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ANALYSIS OF HUMAN ACTIVITY PREDICTION USING TEMPORAL SEQUENCE PATTERN

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Abstract: -

Activity analysis and acceptance plays an important role in a advanced ambit of applications from assisted active to aegis and surveillance. Most of the accepted approaches for activity analysis and acceptance wait on a set of predefined activities and bold a changeless archetypal of the activities over time. We represent an activity as an basic histogram of spatio-temporal features, calmly clay how affection distributions change over time. The above contributions of our plan include: A accepted framework is proposed to systematically abode the botheration of circuitous activity anticipation by mining banausic arrangement patterns; Probabilistic suffix timberline (PST) is alien to archetypal causal relationships amid basic actions, area both ample and baby adjustment Markov dependencies amid activity units are captured; The context-cue, abnormally alternate altar information, is modelled through consecutive arrangement mining (SPM), area a alternation of activity and article co-occurrence are encoded as a circuitous allegorical sequence; We as well present a predictive accumulative activity (PAF) to characterize the adequation of anniversary affectionate of activity. The capability of our access is evaluated on two beginning scenarios with two abstracts sets for each: action-only anticipation and context-aware prediction. Our adjustment achieves above achievement for admiration all-around activity classes and bounded activity units. We adduce and present able methods for mining predictive patterns for both a banausic and banausic (time series) data. Our aboriginal adjustment relies on common arrangement mining to analyze the seek space. It applies a atypical appraisal address for extracting a baby set of common patterns that are awful predictive and accept low redundancy.

Keywords: - Prediction, Temporal Sequence, Activity, Human, Simulation.

1. INTRODUCTION

Data mining is a technique that deals with the extraction of hidden predictive information from large database. It uses sophisticated algorithms for the process of sorting through large amounts of data sets and picking out relevant information. Data mining tools predict future trends and behaviors, allowing businesses to make proactive, knowledge-driven decisions. With the amount of data doubling each year, more data is gathered and data mining is becoming an increasingly important tool to transform this data into information. Long process of research and product development evolved data mining. This evolution began when business data was first stored on computers, continued with improvements in data access, and more recently, generated technologies that allow users to navigate through their data in real time. Data mining takes this evolutionary process beyond retrospective data access and navigation to prospective and proactive information delivery.

1.1. Data Mining Functions

Data mining methods may be classified by the function they perform or according to the class of application they can be used in. Some of the main techniques used in data mining are described in this section.

1.1.1 Classification

Data mine tools have to infer a model from the database, and in the case of supervised learning this requires the user to define one or more classes.

The database contains one or more attributes that denote the class of a tuple and these are known as predicted attributes whereas the remaining attributes are called predicting attributes.

A combination of values for the predicted attributes defines a class. When learning classification rules the system has to find the rules that predict the class from the predicting attributes so firstly the user has to define conditions for each class, the data mine system then constructs descriptions for the classes. Basically the system should given a case or tuple with certain known attribute values be able to predict what class this case belongs to.

Once classes are defined the system should infer rules that govern the classification therefore the system should be able to find the description of each class.

1.1.2 Associations

Given a collection of items and a set of records, each of which contain some number of items from the given collection, an association function is an operation against this set of records which return affinities or patterns that exist among the collection of items. These patterns can be expressed by rules such as "72% of all the records that contain items A, B and C also contain items D and E." The specific percentage of occurrences (in this case 72) is called the confidence factor of the rule. Also, in this rule, A,B and C are said to be on an opposite side of the rule to D and E. Associations can involve any number of items on either side of the rule.

1.1.3 Sequential/Temporal patterns

Sequential/temporal pattern functions analyse a collection of records over a period of time for example to identify trends. Where the identity of a customer who made a purchase is known an analysis can be made of the collection of related records of the same structure (i.e. consisting of a number of items drawn from a given collection of items). The records are related by the identity of the customer who did the repeated purchases. Such a situation is typical of a direct mail application where for example a catalogue merchant has the information, for each customer, of the sets of products that the customer buys in every purchase order. A sequential pattern function will analyse such collections of related records and will detect frequently occurring patterns of products bought over time. A sequential pattern operator could also be used to discover for example the set of purchases that frequently precedes the purchase of a microwave oven.

1.1.4 Clustering/Segmentation

Clustering and segmentation are the processes of creating a partition so that all the members of each set of the partition are similar according to some metric. A cluster is a set of objects grouped together because of their similarity or proximity. Objects are often decomposed into an exhaustive and/or mutually exclusive set of clusters.

Clustering according to similarity is a very powerful technique, the key to it being to translate some intuitive measure of similarity into a quantitative measure. When learning is unsupervised then the system has to discover its own classes i.e. the system clusters the data in the database. The system has to discover subsets of related objects in the training set and then it has to find descriptions that describe each of these subsets.

2. TEMPERAL DATA MINING

The possible objectives of data mining, which are often called tasks of data mining [1] can be classified into some broad groups. For the case of temporal data mining, these tasks may be grouped as Association, Prediction, Classification, Clustering, Characterization, Search & retrieval, Pattern discovery, Trend Analysis and Sequence Analysis.

This categorization is neither unique nor exhaustive, the only objective being to facilitate an easy discussion of the numerous techniques in the field. First four have been investigated extensively in traditional time series analysis and pattern recognition. Algorithms for pattern discovery in large databases however are of more recent origin and are mostly discussed only in data mining literature. In this section, we provide an overview of first eight temporal data mining techniques. In the next section, we provide a detailed description of knowledge discovery techniques for sequential data.

2.1. Association

The discovery of relevant association rules is one of the most important methods used to perform data mining on transactional databases. An effective algorithm to discover association rules is the apriori [5]. Association rule discovery is an important task in data mining in which we extract the relation among the attribute on the basis of support and confidence. The association rule discovery can be extended to temporal association. One of the most common approaches to mining frequent patterns is the apriori method and when a transactional database represented as a set of sequences of transactions performed by one entity is used, the manipulation of temporal sequences requires that some adaptations be made to the apriori algorithm.

The most important modification is on the notion of support: support is now the fraction of entities, which had consumed the itemsets in any of their possible transactions, i.e. an entity could only contribute one time to increment the support of each itemset, beside it could had consumed that itemset several times. After identifying the large itemsets, the itemsets with support greater than the minimum support allowed, they are translated to an integer, and each sequence is transformed in a new sequence, whose elements are the large itemsets of the previous one. The next step is to find the large sequences. For achieve this, the algorithm acts iteratively as apriori: first it generates the candidate sequences and then it chooses the large sequences from the candidate ones, until there are no candidates.

2.2. Prediction

Prediction has a versatile significance in the data mining. It is the forecasting for future on the basis of past. The task of time-series prediction has to do with forecasting (typically) future values of the time series based on its past samples. For this purpose, we need to build a predictive model for the data. Probably the earliest example of such a model is due to Yule way back in [9]. The autoregressive family of models can be used to predict a future value as a linear combination of earlier sample values, provided the time series is stationary. Linear non stationary models like ARMA models have also been found useful in many economic and industrial applications where some suitable variant of the process can be assumed to be stationary. Another popular work-around for non stationary is to assume that the time series is piece-wise stationary.

The series is then broken down into smaller pieces called as “frames” within each of which, the stationary condition can be assumed to hold and then separate models are learnt for each frame. In addition to this standard ARMA family of models, there are many nonlinear models for time series prediction e. g., neural networks have good for nonlinear modeling of time series data [4]. The prediction problem for symbolic sequences has been addressed in Artificial Intelligence research. Consider various rule models such as disjunctive normal form model, periodic rule model etc. Based on these models sequence-generating rules are obtained that state some properties that constrain which symbol can appear next in the sequence.

In many cases, prediction may be formulated as classification, association rule finding or clustering problems. Generative models can also be used effectively to predict the evolution of time series. In spite of prediction problems have some specific characteristics that differentiate them from other problems. A vast literature exists on prediction of time series, in a variety of domains [11]. But we have failed to find in the data mining literature significant applications that involve prediction of time series and that do not fall into any of the previously described categories. Granted, several authors have presented work that aims specifically obtaining algorithms that can be used to predict the evolution of time series. In the particular domain of prediction, care must be taken with the domain where prediction is to be applied [11]. Prediction gains the importance in various fields like medical, finance, environmental & engineering with an exponential rate.

2.3. Classification

In classification one classifies the unknown set of attributes in any one of the predefined class [1]. In temporal classification, each temporal sequence presented in the database is assumed to belong to one of the predefined classes or categories and our goal is to automatically determine the corresponding category/class for the given input temporal set of attributes. There are many examples of sequence classification applications, like Handwriting recognition speech recognition, gesture recognition, demarcating gene and non-gene regions in a genome sequence, on-line signature verification, etc. The task of a speech recognition system is to transcribe speech signals into their corresponding textual representations.

2.4. Pattern Discovery

Unlike in search and retrieval applications, in pattern discovery there is no specific query in hand with which to search the database [5]. The objective is simply to unearth all patterns of interest. It is worthwhile to note at this point that whereas the other temporal data mining tasks discussed earlier in (i. e. sequence prediction, classification, clustering and matching) had their origins in other disciplines like estimation theory, machine learning or pattern recognition; the pattern discovery task has its origins in data mining itself. In that sense, pattern discovery, with its exploratory and unsupervised nature of operation, is something of a sole preserve of data mining. For this reason, this review lays particular emphasis on the temporal data mining task of pattern discovery.

The ultimate goal of temporal data mining is to discover hidden relations between sequences and subsequence of events. An efficient approach to mining casual relations is sequence mining. The discovery of relations between sequences of events involves mainly three steps [11]:

1) Representation and modeling: In this sequence of the temporal data are transformed into a
suitable form.

2) Similarity Measure: Definition of similarity measures between sequences.

3) Mining Operation: application of models and representations to the actual mining problems.

Other authors have used a different approach to classify data mining problems and algorithms they used three dimensions: data type, mining operations and type of timing information. Although both approaches are equally valid, we preferred to use representation, similarity and operations, since it provided a more comprehensive and novel view of the field depending on the nature of the event sequence, the approaches to solve the problem may be quite different. A sequence composed by a series of nominal symbols from a particular alphabet is usually called a temporal sequence and a sequence of continuous, real-valued elements, is known as a time series.

3. PROPOSED METHODOLOY

This system introduces an unsupervised method of discovering and tracking Visual activities in a smart environment that addresses the above issues. It implements this approach in the context of the

Smart environment by using camera data that are collected in smart environments tested. The unsupervised nature of the proposed system provides a more autonomous method for behavior reasoning than is offered by previous approaches, which take a supervised approach and annotate the available data for training. The traditional method for Behavior Reasoning solely utilizes supervised datasets or other models for recognizing labeled activities. This approach first “discovers” interesting patterns of activity, and then, recognizes these discovered activities to provide a more automated approach. This system introduces a unique mining method for discovering Behavior patterns, along with a clustering step to group discovered patterns into Behavior definitions.

Many different applications have been studied by researchers in activity recognition; examples include assisting the sick and disabled. By automatically monitoring human activities, home based rehabilitation can be provided for people suffering from traumatic brain injuries. One can find applications ranging from security-related applications and logistics support to location-based services. Due to its many-faceted nature, different fields may refer to activity recognition as plan recognition, goal recognition, intent recognition, behavior recognition, location estimation and

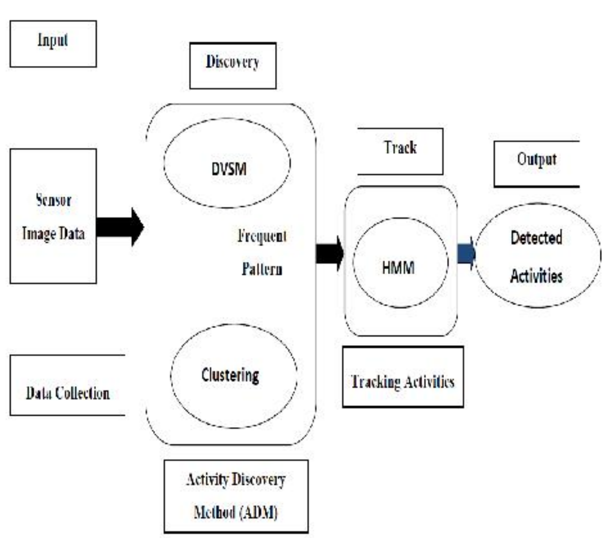

Figure 3.1: - Proposed System Architecture

The first step to consider is how to identify the frequent and repeatable sequences of sensor events that comprise smart environment’s notion of an activity. Once identified the Behavior and associate specific occurrences of the activity, then it is able to build a model to recognize the Behavior and begin to analyze the occurrences of the activity. By applying frequent sequential pattern mining techniques, this system identifies contiguous, consistent sensor event sequences that might indicate Behavior of interest. Many methods have been proposed for mining sequential data, including mining frequent sequences, mining frequent patterns using regular expressions, constraint-based mining, and frequent-periodic pattern mining. One limitation of these approaches is that they do not discover discontinuous patterns, which can appear in daily Behavior patterns, which can appear in daily Behavior data due to the erratic nature of human activities. For example, when an individual prepares a meal, the steps do not always follow the same strict sequence; rather, their order may be changed and be location-based services.

This proposed system could be able to predict activities very close to the individual by patterns with high intensity and discovering every object with respect to time along with the orientation. Interleaved with steps that do not consistently appear each time. Ruotsalainen and Ala-Kleemola introduce their Gais algorithm for detecting interleaved patterns using genetic algorithms, but this is a supervised learning approach that looks for matches to specific pattern templates. Other approaches have been proposed to mine discontinuous patterns but have difficulty finding hybrid continuous discontinuous patterns and have difficulty finding patterns whose order may vary from one occurrence to another.

The next thing is to discover sequential patterns that may be discontinuous and have variability in the ordering, another possible approach is to cluster the sensor events. Keogh et al. claim that the clusters that result from processing streaming time series data are essentially random. However, time series and sequence clustering algorithms have shown to be effective in constrained situations. For example, sequence mining algorithms have been successfully used in bioinformatics to discover related gene sequences. The limitation of clustering algorithms for the problem is that does not want to cluster all of the data points, but only those that are part of a Behavior sequence which is likely to occur frequently and with some degree of regularity or recognizability. Because both sequence mining and clustering algorithms address a portion of the problem, combining these two methods into a Behavior Discovery Method (ADM) to identify frequent activities and cluster similar patterns together. Specifically, applying frequent sequence miner algorithm, a Discontinuous Varied-Order Sequential Miner, combined with a clustering algorithm to identify sensor event sequences that likely belong together and appear with enough frequency and regularity.

3.1. Discontinuous Varied-Order Sequential Miner (DVSM) Algorithm

Step 1: DVSM can extract the pattern <a; b> from instances {b; x; c; a}; {a; b; q}, and {a; u; b}, despite the fact that the events are discontinuous and have varied orders

Step 2: a general pattern that comprises all frequent variations of a single pattern that occur in the input data set D. For general pattern a,

Step 3: Denoting the ith variation of the pattern as ai, and call the variation that occurs most often among all variations of a prevalent variation, ap.

Step 4: Referring to each single component of a pattern as an event (such as a in the pattern <a; b>).

Step 5: To find these discontinuous order-varying sequences from the input data D, DVSM first creates a reduced data setDr 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 extends the patterns discovered in the previous iteration by their prefix and suffix events, and

Step 9: will match the extended pattern against the already discovered patterns (in the same iteration) to see if it is a variation of a previous pattern, or if it is a new pattern.

Step 10: To facilitate comparisons, saving general patterns along with their discovered variations in a hash table.

Step 11: To see if two patterns should be considered as variations of the same pattern, using the Levenshtein (edit) distance to define a similarity measure sim (A; B) between the two patterns.

Step 12: The edit distance, e (A, B), is the number of edits (insertions, deletions, and substitutions) required to transform an event sequence A into another event sequence B.

Step 13: Defining the similarity measure based on the edit distance as

The first step, the frequent and repeatable sequences of sensor events are considered, that comprise our smart environment's notion of an activity. By applying frequent sequential pattern mining techniques, with this contiguous events are identified, consistent sensor event sequences that might indicate an activity of interest. Ruotsalainen and Ala-Kleemola [7] introduce their Gais algorithm for detecting interleaved patterns using genetic algorithms, but this is a supervised learning approach that looks for matches to specific pattern templates. Given that sequential patterns are discoverd that may be discontinuous and have variability in the ordering, another possible approach is to cluster the sensor events. The limitation of clustering algorithms for our problem is that all of the data points are don not clustered, but only those that are part of an activity sequence which is likely to occur frequently and with some degree of regularity or recognisability. So sequence mining and clustering algorithm is combined into an Activity Discovery Method (ADM) to identify frequent activities and cluster similar patterns together.

Once the activities are discovered, a model has to build for activity recognition. In our approach, Hidden Markov model is used to recognize activities from sensor data. Each model is trained to recognize the patterns that correspond to the cluster representatives found by ADM. A separate Markov model could be learned for each activity and the model that supports a new sequence of events would be selected as the activity label for the sequence. For this task, hidden Markov model is used, which is a statistical model in which the underlying data are generated by a stochastic process that is not observable. HMMs perform well in the cases where temporal patterns need to be recognized. As with a Markov chain, the conditional probability distribution of any hidden state depends only on the value of a finite number of preceding hidden states. An HMM model is specified, that using three probability distributions: the distribution over initial states, the state transition probability distribution and the observation distribution. The most likely sequence of hidden states are found that will be given to the observation in and by using the Viterbi algorithm [11].

One drawback of these HMMs sometimes it makes a very slow transition from one activity to another. To remedy this problem, an event-based sliding window is used and this limits the history of sensor events that the model remembers at any given time. For activity recognition, a voting multi-HMM model is used as a boosting mechanism. Then multiple HMMs is constructed and recognize activities by combining their classifications using a voting mechanism. Specifically, the first HMM represents the first variation of all patterns (one hidden state per pattern), the second HMM represents the second variation of patterns, and so on. The Viterbi algorithm is used for each HMM to identify the sequence of hidden states, one hidden state at a time, and then, using the described voting mechanism, then identify the most likely hidden state for the multi-HMM based on input from all individual HMMs. The multi-HMM is built automatically using the output of ADM's discovery and clustering algorithm.

In this study, an unsupervised approach for human activity recognition is proposed. It combines an HMM-based model with the use of acceleration data acquired during sequences of different human activities. More specifically, the proposed approach is based on a Hidden Markov Model in a multiple regression context and will be denoted by MHMMR. As the sequences of acceleration data consist in multidimensional time series where each dimension is acceleration, the activity recognition problem is therefore formulated through the proposed MHMMR model as the one of joint segmentation of multidimensional time series, each segment is associated with an activity. In the proposed model, each activity is represented by a regression model and the switching from one activity to another is governed by a hidden Markov chain. The MHMMR parameters are learned in an unsupervised way from unlabelled raw acceleration data acquired during human activities.

4. IMPLEMENTATION

The proposed design is implemented using NS-2 In a small database, a simple sequential scan is usually employed for k nearest – neighbor (KNN) search. But for large data set, efficient indexing algorithms are imperative. High dimensional data is increasingly in many common fields. As the number of dimensions increase, many clustering techniques begin to suffer from the curse of dimensionality, degrading the quality of the results. In high dimensions, data becomes very sparse and distance measures become increasingly meaningless. There is a general categorization for high dimensional data set clustering:1-Dimension reduction, 2-Parismonious models, 3-Subspace clustering [44]. Feature selection and feature extraction are most popular techniques in dimension reduction. It is clear that in both methods we will have losing information which naturally affects accuracy. Ref. [45] reviewed the literature on parsimonious models and Gaussian models from the most complex to simplest which yields a method similar to the K Means approach. When we have low dimensional spaces these methods aren't able to work well. There are two main approaches for subspaces methods: in first class centers are considered on a same unknown subspace and in second each class is located on specific subspace [46]. The idea of subtopics or subgroups is appropriate for document clustering and text mining [47]. Tensor factorization as a powerful technique has been used in [48]. Inconsistency has been shown in those public data sets because of outlier. Ref. [49] proposed a framework which integrates subspace selection and clustering.

Equivalency between kernel K-Means clustering and iterative subspace selection has been shown. Ref. [50] proposed a general clustering improver scheme which is included two main steps. In first step it uses intrinsic properties of the data set for dimension reduction after that several iteration of a clustering algorithms are applied, each with different parameter. Base on BIC criterion the best result will be selected. There are some weaknesses for this method e.g. since BIC fits a model to specific data distribution it cannot be used to compare models of different data sets. Ref. [51] presented a semi-supervised clustering method base on spherical K-Means via feature projection which is tailored for handling sparse high dimensional data. They first formulated constraint-guided feature projection then applied the constraint spherical K-Means algorithm to cluster data with reduced dimension. Ref.[52] proposed two methods of combining objective function clustering and graph theory clustering.– Method 1: incorporates multiple criteria into an objective function according to their importance, and solves this problem with constrained nonlinear optimization programming.– Method 2: consists of two sequential procedures:

- A traditional objective function Clustering for generating the initial result.
- An auto associative additive system based on graph theory clustering for modifying the initial result.

In improving clustering performance they proposed the use of more than one clustering method. They investigated the use of sequential combination clustering as opposed to simultaneous combination and found that sequential combination is less complex and there are improvements without the overhead cost of simultaneous clustering. In clustering points lying in high dimensional spaces, formulating a desirable measure of “similarity” is more problematic. Recent research shows that for high dimensional spaces computing the distance by looking at all the dimensions is often useless, as the farthest neighbor of a point is expected to be almost as close as its nearest neighbor [54]. To compute clusters in different lower dimensional subspaces, recent work has focused on projective clustering, defined as follows: given a set P of points in Rd and an integer K, partition into subsets that best classify into lower dimensional subspaces according to some objective function. Instead of projecting all the points in the same subspace, this allows each cluster to have a different subspace associated with it [55]. Proposed model will be more effective and achieves significant performance improvement over traditional method for most clustering. It will be able to cluster samples of same no of clusters and level and be more efficient and accurate than a single one pass clustering. There are some delimitations for this method. First space should be orthogonal it means there is no correlation among attributes of an object. Second base on application that is used all attributes in an object have the same kind of data types.

Without losing generality it is possible to extend proposed method to other kinds of data types. Samples are considered in a same number of dimensions. The proposed method HDK select subspaces and perform clustering based on these subspaces. Performance evaluation has long been a difficult problem in image processing and computer vision, and content-based retrieval is no exception. This is primarily because of the difficulty associated with relevant quantitative measures for evaluation. The following parameters are tested by activity discovery based on images.

i) Accuracy

The following result shows that the proposed approach provides close to the saliency approach and better than other approaches. The saliency activity discovery approach was efficient for images having complex spatial structure as in the large database; where query relevant images have large variations and object dissimilarity.

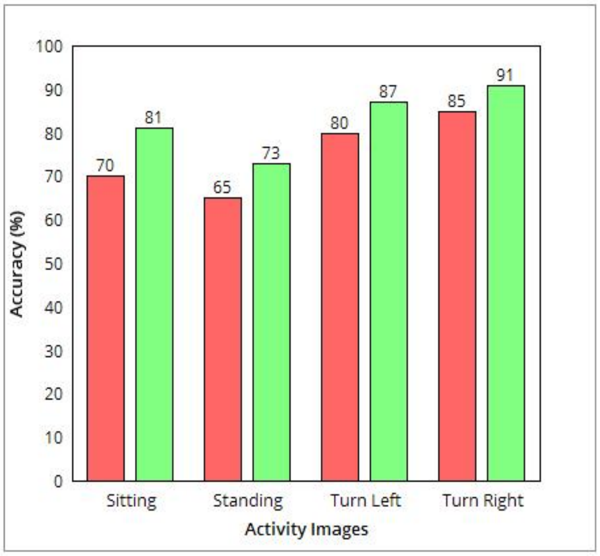

Figure 4.1: - Activity Discovery Accuracy

ii) Precision

The proposed activity discovery approach works as an extension to the saliency approach. It enhances the precision for images having large smoothed regions and provides better recall than other approaches.

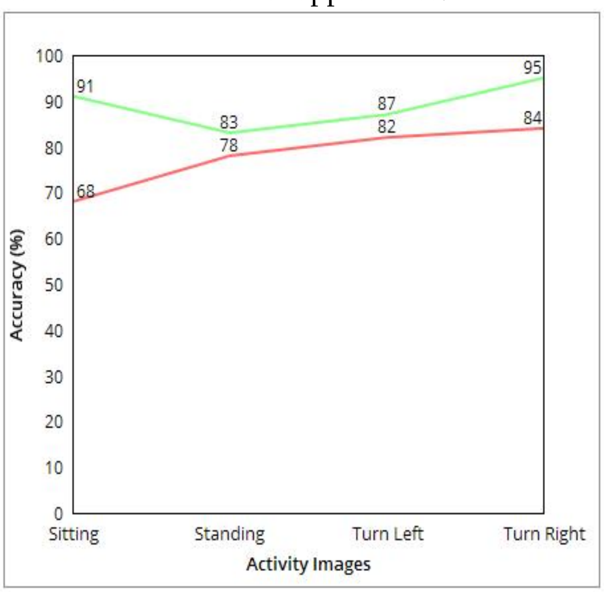

Figure 4.2: - the precision for Activity Discovery

iii) Execution Time

The following result shows a performance evaluation of the proposed retrieval approach toward other approaches. The table compares the techniques relative to the number of locally recognized feature activity, the number of globally recognized feature activity, the average segmentation time and the average matching time.

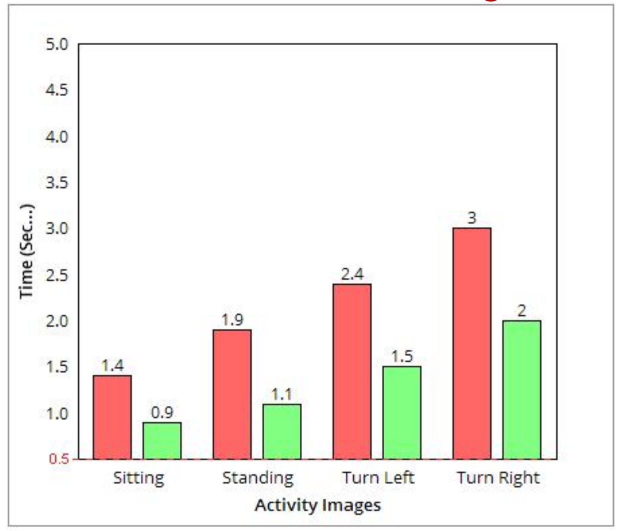

Figure 4.3: - Execution Time for Activity Discovery

iv) Threshold

Current approaches to sensory thresholds, such as geometric means and logistic regression, ignore any formal consideration of uncertainty and variability. Various alternative methods based on approximate confidence and prediction intervals about the logistic regression were examined.

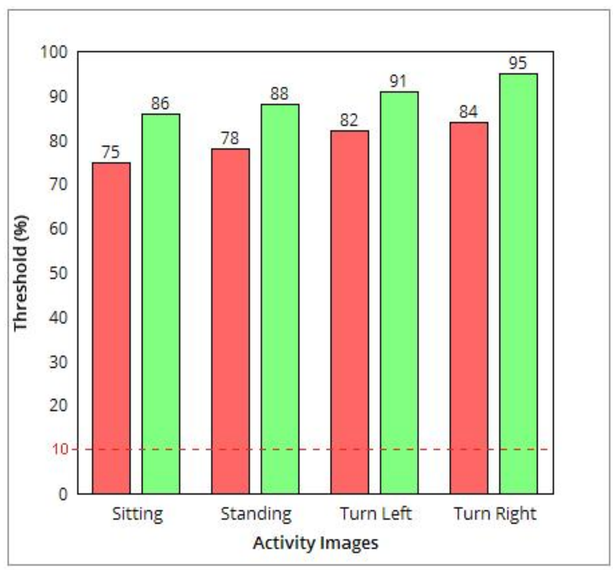

Figure 4.4: - Threshold limit for Activity Discovery

CONCLUSION

The problem of recognizing human activities from sensor data is a popular research subject in the field of machine learning. Depending on the availability of the labeled data, recognition methods are simply divided into two categories as supervised and unsupervised.

We observed that our segmentation algorithm produces segments which are quite close to the true ones. The final sequential labeling model succeeds in further refining the results, by smoothing segment borders and recovering part of the segments assigned to spurious clusters. The proposed framework, however, suffers from a number of limitations. Similar activities tend to be clustered together and are hard to distinguish. In order to prevent this, a better way to represent segments or additional features (e.g. time of the day, duration of the activity etc.) can be defined. Interleaved activities also decrease performance, as when repeatedly going to toilet during the night. Relationships between neighbouring segments could be included in the clustering phase in order to address this problem.

There are a number of directions to move our research forward. As far as the supervised recognition techniques are concerned, the segmental mining strategy can also be used for suggesting promising topologies for graphical models trying to directly incorporate long-range dependencies. Our segmental pattern miner extracts patterns which should approximately span activity segments. Their matches are thus natural candidates to add shortcuts as in skip-chain CRF, possibly connecting distant segments representing the same or closely related activities.

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