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SARF: Smart Activity Recognition Framework in Ambient Assisted Living

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Abstract—**Human activity recognition in Ambient Assisted Living (AAL) is an important application in health care systems and allows us to track regular activities or even predict these activities in order to monitor healthcare and find changes in patterns and lifestyles. A review of the literature reveals various approaches to discovering and recognizing human activities. The presence of a vast number of activity recognition issues and approaches has made it difficult to make adequate comparisons and accurate assessment. Introducing the five basic components of activity recognition in the smart homes as a famous environment to remote monitoring of patients and independent living for elderly, the present paper proposes SARF framework to classify each of activity recognition approaches and then it is evaluated based on the proposed classification by some proposed measures. Using SARF proposed framework can play an effective role in selecting the appropriate method for human activity recognition in smart homes and beneficial in analysis and evaluation of different methods for various challenges in this field.**

I. Introduction

In recent years automatic human activity recognition has received considerable attention due to the growing demand in many applications such as healthcare systems for monitoring the Activities of Daily Living (ADL) in smart homes, especially due to the rapid growth of elderly population, in surveillance and security environments to automatic detection of abnormal activities to alert the relevant authorities about the potential criminal or terrorist behavior, in activity-aware services to convert ideas like smart meeting rooms, home automation, personal digital assistants from science fiction to everyday fact and in entertainment environments to improve human interaction with computers [1][2][3].

Due to the many uses of activity recognition in smart homes and the availability of various approaches in this field, comparison and accurate evaluation of existing methods is difficult. Therefore, providing an account of these activity recognition approaches seems to be essential. The main contribution of this paper, after briefly introducing five basic components of human activity recognition in smart homes, is proposing SARF framework to classify different methods in this field. Then, this framework is analyzed in terms of approaches, their characteristics, challenges and also proposed measures.

The remainder of this paper is organized as follows: In Section II, basic definition for human activity recognition and its capabilities in healthcare systems will be introduced. In Section III, the overall structure of human activity recognition process in smart homes will be described in form of five basic components. In Section IV is represented the proposed SARF framework according to various activity recognition approaches and in Section V the proposed classification based on proposed measures will be evaluated.

II. Human Activity Recognition in Ambient Assisted Living

Nowadays learning and understanding the observed activity [2][4] and event mining [5][6] are central to many fields of studies. The activities of an individual affect him/her, the people around him/her, society and environment [1]. Activities refer to complex behaviors consisting of a sequence of actions and/or overlapped and interwoven actions that can be performed by a single individual or several individuals interacting with each other [1][4]. Activity recognition in healthcare systems considered as a way to facilitate the work of healthcare in order to treat and care for patients, reduce the workload of medical staff, decrease hospital stays for patients, reduce costs and improve the quality of life for people who need care [1][2]. Medical experts believe one of the best ways to identify and explore emerging medical conditions is to monitor changes in daily activities, before these conditions become serious [7].

Recently human-activity discovery [8], recognition [9], prediction [10], and abnormalities detection [11], have attracted great interest because of their high potential in context-aware computing systems such as smart environments. Activity recognition in smart homes has made it possible to track occurrences of regular activities in order to monitor healthcare and find changes in activity patterns and lifestyles, so can be a great help in providing automation, security and most importantly remote health monitoring for elderly or people with disabilities [7][8].

Thus, in recent years activity recognition has become one of the application areas in healthcare systems such as AAL and is leading important research activities including CareLab, CASAS, Gator-Tech, HIS, Aware Home, SELF, iDorm, MavHom [12].

In this study, a comprehensive classification and evaluation of human activity recognition techniques in smart homes as an AAL system is introduced which tries to cover all existing approaches.

III. Basic Components in Human Activity Recognition Process

The process of human activity recognition follows five steps including Sensing, Preprocessing, Feature Extraction, Feature Selection and Activity Learning Techniques [1][13]. Fig. 1 represents basic components of human activity recognition. Note that, depending on environmental conditions, the types of sensors used and the type of data collected, some of these steps may not be needed. Each of these steps will investigate in the following sections.

A. Sensing

In the first step sensing is performed by the sensors and the data are collected in a database [4]. In fact, this step is responsible for collecting sensor data from smart home environment [13]. The data is sent as a signal to perform preprocessing. Signals contain information about the object which is observed and measured [1] and can be numeric, time, multimedia or even quality signals.

In order to monitor human activities in smart homes wide variety of sensors have been used and there are different perspectives to sensors classification. The sensor classification from two general perspectives is also shown in Fig. 1.

The discrete sensors including Passive Infra-Red (PIR), Contact Switch Sensors (CSS) and Radio-Frequency Identification (RFID) have binary output. Due to simplicity and unobtrusiveness nature of captured data from detected objects or residents states, they are very popular. Opposite side of discrete sensors are continuous sensors including Physiological, Ambient and Multimedia sensors with simple or complex data streams such as real numbers, images or voices [1][3][14].

In one point of view, sensors are wearable or environmental. The wearable sensors including Inertial (e.g. Accelerometers and Gyroscopes) and Vital Signs sensors (e.g. Bio-sensors) [3]. Individuals use wearable sensors to generate more information about posture, motion, location and people interaction [15]. Environmental sensors are used to capture data about smart home environment such as temperature, humidity, light, pressure, noise, and etc. [14]. They are not customized for a single resident; therefore, they can be used to group activity monitoring but they cannot discriminate between residents motions or actions [1]. The example of gathered sensor data which has a binary output shown in Fig. 2 generated by the CASAS data collection system automatically.

B. Preprocessing

The aim of preprocessing is to reveal information on signal, noise reduction and to remove excess information [3]. Cleaning, completing and normalizing data are the basic tasks in preprocessing including particle filters, median filters, kalman filter, low-pass filter and discrete wavelet package shrinkage and etc. to noise reduction. Also, linear and nearest neighbour and cubic interpolation using to fill in the missing values [3][16]. Because of the continuous flow of sensor-based information, it should be divided into segments to be easily recognizable by a trained classifier [3][17].

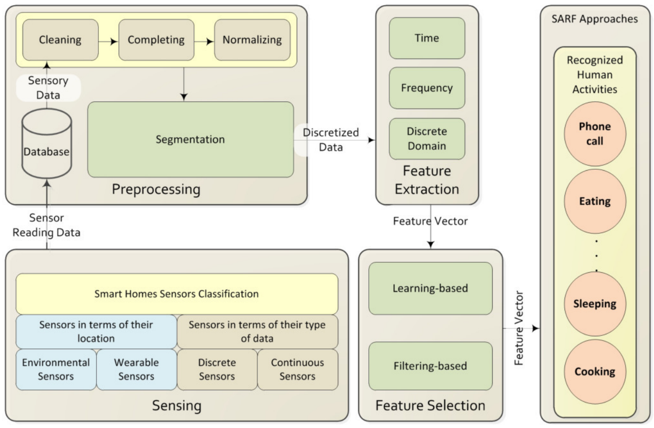

Fig. 1. Basic components of activity recognition process

Various approaches can be used to address segmentation of sensor events for activity recognition such as Change Point Detection (CPD), Time Slice based Windowing (TSW) and Sensor Event based Windowing (SEW) [1][17]. The CPD is an unsupervised segmentation and the idea is to find sudden changes in time series and recognize similar activity borders in real time [1]. The TSW is segment readings provided by inertial sensors and widely used in physical activity recognition. The SEW contains the same number of sensor events and segments the streaming data into sub-sequences [17]. Fig. 3 represents the schema of TSWs and SEWs segmentation.

In some cases (i.e. using supervised learning) at this step data annotation is done [13]. Accurate annotation of activities is important for performance evaluation of recognition models [9]. Annotation methods are divided in to two categories: Offline and Online methods. In Table I characteristics of different approaches in data annotation are represented. The output of this step as discretized data will be sent to Feature extraction step.

C. Feature Extraction

At this step the discretized data is considered as input and the feature vector as output. The purpose of this step is to select and maintain features that contribute to activity recognition. Depending on the kind of data, this step can vary [11]. The most commonly used approaches in this area

2009-10-16	08:43:59.000024	M008	ON	Watch TV begin
2009-10-16	08:44:00.000043	M026	ON	
2009-10-16	08:44:01.000095	M026	OFF	
2009-10-16	08:44:02.000079	M008	OFF	
2009-10-16	08:44:13.000093	M026	ON	
2009-10-16	08:44:17.000043	M026	OFF	
2009-10-16	08:44:24	M026	ON	
2009-10-16	08:44:26.000088	M008	ON	
2009-10-16	08:44:28.000077	M026	OFF	
2009-10-16	08:44:29.000026	M008	OFF	Watch TV end

Fig. 2. Raw data from discrete sensors

TABLE I
COMPARISON OF DIFFERENT ANNOTATION APPROACHES

Annotation Approach		Description	Advantages	Disadvantages
Off-line	Minimum Intervention	Inferences are done by using cameras, video data or recorded voices.	High Accuracy No need to user annotation	Time consuming and computationally expensive Based on resident tracking before data analysis Lack of scalability in resident and activity increasing Lack of privacy preserving
	Indirect Observation	Utilizing self-inference and sensor activation visualization by location, time and sensor location. Annotation has been done by residents and supervisors or just residents. Then these annotated data will store in a database.	High Accuracy No need to user annotation	Time consuming and computationally expensive Based on resident tracking before data analysis Lack of scalability in resident and activity increasing Lack of privacy preserving
Online	Experience Sampling	Utilizing self-report such as record activity information on paper or PDAs. This method is based on periodic alarm in resident environment to do annotation.	Reduce errors Fast Easy to use Better in convergence	Make one-sided or unrealistic data Make interruptions in residents activities Useless in a smart homes with elderly residents with dementia disease
	Direct Observation	In this method supervisor determine specific activities which have to be done by residents so the right activity label even before performing activities are clear.	Accurate annotation	Time consuming
	Time Diary	Use topic models such as LDA in order to provide brief description from activities in data, automatically.	Specify brief description of the activities in data, automatically No need to user annotation	Need to large volume of data Word order does not matter

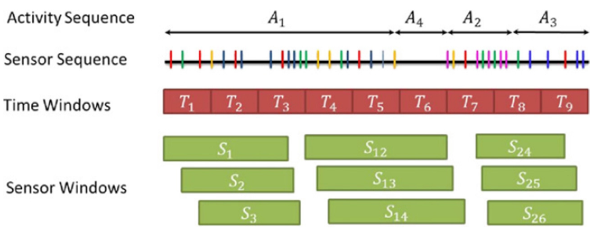

Fig. 3. Illustration of TSW and SEW approaches in Preprocessing step [18]

operate in three fields: time (e.g. Mean, Median, and Standard Deviation etc.), frequency (e.g. Wavelet Transformation and Fourier Transform) and discrete domain (e.g. Euclidean-based Distances and Dynamic Time Warping etc.) [3][15].

Actually, there is no general rule for feature extraction and it depends on the type of problem, our understanding of the problem etc. Thus, it can be done in different ways by different characteristics consideration.

Generally, sensor data features can classify into four groups: Features describing characteristics of the sensor event sequence, Features describing characteristics of discrete sensor values, Features describing characteristics of continuous sensor values, and Activity context [1].

D. Feature Selection

The purpose of this phase is to increase the accuracy of the resulting model by selecting more discriminative features. Also, to provide more robust model, reducing the dimensionality of feature vector and removing features with noise or features with irrelevant information are effective.

It should be noted, additional features will increase computational complexity and classification errors [3][13][19]. There are different approaches to feature selection in human activity recognition approaches including Learning-based and Filtering-based methods.

The Learning-based methods such as Simulated Annealing, Best First Search [1], or Genetic Algorithms [19]interact with the classifier to optimize the feature subset but makes classifier selection become an important process [19]. The idea behind the Learning-based methods is shown in Fig. 4. In the Filtering-based methods such as Minimum Redundancy-Maximum Relevance, the basic idea is not using features which are highly correlated among themselves [13]. Information Gain based on entropy ranks and weights each feature based on its ability to separate the activity instances of different classes [20]. Also Principle Component Analysis [21]

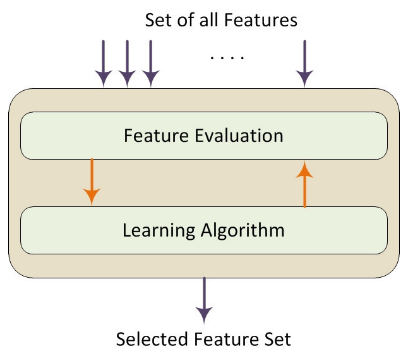

Fig. 4. The Learning-based approach to feature subset selection

TABLE II
COMPARISON OF DIFFERENT FEATURE SELECTION APPROACHES

Feature Selection Approaches	Method Example	Advantages	Disadvantages
Filtering-based Methods	Minimum Redundancy-Maximum Relevance, Information Gain based on Entropy, Principle Component Analysis	Fast Scalable Acceptable computational complexity Independent from classifier	No interaction with classifier Ignore effect of selected feature on classifier Ignore correlation between features Lack of appropriate criteria to specify number of required features
Learning-based Methods	Simulated Annealing, Best First Search, Genetic Algorithms	Choose simple features with low computation Interaction with classifier Consider correlation between features	Dependent to type of classifier Time-consuming in high dimension Suffer from over-fitting

is a linear technique and depends on data scaling. In this method principal components are not always easy to interpret [22]. In fact filter methods are fast, scalable and provide good computational complexity but they ignore interaction with the classifiers [19]. Table II is represented properties of different feature selections approaches in human activity recognition in smart homes.

E. Activity Learning Techniques

In this step machine learning methods are applied for learning activity using selected features [1]. Most smart homes activity recognition studies focus on the Katz index which is usually used in healthcare to evaluate the dependence level, physical and cognitive abilities of elderly people [9]. Generally, new algorithms that correlate the sensor firings, activity labels and predict activities from new sensor firings are required to identify activities from sensor activations alone [23].

A proposed general classification of different methods will address in the following section which tries to cover all existing approaches in human activity recognition in smart homes.

IV. SARF: SMART ACTIVITY RECOGNITION FRAMEWORK IN SMART HOMES

As mentioned before, when the problem of activity recognition in smart home arises, we track occurrences of regular activities in order to monitor health care and find changes in patterns and individuals lifestyle [8]. Since there are different approaches to activity recognition in related areas, presenting a general classification and examining each approach according to the applications and existing challenges seems necessary. Several categories have been presented to classify these approaches and a well-known classification is presented in [4]. This classification must be updated with new concepts and represent new challenges and future work which should be taken into consideration. This work is done by SARF framework.

In our viewpoint, human activity recognition methods can be categorized into three approaches including Bottom-Up, Top-Down and Hybrid approaches which are summarized in Fig. 5. Each of these approaches considers activity recognition intelligible from different perspectives. In this section, the SARF proposed framework will be analyzed.

A. Bottom-Up Approaches

In Bottom-Up activity recognition methods, a learning activity model uses a large collection of user behavior data obtained by the sensor through data mining and machine learning techniques and try to recognize performed activities [24]. These methods can be divided into three categories: Probability-based, Similarity-based and Integration-based methods.

1) Probability-based Methods: These methods improve the generalization ability by modeling the underlying distribution of classes from the obtained feature space [25]. These methods are flexible, since they learn the structure and relationship between the classes by exploiting prior knowledge for a given task such as Markov assumptions, prior distributions and probabilistic reasoning, although the parameters are not optimized [4][26].

An example of a Probability-based approach is to use Nave Bayes [23] classifier that estimates the parameters distribution based on the independence assumption. Let I_{js} which is an activity instances is assigned to the class A_s for which it has maximum posterior probability given by (1) in accordance Bayes Theorem. Each I_{js} observed by R sensors and represented by feature set $F_{js} = \{f_{js}^r\}_{r=1}^R$

$$p(A_s|I_{js}) > p(A_m|I_{js})\ \forall m.s.t.1 \geq m \leq S, \quad s \neq j \quad (1)$$

The classifier resulting from the assumption mentioned before is known as the Nave Bayes classifier given by (2).

$$p(A_s|I_{js}) = \prod_{r=1}^{R} p\left(f_{js}^r|A_s\right) \quad (2)$$

Where $p(A_s|I_{js})$ is the product of the values of features $\{f_{js}^r\}_{r=1}^R$ of an activity instance I_{js} for a given class A_s [27].

2) Similarity-based Methods: The Similarity-based approaches when training data size is large enough, lead to higher efficiency in generalization [25]. However, these methods may suffer from over-fitting, thus making recognition models inconsistent [26]. In these methods, it is important to define the similarity measurement in order to perform patterns selection. Many approaches have been proposed to calculate the distance between different sequences, and one of the most commonly used methods is the edit distance [17].

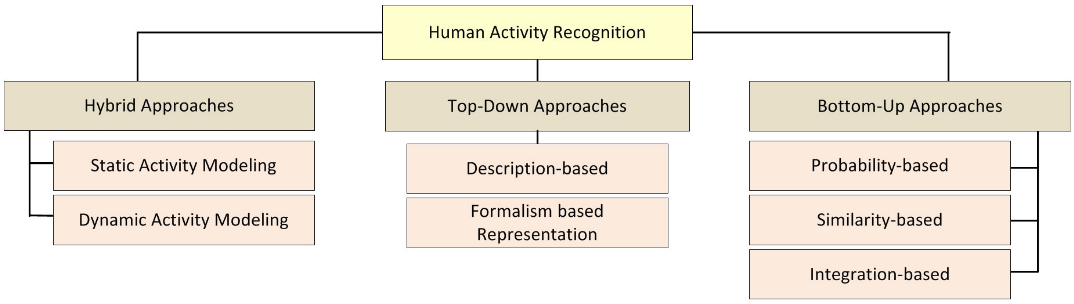

Fig. 5. The SARF proposed framework to analyze various approaches to human activity recognition

Accordingly, the similarity function between two patterns (X,Y) is defined as in (3).

$$Similarity(X,Y) = 1 - \left(\frac{e(X,Y)}{\max(|X|,|Y|)}\right) \quad (3)$$

Where $e(X,Y)$ is the number of edits required to transform an event sequence X into event sequence Y [8].

3) Integration-based Methods: Classification performance and accuracy can often be improved by combining multiple models together, instead of using a single model [28]. This is the basic idea of introducing integration based methods.

In some studies ensembles models are used in human activity recognition in smart homes such as what is done in [29]. Hence, a combination of the models, such as a voting strategy, a simple average among the models [1] and Genetic Algorithm [30] used to combine fusion weight selection of classifier within ensembles, which will decide the winning label for a particular data point and optimizing the output of multiple classifiers.

On the other hand, some studies proposed an activity recognition approach that integrates Probability-based with Similarity-based methods. For example, Fahad and Rajarajan in [28] to improve the reliability of recognitions, integrates the distance minimization and probability estimation approaches. Fig. 6 represents the Block diagram of the proposed activity recognition approach in [28].

B. Top-Down Approaches

In Top-Down activity recognition approaches activity models exploit rich prior knowledge to construct activity models directly using knowledge engineering and management technologies. This usually involves knowledge acquisition, formal modeling, and representation [4]. These methods can be divided into two categories: Description-based Activity Modeling and Formalism-based Representation Methods.

1) Description-based Activity Modeling: The Description-based activity modeling represented activity as an object and models activities as a hierarchy of classes where each class can be described by a number of properties so these approaches including a set of representational concepts [4][31]. The generated activity models are able to capture built-in interrelations between objects and activities such as proposed method in

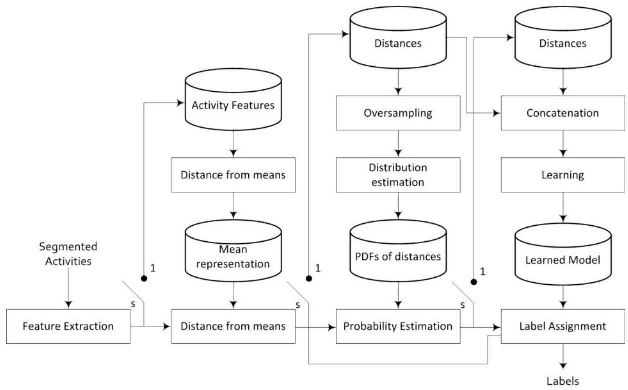

Fig. 6. Block diagram of the proposed activity recognition approach in [28]. Switch s = 1 is training.

[32]. For example, to detect activity "clean up" which is a complex activity, recognition in the form of the simpler components carried out and the following axioms represented in (4) and (5) are added to the knowledge base [31].

$$CLEANUP \sqsubseteq COMPLEXACTIVITY \sqcap \forall HASACTOR.(PERSON \sqcap \exists HASSIMPLEACTIVITY.PUTINDISHWASHER) \quad (4)$$

$$CLEANUP \sqsubseteq COMPLEXACTIVITY \sqcap \forall HASACTOR.(PERSON \sqcap \exists HASSIMPLEACTIVITY.CLEANTABLE) \quad (5)$$

2) Formalism-based Representation Methods: These methods views an activity as a knowledge model that can be formally specified using various logical formalisms. Activity models generated in these methods are normally used for activity recognition or prediction through formal logical reasoning, e.g., deduction, induction, or abduction [4].

Bouchard, Giroux, and Bouzouane in [33] proposed a formal framework for the recognition process based on lattice theory and action Description Logic (DL). This framework minimizes the uncertainty about observed actors activity by bounding the plausible plans set.

C. Hybrid Approaches

The objective of these kinds of approaches is taking advantage of the features of both Bottom-Up and Top-Down modeling and fusing them in a single modeling approach [24]. Modeling ADLs is a challenging task due to their unique characteristics. For example, there are a large number of ADLs in a variety of categories which can all be modeled at multiple levels of granularity [3]. In addition, most ADLs involve performing a number of actions. The sequence of the actions to be performed is usually dependent on an individuals own preferences [34]. As mentioned before, some actions for different activities may occur together and make overlapped or interleave activities [1][4]. Thus the ideas of using Hybrid approaches have been introduced, which can be divided into two categories: Static Activity Modeling and Dynamic Activity Modeling.

1) Static Activity Modeling: The static activity modeling systems cannot automatically be adapted to accommodate new features in activities performed by the user [35]. Also Top-Down approaches are static and they cannot automatically evolve [24] such as the proposed method in [32]. Some Integration-based Bottom-Up approaches only used to model static characteristics of activities. Dynamic Activity Modeling exposed to discussion due to the modeling dynamic nature of human activities.

2) Dynamic Activity Modeling: The idea of using dynamic modeling is based on the dense sensing paradigm, which establishes the idea of inferring activities by monitoring Human-Object Interactions (HOI) through the usage of multiple multi-modal miniaturized sensors [4][24]. Actually in these kinds of modeling want to model high-level activities usually share common sets of physical actions, and are difficult to differentiate based solely on physical signals [36]. To make Top-Down activity recognition systems work in real world applications, activity models have to evolve automatically to adapt to users varying behaviors. The Bottom-Up approaches can be properly addressed to model adaptability and evolution [24]. The goal of this kind of modeling is represented in Fig. 7 as an example.

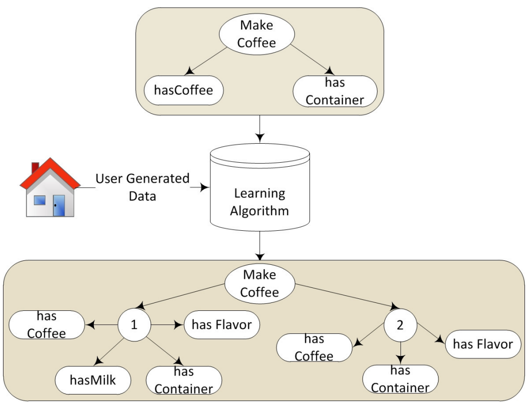

Fig. 7. Dynamic Activity Modeling objective [24]

V. Evaluation of SARF Framework

Due to a wide variety of approaches in human activity recognition, these approaches are classified as SARF framework. Table III represents each of the approaches in this proposed framework according to their characteristics and challenges as a general classification.

Particularly, it is essential to introduce specific measures to evaluate and compare these approaches accurately. The goal of evaluation is analyzing the effects of proposed approaches in human activity recognition and ensure of algorithm performance. Utilizing appropriate measures can lead to well understanding of different approaches for activity recognition in smart homes and also take advantages of them in a systematic and correct way based on the requirements.

A. Proposed Measures

There are different ways to evaluate activity recognition algorithm but generally authors use classifier-based criterias such as F-measure, Precision, Recall and most importantly Accuracy [9][37], and also Sensitivity and Specificity to ignore detailed information about the errors [25] or frameworks such as N-Fold cross validation [37] and Leave-one-day-out [25].

Basically, human activity recognition process has two overall phases: Training and Test. In N-Fold cross validation, the set of data points is split into N non-overlapping subsets. The model is trained and tested N times, on each iteration, one of the N partitions is held out for model testing and the other N-1 partitions are used to train [37]. The performance is averaged over the N iterations. In Leave-one-day-out technique the sensor readings of a whole day are used for testing and the remaining days used for training [38].

In our viewpoint along with other mentioned evaluation measures, there are some important criteria which should be taken into consideration by researchers. Thus, in this section along with Accuracy, as an important measure, these evaluation measures have been proposed.

Data Requirements: In some approaches, due to the needs of large volume of data to support training for each ADL, there is a possibility to face data scarcity which may lead to accuracy and performance reduction [4]. This issue will be increased in the assisted living context which residents are reluctant to reveal their behavioral data due to privacy and ethical considerations [34]. In Top-Down methods there is no data scarcity problem unlike Bottom-Up approaches. Therefore, volume of required data and its importance for human activity recognition in AAL systems such as smart homes must be considered by researchers.

Noise Effect: In general, sensory data are inherently noisy and has untrustworthy nature which leads to lack of reliability in the Bottom-Up, Top-Down and Hybrid approaches [29][31]. As mentioned before, there is possibility of noise existence in annotation process too and lead to accuracy reduction, increase computational complexity and classification error in activity recognition unless some actions such as what is done in [24] using hybrid approaches have been considered.

TABLE III
COMPARISON OF SARF APPROACHES

Activity Learning Approaches		Learning Examples	Main Idea	Characteristics	Challenges
Bottom-UP	Probability-based Methods	Hidden Markov Model[9], Nave Bayes[23]	Probabilistic Classification	Modeling uncertainty and temporal information Generalization Flexibility Dynamic activity modeling	Data scarcity problem Reusability Handling temporal information Dataset annotation
	Similarity-based Methods	Rashidi[8], Conditional Random Field[9], Support Vector Machine[21]	Define the similarity measurement in order to perform patterns selection	Simple and dynamic activity modeling Modeling uncertainty and temporal information Heuristic	Data scarcity problem Reusability Dataset annotation Over-fitting
	Integration-based Methods	Fahad[28], Fahim[29], Chernbumroong[30]	Integration of Similarity or Probability-based methods, or combination of both of these methods	Accuracy Reliability Generalization Efficient Reduce uncertainty in decision making Allow to recognize complex activity	The data scarcity problem Dataset annotation Number and types of classifiers Combination techniques
Top-Down	Description-based Activity Modeling Methods	Zolfaghari[31], Chen[32], Chen[34]	Using semantic and context reasoning to describe concepts and relationships, in a high-level and formal expressiveness	Lack of the data scarcity problem Clear semantic on modeling and inference Interoperability and reusability Preserve decidability Allow to recognize complex activity	Handling uncertainty and ambiguity information Handling temporal information Adaptability Scalability Static activity modeling
	Formalism-based Representation Methods	Bouchard[33]	Logical formalisms inference e.g. deduction, induction, abduction	Lack of the data scarcity problem Clear semantic on modeling and inference	Handling fuzziness and uncertainty information Adaptability Scalability Static activity modeling Flexibility
Hybrid	Static Activity Modeling	Chen[32], Bouchard[33]	Using Probability-based or Similarity-based methods and fusion them with one of Top-Down approaches	Using multiple data sources Accuracy Reliability Allow to recognize complex activity	Limited to initially defined activities Adaptability Performance
	Dynamic Activity Modeling	Azkune[24], Okeyo[35], Wen[36]	Using Probability-based or Similarity-based methods and fusion them with one of Top-Down approaches	Using multiple data sources Adaptability Reusability Allow to recognize complex activity	Common terminology Interoperability Limited to descriptive characteristics Limited to user preferences and implementation tools

Accuracy: Accuracy is the most common criteria in classifier performance analysis and human activity recognition. It should be noted, noise, class-imbalanced datasets and datasets with inappropriate features lead to accuracy reduction [1][7][13]. Higher accuracy of methods leads to error reduction and increase efficiency [16].

Scalability: In general, human activity recognition systems are performing on a particular or public datasets or considering limitation conditions. In fact, the main problem is the needs to real world data which make them inapplicable in other environments with different settings [14]. Furthermore, most of the built models are used for a specific ADL and do not change over time. Also, they do not consider ADL patterns may change due to the dynamic nature of human activities which lead to inconsistency and scalability reduction in built model. In fact, scalability in activity models is an important factor in presence of new activities and new residents in order to constructing a general model for all activities [14], new residents or transfer learning to environment with different layouts [39].

B. *Evaluation of Methods According to Proposed Measures*

In this section efficiency of human activity recognition approaches classified as proposed SARF framework shown in Fig. 5 is evaluated by proposed measures formerly. Table IV shows the results of this evaluation. It should be noted the values of proposed measures are relative and they are based on research investigation in this field.

As represented in Table IV, due to the Data-Driven nature of Bottom-Up approaches, they require large volume of data to make recognition unlike Top-Down approaches which utilizing prior knowledge and knowledge engineering to human activity recognition in smart homes; therefore, they need to sensory data as lower as other approaches as well as effects of noise on them. On the other hand, there are Hybrid approaches which using Bottom-Up and Top-Down methods all together

TABLE IV
EVALUATION OF PROPOSED SARF FRAMEWORK BASED ON PROPOSED MEASURES

The Proposed SARF Framework		**Proposed Evaluation Measures**			
		Data Requirement	**Noise Effects**	**Accuracy**	**Scalability**
Bottom-Up	Probability-based Methods	High	High	Medium	Almost Medium
	Similarity-based Methods	High	High	Medium	Almost Medium
	Integration-based Methods	High	Medium	Almost High	Almost Medium
Top-Down	Description-based Activity Modeling	Low	Low	Medium	Almost Medium
	Formalism-based Representation Methods	Low	Low	Medium	Low
Hybrid	Static Activity Modeling	Medium	Medium	Almost High	Medium
	Dynamic Activity Modeling	Medium	Medium	Medium	High

to achieve acceptable scalability along with adaptability to dynamic nature of human behavior especially in dynamic activity modeling. Therefore, in these kinds of approaches we face to sensor data requirement as well as noise effect but not as much as Bottom-Up approaches.

As mentioned in proposed SARF framework, combining multiple methods together can improve accuracy of human activity recognition in smart homes as well as using Hybrid approaches especially static activity modeling due to its static assumption. Furthermore, there is data requirement in Integration-based methods due to its Bottom-Up nature. Also, inherently noisy sensory data can lead to accuracy reduction in these methods. However, the most effective way to reduce noise impacts, as mentioned in preprocessing phase, is cleaning, completing and normalizing. As represented in Table IV, the other approaches can achieve medium and almost acceptable accuracy in human activity recognition in smart homes.

VI. CONCLUSION

In this paper different approaches to human activity recognition in smart homes investigated and described how to evaluate these approaches were classified and presented in the proposed framework, i.e. SARF, using the obtained results. In order to provide a convenient tool for selecting appropriate approaches, results presented in the form of diagrams and characteristics of each group were investigated and evaluate based on proposed measures represented in form of tables.

The results of this study show that there is no unique way to introduce a single approach, as an optimal approach, to human activity recognition in AAL systems. Since each approach is used for a specific purpose comparing the approaches does not make any sense. One of the most important issues in human activity recognition is to remove the challenges and improve the efficiency of algorithms which is a dynamic research domain warranting further investigation. Using the SARF proposed framework in this paper can play an important role in development of our knowledge in this area and a starting point to resolve some of the challenges which were outlined in this paper.

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