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CURRENT TRENDS IN COMPLEX HUMAN ACTIVITY RECOGNITION

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ABSTRACT

Recognition of human activities is a challenging task due to human's tendency to perform activities not only in a simple way, but also in a complex and multitasking way. Many research attempts address the recognition of simple activities, but little work targets the recognition of complex activities. Currently research on complex activity recognition using sensors is growing in many application domains. This paper provides an analysis of the most prominent complex sensor-based activity recognition. We analyze the structure and working methodology of the existing complex activities recognition systems, discuss their strengths and weaknesses. In addition, we evaluate existing proposals from three different perspectives including overall system evaluation, performance evaluation, and dataset evaluation.

Keywords: *Complex Human Activities Recognition, Conditional Random Field, Hidden Markov Model, Bayesian Network, Random Forest, Context Modeling, Semantic Reasoning*

1. INTRODUCTION

Recent years witnessed an explosive growth in the field of pervasive computing [1]. This growth was the result of the rapid development of microelectronics that allows sensors and mobile devices with massive features such as small size, and low cost. As a result, multiple levels of people can deploy sensor and mobile devices in their daily lives.

One of the promising research themes in pervasive computing is activity recognition. Activity recognition refers to monitoring the user and their environment using computing devices and infers a user's activities from user-triggered events. Four basic steps can describe this. Initially, appropriate sensors are attached to objects/users and environments to monitor user behavior within the environment. Then the perceived information is collected, stored, and processed using the appropriate representation and analysis techniques. After that, a suitable activity recognition model will be developed to allow reasoning and manipulation. Finally, a reasoning algorithm is developed to allow users to derive activities based on received data [2]. These tasks can be summarized in three main steps: activity monitoring, modeling, and recognition, respectively.

The increasing interest in Human Activity Recognition (HAR) research stems from the wide range of applications that it can serve, such as medical, military to security applications. Medical applications gain a lot of interest and contain a variety of subsequent applications that include, healthcare monitoring and diagnosis, child and eldercare, and rehabilitation. For instance, physical activity routines like walking, running or cycling are required as a part of treatment for patients suffering from diabetes, cardiovascular disease, insomnia or obesity. Todays, sports and gaming applications are growing faster because of their flexibility in accuracy and privacy than medical applications. For example recognition of the cricket batting strokes using sequences of body and bat postures [3]. Microsoft Kinect [4] is one of the famous interactive games for activity recognition, reflecting the physical movement in a virtual character. Leisure and entertainment applications are also considered to increase the quality of life e.g. home and office automation [5], [6]. Security, surveillance, and military applications are considered the most critical. For example, soldiers activities as well as other conditions such as their locations, health status, and safety, are very important [7].

Humans perform activities at different levels of granularity, so the term 'activity' must be clarified. An activity can be classified into three main classes: atomic, simple, and composite/complex. An atomic activity refers to any indivisible activity such as holding a cup. A simple activity is an ordered sequence of atomics within a given time interval, like making tea. A collection of two or more simple activities that occur within a given time interval, is considered a complex activity. Complex activities can be executed sequentially or in parallel (i.e. concurrent and interleaved) as illustrated in Figure 1. Concurrent activity is a collection of simple activities occurring simultaneously. For example, a user can drink coffee while reading a book. Interleaved activity is a collection of simple activities switching between their atomic activities. For example, while cooking dinner in the kitchen, a user may go to the living room to answer a phone call and come back to resume the dinner. The most common human activities that could be recognized are classified into seven groups: ambulation, transportation, phone usage, daily activities, exercise, military, and upper body activities [7].

The problem of activity recognition can be viewed from three dimensions; the complexity of the activity, the monitoring mechanisms, and the modeling and recognition approaches as shown in Figure 2. For the complexity of the activity, most of the existing work on activity recognition focuses on the simplified scenarios involving the recognition of single activity performed by a single. However, in real world human performs activities in complex scenarios. Monitoring mechanisms have also increased from vision-based methods to single/multi sensor monitoring methods as explained in section 2.1. Finally, modeling and recognition approaches (e.g. data-driven, knowledge-driven, or hybrid) applied for simple scenarios cannot be applied directly to complex application scenarios.

Although the work on HAR-based on sensors has started decades ago, the number of research attempts in sensor-based HAR is not enough compared to vision-based HAR. In addition, these attempts focused on the problem of recognizing the individual activity of a single user [8]–[22]. Given the increase in HAR applications and considering the nature of humans to perform complex activities in random (i.e. interleaved and concurrent) scenarios, a systematic review with an in-depth comprehensive overview on the recent work accomplished in the field of complex HAR will be of high scientific value.

This paper provides a systematic analysis with an in-depth comprehensive overview on the recent work accomplished in the field of complex HAR. In this paper, we will track the lifecycle of the HAR process (e.g. monitoring, modeling, and recognition) with a focus on comparing various modeling and recognition approaches and methods and highlighting the strengths and weaknesses of these methods. In addition, these previous attempts will be evaluated from three different aspects: overall system comparison, performance evaluation, and dataset comparison.

In this paper, section 2 presents an overview of the activity recognition process and identifies its main steps. Next, in section 3, we review the baseline modeling and inference techniques of complex activities, specifying their main structure and working methodology, and summarizing their strengths and weaknesses. In section 4, we discuss the most obvious challenges to the problem of complex human activity recognition. Finally, section 5 evaluates the models analyzed based on a set of pre-defined aspects of evaluation.

2. GENERAL STRUCTURE OF HUMAN ACTIVITY RECOGNITION PROCESS

From machine learning perspective, activity recognition is a pattern classification problem that requires the following standard stages: (i) data acquisition and preprocessing, (ii) data segmentation, (iii) feature extraction and selection, and (v) learning/inference. For activity recognition, these stages are organized in two main stages: (i) activity monitoring; and (ii) modeling and recognition, of the activity as shown in Figure 3. In general, the process works as follows. Initially, datasets are acquired from individuals performing activities. the Dataset is divided into a specific time windows to extract relevant/core information through the feature extraction. Subsequently, machine-learning techniques are used to create an activity model. A quick overview of theses stages is presented in the following subsections.

2.1 Activity Monitoring

Activity monitoring is concerned with collecting data from sensing devices attached to users or objects in the surrounding environment. For observable sources of activity monitoring, activity recognition can be classified into two

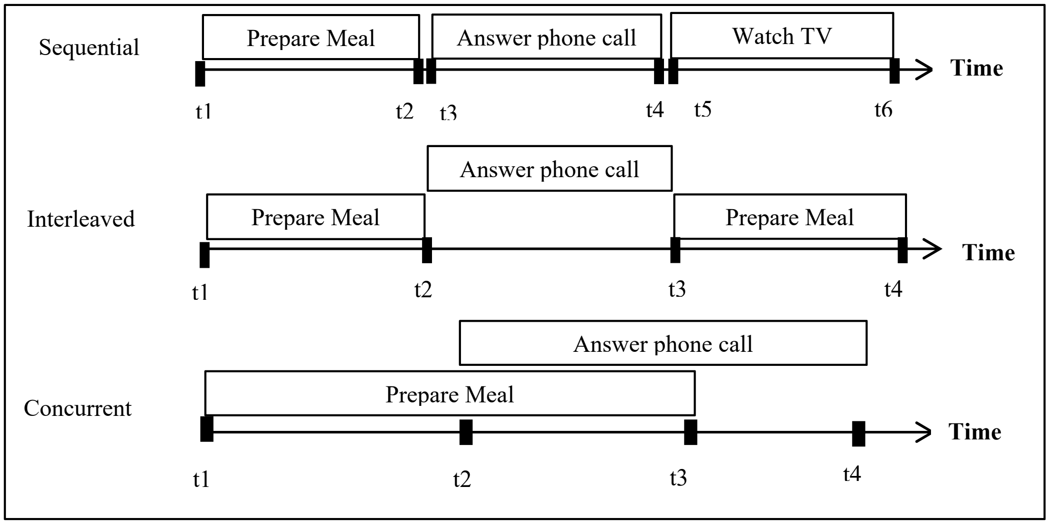

Figure 1: Examples of Sequential, Interleaved, and Concurrent Activity Execution.

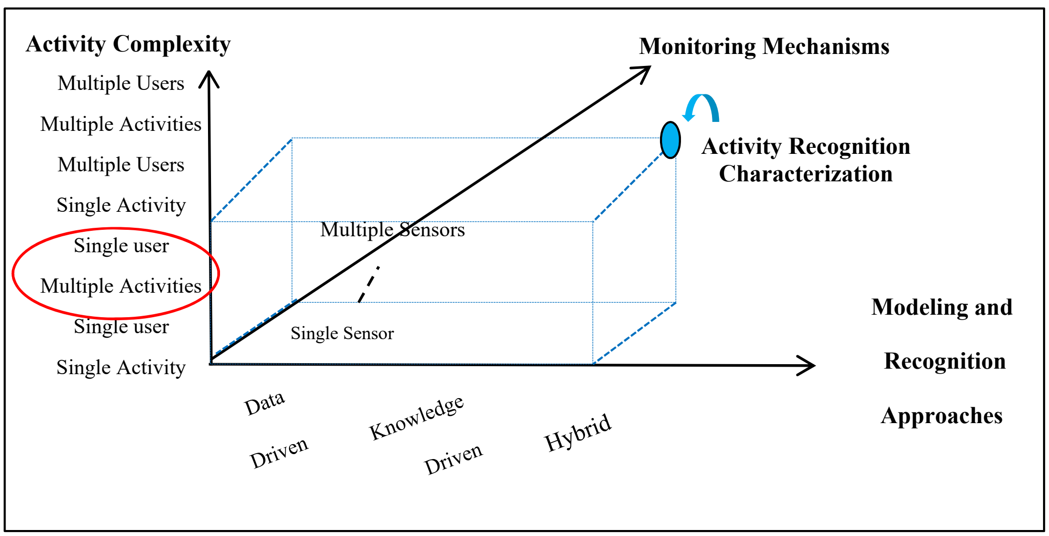

Figure 2: Three Dimensional Characterization for Activity Recognition [2]

main categories: vision-based activity recognition and sensor-based activity recognition. The first category is considered the vanguard in this area of research. Where the sensing devices are fixed at predetermined points of interest to obtain activities resulting from a direct interaction of the users with such devices. Cameras are considered the most common external sensors for activity recognition.

Therefore, sensed data are video sequences that require computer vision techniques (e.g. feature extraction and selection, modeling, segmentation etc.) Although it has a broad research interest, vision-based activity recognition faces some limitations such as privacy, pervasiveness, and complexity [7]. Intelligent homes are typical examples of external sensors [23]–[25]. They are able to recognize different levels of human activities (i.e. simple or complex) by retrieving data from the sensors attached to the target objects with which people interact. However, nothing can be done if the user is outside the range covered by the sensors or perform activities that do not require interaction with the target objects.

The limitations of vision-based activity recognition and the growth in pervasive computing motivate the research direction toward sensor-based activity recognition. In sensor-based activity recognition, sensors are attached to the user/environment. These sensors measures the user movement (e.g. accelerometer or GPS), the environment variables (e.g. temperature and humidity), or the physiological signals (e.g. heart rate and inspiration rate) [7]. The generated sensor data takes the form of time series of various parameter values or environment changes [2].

For sensor-based HAR, the wide range of available sensors can be classified with respect to the method they are employed in activity monitoring applications into two categories: wearable sensors and environmental sensors [2]. Wearable sensors are sensors attached to human body whether directly or indirectly to give signals when the user performs activities. The most common types of wearable sensors are acceleration and physiological sensors [7]. Wearable sensors suffer from some limitations such as obtrusiveness and continuous operation. A complete review of the latest human activity monitoring systems based on wearable sensors can be found in [26]. Environmental sensors are sensors/tags deployed in surroundings to monitor activities through object-use interaction. Such environmental sensors monitor humans' behavior through temperature, humidity, audio, etc. then provide the context information about an individual's surroundings, so they are usually used in addition to other wearable sensors.

For pervasive and mobile computing, wearable sensors are more suitable, while environmental sensors suits the applications of intelligent/smart environments/homes. However, both types can work together in some applications. The activity monitoring stage begin with two main steps: (i) data acquisition and preprocessing, (ii) data segmentation as briefly presented below.

2.1.1 Data acquisition and preprocessing

There is no standard data acquisition process for HAR; the process depends on the application scenario. However, the authors in [7] presented an architecture for the data acquisition process for HAR systems. First, raw data is collected using a number of wearable sensors and sensors installed in the environment. An integration device (e.g. cell phone, a PDA, a laptop) preprocesses the collected sensor data and forwards the processed data to an application server using a suitable communication protocol (e.g. TCP/IP or UDP/IP). All these steps are not necessarily employed in every HAR system.

2.1.2 Data segmentation

For HAR, smart places would be equipped with sensing devices that would generate continuous data streams that should be segmented for two reasons. First, human activities are performed for a relatively long time compared to the sensor sampling rate, so classifying activities using continuous data streams is a difficult task. Second, the training stage of the classification process requires the maintenance of a training dataset for specific activity streams identified by the corresponding labels. Therefore, it is difficult to retrieve important and useful information from continuous stream of sensor data. The role of data segmentation is to identify specific segments of continuous data streams that contain information about activities to be classified.

Several methods were proposed to address the problem of sensor data segmentation. The most notable are segmentation based on sliding window, segmentation based on energy, and the contextual segmentation. In segmentation based on sliding window, a time window is moved over the data series to extract data segments. The size of the window could be static or dynamic with a fixed number of events that affects the accuracy [27]–[30]. However, the nature of human is to perform activities with different lengths, not as machines, so not all the instances of an activity have the same duration or the same number of events with other activities. Energy-based segmentation is based on the fact that different activities are carried out at different intensities (i.e. energy levels of sensing devices). Therefore, sensor data could be segmented by thresholds in its energy levels [31]. In the segmentation based on contextual sensors, the data of specific sensors are segmented using information derived from other placed sensors [32] or from the surrounding context information, such as location [33]–[35]. However, heavy preprocessing is required, depending on the location.

2.2 Activity Modeling and Recognition

We have seen that in order to obtain a continuous time series of sensor readings, we pass through activity monitoring; in which data acquisition and segmentation are accomplished. Then in activity modeling, the segmented raw data pass through feature extraction and selection to obtain a dataset of extracted features required for building the activity model. In the next subsections sections, the most noticeable remarks on feature extraction, selection and learning methods will be presented.

2.2.1 Feature extraction and selection

This stage reduces incoming data segments into a number of discriminative features for the captured activities. Feature extraction finds the main characteristics of a data segment that accurately represent the original data. The extracted feature vector is then fed as input to classification algorithms instead of the full data segment.

Features can be extracted from time series data using either statistical method or structural method. The statistical feature extraction method extracts features based on the quantitative characteristics of the sensed data. The most common statistical feature extraction methods are the Fourier transform and the Wavelet transform [7]. The structural methods are used for data which contain an inherent, identifiable organization such as image and time-series data [36]. The nature of the sensed signal decides which of these feature extraction methods to choose.

The features extracted from the processed data set may contain superfluous or irrelevant information that negatively affects the recognition accuracy and increases its computation complexity. Feature selection methods select the significant features and remove the superfluous ones. For HAR, the most prominent feature selection methods are Minimum Redundancy and Maximum Relevance (MRMR) [37], and Correlation-based Feature Selection (CFS) [38].

A detailed discussion about various feature extraction and selection techniques with examples are out the scope of this paper and previously covered in [7].

2.2.2 Activity learning methods

In this section, existing modeling and recognition approaches for HAR are classified into three prominent approaches that includes; data-driven (bottom-up), knowledge-driven (top-down), or hybrid approaches. For each approach, the methodology, strengths, weaknesses, and implementation techniques will be introduced.

In data-driven HAR; HAR systems has three options; use machine learning tools, use data mining techniques, or use a time series based classification. In a machine-learning context, pre-existing datasets are used to construct an activity model using machine-learning techniques, and then inference of activity is done on obtained sensor data using previously learned activity models. On the other hand, data mining techniques extract a set of discriminative patterns for each class of activity from a set of given examples or observations. New observations are recognized by computing the likelihood between these observations and discriminative patterns. In time-series based classification [39], [40], a sequence of discrete events forms an activity, and activities are identified by searching for a match between defined subsequences called "Motifs" with similar behavior appearing frequently in time series data. However, this approach is sensitive to the order of the events [41].

The advantages of the data-driven approaches are their ability to deal with uncertainty using well-established machine learning techniques, and the use of temporal information to capture short-term and long-term temporal dependencies [42]. However, the data-driven methods require large amounts of datasets to learn the activity models that lead to the data scarcity or the "cold start" problem. Data-driven approaches also lack reusability and applicability problems due to human nature in performing activities in different ways as a result, an activity model for one user does not match others [2].

For knowledge-driven HAR, knowledge engineers and domain experts specify activity models by capturing domain knowledge about activities, and then the inference of activities could be done using artificial intelligence-based reasoning techniques. This approach gains the benefits of being semantically clear, logically elegant to capture of the semantics of the domain clearly and support automatic reasoning. In addition, it is easy to capture and model domain structure and heuristics, and defined knowledge models could be reused and shared between applications. However, knowledge-driven HAR systems require a priori knowledge that is difficult to find the most optimal model of the activities and sensor data. Moreover, these models lack uncertainty and total dependence on the expertise of experts [2], [43].

A combination of data-driven and knowledge-driven techniques forms hybrid activity recognition approaches. This combination has the ability to solve activity recognition problems by combining contextual information with probabilistic machine learning models. However, large datasets are still needed to train the activity models.

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The taxonomy of recent approaches for modeling and recognition of complex HAR is illustrated in Figure 4.

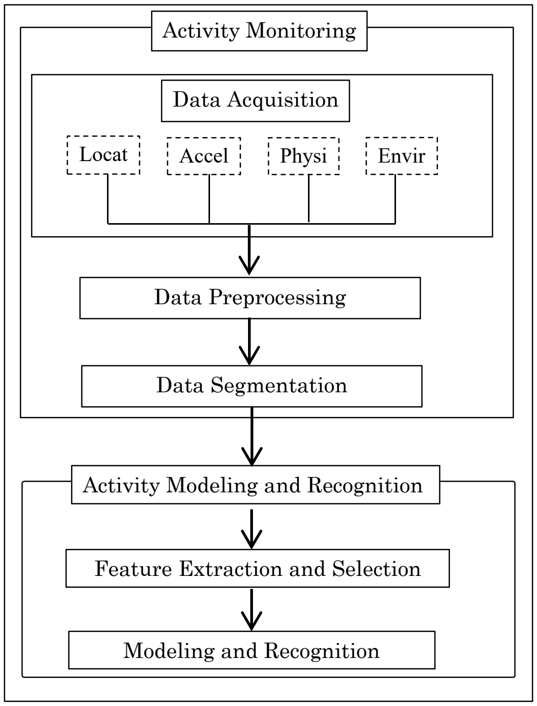

Figure 3: General Stages of Human Activity Recognition Process

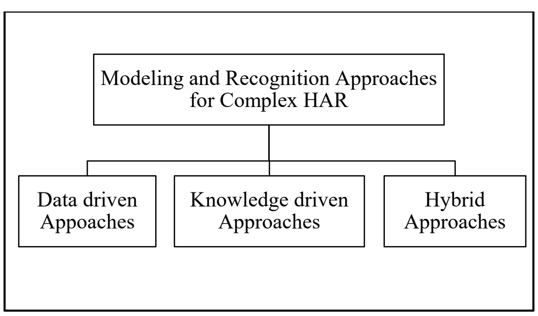

Figure 4: Modeling and Recognition Approaches for Complex HAR

3. EXISTING APPROACHES FOR MODELING AND RECOGNITION OF COMPLEX HUMAN ACTIVITIES

In this section, we will review current research attempts for complex HAR using data-driven, knowledge-driven, and hybrid approaches. In the following subsections, existing HAR models for each approach are briefly analyzed according to their structure and working methodology. In addition, their strengths and weaknesses are also summarized.

3.1 Data-driven Approaches for Modeling and Recognition of Complex Human Activities

In this section, we investigate the common data-driven approaches to complex HAR.

3.1.1 Conditional random fields for complex HAR

Conditional Random Fields (CRF) are structured prediction models combining the advantages of both discriminative (i.e. describing how to take a feature vector x and assign it a label y) and graphical models. An analysis of the current attempts for complex HAR using various versions of CRFs is given below.

In [44] the authors designed a two-level probabilistic model for recognizing concurrent and interleaving activities. At the lower level, interleaved activities are modeled using Skip Chain Conditional Random Fields (SCCRFs). At the higher level; a correlation graph was used to model concurrent activities. Given a newly observed activity, the lower level estimates the probabilities of whether each activity is pursued. Then the computed probabilities are adjusted by minimizing a loss function using Quadratic Programming. This in turn derives more accurate probability of activities and takes into consideration the correlation between activities computed at the upper level.

The authors in [45] presented an activity recognition system for both concurrent and interleaved activities similar to the other HAR proposed in [44]. The only difference between them is that the recognition accuracy of the later depends on the granularity of activities corresponding to the level of activity taxonomy they defined rather than types of sensors employed.

In [46], the authors presented an activity recognition system capable of recognizing concurrent activities using Factorial Conditional Random Fields (FCRFs). This was accomplished using the co-temporal relations between activities in the same time slice besides temporal relations between activities across time slices. Initially, the model is designed to contain a set of hidden random variables and observed random variables. Then, the model involves two processes: learning and inference. The learning process uses the training data and the maximum likelihood parameter estimation to compute required parameters. The inference process is responsible for two tasks: computing the marginal probability of each node pair required at learning and performing Maximum Aprior inference to infer the most possible sequence of activities states.

3.1.2 Hidden markov model for complex HAR

Hidden Markov Model **(**HMM) is a probabilistic model that consists of hidden and observable variables at each time step [47]. When HMM is used in activity recognition, activities are the hidden states and sensor data are the observable outputs.

The authors in [48] investigated the problem of recognizing interleaved activities in smart homes. A number of techniques was evaluated and compared on the basis of the CASAS dataset [8] as; Naïve Bayes classifier, a HMM, a HMM with a time window, a frequency-based HMM with a sliding window and a frequency-based HMM with a shifting window. Naïve Bayes classifiers result in poor accuracy due to ignoring the transition probabilities between activities. The HMM represents each activity as a hidden state and each sensor is considered an observable state. The HMM has produced greater accuracy, but suffers from moving slowly from recognizing one activity to the next.

Sliding window-based HMM was implemented in order to reduce the history of sensor events required for the model to remember, and thus increase the speed. It used a sliding window whose size is governed by the number of sensor events it contains. This technique provided a greater accuracy, but did not detect activities with fewer sensor events. A frequency-based sliding window HMM (FSHMM) labels the sensor event with the most frequent activity in the specified window instead of labeling each sensor event with an activity label. However, this concept of frequency slows the transition from one activity to the other at the time of transition, because the previous activity always has a higher frequency leading to inaccurately labeling the new sensor event and thereby degrading the performance of the algorithm.

[49] proposed a recognition system for multitasked/complex human activities. This system employed a modified interleaved HMM (IHMM) which predicts transition probabilities more efficiently by recording the last object observed in each activity. It also employed a beam search of state space instead of searching full state space at each time step. As a result, this model gains the benefits of HMM for activity recognition and avoids its drawbacks in requiring large number of activities and large state space.

3.1.3 Bayesian network for complex HAR

[50] designed a recognition system for both sequential and interleaved activities. This model used Bayesian Network (BN) for Activity inference, and employed contextual information from both human and the environment, and other reliability factors. The system follows a multiple-layered hierarchical architecture for activity recognition. Firstly, data from multi-modal sensors are collected. Secondly, various features are extracted from collected sensor data. These features are then fused, evaluated and sorted according to their importance. Finally, the selected and sorted features are passed to the enhanced Naïve Bayes for inference.

3.1.4 Data mining for complex HAR

In [51], [52] the authors proposed a pattern mining approach to recognize sequential and complex activities. At the training phase, for each activity, the dataset is mined for the most discriminative features (i.e. patterns) among other activities. Then, in the test phase, the likelihood is calculated between incoming sensor observation and previously computed patterns to obtain its activity label. The novelty of their approach comes from two aspects: the ability to recognize sequential, interleaved and concurrent activities from dataset containing sequential activities only, and the automatic adjustment of sliding time window during execution.

In [53], another recent emerging pattern-based approach was proposed that convert the problem of complex activity recognition into multiple simple activity recognition problems. Then, a dynamic segmentation algorithm segments the incoming stream of sensor observations into simple activity segments based on sensor and time dependency. For each segment, a combination of Random Forest (RF) and Emerging Patterns (EP) assigns the correct activity label.

3.1.5 Time series-based complex HAR

In [54], the authors solve the problem of complex activity recognition using time series analysis. The authors constructed a dictionary of specific time series patterns representing atomic activities, called "shaplets". A complex activity is composed of a set of atomic activities that can be concatenated producing sequential activity, or overlapped producing an interleaved/concurrent activity. Searching the learned dictionary enables recognizing complex activities from sensed data.

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The authors employ a set of rules describing the formations of sequential and complex activities.

Table 1 presents a summary of the strengths and weaknesses of the reviewed data-driven complex HARs. Probabilistic methods (i.e. CRFs, HMM, BN) are based on the strict assumption that sensor data are independent. Therefore, they do not have the ability to characterize the internal relationship among raw sensor data streams. In addition, these models (i.e. CRFs, HMM, DBN) suffer from reusability of their structures for new classes of activity. Furthermore, CRFs fails to recognize interleaved whereas HMM and BN fails to recognize concurrent activity. So these models lose flexibility in recognizing multiple levels of activities [54]. The data-mining and time-series based methods recognize both concurrent and interleaved activities. The data-mining based method presents greater flexibility, requiring the initial training dataset only for simple and sequential activities.

3.2 Knowledge-Driven Approaches for Modeling and Recognition of Complex Human Activities

For recognition of interleaved and concurrent activities, existing knowledge-based approaches are classified into semantic reasoning-based or context-based complex HAR. A brief analysis of these approaches is presented in the following subsections.

3.2.1 Semantic reasoning for complex HAR

The use of semantic reasoning helps to create a generic activity recognition mechanism that can be easily implemented across multiple application domains. This could be implemented using ontology constructs that facilitate the sharing of knowledge between different application domains [55]. Next, we review the most recent work on complex HAR based on semantic reasoning.

In [42], the authors use a generic model for composite activities using three basic elements: ontological activity models, temporal activity models, and entailment rules. Ontological activity models establish relationships between activities and the entities involved. Temporal activity models define relationships between consistent activities of composite activity. The entailment rules support interpretation and inference of composite activities written in Semantic Web Rule Language.

[56] designed a generic unsupervised approach of recognizing multiuser concurrent activities. The novelty of their approach is the ability to automatically segment real time sensor data into semantically meaningful parts corresponding to concurrent activities. Using a two-level hierarchy, activity segmentation and recognition were accomplished. Real time sensor traces are segmented using pre-computed ontologies and similarities. These ontologies model the semantics of activities (e.g. object, location, and sensor) and the similarity between sensors events were computed using Wu's Conceptual Similarity Measure. Then, the recognition of every segment is inferred using a modified Pyramid Match Kernel capable of matching sensor events to ontological activity representation.

In [55], modeling of activities use a combination of ontology constructs of activity, time, and location. This combination provides a general representation of the knowledge of activities. Activity inference was implemented through a hierarchical five layer architecture, in which the inference process depends on the existing level as described below: sensor layer, atomic activity inference layer, complex activity inference layer, ontology layer, and the application layer. Sensor layer contains all available sensors to provide data for subsequent layer. The atomic activity inference layer was designed to infer atomic activities using machine learning techniques and temporal weighted voting mechanisms. The complex activity inference layer performs the reasoning on complex activities by calculating and adding the weights of the atomic activities corresponding to the complex activity, and then locates a match using a predefined threshold. The ontology layer provides definitions, relationships, properties, and rules for different activity classes, location, and time. The interaction with different applications in different domains could be done through the application layer.

3.2.2 Context-based complex HAR

Context can be defined as any information that describes a situation, a scenario of a person or an object. Therefore, context usage (e.g. location of user or light on/off) in activity recognition helps to improve recognition accuracy and reduce computational complexity. The most prominent activity recognition based on context is presented below.

The authors in [57], [58] presented a Situation and Context-Aware Activity Recognition system (SACAAR) to infer concurrent and interleaved complex activities.

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Their proposed system requires no training and minimal annotation during the setup stage.

Table 1: Strengths and Weaknesses of Data- driven Approaches for the recognition of Complex Human Activities.

HAR	Ref.	Strengths	Weaknesses
Condition-al Random Fields	[44]	▪ It gains the advantage of modeling uncertainty. ▪ Requires low computational complexity than Factorial CRFs. ▪ More scalable than Factorial CRFs.	▪ Low detection accuracy. ▪ Enables offline recognition ▪ Ignore the effect of negative and complex correlations in the correlation graph.
	[45]	▪ It gains the advantage of modeling uncertainty. ▪ Recognition accuracy depends only on the granularity of activities not types of sensors employed.	▪ Automatic construction of activity hierarchy instead of by hand. ▪ Employing a fixed size sliding window rather than dynamic one.
	[46]	▪ FCRFs utilize a structure of distributed states to avoid the exponential complexity problem. ▪ Ability to recognize both sequential and concurrent activities using the co-temporal and temporal relationships among activities.	▪ Unable to recognize interleaved activities. ▪ Enables offline recognition.
Hidden Markov Model	[48]	▪ Ability to recognize interleaved activities.	▪ Low recognition accuracy by Naïve Bayes ▪ Slow recognition speed using HMM. ▪ Static size sliding window in SHMM. ▪ Unable to recognize concurrent activity.
	[49]	▪ Increased recognition accuracy for interleaved activities than traditional HMM.	▪ Recognition accuracy depends on obtaining large data set which is difficult. ▪ Unable to recognize concurrent activities.
Bayes Network	[50]	▪ Robustness using reliability factors to avoid fusing failed sensors. ▪ Unobtrusive of wearable sensors.	▪ Unable to recognize concurrent activities.
Data Mining	[51], [52]	▪ Ability to recognize sequential, interleaved and concurrent activities in a unified framework. ▪ Noise tolerant. ▪ Dynamic adjustment of sliding window during execution. ▪ Acceptable computational complexity.	▪ Data collection should be in a more natural than done in a mock scenario. ▪ The coefficients of score function should be obtained from training dataset through statistical learning methods rather than through experiments.
	[53]	▪ Ability to recognize multiple numbers of interwoven activities. ▪ Dynamic sensor data segmentation	▪ Increased time and computational complexity ▪ Low recognition accuracy.
Time series	[54]	▪ Ability to recognize sequential, interleaved and concurrent activities in a unified framework. ▪ Enables the implementation of fast, reusable, and accurate classification using shaplets.	▪ The labeling stage uses a set of predefined rules depending on expert knowledge. ▪ Increased time complexity required for searching the shaplets dictionary.

Initially, Context Driven Activity Theory (CDAT) was used to model atomic and complex activities. This is accomplished using two layers: the sensory layer, and inference layer of the activity. The sensory layer is responsible for collecting the sensors data and context information (e.g. spatial and temporal information). The activity inference layer was divided into three main components: the inference of atomic activity, the spatio-temporal context complexity filter, and the inference of complex activity. Inference of atomic activity uses traditional inference techniques for each type of sensor (e.g. decision trees for motion

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sensors, weighted voting sliding window mechanism to infer RFID object use). The second component infers activity situations using context information from sensory layer and creates linkages between activities. For complex activity inference, they used the proposed inference algorithm in addition to a combination of atomic activities, situations, and activity linkages.

In [59], the authors used the theory of context-driven activity (CDAT) and activity signatures for the recognition of complex activity. They follow the same steps for activity inference that is proposed in [57], but activity modeling was optimized by identifying signatures for each composite activity. In activity modeling, the model first defines atomic activities, complex activities, and contextual information using CDAT. Then, signatures for complex activities are computed using Markov Chain probab1ilistic models. Finally, CDAT are updated using the computed activity signatures and weights. The inference of complex activity use the updated CDAT and defined situations to concentrate on complex activities related to given situation besides signature concentrated atomic activities.

In [60], activity modeling uses a combination of ontological and temporal knowledge modeling formalisms. The activity inference uses ontological reasoning (e.g. instance retrieval or subsumption, and equivalence reasoning) for the recognition of simple activity, and a rule-based temporal inference method for the recognition of composite activity. As a knowledge driven approach, it depends on three knowledge bases coded as: static activity model, dynamic activity model, and context-driven model. Static activity model includes definitions of predefined composite activities, while the dynamic activity model represents qualitative temporal relationships between activities, and context-driven model includes the rules for inferring qualitative temporal relationships. The activity inference involves three consecutive stages: the atomic activity inference and fusion, the simple activity inference, and the composite activity inference. The atomic activity inference and fusion converts the obtained data segment into atomics by checking the static ontology model. These atomics are then grouped to form an activity description. The simple activity inference infers simple activities by mapping incoming activity descriptions to the static activity model. The composite activity inference checks both the dynamic activity and context models to infer relationships between simple activities and infers the complex activity.

In Table 2, we present a summary of the most notable strengths and weaknesses of the reviewed complex knowledge-driven HAR systems.

3.3 Hybrid Approaches for Modeling And Recognition of Complex Human Activities

The hybrid approach for complex HAR comes with the least number of research attempts. Existing models make a combination of knowledge-driven and data-driven techniques to gain advantage of each other and avoid their weaknesses. The following models encode and use temporal knowledge, and require a dataset for extracting some relevant temporal patterns as presented below.

In [61], [62],the authors applied a statistical relational framework for the recognition of composite activities. They use Markov Logic Network (MLN) to incorporate commonsense background knowledge to model qualitative temporal relationships. The authors modified the MLN to incorporate quantitative and qualitative temporal relationships. This modification was done by modeling background knowledge using both hard logical statements and soft uncertain evidence within a unified syntax and semantics.

The authors in [63] used the hidden Markov model (HMM) as a probabilistic data-driven technique to reduce the noise and uncertainty limitations of HAR. However, this technique could not cope well with interleaved activities and could not detect small variations in the human behavior. So, the Allen's temporal relations were combined with HMM to solve these problems. Their proposed model works as follows: first, the input sensor streams were segmented and classified automatically using a set of trained HMM. Then, the qualitative temporal relationships between the identified behaviors were computed using Allen's interval-based temporal calculus. Finally, these relations were used to reason about relationships between the behaviors that HMM cannot directly recognize.

The strengths and weaknesses of the hybrid systems for HAR are presented in Table 3.

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Table 2: Strengths and Weaknesses of Knowledge-Driven Approaches for the Recognition of Complex Human Activities

HAR	Ref.	Strengths	Weaknesses
Semantic Reasoning-based	[42]	▪ Developed a unified activity recognition framework for simple and composite activity recognition.	▪ Insufficient accuracy for composite activity recognition.
	[56]	▪ Online activity segmentation and recognition. ▪ Modeling activities using ontologies and inference using semantic matching results in generality, low engineering effort, and no requirement for training data.	▪ Limited ability in distinguishing coarsely constrained activities from similar but more finely constrained activities. ▪ Unable to recognize sequential and interleaved activities. ▪ Sensor data segmentation algorithm is concentrated on specific type of sensors e.g. RFID or motion sensors.
	[55]	▪ Ability to recognize all types of activities. ▪ Modeling activity, spatial, and temporal ontologies provides a general knowledge representation model to be shared across various application domains and enhancing inference.	▪ Increased response time for offline activity recognition that is expected to increase in on-line recognition by adding network delay to its execution time.
Context-Based	[57], [58]	▪ Flexibility in linking new activities to existing situations during run time. ▪ Eliminate inference of complex activities not involved in current situation.	▪ Increased computational complexity required for multiple atomic activities inference techniques. ▪ Dependency on expert experience in computing atomic activities weights.
	[59]	▪ Increased detection accuracy with reduced time and dataset. ▪ Reduce the amount of sensor information required for complex activity inference by updating CDAT with activity signature and using situation in inference.	▪ Increased computational complexity required for multiple atomic activities inference techniques. ▪ CDAT and Application dependent; collecting specific sensor data whose definitions exist in CDAT definitions.
	[60]	▪ Ability to dynamically update ontology models for newly recognized complex activities. ▪ Automatic updates of sliding window-based segmentation using feedbacks from activity recognition stage.	▪ Increased computational complexity required at distributed stages of activity recognition

Table 3: Strengths and Weaknesses of Hybrid Approaches for the Recognition of Complex Human Activities

Ref.	Strengths	Weaknesses
[61], [62]	▪ Accurately recognize composite activities through combination of statistical and relational features. ▪ Flexibility of Markov Logic by ability to integrate and evaluate more temporal relationships without redeveloping a novel model each time.	▪ Dependency on expert experience rather than automatic extraction of richer background knowledge. ▪ Insufficient evaluation using data set obtained from one type of sensors (e.g. RFID)
[63]	▪ Increase detection accuracy of interleaved activities by combining some temporal reasoning technique with traditional HMM.	▪ Unable to recognize concurrent activities.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4. CHALLENGES FOR SENSOR-BASED RECOGNITION OF COMPLEX HUMAN ACTIVITIES

Although sensor-based HAR started decades ago, there are still several challenges. In this section, we introduce the challenges facing sensor-based HAR. These challenges can be categorized according to sensor deployment, human behavior, or domain-specific challenges as presented below.

4.1 Challenges Related to Sensor Deployment

Challenges related to sensor deployment include: sensor placement, sensor obstruction, sensor inaccuracy, sensor failure, and the resource constraints. For sensor placement, sensors should be placed in precise positions that provide the best results and reduce the risk of failure or damage during human movement.

Regarding sensor obstruction, the HAR system should not be obtrusive to require the user to wear much more sensors. Sensor inaccuracy is another challenge that results from the wireless communication medium and the surrounding environment. Moreover, sensor failure may result from battery exhaustion or inappropriate human interaction and could be eliminated using surrounding context information in addition. Finally, the resource constraints, such as memory and battery, are considered the most common challenges in all fields exhibiting sensing devices.

4.2 Challenges Related to Human Behavior

For challenges related to human behavior, there exist: the nature of the human behavior, and the human privacy. The nature of the human is performing activities in different cultures and in a random scenario (i.e. simple or complex). This natural behavior results in difficulty in activity specification, collection, and recognition. For the human privacy, sensitive user information should be obtained without invading users' private life, and should be transmitted and stored in a secured manner.

4.3 Challenges Related to Application Domain

The most obvious challenges related to the application domain include: the availability of HAR datasets, data collection, and the system flexibility. With respect to the availability of HAR datasets, there is no specific benchmarking data set for HAR due to the diversity of HAR application areas. Therefore each research group creates its own dataset focusing on specific activity set, as a result, there are few publically available datasets [64]. Data collection must be completed under realistic conditions, not in a mock scenario. For the system flexibility, a HAR system should be application independent not specified for a specific application, and flexible enough to support new users without the need to re-train the system.

5. EVALUATION OF COMPLEX HUMAN ACTIVITY RECOGNITION SYSTEMS

As reviewed in the previous sections, several methods have been proposed to solve the complex HAR problem. This section provides an evaluation of the previously discussed complex HAR systems. From the above mentioned challenges to the complex HAR problem. To carry out this evaluation, a serious of evaluation metrics will be defined. Initially, this evaluation will be approached from three different aspects: overall system comparison, performance evaluation, and dataset comparison. Each of these aspects is evaluated using a set of pre-defined evaluation metrics as described in the following subsections.

5.1 Overall System Comparison

We compare the studied HAR systems with regards to specific evaluation metrics [65], which includes: type of system execution, generalization, recognition process, activity observation format, and system model flexibility, as listed in Table 4.

The decision of whether the activity recognition system satisfies these characteristics depends mainly on the application. However, an optimum complex HAR system should achieve the following characteristics. First, the execution should be online, especially for healthcare (e.g. elder care) applications. Second, user-independent HAR should increase flexibility and reusability of the system. Third, the recognition process should obtain a continuous stream of the sensor and automatically identify the atomic activities using an efficient data segmentation technique. Fourth, the system should be able to handle periodic and sporadic activities. Finally, a stateful HAR system should increase robustness and tolerance.

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Table 4: Metrics for Overall System Comparison [65]

Type	Characteristics	Description
Execution	Online	The system acquires and processes sensor data in real time.
	Offline	The system firstly records the sensor data, and then recognition is performed afterwards.
Generalization	User-independent	The system is optimized for working with a large number of users.
	User specific	The system is customized to a specific user.
	Temporal	The system should be robust to temporal variations caused by external conditions (sensor displacement, drifting sensor response)
Recognition	Continuous	The system automatically “spots” the occurrence of activities or gestures in the streaming sensor data.
	Segmented	The system assumes that the sensor data stream is segmented at the start and end of a gesture
Activities	Periodic	Activities exhibiting periodicity, such as walking, running
	Sporadic	The activity occurs sporadically, interspersed with other activities
System model	Static	The system deals with the detection of static postures or static pointing gestures.
	Stateless	The recognition system does not model the state of the world. Activities are recognized by spotting specific sensor signals.
	Stateful	The system uses a model of the environment, such as the user’s context or an environment map with location of objects.

Table 5: Overall Systems Comparison of Complex HAR Systems

Ref.	Execution		Generalization		Recognition		Activities		System Model		
	On-line	Off-line	User-specific	User-independent	Segmented	Continuous	Sporadic	Periodic	Static	Stateless	Stateful
[42]	√			√	√		√				√
[56]	√		√		√		√				√
[55]		√		√		√	√				√
[57]	√		√		√		√				√
[60]	√		√		√		√				√
[59]			√		√		√				√
[44]		√		√		√		√		√	
[46]		√		√		√	√			√	
[45]		√		√		√	√			√	
[48]		√	√		√	√	√			√	
[49]		√		√		√	√			√	
[50]	√		√			√	√				√
[52]	√		√		√		√			√	
[53]	√			√		√	√				√
[54]	√			√		√	√			√	
[61]	√		√			√		√			√
[63]		√	√			√	√			√	

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The overall system comparison of the analyzed complex HAR systems analyzed according to previously defined comparison metrics (Table 4) is summarized in Table 5.

From this comparison, several issues could be observed according to the taxonomy of HAR into Data-Driven, Knowledge-Driven, and Hybrid. Data-driven systems provide flexible HAR that is independent of the user and deals with continuous input data stream, thus avoiding the complexity required for data segmentation algorithms. With respect to the sequence of activity execution, both data-driven and knowledge-driven systems are capable of handling periodic and sporadic activities. On the other hand, knowledge-driven HAR surpasses the data-driven HAR to provide online detection and provide robust and stateful systems that use context information. Hybrid HAR (i.e. data-driven and knowledge-driven) combines the strengths of being on-line, sporadic, stateful, and handling continuous data stream, but requires building user-specific HAR systems.

5.2 Performance Evaluation

In this section, existing complex HAR systems are compared according to their performance. The performance evaluation of the HAR system generally follows the same evaluation metrics as a pattern recognition problem. The results of any pattern recognition can be used to calculate a series of evaluation values called True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These values can be used to compute standard evaluation metrics such as accuracy, precision, recall, and f-measure, as illustrated in [7]. The recognition accuracy of the studied complex HAR depends mainly on two important factors: the recognition algorithm, and the dataset used.

Therefore, existing HAR systems are compared according to one of the standard performance evaluation metrics (i.e. accuracy) in addition to the dataset used. In Table 6, the experimental results (i.e. accuracy) of these reviewed systems are introduced as reported by their authors. Each has its own dataset, environment, application scenario, and evaluation metrics.

In Table 7, we noticed that the accuracy of data-driven systems exceeds that of knowledge-driven systems because they are based on well-developed machine learning models. However, most knowledge-driven systems are able to recognize simple and complex (i.e. interleaved and concurrent) activities, while data-driven systems have a better identification of specific types of complex activities.

5.3 Dataset Comparison

Datasets are considered one of the most critical challenges to the HAR problem. There are some publically available datasets for the single user/single activity HAR and few for single user/complex activities. Datasets play an important role in the recognition accuracy and must meet a set of design principles. These principles can be obtained by comparing the used datasets mentioned in Table 7 according to a set of pre-defined metrics, as shown in Table 8.

These metrics include: Type of activities performed (e.g. Activities of Daily Life (ADL)), type of activity execution (e.g. Sequential(S), Interleaved (I), or Concurrent(C)), existence of pre-defined data collection rules, number of activities performed, number of participants in data collection, and sensors used. An optimal dataset should be able to recognize a variety of human activities and collect sequential and complex activities, and the sensors should not be obtrusive to humans. In addition, data should be collected according to pre-defined rules, not randomly, and using a sufficient number of participants, which increases the variations in the performance of the activity. From the comparison presented in Table 8 , there are two types of datasets: paper-specific datasets [12], [42], [49], [50], [52], [54], [55], [57], [59], [60], [66], and publically available datasets [8], [67], [68]. Most of the complex HAR systems analyzed in this reserarch used their own datasets, while some used publically available datasets. The scarcity of publically available complex HAR datasets is considered a challenging issue, prompting researchers to construct their own specific datasets. In addition, data collection should be accomplished on the basis of pre-defined collection rules not in a mock scenario achieved in only five datasets [8], [49], [50], [59], [67].

Regarding the dataset for human activity recognition, it should be collected based on a set of criteria's that include [70]: (i) Volunteers with various characteristics (e.g. type, age, height, weight, health conditions). (ii) Data collection at various seasons, weather conditions, time, and location. (iii) Predefined rules for data collection not done in a mock scenario. (v) A fully documented dataset that describe the whole process of data collection process, such as, the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

sensors used (i.e. their positions, number and type), participants (gender, age, height, weight, and health conditions), and rules of data collection.

Table 6: Notations used in Table 7, Table8

Notation	Abbreviation	Notation	Abbreviation
S	Sequential Activity	EOA	Execution of Activities
I	Interleaved Activity	CR	Collection Rules
C	Concurrent Activity	NAC	Number of Activity Classes
TOA	Type of Activities (e.g. ADL, sport)	NOP	Number of Participants

Table 7: Performance Evaluation of Complex Human Activity Recognition Systems

Ref.	Overall Accuracy			Dataset
	S	I	C	
[42]	100%	88.26%	88.26%	Paper specific dataset using simulator [42]
[56]	82%	N/A	95%	CASAS "Interleaved ADL" [8]
[55]	95.15%	94.35%	94.35%	Paper specific dataset [55]
[57]	N/A	88.5%	88.5%	Paper specific dataset [57]
[60]	100%	88.26%	88.26%	Paper specific dataset using simulator [60]
[59]	N/A	95.73%	95.73%	Paper specific dataset [59]
[44]	94%	95.3%	95.3%	Chai & Yang 2005 [66]
	N/A	92%	N/A	Patterson et al. 2005 [12]
	N/A	86%	86%	MIT Place Lab dataset (*PLIA1* dataset) [67]
[46]	N/A	N/A	Recall 48.2% Precision 51.5%	MIT House_n data set [67]
[45]	N/A	94.8%	94.8%	Chai & Yang 2005 [66]
	N/A	96%	96%	MIT Place Lab data set [46], [67] (*PLIA1* dataset)
[48]	N/A	NBCs 66.08%, HMM71% SHMM63.55%, FSHMM56.75%	N/A	CASAS dataset [8]
[49]	N/A	97.1%	N/A	Patterson et al. 2005 [12]
	N/A	100%	N/A	Paper specific Dataset [49]
[50]	N/A	92.5%	92.5%	Paper specific dataset [50]
[52]	90.96%	88.10%	82.53%	Paper specific dataset [52]
[53]	98.15 %	~66%		CASAS dataset [8]
[54]	96.54%	N/A	N/A	UCI Repository [68]
	N/A	~ 95%		The Opportunity Dataset [69]
	N/A	77.78 %		Paper specific basketball play dataset [54]
[61]	N/A	N/A	84%	Patterson et al. 2005 [12]
[63]	N/A	N/A	N/A	N/A

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 8: Comparison of Datasets for Complex Human Activity Recognition

Data Set	TOA	EOA	CR	NAC	NP	Sensors used
Paper specific dataset [42]	ADL	S,I,C	N/A	7	N/A	N/A Using Simulator
Paper specific dataset [55]	Selected ADL	S,I,C	No	10	2	Accelerometer, RFID, GPS, Wi-Fi sensors and software based context collection tools
Paper specific dataset [57]	Selected ADL	S,I,C	No	16	2	Accelerometer, RFID, GPS, WLAN, heart rate monitor, and Virtual sensors
Paper specific dataset [60]	Selected ADL	S,I,C	N/A	7	N/A	N/A Using simulator
Paper specific dataset [59]	Selected ADL	S,I,C	Yes	16	2	Accelerometer, RFID, GPS, WLAN, heart rate monitor, and Virtual sensors
Paper specific dataset [49]	Selected activities	S,I	Yes	3	1	RFID
Paper specific dataset [50]	Selected ADL	S,I,C	Yes	12	11	Current flow, floor, switch, mercury, pressure, accelerometer, motion, vibration, RFID, and camera
Paper specific dataset [52]	Selected ADL	S,I,C	No	26	4	Accelerometer, temperature, humidity, light level , and RFID sensors
Paper specific dataset [54]	Basketball play actions	S	No	8	4	Accelerometer, gyroscope and magnetometer
CASAS dataset [8]	Selected ADL	S,I,C	Yes	8	20	Motion, temperature, humidity, contact switches on doors, item sensors, and special purpose sensors
Chai & Yang 2005 [66]	Professor activities.	S,I,C	No	9	1	Wi-Fi
Patterson et al. 2005 [12]	Morning activities	I	No	11	4	RFID and two gloves built by Intel Research Seattle
MIT Place Lab [67]	Selected ADL	S,I,C	Yes	6	1	Accelerometers , switch, current, light, location, movement, humidity, pressure, and water/gas flow
UCI Repository [68]	Daily and sports activities	S	No	18	8	Accelerometer, gyroscope and magnetometer
The Opportunity Dataset [69]	Selected ADL	S,C	No	5	4	72 sensors of 10 different modalities simultaneously deployed either in objects or on the body

6. CONCLUSION AND FUTURE WORK

In this paper, we analyze the most outstanding complex HAR systems for single user environment. A three-level taxonomy has been introduced that organizes methods of recognizing complex human activities in data-driven, knowledge-driven, or hybrid. Little work has addressed the problem of complex activity recognition using sensors, and no attempt has done to analyze or compare existing work. Therefore, this work is considered the first attempt to review the most prominent complex HAR systems by analyzing its structure, methodology of work, and its main strengths and weaknesses.

These systems were evaluated and compared based on three aspects related to the overall system comparison, performance evaluation, and dataset comparison. The former compared them using predefined evaluation characteristics; while the latter compared them according to the performance accuracy calculated in their papers, and the datasets are compared using a set of pre-defined metrics. Finally, from each aspect, we investigate a set of design principles that should be addressed in future research on the complex HAR using sensors.

To conclude, the decision to use a data-driven, knowledge-driven or hybrid approach to

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complex HAR, depends mainly on the scenario and conditions of the application. The variation in accuracy between different recognition approaches depending on many factors: available datasets, amount of available data, the number of dataset residents, and the consistency of the activities themselves. Therefore, for a clear evaluation and comparison, quantitative comparisons of different recognition approaches based on a unified environment (i.e. the same activities and sensor datasets) are required. In addition, attention should be paid to advanced complexity of activity (i.e. complex activity in multiuser environment).

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