Label Based Clustering of Detecting Duplicate Videos in a Large Database

[1]Nagulmeera Sayyed, [2]B.Hari Babu
[1,2]Dept. of CSE, NOVA College of Engineering & Technology, Vijayawada, AP, India

Abstract
The proposed system is an efficient method for detecting duplicate videos using labels created virtually on videos by taking the characteristics(frame rate, Interlacing, Aspect ratio, color space and bits per pixel, bitrate, stereoscopic of a video) as metrics called duplicate detection rules. the system, create a duplicate detection rule for a specific video type finds five different labels for each video in the database, the labels are created according to the Video characteristics. The labels are clusters according to the video type. The duplicate detection rules are imposed on the target video data set and sorted the duplicate videos based on timestamp for a specific source video. Alternatively We follow the previous system work nature to get the accurate results for efficient and accurate method for duplicate video detection in a large database using video fingerprints. We have empirically chosen the color layout descriptor, a compact and robust frame-based descriptor, to create fingerprints which are further encoded by Vector Quantization (VQ). We propose a new nonmetric distance measure to find the similarity between the query and a database video fingerprint and experimentally show its superior performance over other distance measures for accurate duplicate detection. Efficient search cannot be performed for high-dimensional data using a nonmetric distance measure with existing indexing techniques. Therefore, we develop novel search algorithms based on recomputed distances and new dataset pruning techniques yielding practical retrieval times. We perform experiments with a database of 38 000 videos, worth 1600 h of content. For individual queries with an average duration of 60 s (about 50% of the average database video length), the duplicate video is retrieved in 0.032 s, on Intel Xeon with CPU 2.33 GHz, with a very high accuracy of 97.5%.

Keywords
Video Characteristics, Color Layout Descriptor (CLD), Duplicate Detection, Nonmetric Distance, Vector Quantization (VQ), Video Fingerprinting

I. Introduction

With the exponential growth of video sharing websites, e.g. You-Tube, the number of videos being searchable on theWeb has tremendously increased. Analysis on leading social video sharing platforms reveals a high amount of redundancy with overlapping or duplicate content. Wu et al. showed that there are on average 27% duplicates among the search results of 24 popular queries from YouTube, Google Video and Yahoo Video. To avoid being overwhelmed with duplicates in the video search result and utilize such redundancy for other tasks such as mining the internal structure of video database, automatic video tagging], etc.,. COPYRIGHT infringements and data piracy have recently become serious concerns for the ever growing online video repositories. Videos on commercial sites e.g., www.youtube.com and www.metacafe.com, are mainly textually tagged. These tags are of little help in monitoring the content and preventing copyright infringements. Approaches based on Content-Based Copy Detection (CBCD) and watermarking have been used to detect such infringements [20,27]. The watermarking approach tests for the presence of a certain watermark in a video to decide if it is copyrighted. The other approach, CBCD, finds the duplicate by comparing the fingerprint of the query video with the fingerprints of the copyrighted videos. A fingerprint is a compact signature of a video which is robust to the modifications of the individual frames and discriminative enough to distinguish between videos. The noise robustness of the watermarking schemes is not ensured in general [27], whereas the features used for fingerprinting generally ensure that the best match in the signature space remains mostly unchanged even after various noise attacks. Hence, the fingerprinting approach has been more successful.

We define a "duplicate" video as the one consisting entirely of a subset of the frames in the original video—the individual frames may be further modified and their temporal order varied. The assumption that a duplicate video contains frames only from a single video has been used in various copy detection works, e.g., [32,39,42]. In [42], it is shown that for a set of 24 queries searched in YouTube, Google Video and Yahoo Video, 27% of the returned relevant videos are duplicates. In [7], each web video in the database is reported to have an average of five similar copies—the database consisted of 45 000 clips worth 18 h of content. Also, for some popular queries to the Yahoo video search engine, there were two or three duplicates among the top ten retrievals [32]. The block diagram of our duplicate video detection system is shown in fig. 1.

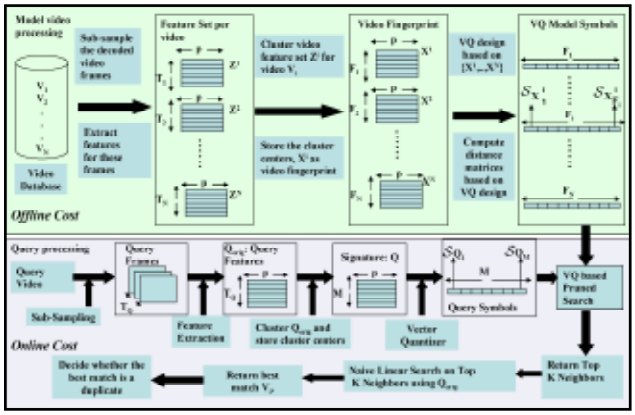


Fig. 1: Block Diagram of the Proposed Duplicate Detection Framework. Symbols Used are Explained in Table 1.

The duplicate detection task is to retrieve the best matching model video fingerprint for a given query fingerprint. The model-to-query distance is computed using a new nonmetric distance measure between the

Table: 1

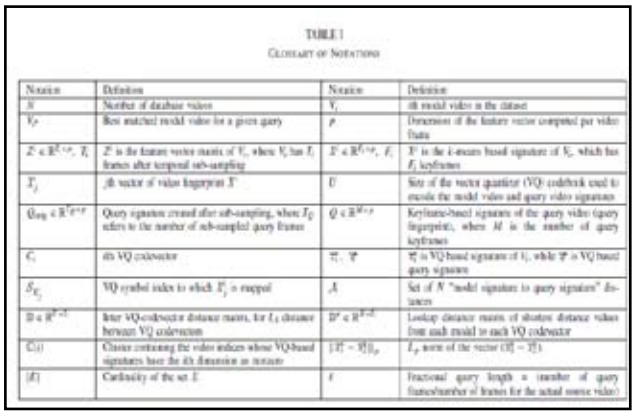


TABLE I
GLOSSARY OF NOTATIONS

Notation	Definition	Notation	Definition
N	Number of database videos	V_i	ith model video in the dataset
V_Q	Best matched model video for a given query	p	Dimension of the feature vector computed per video frame
$Z' \in \mathbb{R}^{L' \times p}$, T_i'	Z' is the feature vector matrix of V_i, where V_i has T_i frames after temporal sub-sampling	$Z' \in \mathbb{R}^{L' \times p}$, T_i'	T_i' is the L-excess based signature of V_i, which has T_i keyframes
T_j	jth vector of video fingerprint $\overline{V}$	U	Size of the vector quantizer (VQ) codebook used to encode the model video and query video signatures
$Q_{sig} \in \mathbb{R}^{M' \times p}$	Query signature created after sub-sampling, where T_Q refers to the number of sub-sampled query frames	$Q \in \mathbb{R}^{M \times p}$	Keyframe-based signature of the query video (query fingerprint), where M is the number of query keyframes
C_i	ith VQ codevector	$\overline{v}_i$, $\overline{V}$	$\overline{V}_i$ is VQ-based signature of V_i, while $\overline{V}$ is VQ-based query signature
S_{T_j}	VQ symbol index to which T_j' is mapped	A	Set of N "model signature to query signature" distances
$\mathbb{D} \in \mathbb{R}^{U \times U}$	Inter VQ-codevector distance matrix, for L_1 distance between VQ codevectors	$D' \in \mathbb{R}^{U \times U}$	Lookup distance matrix of shorter distance values from each symbol to each VQ codevector
$\mathbb{C}(i)$	Cluster containing the video indices whose VQ-based signatures have the ith dimension as nonzero	$\|\overline{v}_i' - \overline{v}_Q'\|_p$	L_p norm of the vector $(\overline{v}_i' - \overline{v}_Q')$
$\|E\|$	Cardinality of the set E	ℓ	Fractional query length = (number of query frames/number of frames for the actual source video)

fingerprints We also empirically show that our distance measure results in significantly higher detection accuracy than traditional distance measures (L_1, partial Hausdorff distance [18-19], Jaccard and cosine distances). We design access methods for fast and accurate retrieval of duplicate videos. The challenge in developing such an access method is twofold. Firstly, indexing using such distances has not been well-studied till date—the recently proposed distance-based hashing [3] performs dataset pruning for arbitrary distances. Secondly, video fingerprints are generally of high dimension and varying length. Current indexing structures (M-tree [10], R-tree [17], kd tree [4]) are not efficient for high-dimensional data.

The main contributions of this paper are as follows.

1. We proposed label based duplicate video detection based on the video stream characteristics.
2. We propose a new nonmetric distance function for duplicate video detection when the query is a noisy subset of a single model video. It performs better than other conventional distance measures.
3. For the VQ-based model signatures retained after dataset pruning, we reduce the search time for the top-K candidates by using suitable precomputed distance tablesand by discarding many noncandidates using just the partially computed distance from these model video signatures to the query.
4. We present a dataset pruning approach, based on our distance measure in the space of VQ-encoded signatures, which returns the top-K NN even after pruning. We obtain significantly higher pruning than that provided by distance-based hashing [3], methods, trained on our distance function.

In this paper, the terms "signature" and "fingerprint" have been used interchangeably. "Fractional query length" refers to the fraction of the model video frames that constitute the query. Also, for a VQ of codebook size U,the 1-NN of a certain codevector is the codevector itself.

II. Related Work

A survey for video copy detection methods can be found in [27]. Many schemes use global features for a fast initial search for prospective duplicates [42]. Then, keyframe-based features are used for a more refined search.

A. Keypoint-Based Features

In an early duplicate detection work by Joly et al. [22], the keyframes correspond to extrema in the global intensity of motion. Local interest points are identified per keyframe using the Harris corner detector and local differential descriptors are computed around each interest point. These descriptors have been subsequently used in other duplicate detection works [20-21,26-27]. In [42], Principal Component Analysis (PCA)–scale invariant feature transform (SIFT) features [25] are computed per keyframe on a host of local keypoints obtained using the Hessian-Affine detector [34]. Similar local descriptors are also used in [45], where nearduplicate keyframe (NDK) identification is performed based on matching, filtering, and learning of local interest points. A recent system for efficient large-scale video copy detection, the Eff2 Videntifier [11], uses Eff2 descriptors [29], from the SIFT family [33]. In [44], a novel measure called scale-rotation invariant pattern entropy is used to identify similar patterns formed by keypoint matching of near-duplicate image pairs. A combination of visual similarity (global histogram for coarser search and local point for finer search) and temporal alignment is used for duplicate detection in [40]. VQ-based techniques are used in [8] to build a SIFT histogram-based signature for duplicate detection.

B. Global Image Features

Some approaches for duplicate detection consider the similarity between sets of sequential video keyframes. A combination of MPEG-7 features such as the scalable color descriptor, CLD [24] and the Edge Histogram Descriptor (EHD) has been used for video-clip matching [5]. For image duplicate detection, the Compact Fourier–Mellin Transform (CFMT) [13] has also been shown to be very effective in [15] and the compactness of the signature makes it suitable for fingerprinting.

C. Video-Based Features

"Ordinal" features [6] have been used as compact signatures for video sequence matching [35]. Li et al. [30] used a binary signature, by merging color histogram with ordinal signatures, for video clip matching. Yuan et al. [43] also used a similar combination of features for robust similarity search and copy detection. UQLIPS, a video clip detection system [39], uses RGB and HSV color histograms as the video features. A Localized Color Histogram (LCH)-based global signature is proposed in [32].

D. Indexing Methods

Each keyframe is represented by a set of interest point-based descriptors. Matching involves comparison of a large number of interest point pairs which is computationally intensive. Several indexing techniques have been proposed for efficient and faster search. Joly et al. [22] use an indexing method based on the Hilbert's space filling curve principle. In [20], the authors propose an improved index structure based on statistical similarity search (S3). A new approximate similarity search technique was used in [21,23,26] where the probabilistic selection of regions in the feature space is based on the distribution of the feature distortion. In [45], an index structure LIP-IS is proposed for fast filtering of keypoints under one-to-one symmetric matching.

E. Hash-Based Index

The above mentioned indexing methods are generally compared with Locality Sensitive Hashing (LSH) [12,16], a popular approximate search method for L2 distances. Since our proposed distance function is nonmetric, LSH cannot be used in our setup as the locality sensitive property holds only for metric distances. Instead, we have compared against Distance Based Hashing (DBH) [3] which can be used for arbitrary distances.

F. Duplicate Confirmation

From the top retrieved candidate, the duplicate detection system has to validate whether the query has been derived from it. The

duplicate video keyframes can be matched with the corresponding frames in the original video using spatiotemporal registration methods. In [21,27], the approximate NN results are post processed to compute the most globally similar candidate based on a registration and vote strategy. In [26], Law-To et al. use the interest points proposed in [22], for trajectory building along the video sequence. A robust voting algorithm utilizes the trajectory information, spatiotemporal registration, and the labels computed during the offline indexing to make the final retrieval decision. In our duplicate detection system, we have a "distance threshold based" and a registration-based framework to determine if the query is a duplicate derived from the best-matched model video.

The advantages of our method over other state-of-the-art methods are summarized as follows:

1. In current duplicate detection methods, the query is assumed to contain a large fraction of the original model video frames. Hence, the query signature, computed over the entire video, is assumed to be similar to the model video signature. This assumption, often used as an initial search strategy to discard outliers, does not hold true when the query is only a small fraction (e.g., 5%) of the original video. For such cases, the query frames have to be individually compared with the best matching model frames, as is done by our distance measure. We observe that our proposed distance measure performs much better than other distances for duplicate detection for shorter queries.
2. We develop a set of efficient querying techniques with the proposed distance measure which achieves much better dataset pruning than DBH. DBH is the state-of the-art method for querying in nonmetric space.
3. In [21,27], the registration step is performed between query frames and other model frames to confirm whether the query is a duplicate. Our distance computation already gives us the inter-vector correspondence between the given query keyframes and the best matching model keyframes facilitating the registration step.

III. Proposed Model

The proposed system is an efficient method for detecting duplicate videos using labels created virtually on videos by taking the characteristics of a video as metrics called duplicate detection rules. To detect duplicates in the system, create a duplicate detection rule for a specific video type. You can create multiple detection rules for the same Video type we can publish a maximum of five duplicate detection rules per video type at one time. A rule can have one or more duplicate detection rule conditions that are represented by the duplicate rule condition video The conditions are combined by the system as in logical AND operation. A duplicate detection rule specifies a base video type and a matching video type. The system then clusters the videos based on the similarity metric function. The system creates a set of labels for each video and follows clustering method; search algorithm on similar labels based on similarity function. The system virtually finds the duplicate videos as label format and set in rank wise priority of same video.

A. The Work Nature of the Proposed System

The proposed system finds five different labels for each video in the database; the labels are created according to the Video characteristics. The labels are clusters according to the video type. The duplicate detection rules are imposed on the target video data set to find the similarity metric, which again compares against the videos labels virtually and sorted the duplicate videos based on Vsize for a specific source video.

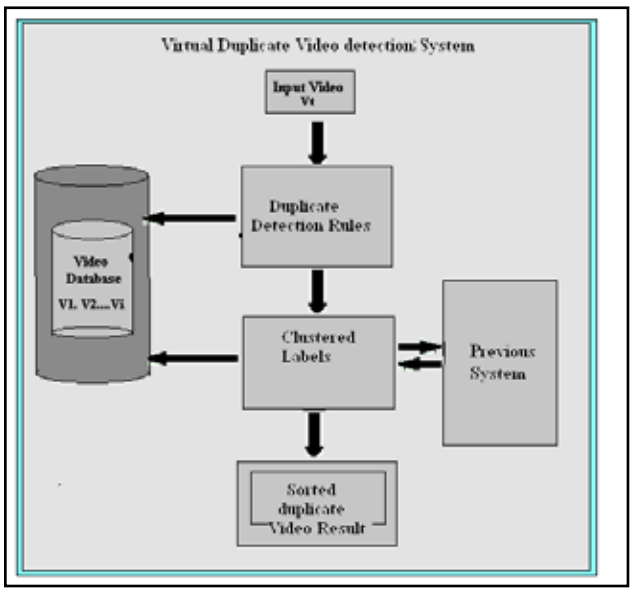


Fig. 2: The Proposed Frame Work

IV. Experimental Setup

We describe the duplicate detection experiments for feature comparison. We use label based duplicate video detection created virtually on videos by taking the characteristics(frame rate, Interlacing, Aspect ratio, color space and bits per pixel, bitrate, stereoscopic of a video) as metrics called duplicate detection rules. We use a database of 1200 video fingerprints and a detection error occurs when the best matched video is not the actual model from which the query was derived. we have shown that the proposed system works better than the previous system .the following figures shows that proposed system outperforms than the traditional systems. We are incorporating the previous system advantages and overcomes limitatations. Storage-wise, our system consumes much less memory compared to methods which store keypoint-based descriptors [11,21]. The most compact keypoint-based descriptor is the 20-dimensional vector proposed in [21], where each dimension is represented by 8 bits and 17 feature vectors are computed per second. The corresponding storage is 10 times that of our system (assuming 18-dimensional CLD features per frame where each dimension is stored as a double, 25 frames/s, temporal sub-sampling by 5, 5% of the sub-sampled frames being used to create the model signature).

We analyze the performance of the proposed algorithms for duplicate detection. The final detection accuracy, for a certain query length, is obtained by averaging over all the (1200× 18) noisy queries.

The performance comparison of the different distance measures shows that the detection accuracy using dVQ is significantly higher than the other distances, especially for small query lengths. For our proposed measure, the effective distance is the sum of distances between "query vector to best matching vector in model signature." For traditional histogram-based distances, the effective distance is computed between corresponding bins in the model and query signatures—this distance is small only when the query signature is similar to the entire model signature, which is true mainly for longer queries. Hence, the advantage of using our asymmetric distance is more obvious for shorter query lengths.

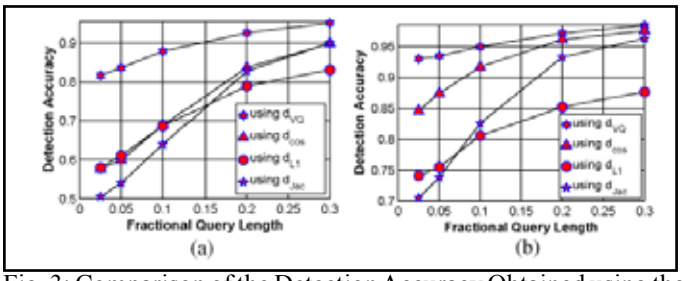


Fig. 3: Comparison of the Detection Accuracy Obtained using the Different VQ-Based Distance, using K=100. Is Shown Results using d_{int} and d_{L1}.Based Results are Shown. Results using d_{vq} are Significantly Better then that using d_{cos} (Which in Trun Performs Better then d_{L1} and d_{jac}) at smaller Query Lengths. (a) Detection results for various distance (K-10). (b) Detection Rsults for Various Distance (K=100)

V. Conclusions

The problem of fast and real-time duplicate detection in a large video database is investigated through a suite of efficient algorithms. We retrieve the duplicate video for about a minute long query in 0.03 s with an average detection accuracy of over 97%. We empirically selected CLD for fingerprinting as it was robust to the duplication attacks. However, if there is extensive cropping, padding, or rotation/shear, salient point based descriptors can be more effective. We developed a new label based method created virtually on videos by taking the characteristics (frame rate, Interlacing, Aspect ratio, color space and bits per pixel, bitrate, stereoscopic of a video) as metrics called duplicate detection rule sand nonmetric distance measure which is effective for shorter queries as long as the query is a noisy subset of a model video and keyframe-based signatures are used. We reduce the computational complexity of our distance measure using precomputed information, PDP, and dataset pruning. This distance measure can be explored in other domains which require subset matching.

In the future, we will explore the scalability of our approach to very large-sized datasets. It would be interesting to study the generalizability of our dataset pruning method for histogram based distances. In our problem, the query is created from a single model video. If, however, a query contains portions of multiple videos, the same asymmetric distance will not be effective. We will address this issue in future using a window based approach

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Mr. Nagul Meera Sayyed is a student of NOVA college of Engineering & Technology, Jangareddy gudem. Presently he is pursuing his M.TECH from this college and He received his M.C.A from Nagarjuna University in the year 2009, and B.SC from Nagarjuna University in the year 2006.



Mr. B.Hari Babu obtained his B.Tech from Kakatiya University. He received his M.Tech in Computer Science and Engineering from JNTU Hyderabad in 2008. Presently he is Pursuing PhD in same theme in the domain of DATA MINING with registration number 1003PH0675 in JNTUH Hyderabad, India. Currently he is working as Associate Professor in the Department of Computer Science and Engineering, NOVA College of Engineering & Technology, Vegavaram, Jangareddygudem, West Godavari (Dist). He is having 8+ years of teaching experience. His area of interest including Data Mining, Network Security, Information Retrieval Systems.