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RECOGNITION OF COMPLEX HUMAN ACTIVITIES USING VISUAL AND SEQUENCE PATTERN MINING

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Abstract: - The human activity prediction using visual and continuous sequence pattern mining technologies found in smart homes offer unprecedented opportunities for providing health monitoring and assistance to individuals experiencing difficulties living independently at home.. In the proposed research, an unsupervised method is introduced to discover and track Visual activities in a smart environment that addresses the above issues. The approach is implemented in the context of the Smart environment by using camera data. The unsupervised nature of the model provides a more automated approach for activity recognition than is offered by previous approaches, which take a supervised approach and annotate the available data for training. The Proposed method Introduces (i) The Naïve Bayesian Algorithm similarity finder activity by using camera data that are collected in the smart apartment tested. (ii) Sequence Pattern Matching and mining mechanisms for annotating camera data which is to evaluate the alternative methods along the dimensions of annotation time, resident burden, and accuracy using sensor data collected in a real smart apartment. Combine with a (iii) Clustering methods to identify sensor event sequences that likely belong together and appear with enough frequency and regularity to comprise an activity that can be tracked and analyze.

Keywords: - Unsupervised Learning, Smart Environment, Bayesian Algorithm

1. Introduction to data mining

Data Mining is nothing but extraction of data from large databases for some specialized work. It is the computational process of discovering patterns in large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems. One important aspect of data mining is that it scans through a large volume of data to discover frequently occurring patterns and correlations. [1]

Classification is a data mining function that assigns items in a collection to target categories or classes. The main goal of classification technique is to accurately predict the target class for each case in the data. Classification routines in data mining also use variety of algorithms and the particular algorithm used can affect the way records are classified.

Researchers have found that different types of sensor information are effective for classifying different types of activities. When trying to recognize actions that involve repetitive body motions (e.g., walking, running, sitting, standing, climbing stairs), data collected from accelerometers positioned on the body has been used. In contrast, other activities are not as easily distinguishable by body position.

The number of machine learning models that have been used for activity recognition varies almost as greatly as the types of sensor data that have been tested. Naïve Bayes classifiers have been use with promising results for activity recognition. Naïve Bayes classifiers identify the activity that corresponds with the greatest probability to the set of sensor values that were observed and conditionally independent .This Activity process is done in Asp.Net

2. Problem Specification

2.1 Overview of the Problem

Activity Recognition is one of the most important components of an automatic monitoring system based on smart home technology. An activity recognition algorithm recognizes resident activity patterns from low level sensor data. It is usually given a sequence of sensor readings.

The increasing aging population in the coming decades will result in many complications for society and in particular for the health care system due to the shortage of health care professionals and health care facilities. To remedy this problem, researchers have pursued developing monitoring systems and assisted living technologies by utilizing recent advances in sensor and tracking technology, as well as in the data mining and machine learning fields. In this thesis, the main report on this fully automated approach for discovering and monitoring patterns of daily activities. Discovering and tracking patterns of daily activities can provide unprecedented opportunities for health monitoring and assisted living applications, especially for older adults and individuals with mental disabilities.

There have been extensive studies done in the past on the classification problem by the statistical, machine learning and database research community. But Activity recognition is a new area of research poses new challenges due to its unique problem nature. Most existing algorithms were not designed with the monitoring health of human in mind. Such a situation of sparseness and high dimensionality is a big challenge for most classification algorithms.

Previous approaches usually rely on pre-selected activities or labeled data to track and monitor daily activities. The proposed work presents a fully automated approach by discovering natural activity patterns and their variations in real life data. The Perception will show how human activity discovery component can be integrated with an activity recognition component to track and monitor various daily activity patterns. The Concept also provides an activity visualization component to allow caregivers to visually observe and examine the activity patterns using a user-friendly interface.

2.3 Existing Methods

2.3.1 Probabilistic Suffix Tree

The probabilistic suffix tree (PST) is based on the traditional suffix tree. Like the suffix tree, the PST represents all the N(N + 1)/2 substrings from the root to the leaf nodes. The PST models variable length Markov models, which means that the string depth is not fixed for every node. In Existing system probabilistic suffix tree (PST) is introduced to model causal relationships between constituent actions, where both large and small order Markov dependencies between action units are captured.[1,2]

2.3.2 Constructing a classifier from the probability model

The discussion has derived the independent feature model, that is, the naive Bayes probability model. The naive Bayes classifier combines this model with a decision rule. One common rule is to pick the hypothesis that is most probable; this is known as the maximum a posteriori or MAP decision rule. The corresponding classifier is the function classify defined as follows:

$$\mathrm{classify}(f_1,\dots,f_n) = \underset{c}{\mathrm{argmax}}\ p(C=c)\prod_{i=1}^{n} p(F_i=f_i|C=c). \tag{1}$$

F- Number of Frames, **P-** Prior Frame

C- Class Variable, argmax-Argument Maximum passed in Posterior

2.3.3 Context – Cue Method

A context cue is something that cues an onlooker in to how something should be viewed. For example, if someone talked at length about rabbits and Watership Down and how a friend of theirs has two pet bunnies, and then asked you to write the word "hare," you would spell it like that, h-a-r-e. However, if someone told a story about a trip to the salon, and how their friend got highlights and layers, and how they really need a new brush, and then asked you to write the word "hair," you would spell it h-a-i-r. In this Existing System context-cue, especially interactive objects information is modeled through sequential pattern mining (SPM), where a series of action and object co-occurrence are encoded as a complex symbolic sequence. [3]

2.3.4 Predictive Accumulative Function (PAF)

There two types of Predictive function which to depict the predictability of each kind activity. The approach proposes the prediction model in two scenarios: action-only and context-aware, which is characterized by what kind of information used for prediction.

3. Proposed Method

3.1 Objectives of Proposed System

The main objective of this proposed method is to

- To compare the behaviour and activities of human from temporal data set and video data sets.
- To differentiate between the non-healthy and healthy person monitoring system at home in the dataset which is taken for consideration.

3.2 Naïve Bayesian Classifications

The Naive Bayes Classifier technique is based on Bayesian theorem. It is a probabilistic classifier. Bayes Theorem is a formula that calculates probability by counting the frequency of values and combinations of values from the historical data. This theorem is suited for problems where the dimensionality of the input is high. Naïve Bayes classification can outperform more sophisticated classification methods. [3,10]

Process steps:

Step 1: First step converts fortune cookie messages into features to be used by a naive Bayes classifier.

Step 2: The second phase, which is the training phase, the naive Bayes classifier reads in the training data along with the training labels and learns the parameters used by the classifier.

Step 3: The next phase, Is the testing phase where the trained naive Bayes classifier classifies the data in the testing data file.

Step 4: Output the accuracy of the naive Bayes classifier by comparing the predicted class label of each message in the testing data to the actual class label. The accuracy is the number of correct predictions divided by the total number of predictions.

The naïve bayes algorithm has both its advantages and disadvantages. Some of them are naïve bayes estimates the parameters which are necessary for classification by using only a small amount of training data.

3.3 Markov Dependency

The goal of activity recognition is to recognize common human activities in real life settings. Accurate activity recognition is challenging because human activity is complex and highly diverse. Several probability-based algorithms have been used to build activity models. The Hidden Markov Model is the
Most popular modeling techniques.

Simple activities can be modeled accurately as Markov Chains. However, complex or unfamiliar activities are often difficult to understand and model. [4,9]

Behavior Recognizing through HMM

Step 1 : generate an Behavior label L for a particular sensor event x,
Step 2 : we apply the sliding window of events that ends in event x for each HMM
Step 3 : choose the Behavior that receives the highest number of votes.
Step 4 : For each individual HMM, we let the hidden states represent the possible activities and encode observable states to represent sensor values.
Step 5 : The multiple HMMs in the multi-HMM model represent alternative variations of the patterns.
Step 6 : the first HMM represents the first variation of all patterns (one hidden state per pattern),
Step 7 : the second HMM represents the second variation of patterns, and so on.
Step 8 : The Behavior label L(x) is calculated Below, where Pk(x;Li) shows the probability of assigning label Li to x by the kth HMM. In this equation, n is the number of HMMs

$$L_m(x) = argmax_i\left(\frac{\sum_{k=1}^{n} P_k(x, L_i)}{n}\right) \quad (2)$$

4. Implementation

4.1 Implementation Process Mainly On Hmm Model

- Probability of an observed sequence
- Probability of an observing sequence
- Probability of the latent variables
- Filtering
- Smoothing

5. Modules

5.1 Discovering frequent pattern and Sequences

This approach is different from frequent item set mining because we consider the order of items as they occur in the data. Unlike many other sequence mining algorithms, the reporting of a general pattern that comprises all frequent variations of a single pattern that occur in the input data set D. For general pattern a, it denote the ith variation of the pattern as ai, and we call the variation that occurs most often among all variations of the prevalent variation, ap. Here, also refer to each single component of a pattern as an event. [5,6]

Fig.2 Activity choosing form

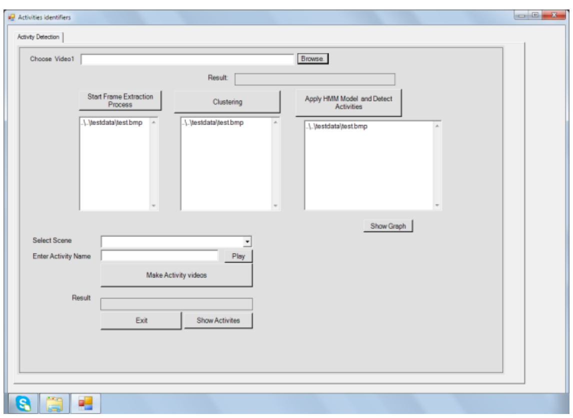
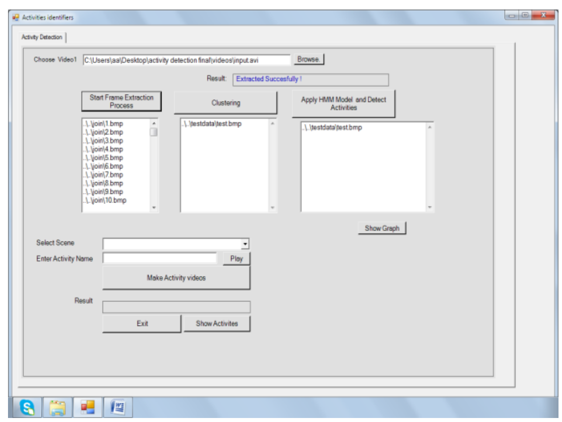


Fig.3 Extract the videos in frames



5.2 Clustering Sequences into Groups Of Activities

The second step of the HMM algorithm is to identify pattern clusters that will represent the set of discovered activities. Specifically, HMM groups the set of discovered patterns P into a set of clusters A. The resulting set of clusters centroids represents the activities that we will model, recognize, and track. Though ADM uses a standard kmeans clustering method, still the work need to define a method for determining cluster centroids and for comparing activities in order to form clusters. [7,8]

Fig.4 Clustering the frames

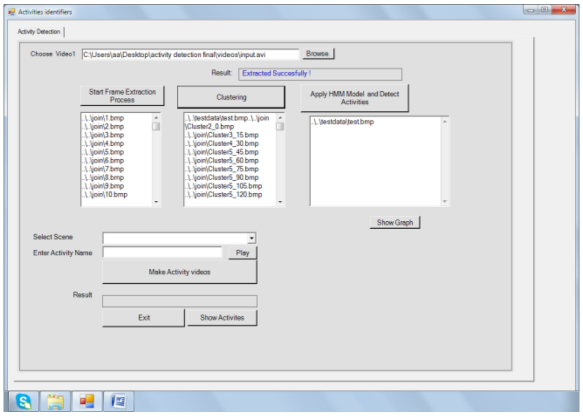
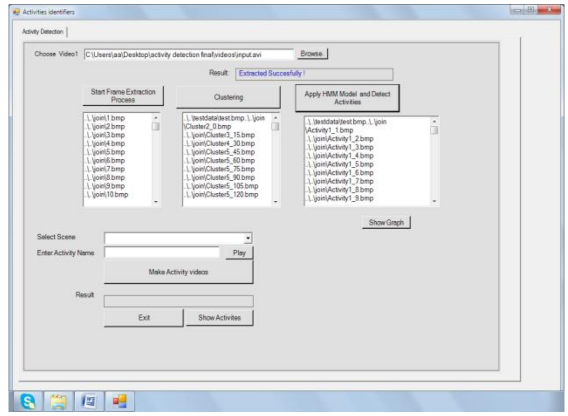


Fig.5 Applying HMM to detect the activity



5.3 Activity Mining

Once the activities are discovered for a particular individual, the system want to build a model that will recognize future executions of the activity. This will allow the smart environment to track each Behavior and determine if an individual's routine is being maintained. As described earlier, researchers have exploited the use of probabilistic models for Activity mining with some success for predefined activities. In this approach, using of a hidden Markov model to recognize activities from sensor data as they are being performed. Each model is trained to recognize the patterns that correspond to the cluster representatives found by HMM.[8,9]

Fig.6 selecting the frames in sequence form

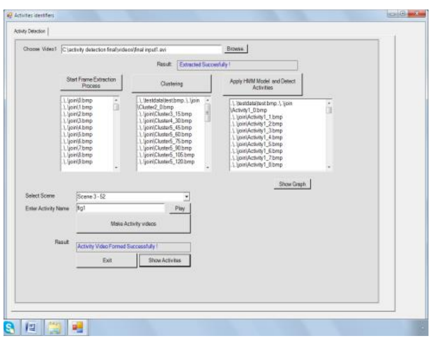


Fig.7 conversion of frames

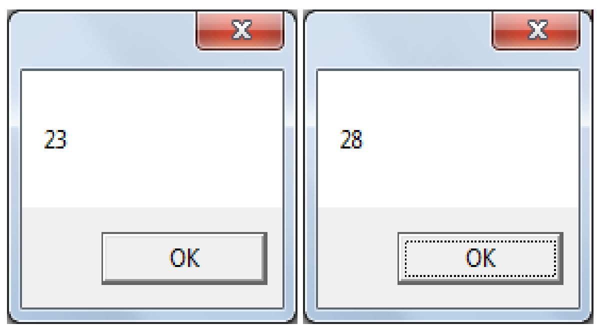
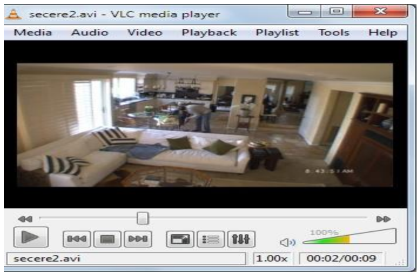


Fig.8 Sequence videos



6. Result and Discussion

The experiments performed in this research work are to evaluate the performance of Naïve Bayes classification algorithm & HMM Model with PST Algorithm and Context-cue method. In the accuracy assessment done by comparing the classified image with Monitored data, it was found that there is slight difference between optimized PST result and the naïve bayes classifier result. The performance of Naive Bayes classifier algorithm is compared with PST algorithm and context-cue method based on time efficiency, Memory efficiency and accuracy. Execution time differs according to the speed, memory capacity of the system and uploading the video data. But whatever the fact may be naive bayes classifier has taken more accuracy when comparing with PST algorithm.

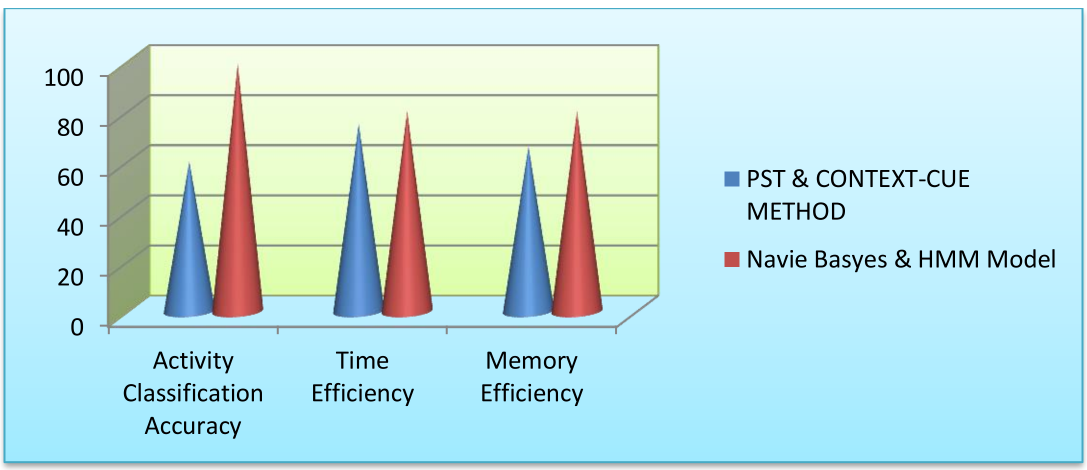


Fig.9 Comparison chart

7. Conclusion

In order to provide robust activity recognizing and tracking capabilities for smart home residents, researchers need to consider techniques for identifying the activities to recognize and track. While most approaches target specific ADLs for tracking, this imposes a burden on annotators and residents and often introduces a source of error in the process. So, introducing an alternative method for tracking activities in smart environments. In this approach, System employ the HMM algorithm to discover frequent activities that regularly and naturally occur in a resident's environment. Models are then learned to recognize these particular activities, and the result findings can be used to assess the functional well-being of smart environment residents. While this is a useful advancement in the field of smart environment technologies for health monitoring and assessment, there is still additional research that can be pursued to enhance the algorithms. Currently, the user specifies a desired number of activities to cluster and model. This type of automated assessment also provides a mechanism for evaluating the effectiveness of alternative health interventions.

7.1 Future Scope

- The proposed algorithm is to design a component of a complete system that performs functional assessment of adults in their everyday environments. This type of automated assessment also provides a mechanism for evaluating the effectiveness of alternative health interventions.
- These activity profiling technologies are valuable for providing automated health monitoring and assistance in an individual's everyday environments as well as applied in different domains such as surveillance and monitoring devices, also an alerting mechanism is dome for unclassified activities occurring in the live video stream., the video recording space is considered as future research to reduce the vast memory usage.

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