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An Information Motivated Framework to Behavioral Reasoning in Smart Locations

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Abstract— **The primary aim of data mining is to analyze data for summarizing useful informations.Video mining is applied for discovery of patterns at an unsupervised environment in audio visual content. Among various video mining methods DVSM is used for discovering activity pattern sequences that may be disrupted or have varied step order. In the proposed system along with frame feature extraction, clustering sequences and discovering discontinuous sequences. The technique namely behavioral reasoning which is based on MHMM is been incorporated for smart video surveillance at places especially like banks, examination centers.**

I. INTRODUCTION

Video mining is a process which cannot automatically extract content and structure of video, features of moving objects, spatial or temporal correlations of those features, but also discover patterns of video structure, objects activities, video events, etc. from vast amounts of video data without little assumption about their contents. Many video mining approaches have been proposed for extracting useful knowledge from video database. Finding desired information in a video clip or in a video database is still a difficult and laborious task due to its semantic gap between the low-level feature and high-level video semantic concepts. Video data mining can be classified in following categories, such as pattern detection, video clustering and classification and video association mining .

II. FRAME FEATURE EXTRACTION

Frame Information extraction is a type of image information retrieval whose goal is to automatically extract structured pixel information, i.e. categorized and contextually and semantically well-defined data from a certain domain, from unstructured machine-readable images. Each frame can be placed as a node along the temporal line of a video. Given a query clip Q and database video S, a short line and a long line can be abstracted, respectively.

Hereafter, each frame is no longer modeled as a high-dimensional point as in the preliminary step, but simply a node.3 Q and S, which are two finite sets of nodes ordered along the temporal lines, are treated as two sides of a bipartite graph.

III. DISCOVERING FREQUENT DISCONTINOUS SEQUENCES

Our Behavior discovery method performs frequent sequence mining using DVSM to discover frequent patterns, and then, groups the similar discovered patterns into clusters. We use DVSM to find sequence patterns from discontinuous instances that might also exhibit varied-order events.

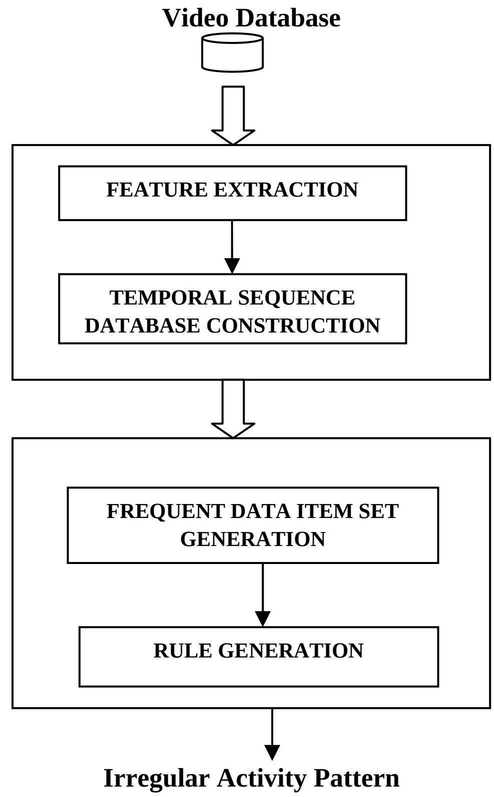

Fig 1 Steps involved in video mining

As an example, DVSM can extract the pattern ha; bi from instances fb; x; c; ag; fa; b; qg, and fa; u; bg, despite the fact that the events are discontinuous and have varied orders.

IV. CLUSTERING SEQUENCES INTO GROUPS OF ACTIVITIES

The second step of the ADM algorithm is to identify pattern clusters that will represent the set of discovered activities. Specifically, ADM 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 , we still need to define a method for determining cluster centroids and for comparing activities in order to form clusters.

A number of methods have been reported in the literature for sequence clustering, such as the CLUSEQ algorithm by Yang and Wang and the ROCK algorithm by Noh et al. The difference between their approach and ours is that they consider purely symbolic sequences with no features attached to them. In contrast, sensor event sequences are not simply strings, but each entry in the sequence also has associated features such as temporal information that needs to be considered during the discovery process.

V. ACTIVITY SEQUENCE DE-SCRAMBLING

The filtering step can be viewed as a rough similarity evaluation disregarding temporal information. Observing that a segment may have multiple 1:1 mappings, and the most similar subsequence in S may only be a portion of , next, we further refine to find the most suitable 1:1 mapping for accurate identification (or ranking), by considering visual content, temporal order and frame alignment simultaneously.

Defining a similarity measure consistent with human perception is crucial for similarity search. First, we present the score function which integrates three factors in judging video relevance for resembling human perception more accurately. The video similarity is computed based on an arbitrary 1:1 mapping out of all the possible 1:1 mappings to locate the most visually similar Activity subsequence.

VI. BEHAVIORAL REASONING

Once the activities are discovered for a particular individual, we want to build a model that will recognize future executions of the activity.

Fig 2 **Example of one image set for one subject**

This will allow the smart environment to track each Behaviour and determine if an individual's routine is being maintained. As described earlier, researchers have exploited the use of probabilistic models for Behavior Reasoning with some success for predefined activities. In our approach, we make use 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 ADM.

VII. CONCLUSION

The robust Behavior Reasoning 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. But in this proposed method introduce an alternative method for tracking activities in smart environments.

ADM algorithm is used to discover frequent activities that occur regularly and naturally in a resident's environment. Models are then learned to recognize these particular activities, and can be used to assess the functional well-being of smart environment residents. This type of automated assessment also provides a mechanism for evaluating the effectiveness of alternative health interventions. Behaviour profiling technologies are valuable for providing automated health monitoring and assistance in an individual's everyday environments.

VIII. FUTURE WORK:

In future a design component for a complete system that performs functional assessment of adults in their everyday environments can be modeled with behavioral reasoning as a base model. The video recording space is considered as future research to reduce the vast memory usage. By applying this technique only videos of few seconds durationcan alone be processed. Hence, in future techniques for long videos will be considered.

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