Sensor-Based Activity Recognition

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***Abstract*—Research on sensor-based activity recognition has, recently, made significant progress and is attracting growing attention in a number of disciplines and application domains. However, there is a lack of high-level overview on this topic that can inform related communities of the research state of the art. In this paper, we present a comprehensive survey to examine the development and current status of various aspects of sensor-based activity recognition. We first discuss the general rationale and distinctions of vision-based and sensor-based activity recognition. Then, we review the major approaches and methods associated with sensor-based activity monitoring, modeling, and recognition from which strengths and weaknesses of those approaches are highlighted. We make a primary distinction in this paper between data-driven and knowledge-driven approaches, and use this distinction to structure our survey. We also discuss some promising directions for future research.**

***Index Terms*—Activity modeling, activity monitoring, activity recognition, dense sensing, pervasive computing.**

I. Introduction

HUMAN activity recognition is one of the most promising research topics for a variety of areas, including pervasive and mobile computing [1], [2], surveillance-based security [3]–[10], context-aware computing [41], [83], [152] and ambient assistive living [76], [93], [103], [126], [146]. It has, recently, received growing attention attributing to the intensive thrusts from the latest technology development and application demands. Over the past decade, sensor technologies, especially low-power, low-cost, high-capacity, and miniaturized sensors, wired and wireless communication networks [11]–[13], and data processing techniques have made substantial progress. The advances and maturity of these supporting technologies have pushed the research focuses of the aforementioned areas to shift from low-level data collection and transmission toward high-level information integration, context processing, and activity recognition and inference. At the same time, solutions for a number of real-world problems have become increasingly reliant on activity recognition. For example, surveillance and security try to make use of activity recognition technologies to address the threats of terrorists. Ambient-assisted living (AAL) aims to exploit activity monitoring, recognition, and assistance to support independent living and ageing in place. Other emerging applications, such as intelligent meeting rooms and smart hospitals, are also dependent on activity recognition in order to provide multimodal interactions, proactive service provision, and context aware personalized activity assistance.

As a result of the technology push and application pull, a substantial number of projects and initiatives have been undertaken, e.g., [49], [50], [52]–[56]. Research related to activity recognition has become regular topics in mainstream international conferences in related areas such as the Association for the Advancement of Artificial Intelligence [14], Computer Vision and Pattern Recognition [15], International Joint Conference on Artificial Intelligence [16], Neural Information Processing Systems [17], PERVASIVE [18], UbiComp [19], PerCom [20], International Symposium on Wearable Computers [21], International Conference on Automated Planning and Scheduling [22], and the International Joint Conference on Ambient Intelligence [23]. In addition, a growing number of workshops have been dedicated to activity recognition research from different research angles and communities. For example, in 2011 alone eight workshops were specifically devoted to activity recognition research, including International Workshop on Frontiers in Activity Recognition [24], International Workshop on Human Activity Understanding from 3D Data [25], International Workshop on Situation, Activity, and Goal Awareness [26], Workshop on Plan, Activity and Intent Recognition [27], Goal, Activity and Plan Recognition [28], and others [29]–[31]. The interest and enthusiasm for this topic is still increasing.

Activity recognition is a complex process that can be roughly characterized by four basic tasks. These tasks include: 1) to choose and deploy appropriate sensors to objects and environments in order to monitor and capture a user's behavior along with the state change of the environment; 2) to collect, store, and process perceived information through data analysis techniques and/or knowledge representation formalisms at appropriate levels of abstraction; 3) to create computational activity models in a way that allows software systems/agents to conduct reasoning and manipulation; and 4) to select or develop reasoning algorithms to infer activities from sensor data. For each individual task, a raft of methods, technologies, and tools are available for use. It is often the case that the selection of a method used for one task is dependent on the method of another task. As such, activity recognition has been classified in the following ways.

Vision-based versus sensor-based activity recognition: In terms of the type of sensor that is used for activity monitoring,

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activity recognition can be generally classified into two categories. The first is referred to as vision-based activity recognition, which is based on the use of visual sensing facilities, such as video cameras, to monitor an actor's behavior and environmental changes. The generated sensor data are video sequences or digitized visual data. The approaches in this category exploit computer vision techniques, including feature extraction, structural modeling, movement segmentation, action extraction, and movement tracking to analyze visual observations for pattern recognition. The second category is referred to as sensor-based activity recognition, which is based on the use of emerging sensor network technologies for activity monitoring. The generated sensor data from sensor-based monitoring are mainly time series of state changes and/or various parameter values that are usually processed through data fusion, probabilistic, or statistical analysis methods and formal knowledge technologies for activity recognition. In these approaches, sensors can be attached to an actor under observation—namely wearable sensors or smart phones, or objects that constitute the activity environment—namely dense sensing. Wearable sensors often use inertial measurement units and radio frequency identification (RFID) tags to gather an actor's behavioral information. This approach is effective to recognize physical movements such as physical exercises. In contrast, dense sensing infers activities by monitoring human–object interactions through the usage of multiple multimodal miniaturized sensors.

Data-driven versus knowledge-driven activity recognition: Although primitive activity data can be obtained through activity monitoring, activity models are critical to interpret the sensor data to infer activities. In particular, the mechanisms activities that are recognized are closely related to the nature and representation of activity models. Generally speaking, activity models can be built using one of two methods. The first is to learn activity models from preexistent large-scale datasets of users' behaviors using data mining and machine learning techniques. This method involves the creation of probabilistic or statistical activity models, followed by training and learning processes. As this method is driven by data, and the ensued activity inference is based on probabilistic or statistical classification, it is often referred to as data-driven or bottom-up approaches. The advantages of the data-driven approaches are the capabilities of handling uncertainty and temporal information. However, this method requires large datasets for training and learning, and suffers from the data scarcity or the "cold start" problem. It is also difficult to apply learnt activity models from one person to another. As such, this method suffers from the problems of scalability and reusability.

The other method to build activity models is to exploit rich prior knowledge in the domain of interest to construct activity models directly using knowledge engineering and management technologies. This usually involves knowledge acquisition, formal modeling, and representation. Activity models generated in this method are normally used for activity recognition or prediction through formal logical reasoning, e.g., deduction, induction, or abduction. As such, this method is referred to as knowledge-driven or top-down approach. Knowledge-driven approaches have the advantages of being semantically clear, logically elegant, and easy to get started. However, they are weak in handling uncertainty and temporal information and the models could be viewed as static and incomplete.

Vision-based activity recognition has been a research focus for a long period of time due to its important role in areas such as surveillance, robot learning, and antiterrorist security. Researchers have used a wide variety of modalities, such as a single or multicamera, stereo, and infrared, to investigate a diversity of application scenarios, for single or groups of individuals. Several survey papers about vision-based activity recognition have been published over the years. Aggarwal and Cai [3] discuss the three important subproblems of an action recognition system—extraction of human body structure from images, tracking across frames, and action recognition. Cedras and Shah [4] present a survey on motion-based approaches to recognition as opposed to structure-based approaches. Gavrila [5] and Poppe [6] present surveys mainly on tracking human movement via 2-D or 3-D models and the enabled action recognition techniques. Moeslund *et al.* [7] present a survey of problems and approaches in human motion capture, tracking, pose estimation, and activity recognition. Yilmaz *et al.* [8] and Weinland *et al.* [10] present surveys of tracking objects for action recognition. More recently, Turaga *et al.* [9] and Aggarwal *et al.* [32] present surveys focusing on high-level representation of complex activities and corresponding recognition techniques. Together, these works have provided an extensive overview on the vision-based approach. Given these existing works, this paper will not review research on vision-based activity recognition. However, it is worth pointing out that while visual monitoring is intuitive and information-rich, vision-based activity recognition suffers from issues relating to privacy and ethics [4], [5], [8] as cameras are generally perceived as recording devices.

Compared with the number of surveys in vision-based activity recognition, and considering the wealth of literature in sensor-based activity recognition, there is a lack of extensive review on the state of the art of sensor-based activity recognition. This may be because the approach only, recently, became feasible when the sensing technologies matured to be realistically deployable in terms of the underpinning communication infrastructure, costs, and sizes. Given the rising population and the potential of the approach in a wide range of application domains, a systematic survey of existing work will be of high scientific value. It will inform researchers and developers in related communities about the current status and best practices and to signpost future directions. This survey is intended to present an in-depth comprehensive overview on the latest development of sensor-based activity recognition. It will cover the lifecycle of the approach, and provide descriptions and comparisons of various approaches and methods from which strengths and weaknesses are highlighted.

In this survey, we review related works based on the classifications we described previously, aiming to provide multidimension views from different angles on the latest research in activity recognition. This review strategy also allows us to independently discuss and compare work with common methods, thus able to discover convincing findings. After a brief introduction to the historical evolution of sensor-based activity recognition in

Section II, we present in Section III an overview of sensor-based activity monitoring. We, then, review major data-driven and knowledge-driven approaches for activity recognition in Sections IV and V, respectively. We present comparison of activity recognition approaches and discuss the impact of related areas in Section VI. Finally, in Section VII, we provide insights into current practices of activity recognition and discuss emerging and potential research directions. The survey is concluded in Section VIII.

II. Sensor-Based Activity Recognition Evolution

Before we embark on an in-depth discussion on activity monitoring, modeling, and recognition, it is useful to distinguish human behaviors at different levels of granularity. For physical behaviors, the terms "action" and "activity" are commonly used in activity recognition communities. In some cases, they are used interchangeably and in other cases they are used to denote behaviors of different complexity and duration. In the latter cases, the term "action" is usually referred to as simple ambulatory behavior executed by a single person and typically lasting for short durations of time. Examples of actions include bending, retrieving a cup from a cupboard, opening a door, putting a teabag into a cup, etc. On the other hand, the term "activities," here, refers to complex behaviors consisting of a sequence of actions and/or interleaving or overlapping actions. They could be performed by a single human or several humans who are required to interact with each other in a constrained manner. They are typically characterized by much longer temporal durations, such as making tea or two persons making meals. As one activity can contain only one action, there will be no cutoff boundary between these two behavior categories. Nevertheless, this simple categorization provides a basic conceptualization and clarity for the discussions in this paper.

The idea of using sensors for activity monitoring and recognition has been existent since the late 1990s. It was initially pioneered and experimented by the work of the Neural Network house [33] in the context of home automation, and a number of location-based applications aiming to adapt systems to users' whereabouts [34]–[36]. The approach was soon found to be more useful and suitable in the area of ubiquitous and mobile computing—an emerging area in the late 1990s, due to its easy deployment. As such, extensive research has been undertaken to investigate the use of sensors in various application scenarios of ubiquitous and mobile computing, leading to considerable work on context awareness [37]–[39], smart appliances [40], [41], and activity recognition [42]–[45], [61]. Most research at that time made use of wearable sensors, either dedicated sensors attached to human bodies or portable devices like mobile phones, with application to ubiquitous computing scenarios such as providing context-aware mobile devices. Activities being monitored in these researches are mainly physical activities like motion, walking, and running. These early works lay a solid foundation for wearable computing and still inspire and influence today's research.

In the early 2000s, a new sensor-based approach that uses sensors attached to objects to monitor human activities appeared. This approach, which was later dubbed as the "dense sensing" approach, performs activity recognition through the inference of user–object interactions [48], [63]. The approach is particular suitable to deal with activities that involve a number of objects within an environment, or instrumental activities of daily living (ADL) [46], [47]. Research on this approach has been heavily driven by the intensive research interests and huge research effort on smart home-based assistive living, such as the EU's AAL program [49]. In particular, sensor-based activity recognition can better address sensitive issues in assistive living such as privacy, ethics, and obtrusiveness than conventional vision-based approaches. This combination of application needs and technological advantages has stimulated considerable research activities in a global scale, which gave rise to a large number of research projects, including the House_n [50], CASAS [51], Gator-Tech [52], inHaus [53], AwareHome [54], DOMUS [55], and iDorm [56] projects, to name but a few. As a result of the wave of intensive investigation, there have seen a plethora of impressive works on sensor-based activity recognition in the past several years [57], [58], [62], [64], [76]–[80], [82], [83], [85], [87], [97].

While substantial research has been undertaken, and significant progress has been made, the two main approaches, wearable sensor-based- and dense sensing-based activity recognition are currently still focuses of study. The former is mainly driven by the ever-popular pervasive and mobile computing, while the latter is predominantly driven by smart environment applications such as AAL. Interests in various novel applications are still increasing and application domains are rapidly expanding.

III. Sensor and Activity Monitoring

Currently, a wide range of sensors, including contact sensors, RFID, accelerometers, audio and motion detectors, to name but a few, are available for activity monitoring. These sensors are different in types, purposes, output signals, underpinning theoretical principles, and technical infrastructure. However, they can be classified into two main categories in terms of the way they are deployed in activity monitoring applications. These are wearable sensors and dense sensors, and are described in details in the following.

A. *Wearable Sensor-Based Activity Monitoring*

Wearable sensors, generally, refer to sensors that are positioned directly or indirectly on human body. They generate signals when the user performs activities. As a result, they can monitor features that are descriptive of the person's physiological state or movement. Wearable sensors can be embedded into clothes, eyeglasses, belts, shoes, wristwatches, mobile devices, or positioned directly on the body. They can be used to collect information such as body position and movement, pulse, and skin temperature. Researchers have found that different types of sensor information are effective to classify different types of activities. In the following, we summarize the common practice in wearable sensor-based activity monitoring.

Accelerometer sensors are probably the most frequently used wearable sensor for activity monitoring. They are particularly effective in monitoring actions that involve repetitive body motions, such as walking, running, sitting, standing, and climbing stairs. Bao and Intille [48] provide a summary of research work that recognizes human activities using acceleration data. Kern *et al*. [57] deploy a network of three-axis accelerometers distributed over the user's body. Each accelerometer provides information about the orientation and movement of the corresponding body part. Lukowicz *et al*. [58] recognize workshop activities using body worn microphones and accelerometers. Measuring acceleration and angular velocity (the angle of the user's thigh) through wearable sensors, such as accelerometers and gyroscopes, Lee and Mase [61] propose a dead-reckoning method to determine a user's location and recognizing sitting, standing, and walking behaviors. Mantyjarvi *et al*. [62] recognize human ambulation and posture on acceleration data collected from the hip.

Global positioning system (GPS) sensors are another widely used wearable sensor for monitoring location-based activities in open pervasive and mobile environments. Patterson *et al*. [63] present details of detecting human high-level behavior from a GPS sensor stream, such as boarding a bus at a particular bus stop, traveling, and disembarking. Ashbrook and Starner [64] use GPS to learn significant locations and predict movement across multiple users. Liao *et al*. [97] learn and infer a user's mode of transportation and their goal in addition to abnormal behaviors (e.g., taking a wrong bus) based on GPS data logs.

Biosensors are an emerging technology aiming to monitor activities through vital signs. A diversity of sensors in different forms has been studied in order to measure the wide range of vital signs such as blood pressure, heart rate, EEG, ECG, and respiratory information. Sung *et al*. [65] monitor the body temperature of soldiers to detect hypothermia. Harms *et al*. [66] use information gathered by a smart garment to identify body posture. Similar work includes [72]–[75].

In addition to the investigation of different wearable sensors for activity monitoring, research on the support and novel application of wearable computing has been undertaken. Pantelopoulos and Bourbakis [59] present a survey on wearable systems for monitoring and early diagnosis for the elderly. Dakopoulos and Bourbakis [60] present a survey on wearable obstacle avoidance electronic travel aids for visually impaired. Yoo *et al*. [67] design on-body and near-body networks that use the human body itself as a channel to create BodyNets. Cooper *et al*. and Au *et al*. use wearable sensors to design and evaluate assistive wheelchairs [68] and smart walking sticks [69]. Kim *et al*. [71] use wearable sensors to recognize gestures. Madan *et al*. [70] characterize a person's social context by evaluating a user's proximity, speech, head movements, and galvanic skin response.

Wearable sensor-based activity monitoring suffers from limitations. Most wearable sensors need to run continuously and be operated hands-free. This may have difficulties in real-world application scenarios. Practical issues include the acceptability or willingness to use wearable sensors and the viability and ability to wear them. Technical issues include the size, ease of use, battery life, and effectiveness of the approach in real-world scenarios. To address these issues, vigorous investigation on smart garments has been carried out, which aims to embed sensors in garments for monitoring [66], [72]–[75]. Another research thread is to make use of existing gadgets that have already been carried in a daily basis like smart phones as intelligent sensors for activity monitoring, recognition, and assistance. This practice has been in place for a while [39], [40] and is expected to gain large-scale uptake given the latest development and affordability of such palm-held electronic devices.

Obviously, wearable sensors are not suitable for monitoring activities that involve complex physical motions and/or multiple interactions with the environment. In some cases, sensor observations from wearable sensors alone are not sufficient to differentiate activities involving simple physical movements (e.g., making tea and making coffee). As a result, dense sensing-based activity monitoring has emerged, which is described in the following.

B. Dense Sensing-Based Activity Monitoring

Dense sensing-based activity monitoring refers to the practice that sensors are attached to objects and activities are monitored by detecting user–object interactions. The approach is based on real-world observations that activities are characterized by the objects that are manipulated during their performance. A simple indication of an object being used can often provide powerful clues about the activity being undertaken. As such, it is assumed that activities can be recognized from sensor data that monitors human interactions with objects in the environment. By dense sensing, we refer to the way and scale with which sensors are used. Using dense sensing, a large number of sensors, normally low-cost low-power, and miniaturized, are deployed in a range of objects or locations within an environment for the purpose of monitoring movement and behavior.

As dense sensing-based monitoring embeds sensors within environments, this makes it more suitable to create ambient intelligent applications such as smart environments. As such, dense sensing-based activity monitoring has been widely adopted in AAL, via the smart home paradigm [46], [47], [50], [52]–[56], [81]. Sensors in an smart homes (SH) can monitor an inhabitant's movements and environmental events so that assistive agents can infer the undergoing activities based on the sensor observations, thus providing just-in-time context-aware ADL assistance. For instance, a switch sensor in the bed can strongly suggest sleeping, and pressure mat sensors can be used to track the movement and position of people within the environment.

Since the introduction of the idea in early 2000s [48], [63], extensive research has been undertaken to investigate the applicability of the approach in terms of sensor types, modalities, and applications. For example, Tapia *et al*. [98] use environmental state-change sensors to collect information about interaction with objects and recognize activities that are of interest to medical professionals such as toileting, bathing, and grooming. Wilson and Atkeson [82] use four kinds of anonymous and binary sensors, motion detectors, break-beam sensors, pressure mats, and contact switches for simultaneous tracking and activity recognition. Wren and Tapia [83] employ networks of passive infrared motion sensors to detect presence and movement of heat sources. With this captured data, they can recognize low-level activities such as walking, loitering, and turning, as well as mid-level activities such as visiting and meeting. Srivastava *et al.* [84] exploit wireless sensor network to develop smart learning environment for young children. Hollosi *et al.* [86] use voice detection techniques to perform acoustic event classification for monitoring in Smart Homes. Simple object sensors are adopted in [85].

Given the abundance of different types and modalities of sensors, sensors have been used in different ways and combinations for dense sensing activity monitoring in many application scenarios. It is impossible to claim that one sensor deployment for a specific application scenario is superior to the other. The suitability and performance are usually down to the nature of the type of activities being assessed and the characteristics of the concrete applications. As such, in this paper, we shall not discuss in detail the different usage of dense sensing in various scenarios but simply introduce its rationale as described previously.

Generally speaking, wearable sensor-based activity monitoring receives more attention in mobile computing, while dense sensing is more suitable for intelligent environment enabled applications. It is worth pointing out that wearable sensors and dense sensing are not mutually exclusive. In some applications, they have to work together. For example, RFID-based activity monitoring requires that objects are instrumented with tags and users wear an RFID reader affixed to a glove or a bracelet. Philipose *et al.* and Fishkin *et al.* [76], [77] developed two devices, iGlove and iBracelet, working as wearable RFID readers that detect when users interact with unobtrusively tagged objects. Patterson *et al.* [78] performed fine-grained activity recognition (i.e., not just recognizing that a person is cooking but determining what they are cooking) by aggregating abstract object usage. Hodges and Pollack [79] proposed to identify individuals from their behavior based on their interaction with the objects they use in performing daily activities. Buettner *et al.* [80] recognize indoor daily activities by using an RFID sensor network. In most cases, wearable sensors and dense sensing are complementary and can be used in combination in order to yield optimal recognition results. For example, Gu *et al.* [87] combine wearable sensors and object sensors to collect multimodal sensor information. Through a pattern-based method, they recognize sequential, interleaved, and concurrent activities.

It is worth pointing out that sensors are substantially variable not only in their types and output signals but also in their size, weight, and cost. Even for one type of sensor, its output, size, weight, and cost can vary significantly. For example, there are eight models of conventional pedometers from four vendors, and four models of personal device-based pedometers (mainly based on smart phones) from four vendors [88]. These sensors are different in size, weights, cost, measurement, mechanism, software, and communication and battery life. A thorough survey of sensor in terms of these attributes is beyond the scope of this paper. It is also impossible with the limited space.

IV. Data-Driven Approaches to Activity Recognition and Modeling

Data-driven activity modeling can be classified into two main categories: generative and discriminative. In the generative approach, one attempts to build a complete description of the input or data space, usually with a probabilistic model such as a Bayesian network. In the discriminative approach, one only models the mapping from inputs (data) to outputs (activity labels). Discriminative approaches include many heuristic (rule-based) approaches, neural networks, conditional random fields (CRFs), and linear or nonlinear discriminative learning (e.g., support vector machines). In the following, we cover major results using each of these methods.

A. Generative Modeling

The simplest possible generative approach is the naïve Bayes classifier (NBC), which has been used with promising results for activity recognition [48], [90], [93], [98], [103], [151]. NBCs model all observations (e.g., sensor readings) as arising from a common causal source: the activity, as given by a discrete label. The dependence of observations on activity labels is modeled as a probabilistic function that can be used to identify the most likely activity given a set of observations. Despite the fact that these classifiers assume conditional independence of the features, the classifiers yield good accuracy when large amounts of sample data are provided. Nevertheless, NBCs do not explicitly model any temporal information, usually considered important in activity recognition.

The hidden Markov model (HMM) is probably the most popular generative approach that includes temporal information. An HMM is a probabilistic model with a particular structure that makes it easy to learn from data, to interpret the data once a model is learned, and is both easy and efficient to implement. It consists of a set of hidden (latent) states coupled in a stochastic Markov chain, such that the distribution over states at some time depends only on the values of states at a finite number of preceding times. The hidden states, then, probabilistically generate observations through a stochastic process. HMMs made their impact initially through use in the speech recognition literature, where latent states correspond to phoneme labels, and observations are features extracted from audio data. HMMs have more recently been adopted as a model of choice in computer vision for modeling sequential (video) data (see [5] and [7] for surveys, and [94] and [102] for early examples). An HMM use a Markov chain over a discrete set of states. A closely relative of the HMM uses continuous states, a model usually referred to as a linear dynamical system (LDS). State estimation in LDSs is better known as a Kalman filter. LDSs have been used with inputs from a variety of sensors for physiological condition monitoring [148] in which a method is also introduced to deal with unmodeled variations in data, one of the major shortcomings of the generative approach.

HMMs form the basis of statistical temporal models. They are, in fact, a special case of the more general dynamic Bayesian networks (DBNs), which are Bayesian networks in which a discrete time index is explicitly represented. Inference and learning in DBNs is simply an application of network propagation in Bayesian networks. DBNs usually make a Markovian assumption, but explicitly represent conditional independences in the variables, allowing for more efficient and accurate inference and learning. A well known early use of DBNs for activity monitoring was in the Lumière project, where a Microsoft Windows user's need for assistance was modeled based on their activities on the screen [149].

A simple DBN extension of HMMs is the coupled HMM for recognition of simultaneous human actions (e.g., pedestrian motions [89]). Coupled HMMs (CHMMs) have two Markovian chains, each modeling a different stream of data, with a coupling between them to model their interdependence. Oliver *et al.* [99] learn a multilayer model of office activity to choose actions for a computational agent. The model uses multimodal inputs, making only very slight use of computer vision. The Assisted Cognition project [95] has made use of DBNs, in particular for opportunity knocks [97], a system designed to provide directional guidance to a user navigating through a city. This system uses a three-level hierarchical Markov model represented as a DBN to infer a user's activities from GPS sensor readings. Movement patterns, which are based on the GPS localization signals, are translated into a probabilistic model using unsupervised learning. From the model and the user's current location, future destinations and the associated mode of transportation can be predicted. Based on the prediction, the system has the ability to prompt the user if an error in route is detected.

Wilson and Atkeson use DBNs to simultaneously track persons and model their activities from a variety of simple sensors (motion detectors, pressure sensors, switches, etc.) [82]. DBNs were also used in the iSTRETCH system, a haptic robotic device to assist a person with stroke rehabilitation [160]. The DBN models the person's current behaviors, their current abilities, and some aspects of their emotional state (e.g., their responsiveness, learning rate, and fatigue level). The person's behaviors correspond to how long they take for each exercise, what type of control they exhibit, and whether they compensate. These behaviors are inferred from sensors on the device and in the person's chair.

Even though they are simple and popular, HMMs and DBNs have some limitations. An HMM is incapable of capturing long-range or transitive dependences of the observations due to its very strict independence assumptions (on the observations). Furthermore, without significant training, an HMM may not be able to recognize all of the possible observation sequences that can be consistent with a particular activity.

B. Discriminative Modeling

A drawback of the generative approach is that enough data must be available to learn the complete probabilistic representations that are required. In this section, we discuss an alternative approach for modeling in which we focus directly on solving the classification problem, rather than on the representation problem. The complete data description of a generative model induces a classification boundary, which can be seen by considering every possible observation and applying the classification rule using inference. The boundary is, thus, implicit in a generative model, but a lot of work is necessary to describe all the data to obtain it. A discriminative approach, on the other hand, considers this boundary to be the primary objective.

Perhaps, the simplest discriminative approach is nearest neighbor (NN), in which a novel sequence of observations is compared with a set of template sequences in a training set, and the most closely matching sequences in the training set vote for their activity labels. This simple approach can often provide very good results. Bao and Intille investigated this method along with numerous other base-level classifiers for the recognition of activities from accelerometer data [48]. They found that the simple NN approach is outperformed by decision trees, a related method, where the training data are partitioned into subsets according to activity labels and a set of rules based on features of the training data. The rules can, then, be used to identify the partition (and hence the activity label) corresponding to a new data sample. Maurer *et al.* [151] employed decision trees to learn logical descriptions of activities from complex sensor readings from a wearable device (the eWatch). The decision tree approach offers the advantage of generating rules that are understandable by the user, but it is often brittle when high-precision numeric data are collected. Stikic and Schiele use a clustering method in which activities are considered as a "bag of features" to learn template models of activities from data with only sparse labels [152].

Many discriminative approaches explicitly take into account the fact that, for classification, it is actually only the points closest to the boundary that are of interest. The ones very far away (the "easy" ones to classify) do not play such a significant role. The challenge is, therefore, to find these "hard" data points (the ones closest to the boundary). These data points will be known as the "support vectors," and actually define the boundary. A support vector machine (SVM) is a machine learning technique to find these support vectors automatically. A recent example of an SVM in use for activity modeling is presented by Brdiczka *et al.* [91] where a model of situations is learned automatically from data by first learning roles of various entities using SVMs and labeled training data, then using unsupervised clustering to build 'situations' or relations between entities, which are then labeled and further refined by end users. The key idea in this study is to use a cognitive model (situation model) based on cognitive theory motivated by models of human perception of behavior in an environment. The CareMedia project [92] also uses an SVM to locate and recognize social interactions in a care facility from multiple sensors, including video and audio. The fusion of video and audio allowed 90% recall and 20% precision in identifying interactions including shaking hands, touching, pushing, and kicking. The CareMedia project's goals are to monitor and report behavior assessments in a care home to caregivers and medical professionals.

Ravi *et al.* also found that SVMs performed consistently well, but also investigated meta-level classifiers that combined the results of multiple base-level classifiers [153]. Features extracted from worn accelerometers are extracted and classified using five different base-level classifiers (decision tables, decision trees, k-NNs, SVM, and Naïve Bayes). The meta-level classifiers are generated through a variety of techniques such as boosting, bagging, voting, cascading, and stacking. For recognizing a set of eight activities, including standing, walking, running, going up/down stairs, vacuuming, and teeth brushing, they found that a simple voting scheme performed the best for three easier experimental settings, whereas boosted SVM performed best for the most difficult setting (test/training separation across users and days).

In practice, many activities may have nondeterministic natures, where some steps of the activities may be performed in any order, and, therefore, are concurrent or interwoven. A CRF is a more flexible alternative to the HMM that addresses such practical requirements. It is a discriminative and generative probabilistic model that represents the dependence of a hidden variable y on an observed variable x [154]. Both HMMs and CRFs are used to find a sequence of hidden states based on observation sequences. Nevertheless, instead of finding a joint probability distribution $p(x,y)$ as the HMM does, a CRF attempts to find only the conditional probability $p(y|x)$. A CRF allows for arbitrary, nonindependent relationships among the observation sequences, hence the added flexibility. Another major difference is the relaxation of the independence assumptions, in which the hidden state probabilities may depend on the past and even future observations. A CRF is modeled as an undirected acyclic graph, flexibly capturing any relation between an observation variable and a hidden state. CRFs are applied to the problem of activity recognition in [155] where they are compared with HMMs, but only in a simple simulated domain. Liao *et al.* use hierarchical CRFs for modeling activities based on GPS data [156]. Hu and Yang use skip-chain CRFs, an extension in which multiple chains interact in a manner reminiscent of the CHMM, to model concurrent and interleaving goals [135], a challenging problem for activity recognition. Mahdaviani and Choudhury show how semisupervised CRFs can be used to learn activity models from wearable sensor data [157].

C. Heuristic/Other Approaches

Many approaches do not fall clearly into discriminative or generative categories, but rather use a combination of both, along with some heuristic information. The Independent Lifestyle Assistant is an example, as it uses a combination of heuristic rules and statistical models of sequential patterns of sensor firings and time intervals to help a person with planning and scheduling [150]. The Planning and Execution Assistant and Trainer (PEAT) is a cognitive assistant that runs on a mobile device, and helps compensate for executive functional impairment. PEAT uses reactive planning to adjust a user's schedule based on their current activities. Activity recognition in PEAT is based on what the user is doing, and on data from sensors on the mobile device. These are fed into an HMM, the outputs of which are combined with the reactive planning engine [158].

Other work has investigated how activities can be modeled with a combination of discriminative and generative approaches [96], how common sense models of everyday activities can be built automatically using data mining techniques [100], [101], and how human activities can be analyzed through the recognition of object use, rather than the recognition of human behavior [104]. This latter work uses DBNs to model various activities around the home, and a variety of RFID tags to bootstrap the learning process. Some authors have attempted to compare discriminative and generative models [48], [153], generally finding the discriminative models yield lower error rates on unseen data, but are less interpretable. Gu *et al.* use the notion of emerging patterns to look for frequent sensor sequences that can be associated with each activity as an aid for recognition [87]. Omar *et al.* present a comparative study of a variety of classification methods to analyze multimodal sensor data from a smart walker [159].

V. Knowledge-Driven Approaches to Activity Recognition and Modeling

Knowledge-driven activity modeling is motivated by real-world observations that for most ADL and working, the list of objects required for a particular activity is limited and functionally similar. Even if the activity can be performed in different ways, the number and type of these involved objects do not vary significantly. For example, it is commonsense that the activity "make coffee" consists of a sequence of actions involving a coffee pot, hot water, a cup, coffee, sugar, and milk; the activity "brush teeth" contains actions involving a toothbrush, toothpaste, water tap, cup, and towel. On the other hand, as humans have different life styles, habits, or abilities, they may perform various activities in different ways. For instance, one may like strong white coffee and another may prefer a special brand of coffee. Even for the same type of activity (e.g., making white coffee), different individuals may use different items (e.g., skimmed milk or whole milk) and in different orders (e.g., adding milk first and then sugar, or *vice versa*). Such domain-dependent activity-specific prior knowledge provides valuable insights into how activities can be constructed in general and how they can be performed by individuals in specific situations.

Similarly, knowledge-driven activity recognition is founded upon the observations that most activities, in particular, routine ADL and working, take place in a relatively specific circumstance of time, location, and space. The space is usually populated with events and entities pertaining to the activities, forming a specific environment for specific purposes. For example, brushing teeth is normally undertaken twice a day in a bathroom in the morning and before going to bed and involves the use of toothpaste and a toothbrush; meals are made in a kitchen with a cooker roughly three times a day. The implicit relationships between activities, related temporal and spatial context, and the entities involved (objects and people) provide a diversity of hints and heuristics to infer activities.

Knowledge-driven activity modeling and recognition intends to make use of rich domain knowledge and heuristics for activity modeling and pattern recognition. The rationale is to use various methods, in particular, knowledge engineering methodologies and techniques, to acquire domain knowledge. The captured knowledge can, then, be encoded in various reusable knowledge structures, including activity models for holding heuristics and prior knowledge in performing activities, and context models for holding relationships between activities, objects, and temporal and spatial contexts. Comparing with data-driven activity modeling that learns models from large-scale datasets and recognizes activities through data intensive processing methods, knowledge-driven activity modeling avoids a number of problems, including the requirement for large amounts of observation data, the inflexibility that arises when each activity model needs to be computationally learned, and the lack of reusability that results when one person's activity model is different from another's.

Knowledge structures can be modeled and represented in different forms, such as schemas, rules, or networks. This will decide the way and the extent to which knowledge is used for following processing such as activity recognition, prediction, and assistance. In terms of the manner in which domain knowledge is captured, represented, and used, knowledge-driven approaches to activity modeling and recognition can be roughly classified into three main categories as presented in the following sections.

A. Mining-Based Approach

The rationale of a mining-based approach is to create activity models by mining existing activity knowledge from publically available sources. More specifically, given a set of activities, the approach seeks to discover from the text corpuses a set of objects used for each activity and extract object usage information to derive their associated usage probabilities. The approach essentially views activity model as a probabilistic translation between activity names (e.g., "make coffee") and the names of involved objects (e.g., "mug" and "milk"). As the correlations between activities and their objects are common sense prior knowledge (e.g., most of us know how to carry out daily activities), such domain knowledge can be gleaned in various sources such as how-tos (e.g., those at ehow.com), recipes (e.g., from epicurious.com), training manuals, experimental protocols, and facility/device user manuals.

A mining-based approach consists of a sequence of distinct tasks. First, it needs to identify activities of concern and relevant sources that describe these activities. Second, it uses various methods, predominantly information retrieval and analysis techniques, to retrieve activity definitions from specific sources and extract phrases that describe the objects used during the performance of the activity. Then, algorithms, predominantly probabilistic and statistic analysis methods such as cooccurrences and association, are used to estimate the object-usage probabilities. Finally, the mined object and usage information are used to create activity models, such as an HMM, that can be used further for activity recognition.

Mining-based activity modeling was initially investigated by researchers from Intel Research [105], [106]. Perkowitz *et al.* [105] proposed the idea of mining the web for large-scale activity modeling. They used the QTag tagger to tag each word in a sentence with its part of speech and a customized regular expression extractor to extract objects used in an activity. They, then, used the Google conditional probabilities application programming interfaces (APIs) to determine automatically the probability values of object usage. The mined object and their usage information are, then, used to construct DBN models through sequential Monte Carlo approximation. They mined the website ehow.com for roughly 2300 directions on performing domestic tasks (from "boiling water in the microwave" to "change your air filter"), and the website ffts.com and epicurious.com for a further 400 and 18 600 recipes, respectively, generating a total 21 300 activity models. Using the DBN activity models, they have performed activity recognition for a combination of real user data and synthetic data. While initial evaluation results were positive, the drawback was that there are no mechanisms to guarantee the mined models capturing completely the sequence probabilities and the idiosyncrasy of certain activities. The inability to capture such intrinsic characteristics may limit the model's accuracy in real deployments.

Wyatt *et al.* [106] followed Perkowitz's approach by mining the web to create DBN activity models. However, this group extended the work in three aspects, aiming to address the idiosyncrasies and to improve model accuracy. To cover the wide variety of activity definition sources, they mined the web in a more discriminative way in a wider scope. They did this by building a specialized genre classifier trained and tested with a large number of labeled web pages. To enhance model applicability, they used the mined models as base activity models and, then, exploited the Viterbi algorithm and maximum likelihood to learn customized activity parameters from unsegmented, unlabeled sensor data. In a bid to improve activity recognition accuracy, they also presented a bootstrap method that produced labeled segmentations automatically. Then, they used the Kullback–Leibler divergence to compute activity similarity.

A difficulty in connecting mined activities with tagged objects [105], [106] is that the activity models may refer to objects synonymously. For example, both a "mug" and "cup" can be used to make tea; and both a "skillet" and "frying pan" can be used to make pasta. This leads to a situation that one activity may have different models with each having the same activity name but different object terms. To address this, Tapia *et al.* [107] proposed to extract collections of synonymous words for the functionally similar objects automatically from WordNet, an online lexical reference system for the English language. The set of terms for similar objects is structured and represented in a hierarchical form known as the object ontology. With the similarity measure provided by the ontology, an activity model will not only cover a fixed number of object terms but also any other object terms that are in the same class in the ontology.

Another shortcoming of early work in the area [105], [106] is that the segmentation is carried out in sequential order based on the duration of an activity. As the duration of performing a specific activity may vary substantially from one to another, this may give rise to applicability issues. In addition, in sequential segmentation, one error in one segment may affect the segmentations of the subsequent traces. To tackle this, Palmes *et al.* [108] proposed an alternate method for activity segmentation and recognition. Instead of relying on the order of object use, they exploited the discriminative trait of the usage frequency of objects in different activities. They constructed activity models by mining the web and extracting relevant objects based on their weights. The weights are, then, utilized to recognize and segment an activity trace containing a sequence of objects used in a number of consecutive and noninterleaving activities. To do this, they proposed an activity recognition algorithm, KeyExtract, which uses the list of discriminatory key objects from all activities to identify the activities present in a trace. They further proposed two heuristic segmentation algorithms, MaxGap and MaxGain, to detect the boundary between each pair of activities identified by KeyExtract. Boundary detection is based on the calculation, aggregation, and comparison of the relative weights of all objects sandwiched in any two key objects representing adjacent activities in a trace. Although the mining-based approach has a number of challenges relating to information retrieval, relation identification, and the disambiguation of term meaning, nevertheless, it provides a feasible alternative to model large amount of activities. Initial research has demonstrated that the approach is promising.

Mining-based approaches are similar to data-driven approaches in that they all adopt probabilistic or statistical activity modeling and recognition. However, they are different from each other in the way the parameters of the activity models are decided. The mining-based approaches make use of publically available data sources avoiding the “cold start” problem.” Nevertheless, they are weak in dealing with idiosyncrasies of activities. On other hand, data-driven approaches have the strength of generating personalized activity models, but they suffer from issues such as “cold start” and model reusability for different users.

B. Logic-Based Approach

A logic-based approach views an activity as a knowledge model that can be formally specified using various logical formalisms. From this perspective, activity modeling is equivalent to knowledge modeling and representation. As such, systematic knowledge engineering methodologies and techniques are used for domain knowledge acquisition and formal construction of activity structures. Knowledge representation formalisms or languages are used to represent these knowledge models and concrete knowledge instances, thus, enabling inference and reasoning. This way, activity recognition and other advanced application features, such as prediction and explanation, can be mapped to knowledge-based inference such as deduction, induction, and abduction.

Logic-based approaches are composed of a number of distinct tasks. Even though each task can be undertaken in different ways, the role of each task is specific and unique. Normally, the first step is to carry out knowledge acquisition, which involves eliciting knowledge from various knowledge sources such as domain experts and activity manuals. The second step is to use various knowledge modeling techniques and tools to build reusable activity structures. This will be followed by a domain formalization process in which all entities, events, and temporal and spatial states pertaining to activities, along with axioms and rules, are formally specified and represented using representation formalism. This process, usually, generates the domain theory. The following step will be the development of a reasoning engine in terms of knowledge representation formalisms to support inference. In addition, a number of supportive system components will be developed, which are responsible for aggregating and transforming sensor data into logical terms and formula. With all functional components in place, activity recognition proceeds by passing the logical representation of sensor data onto the reasoning engine. The engine performs logical reasoning, e.g., deduction, abduction, or induction, against the domain theory. The reasoning will extract a minimal set of covering models of interpretation from the activity models based on a set of observed actions, which could semantically explain the observations.

There exist a number of logical modeling methods and reasoning algorithms in terms of logical theories and representation formalisms. One thread of work is to map activity recognition to the plan recognition problem in the well-studied artificial intelligence field [109]. The problem of plan recognition can be stated in simple terms as: given a sequence of actions performed by an actor, how to infer the goal pursued by the actor, as well as to organize the action sequence in terms of a plan structure. Kautz *et al*. [110] adopted first-order axioms to build a library of hierarchical plans. They proposed a set of hypotheses, such as exhaustiveness, disjointedness, and minimum cardinality, to extract a minimal covering model of interpretation from the hierarchy, based on a set of observed actions. Wobke [111] extends Kautz’s work using situation theory to address the different probabilities of inferred plans by defining a partial order relation between plans in terms of levels of plausibility. Bouchard and Giroux. [112] borrow the idea of plan recognition and apply it to activity recognition. They use action description logic (DL) to formalize actions and entities and variable states in a smart home to create a domain theory. They model a plan as a sequence of actions and represent it as a lattice structure, which, together with the domain theory, provides an interpretation model for activity recognition. As such, given a sequence of action observations, activity recognition amounts to reasoning against the interpretation model to classify the actions through a lattice structure. It was claimed that the proposed DL models can organize the result of the recognition process into a structured interpretation model in the form of lattice, rather than a simple disjunction of possible plans with no classification. This minimizes the uncertainty related to the observed actor’s activity by bounding the plausible plans set.

Another thread of work is to adopt the highly developed logical theory of actions, such as the event calculus (EC) [113], for activity recognition and assistance. The EC formalizes a domain using fluents, events, and predicates. Fluents are any properties of the domain that can change over time. Events are the fundamental instrument of change. All changes to a domain are the result of named events. Predicates define relations between events and fluents that specify what happens when and which fluents hold at what times. Predicates also describe the initial situation and the effects of events. Chen and Nugent [114] proposed an EC-based framework in which sensor activations are modeled as events, and object states as properties. In addition, they developed a set of high-level logical constructors to model compound activities, i.e., the activities consisting of a number of sequential and/or parallel events. In the framework, an activity trace is simply a sequence of events that happen at different time points. Activity recognition is mapped to deductive reasoning tasks, e.g., temporal projection or explanation, and activity assistance or hazard prevention is mapped to abductive reasoning tasks. The major strength of this study is its capability to address temporal reasoning and the use of compound events to handle uncertainty and flexibility of activity modeling.

Logic-based approaches are totally different from data-driven approaches in the way activities are modeled and the mechanisms activities are recognized. They do not require preexisting large-scale dataset, and activity modeling and recognition are semantically clear and elegant in computational reasoning. It is easy to incorporate domain knowledge and heuristics for activity models and data fusion. The weakness of logical approaches is their inability or inherent infeasibility to represent fuzziness and uncertainty, even though there are recent works trying to integrate fuzzy logics into the logical approaches. Another drawback is that logical activity models are viewed as one-size-fits-all, inflexible for adaption to different users' activity habits.

C. Ontology-Based Approach

Using ontologies for activity recognition is a recent endeavor and has gained growing interest. In the vision-based activity recognition community, researchers have realized that symbolic activity definitions based on manual specification of a set of rules suffer from limitations in their applicability, because the definitions are only deployable to the scenarios for which they have been designed. There is a need for a commonly agreed explicit representation of activity definitions or an ontology. Such ontological activity models are independent of algorithmic choices, thus facilitating portability, interoperability, and reuse and sharing of both underlying technologies and systems. Chen *et al.* [115] propose activity ontologies to analyze social interaction in nursing homes, Hakeem and Shah [116] for the classification of meeting videos, and Georis *et al.* [117] for activities in a bank monitoring setting. To consolidate these efforts and to build a common knowledge base of domain ontologies, a collaborative effort has been made to define ontologies for six major domains of video surveillance. This has led to a video event ontology [118] and the corresponding representation language [119]. For instance, Akdemir *et al.* [120] used the video event ontologies for activity recognition in both bank and car park monitoring scenarios. In principle, these studies use ontologies to provide common terms as building primitives for activity definitions. Activity recognition is performed using individually preferred algorithms, such as rule-based systems [116] and finite-state machines [120].

In the dense sensing-based activity recognition community, ontologies have been utilized to construct reliable activity models. Such models are able to match different object names with a term in an ontology that is related to a particular activity. For example, a mug sensor event could be substituted by a cup event in the activity model "MakeTea" as mug and cup can both be used for the "MakeTea" activity. This is particularly useful to address model incompleteness and multiple representations of terms. Tapia *et al.* [107] generate a large object ontology based on functional similarity between objects from WordNet, which can complete mined activity models from the web with similar objects. Yamada *et al.* [122] use ontologies to represent objects in an activity space. By exploiting semantic relationships between things, the reported approach can automatically detect possible activities even given a variety of object characteristics including multiple representation and variability. Similar to vision-based activity recognition, these studies mainly use ontologies to provide activity descriptors for activity definitions. Activity recognition can, then, be performed based on probabilistic and/or statistical reasoning [107], [122].

Ontology-based modeling and representation has been applied to general AAL. Latfi *et al.* [123] propose an ontological architecture of a telehealth-based smart home aiming at high-level intelligent applications for elderly persons suffering from loss of cognitive autonomy. Michael *et al.* [124] developed an ontology-centered design approach to create a reliable and scalable ambient middleware. Chen *et al.* [125] pioneered the notion of semantic smart homes in an attempt to leverage the full potential of semantic technologies in the entire lifecycle of assistive living, i.e., from data modeling, content generation, activity representation, processing techniques, and technologies to assist with the provision and deployment. While these endeavors, together with existing work in both vision- and dense sensing-based activity recognition, provide solid technical underpinnings for ontological data, object, sensor modeling, and representation, there is a gap between semantic descriptions of events/objects related to activities and semantic reasoning for activity recognition. Most works use ontologies either as mapping mechanisms for multiple terms of an object [107] or the categorization of terms [122] or a common conceptual template for data integration, interoperability, and reuse [123]–[125]. Activity ontologies that provide an explicit conceptualization of activities and their interrelationships have only recently emerged and have been used for activity recognition. Chen *et al.* [121], [126] proposed and developed an ontology-based approach to activity recognition. They constructed context and activity ontologies for explicit domain modeling. Sensor activations over a period of time are mapped to individual contextual information and, then, fused to build a context at any specific time point. They made use of subsumption reasoning to classify the constructed context based on the activity ontologies, thus inferring the ongoing activity. Ye *et al.* [127] developed an upper activity ontology that facilitates the capture of domain knowledge to link the meaning implicit in elementary information to higher level information that is of interest to applications. Riboni and Bettini [128] investigated the use of activity ontologies, in particular, the new feature of rule representation and rule-based reasoning from OWL2, to model, represent, and reason complex activities.

Compared with data-driven and mining-based approaches, ontology-based approaches offer several compelling features: First, ontological ADL models can capture and encode rich domain knowledge and heuristics in a machine understandable and processable way. This enables knowledge-based intelligent processing at a higher degree of automation. Second, DL-based

TABLE I
SUMMARY AND COMPARISON OF ACTIVITY RECOGNITION APPROACHES

	Knowledge-Driven Approaches (KDA)				Data-Driven Approaches (DDA)	
	Mining-based	Logic-based	Ontology-based		Generative	Discriminative
Model Type	HMM, DBN, SVM, CRF, NN	Logical formula, e.g., plans, lattices, event trees	HMM, DBN, SVM, CRF, NN	Sensor and Activity ontologies	Naïve Bayes, HMM, LDS, DBNs	NN, SVM, CRF Decision tree
Modeling Mechanism	Information retrieval and analysis	Formal knowledge modeling	(un)supervised learning from datasets	Ontological engineering	(un)supervised learning from datasets	(un)supervised learning from datasets
Activity Recognition Method	Generative or discriminative methods	Logical inference, e.g., deduction, induction	Generative or discriminative methods	Semantic reasoning, e.g., subsumption, consistency	Probabilistic classification	Similarity or rule based reasoning
Advantage	No "Cold Start" problem, Using multiple data sources	No "Cold Start" problem, clear semantics on modeling & inference	Shared terms, interoperability and reusability	No "Cold Start" problem, multiple models, clear semantics on modeling & inference, interoperability & reusability	Modeling uncertainty, temporal information	Modeling uncertainty, temporal information, Heuristics
Disadvantage	The same problems as DDA	Weak in handling uncertainty and scalability	The same problems as DDA	Weak in handling uncertainty and time	"Cold start" problems, Lack of reusability & scalability	"Cold start" Problems, Lack of reusability & scalability

descriptive reasoning along a time line can support incremental progressive activity recognition and assistance as an ADL unfolds. The two levels of abstraction in activity modeling, concepts and instances, also allow coarse-grained and fine-grained activity assistance. Third, as the ADL profile of an inhabitant is essentially a set of instances of ADL concepts, it provides an easy and flexible way to capture a user's activity preferences and styles, thus, facilitating personalized ADL assistance. Finally, the unified modeling, representation and reasoning for ADL modeling, recognition, and assistance, makes it natural and straightforward to support the integration and interoperability between contextual information and ADL recognition. This will support systematic coordinated system development by making use of seamless integration and synergy of a wide range of data and technologies. In the following sections, we use smart home-based AAL to further illustrate these concepts within the realms of ontological activity recognition.

Compared with logic-based approaches, ontology-based approaches have the same mechanisms for activity modeling and recognition. However, ontology-based approaches are supported by a solid technological infrastructure that has been developed in the semantic web and ontology-based knowledge engineering communities. Technologies, tools, and APIs are available to help carry out each task in the ontology-based approach, e.g., ontology editors for context and activity modeling, web ontology languages for activity representation, semantic repository technologies for large-scale semantic data management, and various reasoners for activity inference. This gives ontology-based approaches huge advantage in large-scale adoption, application development, and system prototyping.

VI. DISCUSSION ON ACTIVITY RECOGNITION

This section presents the comparison of different activity recognition approaches and further discusses the relations between activity recognition and other closely related areas. As activity recognition involves a number of research areas, and each area is itself a research topic with considerable literature. The full reviews of these related areas are beyond the scope of this paper.

A. Activity Recognition Approach Comparison

A complete comparison between different approaches in terms of a number of criteria is summarized in Table I. We have collected the experimental results of these surveyed approaches aiming to establish their performance profiles. Initial findings, which are in line with the findings from [132], have found out that the accuracy of different recognition approaches varies dramatically between datasets. The accuracy also varies between individual activities and is affected by the amount of available data, the quality of the labels that were provided for the data, the number of residents in the space that are interacting and performing activities in parallel, and the consistency of the activities themselves. It becomes apparent that the quantitative comparisons of different approaches will only make sense if the experiments are based on the same activities and sensor datasets. Otherwise, the findings may not be applicable to general cases, and even be misleading.

Cook [132] created a single benchmark dataset that contains 11 separate sensor event datasets collected from seven physical testbeds. Using this dataset, a systematic study has been conducted to compare the performance of three activity recognition models: a NBC, an HMM, and a CRF model. The result of recognition accuracy using threefold cross validation over the dataset is 74.87%, 75.05%, and 72.16% for the NBC, HMM, and CRF, respectively.

B. Activity Sensing and Activity Recognition

The outputs of activity sensing, i.e., sensor data, can affect activity recognition in several aspects. First, in a data-driven approach, the sensor type can often drive the selection of an appropriate model. Sensors can yield single or multidimensional data (e.g., an accelerometer would be multidimensional, whereas a temperature sensor would be unidimensional), and sensors can either give continuous or discrete measurements. The models need to be modified to fit whatever type of sensor data is being used. At the very least, the variable representing each sensor in a data-driven model must match the sensor type in dimensionality and arity. For example, Oliver *et al.* [99] use a variety of different sensor types, including audio time of arrival, continuous, and multidimensional computer vision measures, and a set of discrete event from mouse and keyboard, as inputs (observations) of a set of HMMs. Liao *et al.* [156] use continuous 2-D GPS data as input to a CRF. One solution to adapt activity models to sensor types is to include all available sensors in a discriminative or generative model, and allow the model itself to choose the most effective ones for any given situation. This is known as sensor selection or active sensing [133].

Second, the complexity of sensor data will determine to some extent the complexity of activity models. In data-driven approaches, sensor data can be directly fed into the activity models, either generative or discriminative, for model training and/or activity inference. Alternatively, sensor data can be preprocessed, e.g., to reduce the complexity of the data, before they are used in model training and activity inference. There is always a tradeoff between the complexity of the sensor data in the model, and the complexity of the model. As a general principle, the tradeoff is always about reducing the complexity of the model as much as possible without sacrificing representation that is necessary for activity recognition.

For knowledge-driven approaches, sensor data do not directly affect activity models and inference. This is because activity models in knowledge-driven approaches are prespecified based on domain knowledge rather than driven by sensor data. In addition, in knowledge-driven approaches, sensor data are always mapped through preprocessing to the values of properties of the formal activity models. As such, the types and complexity of sensor data will only affect the initial conceptualization of activity models and the complexity of preprocessing but not the model and inference mechanisms.

C. Activity Recognition and Applications

From an application perspective, activity recognition is seldom the final goal but usually one step of an application system. For example, in assistive living, activity recognition is used as input for decision-making support that attempts to detect and provide activity assistance. In security applications, activity recognition helps identify potential troublemakers, providing an input for the following investigation and decision-making processes. While it is beyond the scope of this paper to provide a thorough review on activity recognition applications, Table II summarizes the major application categories and some key application areas for reference.

TABLE II
APPLICATION CATEGORIES AND EXAMPLE AREAS

Application Categories	Example Application Areas
Security	Airport, train station, Banks, car park warning systems
Intelligent Environment	Smart homes, smart offices, meeting rooms, smart hospitals, smart cars, smart classrooms
Healthcare	Activity (physical) tracking, assistive living, well-being monitoring
Military	Soldier monitoring in the battlefield
Pervasive and Mobile Computing	Context-aware interface design, content delivery, mobile task assistance, energy efficiency

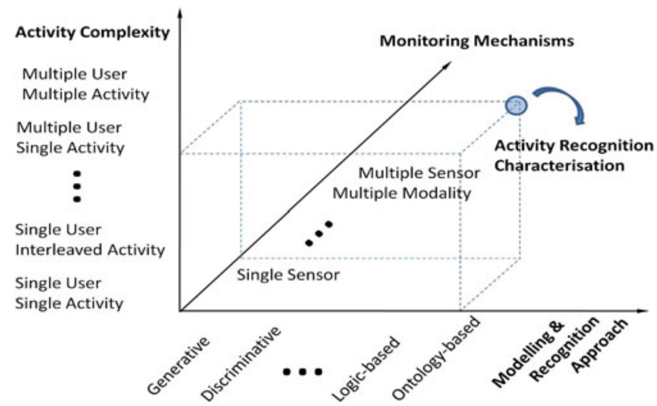

Fig. 1. 3-D characterization for activity recognition.

VII. EMERGING TRENDS AND DIRECTIONS

A. Complex Activity Recognition

Current work on activity recognition has mainly focused on simplified use scenarios involving single-user single-activity recognition. In real-world situations, human activities are often performed in complex manners. These include, for example, that a single actor performs interleaved and concurrent activities, multiple actors perform a cooperative activity, and/or a group of actors interact with each other to perform joint multiple activities. The approaches and algorithms described in previous sections cannot be applied directly to these application scenarios. As such, research focus on activity recognition has shifted toward this new dimension of investigation as depicted in Fig. 1. We present some early work in this direction as follows.

In the modeling and recognition of complex activities of a single user, Wu *et al.* [134] proposed an algorithm using factorial CRF (FCRF) to recognize multiple concurrent activities. This model can handle concurrency but cannot model interleaving activities and cannot be easily scaled up. Hu and Yang [135] proposed a two-level probabilistic and goal-correlation framework that deals with both concurrent and interleaving goals from observed activity sequences. They exploited skip-chain CRFs (SCCRFs) at the lower level to estimate the probabilities of whether each goal is being pursued given a newly observed activity. At the upper level, they used a learnt graph model of goals to infer goals in a "collective classification" manner. Modayil *et al.* [136] introduced interleaved HMMs to model both interactivity and intraactivity dynamics. To reduce the size of the state space, they used an approximation to recognize multitasked activities. Gu *et al.* [87] proposed an emerging pattern-based approach to sequential, interleaved and concurrent activity recognition. They exploit emerging patterns as powerful discriminators to differentiate activities. Different from other learning-based models built upon the training dataset for complex activities, they built activity models by mining a set of emerging patterns from the sequential activity trace only and applied these models in recognizing sequential, interleaved, and concurrent activities.

In the modeling and recognition of complex activities of group or multiple occupants, existing work has mainly focused on vision analysis techniques for activity recognition from video data. Various HMM models have been developed for modeling an individual person's behavior, interactions, and probabilistic data associations. These include the dynamically multilinked HMM model [137], the hierarchical HMM model [138], the coupled HMM [139], the mixed-memory Markov model [140], and the layered HMMs [99]. DBN models are also extensively used to model human interaction activities [141], [142], both using video cameras. Lian and Hsu [143] used FCRF to conduct inference and learning from patterns of multiple concurrent chatting activities based on audio streams. Work on using dense sensing for complex activity recognition is rare. Lin and Fu [144] proposed a layered model to learn multiple users' activity preferences based on sensor readings deployed in a home environment. Nevertheless, their focus is on learning of preference models of multiple users rather than on recognizing their activities. Wang *et al.* [145] used CHMMs to recognize multiuser activities from dense sensor readings in a smart home environment. They developed a multimodal sensing platform and presented a theoretical framework to recognize both single-user and multiuser activities. Singla *et al.* [146] proposed a single HMM model for two residents. The model can not only represent transitions between activities performed by one person, but also represent transitions between residents and transitions between different activities performed by different residents. As such, their probabilistic models of activities are able to recognize activities in complex situations where multiple residents are performing activities in parallel in the same environment. Hoey and Grzes [147] present a multilevel DBN model to provide assistance in multiple simultaneous tasks, where the recognition of activities is implicitly used to tailor assistance based on the recognized activities of the person.

While increasing attention has been drawn into this area, nevertheless, research in this niche field is still at its infancy. With the intensive interest in related areas, such as smart environments, pervasive computing, and novel applications, it is expected that research on activity recognition along this dimension will continue to receive attention and generate results in the next few years.

B. Multilevel Activity Modeling for Scalability and Reusability

Current approaches and algorithms for activity recognition are often carefully handcrafted to well-defined specific scenarios, both activities and the environment. Existing implemented proof-of-concept systems are mainly accomplished by plumbing and hardwiring the fragmented, disjointed, and often ad hoc technologies. This makes these solutions subject to environment layout, sensor types and installation, and specific activities and users. The solutions, thus, suffer from a lack of interoperability and scalability. The latest experiments performed by Biswas *et al.* [166] indicated that it is difficult to replicate and duplicate a solution in different environments even for the same, simplest single-user single-activity application scenario. This highlights the challenge to generalize approaches and algorithms of activity recognition to real-world use cases.

While it is not realistic to predefine one-size-fits-all activity models due to the number of activities and the variation of the way activities are performed, we believe multilevel activity modeling and corresponding inference mechanisms at different levels of details could address the problem of applicability and scalability. The basic idea is similar to the concepts of class and object in object oriented programming (OOP) in that an activity is modeled at both coarse-grained and fine-grained levels. The coarse-grained level activity models are generic like a class in OOP that can be used by any one in many application scenarios. The fine-grained activity models are user specific like an instance in OOP that can accommodate the preference and behavior habits of a particular user. As such, the models and associated recognition methods can be applied to a wide range of scenarios. Chen and Nugent [126] developed activity ontologies where concepts represent the course-grained activity models, while instances represent user activity profiles. Okeyo *et al.* [167] extended this idea by developing learning algorithms to automatically create fine-grained individual-specific activity models, as well as learn new activity models to evolve ontologies toward model completion. Initial results are promising and further work is needed along this line.

C. Abnormal Activity Recognition

Existing research on activity recognition focuses mainly on normal activities that may account for the majority of collected data and processing computation. Nevertheless, the results may contribute significantly less toward the purposes of activity recognition as most applications involving activity recognition intend to detect abnormal activities. This is a particularly important task in security monitoring where suspicious activities need to be dealt with and healthcare applications where assistances need to be provided for incapable users. While this view may generate cost-effective results, solving the problem is challenging. First, the concept of an abnormal activity has not been well defined and elaborated with a variety of interpretations available. For instance, everyone performs activity A; one person carries out activity B. There are different views on whether or not activity B is abnormal. Yin *et al.* [131] defined abnormal activities as events that occur rarely and have not been expected in advance. Second, there is an unbalanced data problem in abnormal activity detection. Much larger proportion of sensing data is about normal activity, while the data for abnormal ones are extremely scarce, which makes training the classification model quite difficult. Knowledge-driven approaches can certainly fit in. The problem is really about the completeness of priori domain knowledge. For example, is it possible to predict the behavior of a terrorist in advance or based on previous experience? Clearly, a raft of research problems and issues are open for further investigation.

D. Systematic View on Activity Recognition

Research on activity recognition has increasingly taken a systematic view, which takes into consideration seamless integration and reuse of activity modeling, representation, inference, and application-specific features. Some of the existing systems have integrated activity modeling with decision making using artificial intelligence techniques [158]. In data-driven approaches, the most successful of these are probably the decision theoretic models that extend the DBNs by adding utilities and actions. These models are known as Markov decision processes (MDPs) and their counterparts partially observable Markov decision processes (POMDPs). These models have been used for scheduling [161] and for assistance with a variety of ADL [160], [162]. POMDPs have also been integrated with high-level knowledge from psychological analyses to generate prompting system for tasks involving dense sensing [163]. In knowledge-driven approaches, ontologies have been used as a conceptual backbone for modeling and representation of sensors, context, and activities, ranging from context management, data integration, interoperation, and sharing, to activity recognition, decision-making support [123]–[126]. As technologies are adaptive toward real-world use cases and transformed into products, it is expected that the systematic view on activity recognition will get growing currency.

Domain knowledge plays a critical role when activity recognition is designed as a component of a complete system, e.g., as an input to support inference and decision making. A typical scenario is to use activity recognition for behavioral or functional assessment of adults in their everyday environments. This type of automated assessment also provides a mechanism to evaluate the effectiveness of alternative health interventions. For example, Patel *et al*. [168] used accelerometer sensor data to analyze and assess activities of patients with Parkinson's disease. They developed analysis metrics and compared the results with assessment criteria from domain experts to estimate the severity of symptoms and motor complications. This demonstrates that domain knowledge about activity profiling and assessment heuristics is valuable to provide automated health monitoring and assistance in an individual's everyday environment.

E. Intent or Goal Recognition

Current activity recognition and its application is roughly a bottom-up approach starting from the lowest sensor data, then discovering the activity and purposes of the user through increasing higher level processing. An emerging trend is to adopt a top-down approach to activity monitoring and recognition, namely, to 1) recognize or discover the intent or goal of a user, 2) identify the activity that can achieve the goal, 3) monitor the user's behavior including the performed actions, 4) decide whether or not the user is doing the right thing in terms of the activity model and the monitored behavior, and, finally, 5) provide personalized context-aware interactions or assistance whenever and wherever needed. Goals can be either explicitly manually specified, such as when a care provider defines goals for a patient to achieve during a day, or learnt based on domain context. Activities are predefined in some flexible way and linked to specific goals. As such, once a goal is specified or identified, applications can instruct/remind users to perform the corresponding activity.

While research on cognitive computation, goal modeling, and representation of motivations, goals, intention, belief, and emotion, has been undertaken widely in AI communities, in particular, within intelligent agent research, the adoption of the knowledge and research results in pervasive computing and smart environments and their applications have so far received little attention [169]. Nevertheless, interest is growing and a recent SAGAware has been organized [170], aiming to facilitate knowledge transfer and synergy, bridge gaps between different research communities/groups, lay down foundation for common purposes, and help identify opportunities and challenges.

F. Infrastructure-Mediated Monitoring

Current practice of installing a large number of sensors and an extensive sensing infrastructure in an environment, e.g., residential homes, has been widely viewed problematic in real-world scenarios. A recent trend for activity monitoring is to leverage a home's existing infrastructure to "reach into the home" with a small set of strategically placed sensors [129]. The residential infrastructure is usually referred to existing water pipes, electrical circuits, meters, heating or venting passages, or facilities within a home. The basic idea is to capture parameter or state changes of an infrastructure from which activities can be monitored and further recognized. Infrastructure-mediated activity monitoring requires selecting appropriate sensors and designing elaborate methods to combine the sensors with the existing infrastructure. Patel and Abowd [130] detected human movement by differential air pressure sensing in HVAC system ductwork. Fogarty *et al*. [129] deploy a small number of low-cost sensors at critical locations in a home's existing water distribution infrastructure. The authors infer activities in the home based on water usage patterns. Infrastructure-mediated activity monitoring is a very promising direction for activity monitoring and recognition, and certainly worth further exploration.

G. Sensor Data Reuse and Repurposing

Currently, sensor data generated from activity monitoring, in particular, in the situations of using multimodal sensors and different types of sensors, are primitive and heterogeneous in format and storage, and separated from each other in both structure and semantics. Such datasets are usually ad hoc, lack of descriptions, thus difficult for exchange, sharing, and reuse. To address these problems, researchers have made use of priori domain knowledge to develop high-level formal data models. Nugent and Finlay [164] proposed a standard extensible markup language schema HomeML for smart home data modeling and exchange; Chen and Nugent [165] proposed context ontologies to provide high-level descriptive sensor data models and related technologies for semantic sensor data management aiming to facilitate semantic data fusion, sharing, and intelligent processing.

We believe that knowledge rich data modeling and standardization supported by relevant communities is a promising direction toward a commonly accepted framework for sensor data modeling, sharing, and repurposing. This idea is also in line with the infrastructure-mediated monitoring, namely deploy once, and reuse for all.

VIII. Conclusion

Activity recognition has become the determinant to the success of the new wave of context-aware personalized applications in a number of emerging computing areas, e.g., pervasive computing and smart environments. Synergistic research in various scientific disciplines, e.g., computer vision, artificial intelligence, sensor networks, and wireless communications, has resulted in a diversity of approaches and methods to address this issue. In this paper, we have presented a survey of the state-of-the-art research on sensor-based activity recognition. We first introduced the rationale, methodology, history, and evolution of the approach. Then, we reviewed the primary approaches and methods in the fields of activity monitoring, modeling, and recognition, respectively. In particular, we identified key characteristics for each individual field and further derived a classification structure to facilitate systematic analysis of the surveyed work. We have conducted in-depth analysis and comparisons of different methods in each category in terms of their robustness to real-world conditions and real-time performance, e.g., applicability, scalability, and reusability. The analysis has led to some valuable insights for activity modeling and recognition.

In addition to the extensive review, we have discussed emerging research trends associated with activity recognition. One primary direction is complex activity recognition focusing on the underlying modeling, representation, and inference of interleaved, concurrent, and parallel activities. The other key direction is to improve reusability, scalability, and applicability of existing approaches. Research in this direction has been undertaken in several strands, including multilevel activity modeling, abnormal activity recognition, infrastructure-mediated monitoring, and sensor data reuse and repurposing. Another noticeable trend is the research on formal activity representation at a higher level of abstraction, e.g., developing dedicated activity representation languages and representing situations and goals. These emerging efforts provide guidance and indication for the future research of activity recognition.

Many research questions have not been touched due to the limited space. For example, we did not elaborate in-depth low-level specific technical issues such as uncertainty, temporal reasoning, and sensor data inconsistency. We believe that the emerged structure of classification of activity recognition approaches and the comparison of their pros and cons can inform and help interested readers for further exploration.

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