

A REVIEW PAPER ON VIDEO CLASSIFICATION USING NEURAL NETWORK AND SUPPORT VECTOR MACHINE

Er. Rajinder Kumar, M.Tech (student), CSE, GCET, Gurdaspur
Er. Rohit Mahajan, Assistant Professor, CSE, GCET, Gurdaspur

Abstract

Data mining is the process of analyzing data from different perspectives and summarizing it into useful information that can be used to increase revenue, cut costs, or both. Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and summarize the relationships identified. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases. Video data mining is to discover and describe interesting patterns from the huge amount of video data as it is one of the core problem areas of the data-mining research community.

Keywords- Neural Network (NN), Decision Tree Induction (DTI), Support Vector Machine (SVM) and Geographical Information System (GIS).

1. INTRODUCTION

Due to the extensive use of information technology and the recent developments in video systems, the amount of video data available to users has increased exponentially. Video is an example of multimedia data as it contains several kinds of data such as text, image, meta-data, visual and audio. Many video mining approaches have been proposed which can be roughly classified into five categories Video pattern mining, Video clustering and classification, Video association mining, Video content structure mining and Video motion mining [2]. It is widely used in many major potential applications like security and surveillance, entertainment, medicine, education programs and sports. Compared to the mining of other types of data, video data mining is still in its infancy. The problem of video data mining combines the area of content-based retrieval, image understanding, data mining, video representation and databases [3]. The temporal aspect of videos prevents the efficient browsing of these very large databases. However, apart from temporal segmentation where it plays an almost exclusive role [1]. Uncover hidden trends and patterns are discovered according to explicit knowledge base domain

knowledge and complicated analytical skills. These patterns and trends form the basis of predictive models that help analysts to produce new observations from existing data. Many video mining approaches have been proposed which can be roughly classified into five categories video pattern mining, video clustering and classification [4], video association mining, video content structure mining and video motion mining. It is widely used in many major potential applications like security and surveillance, entertainment, medicine, education programs and sports. Compared to the mining of other types of data, video data mining is still in its infancy [5], [6], [7].

2.1 Review of Classification Approaches and their Gaps

1. Sports Video Classification

It is proposed that exploitation of the human vision system in perceiving some salient regions inside video frames, which are represented by regions of interests (ROI). The technique first extracts ROIs and then clusters these ROIs to extract color and texture features to classify sports videos. Apart from a complicated algorithm design, the technique does not produce effective classification results observed from the experimental results reported [8].

2. Motion-Based Video Shot Classification

It is proposed that achieved effective results in classifying some motion modes such as jump, run, and other general camera motions. Within such classification scheme, we can classify all types of video clips into subcategories by a multiclass classifier. At first, video clips are classified into two basic classes: patterned and nonpatterned. Then, the patterned class is further classified into two classes: object patterns and camera patterns. In most of the cases, object motion cannot be discriminated from camera motion clearly in video. So we use the following rules to define the two categories. If object

motion is much more dominant than camera motion in a video clip, this clip will be considered as the case of object patterns although sometimes there are also some slight camera motions. If the camera focuses on the objects moving irregularly and both camera and objects do not have dominant motion, then there will be no salient motion patterns. We categorize such clips as non patterned. In order to improve the speed and accuracy of classification, the classification of video clips can be in 3 steps:

- To discriminate patterned from non patterned by a binary classifier.
- To discriminate object patterns from camera patterns by another binary classifier.
- To classify all of the video clips into subcategories within each basic category by a multiclass classifier, respectively. In this way, we need three multiclass classifiers. The reported technique can classify video shots in terms of low-level features, but is not able to tell whether such motion modes belong to specific type of sports [9].

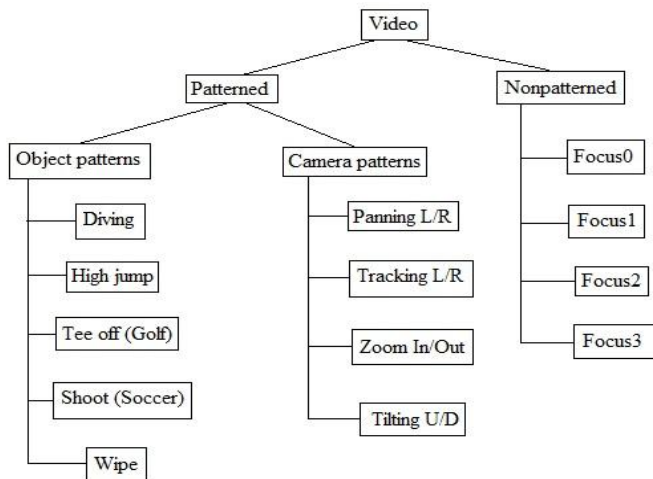


Fig. 2.1 Classification Scheme

3. Hidden Markov Model (HMM)

It is proposed that Block-Based Intensity comparison code is proposed for video classification based on a hidden Markov model (HMM). While the technique has the advantage of being robust to illumination changes, the classification is limited to a small number of video patterns [10].

4. Shot Boundary Based Approach

It uses either of the first, middle or the last frame of the shot

as the shot's key frame. This approach have been seen as the most easy way to extract the key frames but it lacks in capturing the visual content of the video shot. Fig 3.2 summarizes our findings and confirm that a shot boundary detection method will handle programs differently based on its content and will identify different correct shots. Each of the methods was run on the complete corpus and compared individually with the baseline to find the correct shot cuts. R2 and R3 do not uniquely discover many correct shot bounds, but collectively add another 356 correct shots to R1, so as different shot boundary detection methods have different strengths it makes sense to use all the methods instead of relying on the results from just one method [11].

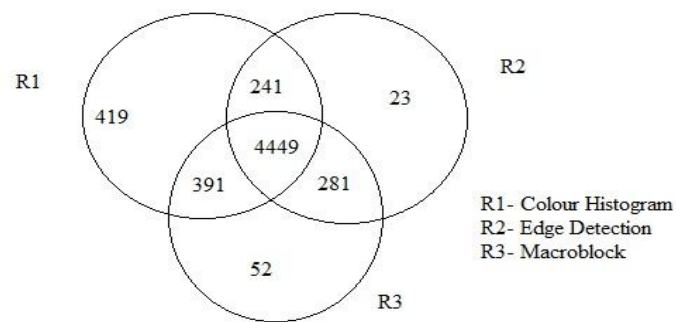


Fig. 2.2 Overlap in correct shot boundaries detected by the methods over the complete corpus.

5. K-Means Clustering

Supervised Learning is proposed to build up a semantics dictionary via a K-means clustering technique to classify sports videos, and such a technique could be very complicated, as the size of semantics dictionaries is constantly increasing [12].

6. Motion Analysis Approach

It computes the optical flow for each frame and then computed a simple motion metric based on the optical flow. This method was quite appreciable, but computationally expensive due to motion analysis [13].

7. Visual Content Based Approach

It is proposed that color and motion features independently to extract key frames. Thresholding technique is used to find the similarity between the current frame and the last extracted key frame. This method is relatively fast, but their performance depends on the choice of the threshold by the user. Threshold adjustment proves a serious issue for this method [14].

8. Multimedia Mining Framework Using Multimodal Analysis and Decision Tree

For the extraction of soccer goal events in soccer videos is proposed by using combined multimodal analysis and decision tree logic. The extracted events can be used to index the soccer videos. We first adopt advanced video shot detection method to produce shot boundaries and some important visual features. Then the visual/audio features are extracted for each shot at different granularities. This rich multi-modal feature set is filtered by a pre-filtering step to clean the noise as well as to reduce the irrelevant data. A decision tree model is built upon the cleaned data set and is used to classify the goal shots.

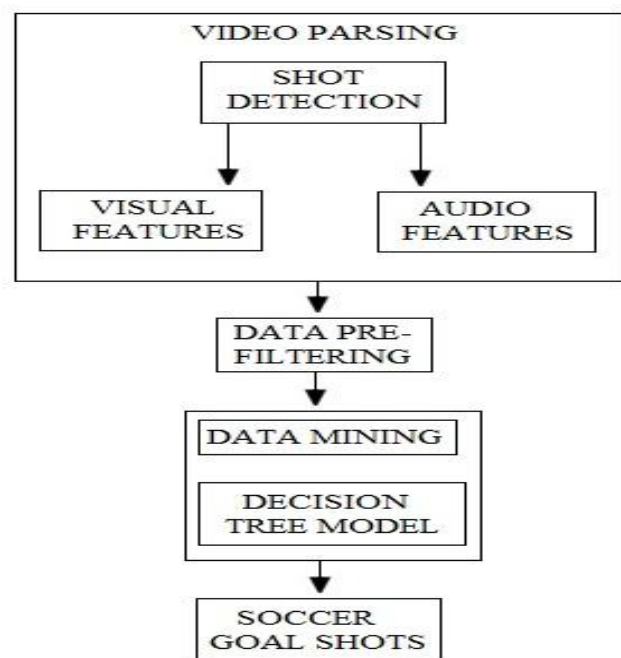


Fig. 2.3 The architecture of the framework

Our experimental results over diverse video data from different sources have demonstrate the recall and precision that the integration of data mining and multimodal processing of video is a viable and powerful approach for effective and efficient extraction of soccer goal events [15].

9. Gender Classification

Computer vision systems are playing an important role in applications include gender detection, face recognition, body tracking and ethnicity identification etc. Automated data analyses techniques help discover regularities and hidden associations in larger volumes of datasets. A number of

classification techniques like decision trees, support vector machine (SVM), nearest neighbors and neural networks etc. have gained popularity in numerous areas of data mining practices. Among these classification techniques, decision trees offer an added advantage of producing easily interpretable rules and logic statements along with generating the classification tree for the given dataset. The attributes are left eye width, Nose Width, Left Eye center to Mouth Left corner , Right Eye center to Mouth Right corner , Left Eye center to Mouth Right corner Mouth Right corner to middle of Chin. Our technique demonstrates robustness and relative scale invariance for gender classification. The experiments provide a new insight into gender classification methodology that not only serves as a classifier but also outlines the clear and easy to understand discriminant rules. This study may be useful for extracting the rule set for a decision support system which involves a large volume of dataset having several decision parameters. Classifier accuracy is calculated over incorrectly and correctly results [16].

10. Online Examination using Decision Tree

One way to achieve highest level of quality in higher education system is by discovering knowledge for prediction regarding enrolment of students in a particular course, alienation of traditional classroom teaching model, detection of unfair means used in online examination, detection of abnormal values in the result sheets of the students, prediction about student's performance and so on. Information like Attendance, Class test, Seminar and Assignment marks were collected from the student's previous database, to predict the performance at the end of the semester. This helps to the students and the teachers to improve the division of the student based on performance which is calculated by entropy using information gain of every student [17], [18].

3. CONCLUSION

In this paper different efficient algorithms are used to extract the features from the video that results in the relevant information which is unknown previously. Video classification plays an important role in content based video retrieval. The numbers of systems are designed to classify videos according to their contents but each of these systems differs by the techniques used to do the classification. In the past, video databases have been relatively small, and indexing and retrieval have been based on keywords annotated manually. More recently, these databases have become much larger and content-based indexing and retrieval is required, based on the automatic analysis of videos with the minimum of human participation.

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