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A New Approach to Behavioral Reasoning in Smart Homes using DVSM Algorithm

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Abstract: Smart Homes (SH) have gradually visible as realistic assistive environments capable of providing assistive living for the elderly and the disabled people.The machine learning and the sensing technology are implemented in the smart homes. The technologies are designed to recognize and track normal activities of people in routine life. The labeled training data are available for activities that are preselected. A computerized access is used to Behavior tracking that analyze frequent activities. We can then track the reliability of continuous behavioral activities to observe the functional health and to make changes in an individual's sequence and resident's lifestyle. In this work, we discuss about the Behavior mining and tracking approach, and validate our HMM and the DVSM algorithms based on the data collected in physical smart environments.

Keywords: Pervasive sensing technology, Smart homes, Health monitoring, Behavior tracking, Behavior mining.

I. INTRODUCTION

In this modernistic world with huge population and resources, innovative technology driven healthcare independent existing has concerned growing sums of attention. The perceptions of Smart Homes (SH) have just developed as a main-stream of approach for the achievement of independent living [1]. A SH is a residential home setting along with sensing elements and devices which perform storage and communication based on operations. An assistive system in a SH can process the perceived data and make timely decisions/actions.

The number of SH tasks have been established for the purpose exclusive living in count to the instituting of existent successful locations [2]. There is a extensive series of qualifying knowledge as device systems, data communications and strategies which offer remnants of the necessary functionality essential for the SH [3]. Growing skills of generating immense extents of device facts related to SH settings, residents and procedures, the high expectancy of provided that innovative original Activities of Daily Living(ADL) appreciation and support. Developments in the extent of SH-based assistive living poignant from location centered notice classifications or alternative oriented volatile alert structures [4]. To achieve the objective of a smart home it is necessary to (a) view the behavior of humans and their background in real time, (b) combining the sensed information and also their features, (c) infer and recognize behaviors, alterations or differences, endlessly in real time in a enlightened method, and (d) delivers the support to help the residents achieve the planned behavioral actions based on incrementally collected device data. There is a foremost break among data compeers and the assistance facility. The vital problem schedule the break is the absence of originality in behavioral activity recognition which is truly scalable.

Firstly, ADLs are supported with a high point of variances such as altered lifestyles, behaviors or facilities with their own distinct way of routine. Secondly, altered sensors exist in a Smart Home. They create assorted data variance in both set-ups and semantics. Regularly it is required to associate and construe device data from numerous bases in order to create the framework of the Activity Data Living. Finally, furthermost Activity Data Living is together with the arrangement of temporally linked schedules. The device records to Activity Data Living are composed incrementally as the Activity Data Living spread. In order to present context-aware support for a SH resident, activity recognition should be per-formed at distinct time points in advanced method.

Modern researches on activity recognition have mainly attentive on the use of probabilistic and arithmetic investigation methods, The data-driven approach, for individual user with individual behavioral activity scenarios [5,6]. The knowledge-driven approach is introduced in this paper to process the multi-source sensor data streams for the intend of behavioral activity recognition. The main purpose of this paper is to change the behavioral activity recognition example that can communicate the above mentioned challenges. The behavioral approach is caused by the remarks that ADLs are unremarkable full of reasonable knowledge provided that loaded links between the surroundings, behavioral events and behavioral activities. The domain and prior knowledge is important in making behavioral ADL models, which avoids the requirements of large-scale dataset group and guidance.

The fundamental approach is the unambiguous onto-logical modeling and illustration of the SH domain. The SH framework and ADLs are included in the SH domain. Ontological behavioral activity modeling furnishes a description based modeling process. It model activities as a hierarchy of classes with each class depicts the number of properties.

The created behavioral activity models are used to capture the built in interrelations between objects and behavioral activities inapplicable of the sequence in which the behavioral objects are applied. Context ontologies works as a situation model that connects the various resource sensor data are used to construct a situation at explicit time constraints. These situations been interpreted in terms of the behavioral ADL models to gather activities. ADL ontologies can be used as a seed ADL classification model. The beginning model can be directly used to read situations for behavioral activity recognition, and undefined learning is undefined activity patterns from ongoing image mining. The proposed approach obtained in this paper, the behavioral activity recognition is comparable to execute subsumption interpretation using energetically trace SH situations against ADL imagery. Behavioral Activity assistance is simplified to instance checking in ontological reasoning. It is used to notice the majority closely-matched behavioral activity domain for individual user with regard to the recognized behavioral activities and consequently to use the misplaced properties for backing condition.

There are three main sections are assisted from the current study. Firstly, a behavioral approach is used to behavioral activity recognition for the SH individual residents. The behavioral approach inter communicates the elusive of behavioral activity modeling caused by the diversity of ADLs and the flexibility of executing the ADLs which provides the combined unambiguous ontological behavioral activity simulations. Secondly, a specific algorithm for behavioral activity recognition of description logic is used newly. The main portion of the behavioral activity recognition algorithm is used to categorize the behavioral activity recognition results into a process of behavioral activities at various levels of generalization at an explicit position in instant. The recognized activities will be gradually limited down from high-level to low-level specific activities and at the end to a concrete activity. Thirdly, an aspect-rich system accomplishment for the proposed approach and organize it in our SH research laboratory. The proposed system is tested with real sensor operations and use cases and estimated by a number of metrics.

The smart environment is believed as an intelligent agent that identifies the state of the resident by the help of the sensors and acts on the environment by using the controllers to specific performance measured is enhanced. Researchers have generated ideas for designing smart environment software algorithms that traces the location and activities that create reminders in which it reacts to unpredictable situations. One limiting factor of these projects is that very few of them test algorithms on data collected from physical environments and even fewer focus on research for automated functional assessment and intervention.

The remnants of the paper is categorize as follows: Section 2 discuss about related work. Section 3 represents the proposed system. Section 4 represents the ontological context modeling. Section 5 represents the outlines of the system architecture for the proposed approach. Sections 6 characterize the methodologies and algorithms. In section 7 discusses the results and concludes the paper in Section 8. Section 9 presents the future enhancements.

II. RELATED WORK

Context for modeling human behavior in a smart environment is represented by a situation model describing environment is represented by a situation model describing environments, and activities [7]. The behavioral activity approaches in this category develop computer vision techniques to evaluate visual annotations for behavioral pattern recognition [8,9]. The second grouping is based on the use of rising sensor association technologies for activity pattern monitoring. The sensor activities of data are analyzed using data mining and machine learning techniques to build behavioral activity models that are used for the basis of behavioral activity recognition. The sensor is distant to observation like wearable sensors, or objects that correspond to the activity environment like dense sensing. Wearable sensors often use inertial extent units and RFID tags to group an individual actor's behavioral activity information [10]. This approach is effective for recognizing substantial movements [11]. In compare, dense sensing deducts the behavioral activities by monitoring the individual activities [12] through the usage of low-power and low-cost sensors.

Incorporating various assorted elements is mostly non automatic process. Inserting a new element requires researching its features and behavior in which it determines to arrange and consolidate which are enervating and replicated testing is avoided which causes conflicts or indeterminate behavior in the overall system [13].

Our approach is based on Application of smart environment technologies provides with various areas like interactive conference rooms, offices with flawless integration work environments. To achieve intelligent behaviors in smart home applications, different computational intelligence techniques have been proposed to support the creation of smart homes, including Discovering Frequent discontinuous Sequences, Clustering sequence into group of activities, Behavioral reasoning. We introduce CASAS for the smart home system. The input CASAS consists of sensor data collected by the smart environment, such as motion sensors and light sensors. This data is mined by our frequent patterns mining to discover activity patterns of interest for automation.

Capturing and concealing the human variability is a main issue in human behavior models (HBMs) for military imaging. It considers the sources of variability in human behavior, and it frames an approach to change ability which allows analyzing the approaches to nominal cost.

The behavioral activity recognition can be performed in various numbers of strands with the basic differences linking to the method in which behavioral activities and a Behavioral ADL profile are formed. One strand is referred to as the generative approach, which attempts to build a complete description of the input or data space, usually with probabilistic analysis methods such as Markov models [5] and Bayesian networks [14] for activity modeling. These methods incorporate an inhabitant's preferences by tuning the initial values of the parameters of the probabilistic models. The major disadvantage with such methods is that the model is static and subjective in terms of probabilistic variable configuration. An alternative approach is referred to as the discriminative approach, which only models the mapping from inputs (data) to outputs (activity labels). Discriminative approaches include many heuristic (rule-based) approaches, for example, neural networks, linear or non-linear discriminate learning. They use machine learning techniques to extract ADL patterns from observed daily activities, and later use the patterns as predictive models [7]. Both approaches require large datasets for training models, thus suffer from the data scarcity or the "Cold Start" problem. It is also difficult to apply modeling and learning results from one person to another.

III. PROPOSED SYSTEM

We introduce an individual method of determining and following activities in smart residents that notices the above problems. The new approach is implemented in the context of the CASAS (Continuous Adaptive Smart home Access System) project by using camera data that are collected in the CASAS. The independent nature of the model performs various automated approach for Behavior Reasoning than is offered by previous approaches. This approach first "discovers" continuous frames of activities, and it recognizes the discovered activities to provide a more structured approach. A unique mining method is introduced for discovering Behavior patterns and the clustering step to group discovered frames into Behavior definitions.

Machine learning techniques perform the tasks but the software algorithms believe on the large amounts of sample data which is suitably designate with the matching behavioral activity. Classification or compose the various sensor data with the equivalent Behavior activities which can be override. It requires the valid input from the smart home domain. In this paper the four different mechanisms are considered for compose sensor data with an equivalent Behavioral marker. We estimate the different methods along the dimensions of marginal time, resident burden, and exactness using sensor data which are collected in the smart home residents and apartment.

IV. ONTOLOGICAL CONTEXT MODELING

Ontological modeling is the method which indicates the properties and their key concepts for the particular problem field. These concepts are ordered in a hierarchical relationship and the properties to form super-class and sub-class relations [1]. Ontologies allocate software agents to read data and source against ontological contexts. It improves the potential of automatic data analysis and assumption.

Smart Homes perform behavioral reasoning in environmental contexts. Spatial contexts refer with data placements. Event contexts contain behind the activities and active state changes of appliances and devices. Event contexts are poised of ecological information such as high temperature, moisture and broad weather conditions. There is a high relationship between ADLs and contexts. Contextual information is usually captivated through several sensors. Each sensor reminds and speculates one prospect of a position. This framework modeling is central on ontological sensor modeling. Sensors are absolutely connected to a various substantial entities like substance, position and situation. The objective and situation from the established the sensors which are consequently incarcerate and encode the domain knowledge in a sensor model. ADL connects between the data from several, unrelated sensor sources to conclude the high-level behavioral activities. It requires combining a series of sensor activities to create a condition within in an explicit time point. Individual sensor contains with the default state value for each individual state property. It denotes the state of the purpose to which it is attached. The state property will modify when the sensor is activated. The classification will translate the state change as an event of a user object relations at the explicit time. It is common to achieve a sensor commencement as a user-object interaction is equivalent to immediate sensor establishment.

V. SYSTEM ARCHITECTURE

In the first step it considers to identify the repeated orders of sensor events that contain the smart environment's conception of an activity. Once the Behavior and associate specific occurrences of the activity is identified, the model is built to identify the Behavior and starts to analyze the development of the activity. By applying frequent sequential pattern mining techniques. The contiguous, consistent sensor event sequences are identified which might indicate behavior of interest. It limits the clustering algorithms in this problem is that all the data points are not clustered, but only frequent Behavior sequence with degree of constancy and recognizability. The architecture model of our system is shown in Fig: 1.

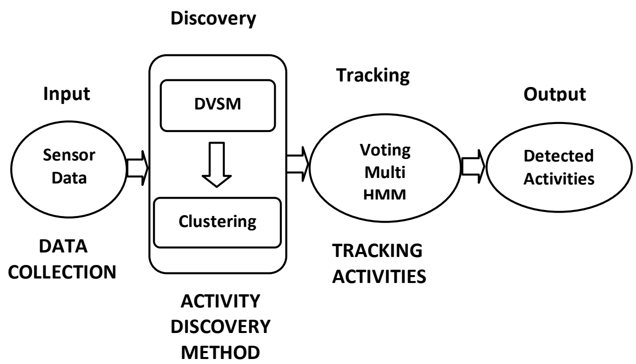

Fig: 1 Proposed System Architecture

The sequence mining as well as the clustering algorithm directs a portion of the problem. These two methods are combined together into a Behavior Discovery Method to finds the frequent occurrence of the activities and cluster continues familiar patterns together. The specific frequent sequence miner algorithm Discontinuous Varied-Order Sequential Miner (DVSM) is applied. This algorithm combined with a clustering algorithm to finds the continuous sensor event sequences which belongs together and occur with frequency and consistency to compose a Behavior that are tracked and analyzed.

VI. METHODOLOGY AND ALGORITHMS

i. DISCOVERING FREQUENT DISCONTINUOUS SEQUENCES

The Behavior discovery method performs frequent sequence mining using DVSM algorithm to identify the frequent continuous patterns and the similar discovered patterns are grouped into clusters. The DVSM algorithm is used to find the continuous frames and patterns from discontinuous occurrence which exhibit varied-order occurrence. This algorithm is also used to find the continuous frames by considering them as patterns with continuity. Unlike many other sequence mining algorithms, this algorithm represents the normal patterns which consists of all continuous variations of a single pattern that appear in the input data set. For general pattern 'a', we denote the i^{th} variation of the pattern as ai, and denote the variation which occurs the majority of all variations of 'a' the established distinction. Each individual component of a pattern is referred as an event.

ii. CLUSTERING SEQUENCES INTO GROUPS OF ACTIVITIES

The BDM algorithm is considered being the second step to identify pattern clusters which represent the set of discovered behavioral activities. The final set of clusters centroids specifies the behavioral activities which identify and track. The BDM uses a standard k -means clustering algorithm. It should define a method for deciding cluster centroids and for examining behavioral activities to form clusters. Various approaches are recorded in the series of clustering the CLUSEQ algorithm [8] and the ROCK algorithm [9]. The difference between their approach and the proposed algorithm is absolutely representative sequences. In difference, pattern event sequences are not strings and individual entry in the sequence also have temporal information which needs to be considered during the discovery process.

iii. BEHAVIORAL REASONING

Once the activities are considered for a specific distinctive individual. A specific model is been built that will recognize future executions of the behavioral activity. It allows the smart environment to identifies Behavioral activity and examine any individual's routine is maintained. Researchers have attained the use of probabilistic models for the Behavioral Reasoning [6].In this new approach, the hidden Markov model is used to recognize activities from sensor data which they being performed. Individual model is executed to identify the patterns which compare to the cluster representatives found by BDM.

iv. FREQUENT PATTERNS MINING: DISCONTINUOUS VARIED-ORDER SEQUENTIAL MINER (DVSM) ALGORITHM

Step 1: DVSM algorithm which extort the specific pattern <a; b> from the occurrence of {b; x; c; a}; {a; b; q}, and {a; u; b}, although the fact and events are alternating and includes varied orders.

Step 2: A general pattern which exhibits all frequent variations of an individual pattern which take place in the input data set D. For general pattern 'a'.

Step 3: We denote the i^{th} difference of the pattern as ai, and we call the difference which occurs most often among all the difference of 'a' the accepted difference, ap.

Step 4: We also mention to individual constituent of a model as an occurrence (such as a in the pattern <a; b>).

Step 5: To find the discontinuous varied order sequences from the input data D, DVSM creates a minimize data set containing the top most frequent events.

Step 6: DVSM slides a window of size 2 across Dr to find patterns of length 2.

Step 7: After first iteration, the whole data set does not need to be scanned again.

Step 8: Instead, DVSM develops the discovered patterns in the last iteration by their prefix and suffix events

Step 9: It meets the developed pattern against the preceding revealed patterns in the same iteration to see the difference of a last pattern, or it is a new behavior pattern.

Step 10: To assist the progress of differences, we save general patterns with the discovered difference in a hash table.

Step 11: if two patterns are allow the difference of the same model, we use the Levenshtein long reserve to classify a corresponding assess sim (A;B) between the two patterns.

$$sim(A,B) = 1 - \left(\frac{e(A,B)}{\max(|A|,|B|)}\right)$$

Step 12: The edit period e (A; B), is the numeral of edits (insertions, deletions, and substitution) consider to transform an event progression A into another event cycle B.

Step 13: We analyse the similarity of measure based on the edit distance.

v. BEHAVIOUR DISCOVERY METHOD ALGORITHM (BDM)

Step 1: Compute the fraction of clusters that map to the actual defined Behavior groups.

Step 2: If the number of actual defined Behavior groups is denoted by |A|, and

Step 3: The number of detected clusters which representative's label maps to a different Behavior group is |S|,

Step 4: Then our cluster metric Q1are denoted as

Q1= (|S|) / (|A|)

Step 5: Compute the division part of behavioral activities in individual cluster which belongs to the similar classified Behavior group identified by the cluster representative.

Step 6: If we denote the cluster Si representative by mi and its actual label as L (mi).
Step 7: we also denote each Behavior in the cluster as aj, its actual label as L (aj), and

Step 8: it is identified label as DL (aj), then the second cluster excellence metric Q2 will be defined as,

$$Q_2 = \frac{\sum_{j=1}^{|S_i|} \delta(a_j)}{|S_i|}$$

$$\delta = \begin{cases} 0, & if \quad L(a_j) \neq DL(a_j) \\ 1, & Otherwise \end{cases}$$

Step 9: These explication does not plays a task in the innovation and detection of the behavioral activities.

Step 10: The BDM algorithm provides cluster representatives along with the defined behavioral activities for maximum percent of the cases (Q1).

Step 11: highest percent of the various sensor events are defined to the particular clusters, or to the Behavior activity clusters which generates the events (Q2).

vi. BEHAVIOUR REASONING: VOTING MULTI-HMM

Step 1: Produce the Behavior label L for a specific reference of pattern event (x).

Step 2: we administrate the sliding window of events which terminates the particular event x for each HMM.

Step 3: choose the Behavior that receives the highest number of votes.

Step 4: For each and every instance of HMM, the hidden states specifies the possible behavioral activities and encode states which specifies the particular sensor values.

Step 5: The multi HMM model specifies the other differences of the specific patterns.

Step 6: The multi HMM identifies the first difference of all patterns.

Step 7: the second state HMM specifies the second difference of individual behavioral patterns, and so on.

Step 8: The Behavior label L(x) is calculated below, where P(x; Li) shows the probability of assigning label Li to x by the k^{th} multi-HMM.

Lm(x) =argmaxi $\left(\frac{\sum_{k=1}^{n} P(x,L_i)}{n}\right)$

VII. RESULT AND DISCUSSIONS

To discover continuous behavioral patterns which are varied order that consists with the difference in the ordering in table 1.The bounds of clustering algorithms for the specified problem to cluster all the data points, only some part of a Behavior sequence which occurs frequently with some degree of routine or recognition.

Both sequence mining and clustering algorithms indulge a specific portion of the problem, these two methods sequenced together into a Behavior Discovery Method (BDM) to identify frequent activities and cluster similar patterns together.

Table 1: Number of frequent events occurring in the discovered patterns

Number of discovered patterns	Number of top frequent events in %
50	20
100	35
200	45
300	52
400	55
500	60
600	63
700	67
800	80
810	89
830	95

Explicitly, the frequent sequence miner algorithm is applied, a DVSM, added with a clustering algorithm to specify the sensor event sequences which belongs common and emerge with sufficient occurrence and reliability to compose a Behavior which are analyzed.

The BDM can specify activities which performed in a presequence behavior in the CASAS analysis. In this case, the situation complicates by allowing the behavioral activities to be intersect together when they performed. BDM specifies the problem of sequence as a part of the discovery process. The technology is used to perform Behavior discovery method when the individual people are functionally dependent, to ascertain a baseline of regular behavioral activities.

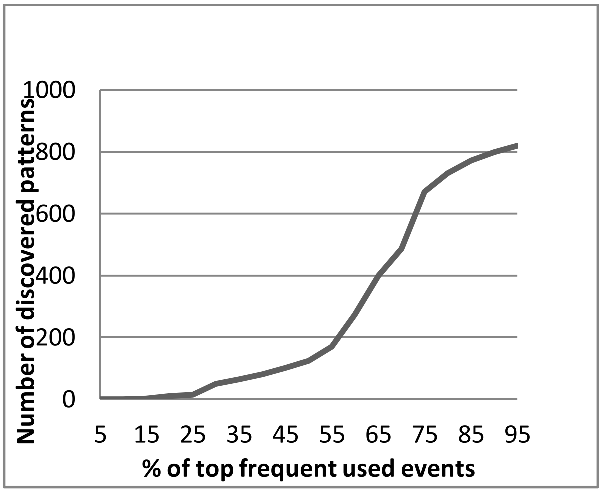

Fig: 1 frequently occurring events

The BDM tracks the activities which performed in the smart home residents. The individual can view the reported Behavior times to specify the behavioral activities that are executed at a regular interval time. Comparatively, various provision analysis and data mining algorithms is used to identify the trends of the activities. To exhibits the BDM been used between Behavior discovery methods and behavioral tracking. This process is applied to a large data collection in CASAS smart environment. We collected three months of daily Behavior data collections from the smart residents which two individual residents performed the normal activities. Sensor data are collected continuously results 567,891 sensor events. The Behavior discovery algorithms are applied to the collected data. The parameter settings are considered to be similar when compared with the previous experiments. The threshold values of frequent events are modified and used in pattern discovery.

VIII. CONCLUSION

In this paper we proposed a knowledge driven approach to activity recognition based on ontological modeling and behavioral reasoning. We conceived and designed an integrate system architecture to instance the recognition of the proposed approach. The feature of the system is to integrate ontological modeling and representation for both sensor data and activities. It alleviates the domain knowledge as well as behavioral reasoning for the activity recognition. We developed a Behavior discovery method which exhibits the frequent sequence mining techniques by using DVSM algorithm is used to discover frequent sequence of frames, and groups the frequent continuous patterns into clusters.

An alternative method for tracking activities in smart Homes is introduced in this work. The DVSM algorithm is used to sort the continuous sequence frames from discontinuous activities which exhibits the varied-order sequential events. The DVSM algorithm is used to discover frequent activities that are continuously recorded in a smart environment. Particular models are then observing the specific behavioral activities which results are used to perceive the behavioral wellness of smart environment residents. This is the positive expansion in the field of behavioral smart environment knowledge for health observe and consideration. The user emphasizes the number of behavioral activities to cluster the models. This systematic assessment considers a mechanism for apprises the effortless of alternative health interventions. The feature rich acknowledgement and assistance systems are accessed. The behavioral continuous systems have been executed and tested in both real behavioral activities and simulated activities. Initial result performed the access is simple and potent in real-world use cases. These Behavioral technologies are evaluated to provide systematic health monitoring and assistance in an individual's smart environments.

FUTURE ENHANCEMENT

Future work of the proposed algorithm is to design fundamentals of the entire smart residents system which behave the functional analysis of people in their every location. This form of systematic approach considers workings for estimates the valid health interference. These Behavioral activities effectively provides the systematic health monitoring and assistance in an individual's routine in smart environments which applied in various fields like surveillance, alerting mechanism and monitoring devices which validates for unexceptional behavioral activities provides in the live video stream., the video recording space is contemplate as future research to reduce the extensive memory usage.

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