPS readings which are completely observable), information on nearby bus stops and parking lots as well as the mode and the velocity of transport. The learning algorithm is unsupervised, requiring GPS data only, and could both infer a user's behaviour and predict future steps. In [15], the authors compare layered HMMs and dynamic Bayesian networks for recognising office activities using a set of sensors, including video, audio and the user's interaction with the computer. Dynamic Bayesian networks are only included at higher levels of the layered HMM, where the results of previous layers (inferential layers using HMMs) are used. The dynamic Bayesian network layer is able to discover connections in the data that are missing in the HMM, and is less sensitive to missing data.

3.2. Discriminative approaches for behaviour recognition

Discriminative approaches for behaviour recognition aim at discriminating between activities rather than modelling activity classes or behaviour variability. Several classifiers can be used in this case, such as Naive Bayes, k-means, multidimensional indexing [96], support vector machines and boosting techniques [97]. Feature extraction and selection can directly affect classification results. Although several studies use the same classifiers, it is difficult to compare recognition rates directly as the features extracted and selected vary between studies. Hybrid approaches usually refer to combining discriminative and generative techniques. An example is the work by Lester et al. [98], who use AdaBoost to automatically select sensor features and learn an ensemble of static classifiers, then use the outputs of these classifiers as inputs to HMMs to classify activities. The static classifiers ensure that the margins between different classes are maximised, whereas the HMMs provide temporal smoothness and correct activity classification. An inverse approach is used in [99], where HMMs are used to learn the dynamics of each action class from a 3D joint space (from video). The observation probability of these HMMs form weak classifiers that are used in a boosting algorithm (AdaBoost) to segment and recognise actions simultaneously.

3.3. Behaviour clustering, variability and anomaly detection

With the abundance of sensor data acquired over long periods of time, providing methods for detecting similarities in behavioural patterns or deviations from standard behaviours becomes an important challenge for pervasive monitoring. In this survey, we will group together the highly inter-related studies of behaviour clustering and variability. Using an extension of the clustering approach for a variability or anomaly studies is natural as distances to cluster centres could indicate similarities between different subjects, or between the behaviour patterns of a person at different instances of time [100]. Anomaly detection can be considered as a deviation from a learnt model of behaviour and class distances can be used to indicate the level of anomaly. Although useful in many studies, model-based approaches (such as conditional random fields and dynamic Bayesian networks) could suffer from problems of over-fitting and poor generalisation. This could occur whenever the number of unusual activities surpasses observed or 'normal' activities, or whenever human-based labelling causes a bias in the model. For this reason, the following paragraphs will be dedicated to unsupervised methods that can deal with these problems.

To give an example of an unsupervised approach for discovering abnormal activities, we refer to [101], where the video is divided into segments, and the extracted features are classified into prototypes from which a prototype–segment co-occurrence matrix is calculated. Similarity between prototypes and video segments indicates correspondence and highlights 'unusual' patterns. In [102], an event-based statistical distance between video sequences is used for the segmentation of video to a set of activities without having to pre-label the whole video sequence. Two sequences are considered similar if they show similar empirical distributions at corresponding temporal scales. This similarity measure can also be used for video-indexing, clustering and the analysis of dynamic behaviours in video sequences [103]. Another similarity measure is used in [104] where a local space–time self-similarity descriptor is investigated. Turaga et al. [105] treat the problem of activity clustering from video sequences as a problem of simultaneously locating activity boundaries and clustering activity subsequences. An activity is considered as a cascade of linear dynamical models (representing action elements). An algorithm for automatic segmentation of video and learning the model parameters is also described for the unsupervised segmentation of video. In [106], a Gaussian mixture model is used to model the joint distribution of system state change and observed state history of non-linear behaviours with non-stationary stochastic components. This is applied to pedestrian trajectory modelling scenarios, where it is used in recognition and synthesis of behaviour. An affinity matrix that represents the similarity between different behaviours is investigated in [107], where the affinity between two behaviour models is defined as the likelihood of a model trained on one to predict the other. A multi-observation HMM (Fig. 3(h)) is used to model each behaviour pattern. Novel behaviour patterns that have not been seen can then be recognised and added to the existing set.

Similarity measures for trajectory clustering in outdoor scenes were investigated in [108], where simple Euclidian measures combined with PCA were adequate for the trajectories used. These clustering approaches can be extended to provide tools for behaviour variability and abnormality detection. However, they generally require labelling data into classes or activities, which could introduce the human-bias problem. Thus, many groups have attempted to look at behaviour variability without specifically labelling activities. Location sequences were used in [31] to cluster behaviours and detect variability using an HMM clustering framework. Location sequences were also used in [109], where entropy was selected as a means of quantifying structure in a person's behaviour. Structure in human behaviour was identified in [110] by using mobile-phone data during the 'reality mining' study[4] providing information on locations, proximity to others and communications for 100 subjects over 9 months. The structure of someone's behaviour was represented by the principal components of the complete behavioural dataset, termed 'eigenbehaviours'. Thus, an individual's behaviour over a day was approximated by a weighted sum of that person's primary eigenbehaviours. This study proved that eigenbehaviours can be efficiently used to predict behaviour, cluster people and analyse group affiliations. An influence model was used to analyse the proximity data from this dataset, which was able to predict friendships and work group affiliations highly accurately [110].

4. Interaction as a means of describing human behaviour

Analysis of interactions between humans provides a means of understanding group behaviour by studying gestures, handshakes, turn taking patterns, discussions, argumentation and visual interactions. We will highlight some of the recent work on using pervasive sensing for studying interaction between people (focusing on meetings, surveillance, healthcare and sports) as well as interaction with objects in the environment.

4.1. Human interaction

4.1.1. Interaction in meetings

Studies in Psychology that focus on interaction in meetings form a rich background that can be used to understand the complexity of meeting tasks before pervasive sensing is used. In [111], meeting actions are divided into the following: monologue, presentation, white board, discussion and note-taking. Group actions are modelled using different HMM-based approaches, where the observations are provided by a set of audio-visual features monitoring the actions of individuals in a meeting room. Clustering of faces in meetings is investigated in [112], where an automatic approach to detect, track and cluster people's faces in video is presented. A gesture recogniser is combined with a speaker turn detector in [113] for a multi-modal analysis of meeting events. Visual information is combined with audio in [114] in order to recognise meeting activities. This approach can deal with problems of occlusion and disturbed data. An influence model is used in [115] to recognise functional roles played by different meeting participants.

4 http://reality.media.mit.edu/dataset.php.

4.1.2. Visual surveillance and interaction

The analysis of group activities for surveillance has been the subject of special issues of several journals [116,117]. Although many surveillance applications focus on observing individuals and tracking an individual's behaviour, several applications also look at interaction to identify irregularities in group behaviour such as stalking, armed robbery and hazardous conditions. Intelligent visual surveillance in complex situations attempts to detect, recognise and track certain moving objects from video sequences, to understand and predict behaviour. Detailed literature surveys focusing on visual surveillance are given in [118,119], where the surveillance applications were categorised into the following: Access control in special areas, person-specific identification in certain scenes, crowd flux statistics and congestion analysis, anomaly detection and alarming, and interactive surveillance using multiple cameras. Group interactions can be used to observe abnormalities in group behaviour. A framework for detecting unusual events is described in [120], where multiple video streams are combined in the inference level with coupled HMMs. A framework for identifying armed robbery from video is provided in [121], where silhouettes are analysed from video and classic holdup positions are recognised. A system using discrete HMMs is defined in [122], where discrete HMMs are used to detect activities in a corridor. Each HMM is trained to recognise one of the activities, and anomalous activities are those which present low likelihoods for all the HMMs.

Park et al. [123] present a framework for studying interaction between two people based on a hierarchical Bayesian network. They use the low levels of the Bayesian network to estimate the poses of simultaneously tracked body parts, whereas the overall body pose is estimated at the high level of the Bayesian network. In [61], a Bayesian computer vision system is presented to model interacting people in a visual surveillance task. HMMs are compared with coupled HMMs, and the latter are shown to work more efficiently.

The analysis of crowd behaviour presents an area of extensive interest in the surveillance domain [124] as it could serve as a useful tool in pre-screening large amounts of data collected by multiple cameras for the detection of behaviour abnormalities [119]. In [125], a block-matching technique was investigated to estimate the general trends of crowd motion using the frequency distributions of velocity directions. Valera et al. [117] present a survey of several surveillance systems capable of detecting unusual events including congestion, unusual directions of motion, intrusion and stationarity.

4.1.3. Social and team interaction in healthcare and sports

Social interaction is an important indicator of a person's well-being. Although several simulated studies and requirements analysis surveys have been conducted, the analysis of social interaction with sensors for healthcare applications is relatively a new domain. Chen et al. [126] have used audio and video sensors to observe interaction between elderly people. Human–computer interaction is used as a means of encouraging physical activity [127], and would definitely provide means of providing feedback that could result in improved well-being in the long run.

Despite encouraging results obtained from analysing group behaviours in particular sports, it is often difficult to extend these results to all sports. However, there are a few methods that show a good level of generality. An example is the use of probabilistic models to represent complex multi-agent interactions, as done in [128] to classify pre-defined plays within American football. Dynamic system trees are used in [129] to model group behaviour (also for American football), as they provide a hierarchical tree architecture to aggregate several players' trajectories into a Markov process that represent the team activity. In [130], two approaches of modelling team behaviour in European handball are compared: individual and group modelling. Individual modelling aims at modelling each player [129], then combining all model outputs into higher level team activity. Group models, on the other hand, use input features from all players and a support vector machine framework for classification, providing better results for the selected team sport.

4.2. Interaction with objects

Several research projects have defined behaviour in relation with the objects that a person uses or interacts with. These interactions are generally used for the determination of Activities of Daily Living (ADLs), mainly for healthcare applications. Medication compliance, for example, is investigated in [131] by using RFID tags. Meal preparation is studied in [132] using temperature switches, contact switches and pressure sensors. In [133], cameras and a bracelet are used to infer hand-washing. In [134], a custom-built medication pad in combination with motion and contact sensors are used to observe activities such as meal preparation and taking medications. Guralnik et al. [135] provide a description of general behaviour by using motion sensors, door latch sensors and toilet flush sensors, among others. Research in MIT's House_*n* project also looks into the ADL description by observing sensor readings from sensors placed around the house.[5] In [136], RFID technology is combined with data-mining techniques and an inferencing engine to recognise ADLs based on the objects people use. Information from RFID tagged objects is also used in combination with video to jointly infer activity and object labels in [137]. In [138], the authors provide a syntactic approach to recognise human activities with objects. They use a stochastic grammar to pool evidence through time, recover from local errors and find a consistent overall interpretation of activity. Nevatia et al. [139] present a hierarchical language-based representation of events in video streams, where events can be defined in terms of interaction with objects. Moore et al. [140] construct a system that can compensate for errors

5 http://architecture.mit.edu/house_n/.

in object classification by using the recognition results of the actions dealing with these objects. Ryoo et al. [4] provide a system that integrates object recognition, motion estimation and semantic level recognition of hierarchical human–object interactions, where a failure in one layer can be probabilistically compensated by other layers. In [56], the effect of object properties is modelled on human actions using parametric HMMs. Gupta et al. [10] also propose a probabilistic framework by combining the inference processes in object recognition and action understanding. This is achieved by using Bayesian networks that can simultaneously estimate the object type, location and type of activity (manipulation movements).

Detecting unattended objects is of high importance for airport and train station security. In [141], the authors introduce a surveillance system that identifies objects with no humans in close proximity. A distributed video surveillance system is used in [142], using image features to detect unattended objects. A similar framework is used in [143], where Gaussian mixture models are used to detect static regions. In [144], the relationship between unattended objects and humans is studied, to determine package ownership.

5. Discussion

In this survey, activity detection has been considered as a pre-processing step for behaviour modelling and profiling. The types of sensors available and the applications selected generally dictate which method to choose for behaviour profiling. Based on the previous sections, this section aims at summarising techniques that are appropriate for different applications.

If the user is only interested in discriminating between different types of behaviours, say determining if a patient has a sedentary or an active lifestyle, discriminative approaches would be appropriate without the need to explicitly model a patient's behaviour. In this case, neural networks, support vector machines or simply dimensionality reduction techniques would be suitable. If, in addition to discriminating between behaviours, the user wants to utilise temporal information, conditional random fields and their extensions might be suitable. However, if abnormality detection or behaviour variability is in question, behaviour modelling becomes more relevant.

Probabilistic models of human behaviour have the advantage of combining prior knowledge of a certain situation with the evidence observed from a variety of sensors, offering means of observing relationships, interactions and variations over time. If the application is generally simple, including several variables that vary over time, say a sequence of discrete locations of a person, then a model with high complexity would not be necessary as HMMs could be appropriate for this task. If, on the other hand, the activities are made of sub-activities that need to be included in the model, extensions of HMMs that allow duration representation like semi-HMMs or variable-length Markov models could be more suitable. Prior knowledge that many observed sequences are intercorrelated, such as interactions between two subjects in a meeting, can be represented by coupled HMMs that model coupling between these sequences and offer better means of discrimination (compared to simple HMMs). Adding sub-activities (or modelling durations) is also possible by extending these models to coupled semi-HMMs. Including a global variation parameter (as done in parametric HMMs) to the model can help fine-tune an HMM to a specific user, if known in advance.

Hierarchical models are very useful whenever we want to model relationships between sub-activities as well as different time granularities. The simplest version of hierarchical models is that of a layered HMM, but other extensions could offer advantages, such as hierarchical HMMs, where each of the hidden states in the model can be considered as an almost 'anonymous' probabilistic model. Factorial HMMs are also another extension that represents a layered model, where observations are related to all hidden states at that time. These models are useful to represent activities and sub-activities at different levels and could be advantageous for sensor fusion applications and sequences of activities of daily living that are composed of sub-activities. The complexity of these models, however, is a factor that should be taken into consideration, and techniques for providing minimal models that can best represent an application are of great importance. The extension of HMMs to dynamic Bayesian networks offers more general means of representation for time-varying activities which could provide better modelling and classification of behaviour patterns. The main disadvantages of these models, however, include model complexity and the difficulty of exact probabilistic inference.

Anomaly detection and variability can be considered as subsets of behaviour modelling, and the techniques mentioned above are generally used to look at deviations over time of certain behaviour patterns. However, unsupervised approaches of observing behaviour variability are also of use whenever human labelling presents a bias or uncertainty. Options include using feature clustering, similarity matrices and dimensionality reduction. Clustering techniques generally requires the definition of the criteria that can be used to split and merge clusters to be defined in advance. Distances to cluster centres can also be dependent on the features selected, as relevant features, for example, would offer better clustering of different behavioural patterns.

Modelling interactions required a separate section to highlight its importance as an application of human behaviour modelling. The probabilistic models detailed in this work offer efficient means of modelling interactions. However, complex situations, such as modelling team sports, require the combination of individual and group behavioural models for a better understanding of an individual's behaviour within a team. This could involve, for example, a simple model (such as an HMM) for individual players, and a committee of HMMs or a dynamic Bayesian network for team modelling. Interaction analysis is also relevant for studying dynamics in meeting activities as well as healthcare scenarios where social interaction between medical professionals and patients is important.

Table 2
Challenges in behaviour recognition from pervasive sensing, with possible scenarios and a comparison of some of the existing methods that can be used.

Challenge	Example scenarios	Possible approaches	Comments
Behaviour discrimination	Activities of daily living (ADLs), sports, meeting activities and gesture recognition	Discriminative approaches (neural networks, kernel methods and decision trees)	Able to use class distances and class margins to optimise classification, no class models needed.
		Probabilistic (generative) models (HMMs, CRFs and DBNs, for example)	Able to learn models of data distribution in addition to classifying.
		Combination of both discriminative and generative approaches	Able to use both class discriminating information and models of data for better class separation.
Incorporating temporal information in behaviour modelling	Sports performance, skill analysis over time, deterioration of health patterns, meetings and interactions	HMM	Able to learn data model, assumes observations are independent, difficulty in encoding high-order dependences.
		Coupled HMM	Useful when modelling related processes evolving at the same time
		Semi-HMM	Learning both event state transitions as well as the *a priori* duration of events
		CRF	Models the conditional probability of observations for better class discrimination. Methods available for making training less computationally demanding.
		DBN	A generalisation of above models (HMM/CRF). Incorporates intricate relationships between variables over time. Problems could arise when inferencing but could be solved by using tractable variational algorithms.
Incorporating hierarchical modelling of sub-activities	Complex behaviours involving a set of ADLs, plan recognition, analysis of goals and context modelling	Layered HMM	Able to model sequences at different temporal granularity which is not possible with a simple HMM.
		Hierarchical HMM	Include a hierarchy of hidden states, recursive activation of sub-states. Can use transitions at the state or sub-state level. Could represent activity granularities.
		Abstract HMM	Similar to hierarchical HMMs but the states are linked to abstract policies and a flag is used to indicate changing policies, which could be better to model goals and contextual information.
		DBN	A generalisation of the above approaches that offers more flexibility in representing relationships between activities and sub-activities. Problems could arise when inferencing but could be solved by using tractable variational algorithms.
Unsupervised anomaly detection	Security applications where labelling is unavailable, data-mining of sensor databases and detecting irregular or abnormal behaviour in healthcare applications	Clustering approaches then using distance from class centres to indicate degree of irregularity	Generally the need to define criteria for splitting/merging clusters. Distances to class centres could depend on features selected.
		Training probabilistic models then using similarity/affinity matrices to look at sample similarity	Could increase complexity as number of probabilistic models could be equal to the number of available time sequences. Could also offer a better understanding of behaviour models as opposed to discriminate approaches.

Table 2 summarises this section by presenting a comparative analysis of possible techniques for different problems that can be encountered while using pervasive sensing for behaviour recognition, indicating some of the scenarios where these problems might be encountered.

6. Challenges and future opportunities

Technological advances in pervasive sensing are playing an important role in the way we understand our environment, our own behaviour and the interaction between the two. However, the use of pervasive sensing to acquire such large datasets poses several challenges in terms of data acquisition and analysis.

One of the main challenges is that of human labelling and the bias introduced whenever people are asked to label behaviour sequences. Drawing boundaries between activities is difficult, especially when people are performing several concurrent activities at the same time, such as eating while walking, or talking while flipping the pages of a book (as shown in Fig. 1(b)). Most model-based techniques surveyed in this article, from HMMs to dynamic Bayesian networks, depend on such labelling for training. Thus, errors in labelling could really affect the results as they can vary the training of such models. This highlights the importance of recognising sub-activities and catering for their variability while labelling an activity sequence. Concurrent and interleaving sub-activities pose a challenge for behaviour recognition, and need to be included in behavioural models at different time granularities. Transitioning between activities is also an important area of research that is generally overlooked when modelling long behavioural sequences. Correct recognition of transitional behaviours and observing inter-subject and intra-subject differences would offer a clearer idea of behaviour variation, and can be used to observe gait balance and disease progression, in healthcare applications, for example [145].

Making positive use of negative information [35] is also challenging, as the loss of data is normally treated as missing data. However, this does not have to be always the case, as the loss of ambient data for a person could easily mean that the person is out of the range of the sensors, which is a state on its own. Thus, missing data in general should be considered when analysing the system as a whole. The amount of data provided could include a significant amount of redundant data, as some sensors could be irrelevant for certain types of activities. For such cases, distributed frameworks of data analysis could prove to be essential in saving processing time and optimising networks.

Thus far, datasets that can be used to compare different studies for behaviour analysis are limited. Having standard datasets that show multi-dimensional sensor data for a large number of subjects over a period of time could provide a common ground for the comparison of different techniques for data analysis. For this reason, it is difficult to compare success rates of different methods as the datasets used in previous studies were in most cases completely different, so were the activities modelled.

Another problem of the methodologies used is the lack of generality, as methods are devised for the analysis of a certain problem, group interaction in a particular sport, for example, and cannot be extended to other areas of behaviour modelling. It is rare to find techniques that have a broad spectrum of use for general applications of behaviour analysis. Sensor positioning, in both wearable and ambient scenarios, poses a physical problem that can cause sensor data variability. Other challenges to behaviour monitoring in pervasive sensing environments include energy optimisation and developing reliable algorithms that are robust to sensor variability and tolerant of discontinuous or missing data.

Combining data obtained from physiological sensors with ambient and wearable sensor data poses several research challenges. These include learning the relationship between physiological parameters and activity, which could be variable between subjects [146,147]. Motivating subjects to increase their activity and providing 'persuasive' behaviour modelling is also quite important if pervasive frameworks are to be used for encouraging daily activity in healthcare applications [148], providing feedback for rehabilitation (as in the MIT LiveNet system) [149] and detecting variations in physiological parameters over time [150].

The applications that could benefit from such studies present exciting opportunities for further research. Pattern recognition, for example, is now transcending from simple activity recognition to behaviour profiling, and therefore bringing new challenges that need to be addressed. Healthcare is becoming highly dependent on advances in sensing; so are other fields, such as sports, entertainment, psychology and most importantly national security. The next decade will most likely witness a convergence of machine learning, pervasive and embedded sensing to provide novel means of behaviour analysis and long-term trend analysis.

Acknowledgements

This work was supported by the TSB (Technology Strategy Board) project SAPHE (Smart and Aware Pervasive Healthcare Environments) and the EU-funded project WASP (Wirelessly Accessible Sensor Protocols).

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Louis Atallah received his Diplome D'Ingenieur degree from the Lebanese University Faculty of Engineering in 2000 and his D.Phil. in Engineering Science from Oxford University in 2004. Currently, he is a Research Associate at the Department of Computing, Imperial College, London. His research interests include machine learning, data mining, and pervasive sensing.

Guang-Zhong Yang received his Ph.D. in Computer Science from Imperial College, London, and is the Director of Imperial College Centre for Pervasive Sensing. He is an associate editor of IEEE Transactions on Medical Imaging and a referee for a large number of international medical imaging journals. His main research interests include biomedical imaging, sensing and robotics. He has received several awards, including the Royal Society Research Merit Award and I.I. Rabi Award from the International Society for Magnetic Resonance in Medicine. He is a Fellow of the IEE and has published over 200 original peer-reviewed research articles including over 100 peer-reviewed academic journal papers.