ISSN: 2321-7782 (Online)
Volume 2, Issue 8, August 2014
International Journal of Advance Research in Computer Science and Management Studies
Research Article / Survey Paper / Case Study
Available online at: www.ijarcsms.com

Automatic Extraction of similar video using visual query clip based on Naïve Bayesian Classifier: A Survey

T.Madhanya[1]
Research Scholar, Department of Computer Science
Sri Krishna Arts and Science College
Coimbatore – India

K.S.Jeen Marseline[2]
HOD
Department of ICT
Sri Krishna Arts and Science College
Coimbatore – India

Abstract: A Video Retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital videos. Methods of video retrieval utilize some method of adding metadata such as captioning, keywords or description to the videos so that retrieval can be performed over the annotation words. Manual video annotation is time-consuming, laborious and expensive. A large amount of research under progress process on automatic video retrieval.

Keywords: Naïve Bayes Classifier, Video retrieval, Similar Video Extraction, Visual query clip.

I. INTRODUCTION

Video query based historic video sequence extraction by the spatial relationship is the convenience of video retrieval in large storage device, a new efficient video similarity search approach. The Video similarity is measured based on the calculation of the number of similar video components. There are two solving problems in this method: Similarity Measurement and search method, a novel feature computation of image characteristic code is based on spatial- relationship distribution of video frame sequence. A new search method according to clustering index table was presented by index clustering. The experimental results in large database query tests show the method of efficient and effective for similar video search.

A fast search approach for scalable computing was presented on the method of an indexing table. Proposed feature computation and the index clustering, the video sequence extraction can be implemented very efficiently with satisfying recall and precision rate. Proposed search method is easy to be implemented, it can be deployed in various storage devices for video similarity search.

Our robust model evaluating video similarity is not only based on the percentage of similar frames, which is essence ignores the temporal characteristics of videos. Approach involves the shot boundary detection and shot resolution which could be a few seconds in duration. The particular problem of measuring video similarity, when dealing with temporal order, frame alignment, gap and noise together, all the existing multidimensional sequences similarity measures such as normalized pair-wise distance.

Our approach based on frame sub sampling is capable of identifying video content containing ambiguous shot boundaries such as dynamic commercial, TV program lead-in and lead-out subsequences. The fast sequential search scheme applying temporal pruning to accelerate the search process which assumes query and target subsequences are strictly of the same ordering and length. It adopts spatial pruning to avoid seeking over the entire database sequence of feature vectors for exhaustive comparison.

II. Related Work

An automatic semantic content extraction framework is accomplished through the development of an ontology-based semantic content model and semantic content extraction algorithms. Our work differs from other semantic content extraction and representation studies in many ways and contributes to semantic video modeling and semantic content extraction research areas. [1]. Video content-based retrieval requires many changes in a multimedia database management system relative to a traditional database management system. [2].

A region is a contiguous set of pixels that is homogeneous in texture, color, shape, and motion properties. A video object as a collection of regions, which have been grouped together by some criteria defined by the domain knowledge. [3].

Multimedia content is widely used for many applications in today's world, and accessing it from repositories with vast amount of information has been a driving stimulus both commercially and academically. Spatio-temporal queries that contain any combination of spatial, temporal, object-appearance, external-predicate, trajectory-projection, and similarity-based object-trajectory conditions by a rule-based system built on a knowledge-base, while utilizing an object-relational database to respond to semantic (keyword, event/activity, and category-based), color, shape, and texture queries.[4].

Multimedia databases have gained popularity due to rapidly growing quantities of multimedia data and the need to perform efficient indexing, retrieval and analysis of this data. Our system aims to reduce the work for manual selection and labeling of objects significantly by detecting and tracking the salient objects. The rapid increase in the amount of multimedia data has features that can be queried. [5].

Data model is focused on the semantic content of video streams. Objects, events, activities performed by objects are main interests of the model. The model is flexible enough to define new spatial relationship types between objects without changing the basic data model. [6].

Bridging the gap between low-level representative features and high-level semantic concepts from a human point of view. Retrieval is performed by matching the feature attributes of the query object with those of videos in the database that are nearest to the query object in high dimensional spaces. The query-based video database access approaches typically require that users provide an example video or sketch, and a database is then searched for videos which are relevant to the query. [7].

Feature extraction, shot detection and object recognition is important phases in developing general purpose video content analysis. [8]. Representation and recognition of events in a video is important for a number of tasks such as video surveillance, video browsing and content based video indexing. VERL (Video Event Representation Language) and a companion language called VEML (Video Event Markup Language) to annotate instances of the events [9].

Recent increase in the use of video-based applications has revealed the need for extracting the content in videos. Manual techniques, which are inefficient, subjective and costly in time and limit the querying capabilities, are being used to bridge the gap between low-level representative features and high-level semantic content. [10]. Semantic concepts in the context of the video event are described in one specific domain enriched with qualitative attributes of the semantic objects, multimedia processing approaches and domain independent factors: low level features (pixel color, motion vectors and spatio-temporal relationship). [11].

Spatial relationships between objects are important features for designing a content-based image retrieval system. Image database systems such as visualization, browsing, spatial reasoning, iconic indexing, and similarity retrieval can be easily achieved. It provides a wide range of fuzzy matching capability in similarity retrieval to meet different user's requirements. [12].

 ISSN: 2321-7782 (Online)

III. NAÏVE BAYES CLASSIFIER

Naïve's Bayes classifier can be viewed as a specialized form of a Bayesian network termed Naïve because it relies on two important simplifying assumptions as independence and normality.

IV. PARTITIONING METHODS

Video Retrieval is the process of the number of similar video components. The video feature extraction of image and video was achieved by image characteristic code based on the statistic relation distribution.

A. NAIVE BAYES CLASSIIFIER

The Naïve bayes classifier can be viewed as a specialized form of a Bayesian Network, termed naïve because it relies on two important simplifying assumptions:

- Independence
- Normality

- The predictive attributes *xik* of an observed image xi are conditionally independent given the class *cj*.
- Naïve Bayes Classifier is often represented graphically where the direction of the arrows state that the predictive attributes *xi1*, *xi2,…xin* are conditionally independent given the class *cj*.
- A set of classes *C = c1.c2,…...Cm* denote the classes of the observed images(training set) *X = x1, x2,….x5*.
- Each observed image xi as a vector of random variables denoting the predictive attribute values xi1,xi2,*….xin*.
- A test instance x to be classified first using Bayes rule (Eq. 1) the posterior probabilities of each class and then predict the class with the highest probability as the class of *x*.

$$P(c_j \mid x_i) = \frac{P(x_i \mid c_j)P(c_j)}{P(x_i)} \qquad (1)$$

- From the training set, *P(cj)* is computed by counting the number of occurrences of *cj*.
- For each attribute *xik* the number of occurrences is counted to determine *P(xi).*
- Similarly, assuming categorical attributes, the probability *p(xi/cj)* can be estimated by counting how often each value *xik* occurs in the class in the training set.
- The values of attributes of each class are normally distributed and represented by its mean μ and standard deviation σ.
- A probability of an observed value can be efficiently estimated by Eq. 2.

$$P(x_{ik} \mid c_j) = \frac{1}{\sqrt{2\Pi}\sigma_j} e^{\frac{(x-\mu_j)^2}{2\sigma_j^2}} \qquad (2)$$

- Since an image has *n* independent attributes, we compute *P (xik|cj)* for every attribute.
- Estimate *P (xi|cj)* by the conjunction of all conditional probabilities of the attributes as shown in Eq. 3.

$$P(x_i \mid c_j) = \prod_{k=1}^{n} P(x_{ik} \mid c_j) \qquad (3)$$

- The posterior probability, Eq. 1, is estimated for every class and then predict the class with the highest probability as the class of the test instance *x*.

V. CONCLUSION

An Effective and efficient query processing strategy for temporal localization of similar content from a long unsegmented video stream using Naïve similarity search algorithm. The similar frames of query clip are retrieved by a batch query algorithm. Similar videos may exhibit with different ordering due to content editing, which yields some intrinsic cross managers. Color feature is used in the experiment, the proposed approach inherently supports other features, such as ordinal signature. The method is used to find about the relevant video data. In future, we have to implement the algorithm and discuss the results.

References

1. Yakup Yildirim, Adnan Yazici, Turgay Yilmaz,"Automatic Semantic Content Extraction in Videos Using a Fuzzy Ontology and Rule-Based Model".
2. M. Petkovic and W. Jonker, "An Overview of Data Models and Query Languages for Content-Based Video Retrieval,".
3. M. Petkovic and W. Jonker, "Content-Based Video Retrieval by Integrating Spatio-Temporal and Stochastic Recognition of Events,".
4. M.E. Donderler, E. Saykol, U. Arslan, O.Ulusoy, and U. Gudukbay, "BilVideo: Design and Implementation of a Video Database Management System.
5. Sevilmis, M. Bastan, U. Gudukbay, and O.Ulusoy, "Automatic Detection of Salient Objects and Spatial Relations in Videos for a Video Database System".
6. M. Koprulu, N.K. Cicekli, and A. Yazici, "Spatio-Temporal Querying in Video Databases".
7. J. Fan, W. Aref, A. Elmagarmid, M. Hacid, M. Marzouk, and X. Zhu, "Multiview: Multilevel Video Content Representation and Retrieval".
8. L. Bai, S.Y. Lao, G. Jones, and A.F. Smeaton, "Video Semantic Content Analysis Based on Ontology".
9. Nevatia, J. Hobbs, and B. Bolles, "An Ontology for Video Event Representation".
10. Y. Yildirim, "Automatic Semantic Content Extraction in Video Using a Spatio-temporal Ontology Model".
11. D. Song, H.T. Liu, M. Cho, H. Kim, and P. Kim, "Domain Knowledge Ontology Building for Semantic Video Event Description".
12. P.-W. Huang and C.-H. Lee, "Image Database Design Based on 9 D-SPA Representations for Spatial Relations".

AUTHOR(S) PROFILE

T. Madhanya has graduated M.Sc. (Software Systems) in Bharathiar University. Currently doing Mphil in Sri Krishna Arts and Science College.

Published various papers National and International conferences.