

Generalization of Determinant Kernels for Non-Square Matrix and its Application in Video Retrieval

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Abstract— For a specific set of features selected for representing videos, the performance of a content-based video retrieval system depends critically on the similarity or dissimilarity measures used. In this paper, we propose a kernel approach to improve the retrieval performance of content-based video retrieval systems namely determinant kernel. The input of this kernel is the dot product of feature matrices that extracted from shot visual information. Due to the variation in the number of each shot frames, the size of feature matrices are different and so the result of dot product become a non-square matrices. Almost all available techniques use summarizing methods to equalize the size of the matrices which lead to loss some parts of information. To solve this problem, we present a non-square determinant kernel based on Radic's definition. We evaluate the performance of the derived Kernels by retrieving video shots of news and speaking videos. Experimental results confirm the effectiveness of our proposed algorithm.

Keywords- Content-based video retrieval; determinant kernel; non-square matrices; similarity measurement; feature matrix

I. INTRODUCTION

Today people have access to a tremendous amount of video information in the internet. With a large video data collection, it is infeasible for a human to classify or cluster the video scenes or to find either the appropriate video scene, or the desired portions of the video. Video retrieval is an essential technology to design video search engines with serve as an information filter and sifts out an initial set of relevant videos from database. In video retrieval, finding the interesting video scene requires an efficient technique to determine the similarity between shots. Shot is a sequence of frames captured by one camera in a single continuous action in time and space [1]. Finding desirable shots are computationally intensive and extremely sensitive to similarity measure and visual features.

In quick overview, video retrieval contains three main sections [2]. First section is video structure analysis that is divided into shot boundary detection [3, 4] and key frame extraction subsections [5-8].

Feature extraction is the second section. Extracting features is the base of video retrieval. There are different features can be extracted from images and video files such as color-based features [9], texture-based features [10], or shape-based features [11]. Color-based features are the most efficient feature in video retrieval. In particular, color histogram is simple but competent descriptor [2]. In this paper, we have used color histogram of RGB color space with 255 blocks.

Finally, the third section is query and retrieval. There are several query types: query by example [2], query by sketch [12], query by objects [13], query by keyword, query by natural language [14] and combination-based query [15]. In this paper, we have used query by example. On receiving a query, a similarity method can be used to find nearest shots.

Similarity measurements play an important role in retrieving a video shot. Similarity methods are categorized into feature matching [16], text matching [17], ontology based matching [11,18] and combination-based matching [10]. Here, we have proposed a novel similarity method based on determinant kernel.

Kernel-based methods for multimedia retrieval have shown their robustness for many tasks, in shape recognition [19], image retrieval [20], and event detection [21] for instance. Most methods first build a kernel function, usually from supervised data [22], and then train a classifier such as support vector machines (SVM). Recently, kernel techniques for semi-supervised Metric learning have been proposed in some studies [23-25]. In Ref. [24], two kernel-based metric learning methods (i.e., Kernel-A and Kernel-b) using pair wise similarity constraints were introduced [24]. Yeung and Chang [25] extended the Kernel-b method introduced in Ref. [24].

In this paper, we introduce a proper similarity measure from kernels. Kernel functions specify the inner product between the shot-feature matrices and return a real number. There are several kernel functions such as KPCA [26], KLDA [27], RBF and Fisher kernel [28]. Basely, kernel functions

works on vectors and square matrices; but presentation matrices of real data such as shot-feature matrices are not square matrices. Almost all current techniques summarize input non-square matrix to make it compatible to kernel function in which part of data is missed.

In this paper, we have generalized the determinant kernel proposed in [29] for non-square matrix based on Radic's definition [30] and evaluate the performance of the derived Kernels by retrieving video shots of news and speaking videos in TRECVID2006 standard dataset.

The rest of this paper is organized as follows. In Section 2, Radic's definition for calculating Non-square determinants is introduced. In section 3, we mention the justification of using determinant kernel in video retrieval based on vector view point. Section 4 shows empirical evaluations of our approach and implementations on video retrieval task. Section 5 sets out our conclusions and discusses some future works.

II. DETERMINANT OF NON-SQUARE MATRIX

Radic's definition [31] for calculating the determinant of non-square matrices has numerous significant properties and advantages to compare with other definitions. Specially, it has almost all the properties of determinant of square matrices [30]. Below, we first present Radic's definition for determinant of non-square matrices.

Definition 1. Let $A = [a_{ij}]$ be a $m \times n$ matrix with $m \leq n$. The determinant of A , is defined as:

$$\det(A) = \sum_{1 \leq j_1 < \dots < j_m \leq n} (-1)^{r+s} \det \begin{bmatrix} a_{1j_1} & \dots & a_{1j_m} \\ \vdots & \ddots & \vdots \\ a_{mj_1} & \dots & a_{mj_m} \end{bmatrix}, \quad (1)$$

Where $j_1, j_2, \dots, j_m \in \mathbb{N}$, $r = 1 + 2 + \dots + m$ and $s = j_1 + \dots + j_m$. If $m > n$, then we define $\det(A) = 0$.

According to this definition, it is evident that the determinant of a non-square matrix can be computed as sum of specially signed square sub matrices. These sub matrices is obtained by calculating specific permutation of columns of non-square matrix. Although this definition is easy to compute and understand, it has exponential time complexity. In other words, computing $\det(A)$ requires computing determinants of C_m^n number of square sub matrices of order $m \times m$, which lead to exponential time complexity. Regarding to the previous works, it is obvious that applying column and row operations for computing the determinant of non-square matrices is inefficient [30]. In addition, due to the dependency between determining square sub matrices, it is impossible to design an efficient parallel algorithm based on this definition.

III. DETERMINANT KERNELS BETWEEN MATRICES

Suppose $A = [a_{ij}]_{f \times m}$ and $B = [b_{ij}]_{f \times n}$ that satisfying $m \leq n$, we want to define a determinant kernel function $k_d(A, B)$. The proposed kernel is based on so-called Gram

matrix which is defined as a dot product between two matrices A and B :

$$G_{\text{mat}(A,B)} = A' \cdot B = [a_{ji}]_{m \times f} \cdot [b_{ij}]_{f \times n} \quad (2)$$

The determinant kernel is defined as

$$k_d(A, B) = \det(A' \cdot B). \quad (3)$$

IV. VIDEO RETRIEVAL USING DETERMINANT KERNEL JUSTIFICATION

In this paper, we introduce non-square determinant of matrices to retrieve an input shot in a video file. According to Radic's definition and due to its specifications [30], if there are two equal rows in a matrix or there is a dependency between some rows of it, then its determinant would be zero. Using vector viewpoint, we can suppose matrix rows as vectors. So, as you see in figure 1. Rows' dependency can be interpreted as if two vectors fall upon each other. Whatever the angle between two vectors become smaller, the corresponding rows in the matrix are more dependent and determinant closes to zero.



Figure 1. The relationship of determinant and the angle between two vectors.

Therefore, if A is feature-matrix of a shot with n key frames and B is feature-matrix of a shot with m key frames, then for $C_{m \times n}$ ($m \leq n$), we have:

$$\begin{aligned} C_{m \times n} &= A' \cdot B \\ &= \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_m \end{bmatrix} \begin{bmatrix} f_{1,1} & f_{1,2} & \dots & f_{1,125} \\ f_{2,1} & f_{2,2} & \dots & f_{2,125} \\ \vdots & \vdots & \ddots & \vdots \\ f_{m,1} & f_{m,2} & \dots & f_{m,125} \end{bmatrix}_{m \times 125} \cdot \begin{bmatrix} F'_1 & F'_2 & \dots & F'_n \\ f'_{1,1} & f'_{2,1} & \dots & f'_{n,1} \\ f'_{1,2} & f'_{2,2} & \dots & f'_{n,2} \\ \vdots & \vdots & \ddots & \vdots \\ f'_{1,125} & f'_{2,125} & \dots & f'_{n,125} \end{bmatrix}_{125 \times n} \\ C_{m \times n} &= \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_m \end{bmatrix} \begin{bmatrix} F_1 F'_1 & F_1 F'_2 & \dots & F_1 F'_n \\ F_2 F'_1 & F_2 F'_2 & \dots & F_2 F'_n \\ \vdots & \vdots & \ddots & \vdots \\ F_m F'_1 & F_m F'_2 & \dots & F_m F'_n \end{bmatrix}_{m \times n} \end{aligned} \quad (2)$$

And if $m > n$, $C_{m \times n} = B' \cdot A$.

Regarding our discussion, whatever the dependency between U_i and U_j vectors is more, then determinant of $C_{m \times n}$ is closer to zero.

Let equation 3:

$$\begin{aligned} U_i &= [F_i F'_1 \quad F_i F'_2 \quad \dots \quad F_i F'_n] \\ U_j &= [F_j F'_1 \quad F_j F'_2 \quad \dots \quad F_j F'_n] \end{aligned} \quad (3)$$

Whatever the frames in shot A are more similar to the frames of shot B, then U_i would become closer to U_j and so the determinant of $C_{m \times n}$ would be smaller. On the other hand as

equation 3 show, the similarity between F_i and F_j has effect on measure of dependency between U_i and U_j . Therefore, it seems this approach would work better on less dynamic videos. In

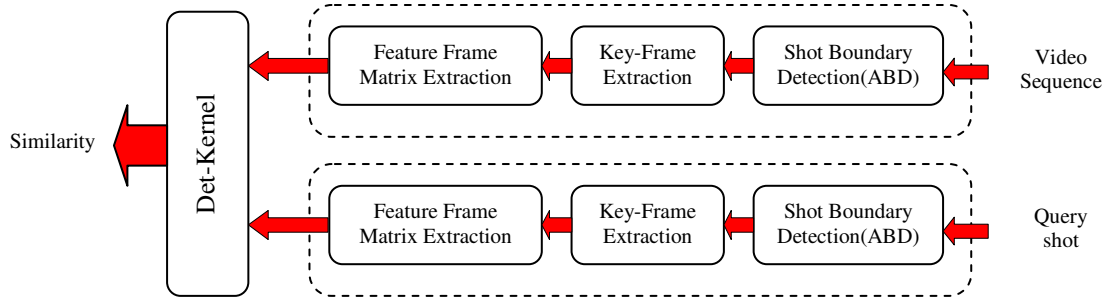


Figure 2. Block diagram of the proposed video retrieval system

[32], the authors defined some criteria for measuring dynamicity in shot, scene and video levels. If a shot has many self-motivated frames with different visual concepts, then the Shot-Dynamicity measure will be limited to 1 and if a shot includes some static frames, then the Shot-Dynamicity measure will be limited to 0.

V. SYSTEM OVERVIEW

The proposed system in this paper is shown in Figure 2. As can be seen in Figure 2, to find arbitrary shots in a video file, at first, this file must be decomposed into shots. There are many studies in shot boundary detection [33].

In this paper we have used the standard video data set TrecVID2006 in which the shot boundaries are specified manually. At the next step, key frames must be extracted. Among the works that have been done in this field[32], we utilize the approach presented in [32]. Suppose for shot S_i , the extracted key frames are $Keys_i = \{K_1^{(i)}, \dots, K_{n_i}^{(i)}\}$. In order to represent the key frames in a compact form, a feature matrix has been extracted from each key frame. There are various types of visual and semantic features. Among the visual features, one of the appropriate features is the color histogram [9].

Extracting the m -dimensional Feature vector from an arbitrary frame $K_j^{(i)}$, the vector $A_j^{(i)} = [A_{j,1}^{(i)}, \dots, A_{j,m}^{(i)}]^T$ has been created. If j (where $1 \leq j \leq n_i$) is the index of the i th shot's feature vector, the extracted feature matrix $A^{(i)}$ of shot i with n key frames will be as (2)

$$A^{(i)} = \begin{bmatrix} A_{1,1}^{(i)} & A_{2,1}^{(i)} & \dots & A_{n_i,1}^{(i)} \\ A_{1,2}^{(i)} & A_{2,2}^{(i)} & \dots & A_{n_i,2}^{(i)} \\ \vdots & \vdots & \ddots & \vdots \\ A_{1,m}^{(i)} & A_{2,m}^{(i)} & \dots & A_{n_i,m}^{(i)} \end{bmatrix}$$

For the query shot with p Key frames, the same procedure was also performed to construct the feature matrix $B_{m \times p}$. Then the two feature matrices have been compared by using determinant kernel for non-square matrices. The output is a real number. According to what was explained in section 1, however the absolute value of this number is close to zero, the tow shots are more similar to each other.

VI. EXPERIMENTAL RESULTS

In order to evaluate the proposed video retrieval system with standard data sets, we demonstrate the outcomes of the tests using a large-scale test set provided by the TRECVID 2006 [34].

While as there are various features that can be used to form a shot feature matrix, in this paper, the color histogram was chosen as the shot feature. Due to the different size of shots, the elements of extracted feature matrices from large shots is greater than small shots', so we should normalize feature matrices by dividing all elements to the number of whole color in each shot. Therefore, regardless the size of the shot, the summation of all elements in feature matrix is equal to one.

As mentioned in section 4, the results of retrieving the video using determinant kernel is strictly impacted from shot movement. According to [32], we assign each shot a number between 0 and 1 to indicate the amount of shot's movement.

Figure 3 illustrates the key frames of some shots of "20051101_142800_LBC_NAHAR_ARB.mpg" file in TRECVID 2006.

It is evident that the first and 9th shots, and 7th and 5th are very similar. The similarity of these shots using determinant kernel is demonstrated in tow following table. In Table 1, the first shot, which is the most static shot among the others, is compared with the other sample shots. These results confirm the effectiveness of the proposed kernel function.

TABLE I. Measuring The Similarities Between first shot and other Shots Of Fig.3

Compared shots		k_d
1	9	2.8993E-100
1	5	1.74553E-89
1	7	7.5363E-87

In Table 2, the 7th shot, which is the most dynamic shot among the others, is compared with the other sample shots. The results show dynamicity has undesirable impact on functionality of determinant kernel.

TABLE II. Measuring The Similarities Between 7th shot and other Shots Of Figure 3

Compared shots		k_d
7	1	6.5412E-76
7	5	2.0043E-68
7	9	3.4267E-59

In the experiments, to assess the efficiency of the determinant kernel, we first extract the dynamicity of each query shot then compute the precision measure. The Precision measure defined as the ratio of correct experimental detections over the number of all experimental detections. It measures the ability of a system to present only relevant items.

$$\text{precision} = \frac{\text{number of correct detections}}{\text{number of all detections}}$$

Figure 4 compares the precision of 600 shot queries with different dynamicity in video retrieval systems that use determinant kernel. These results confirm the effectiveness of the proposed algorithm for static shots and the impact of shot-dynamicity on the proposed kernel.



Figure 3. Key frames of some shots of file 20051101_142800_LBC_NAHAR_ARB.mpg in TRECVID 2006

It is affirmed in [35] the Generalized-Trace-Kernel is an effective method to retrieve similar video shots. As shown in figure 4, generalized determinant kernel is as efficient as trace kernel for static shots. The proposed method has the privilege of parallel computation, which is considerable in real time systems and queries in huge data bases.

VII. CONCLUSION

In this paper, we generalized determinant kernel for non square matrices regarding to Radic's definition. Using this method, the shots in different size can be compared without to summarization. The proposed algorithm is implemented and evaluated on TRECVID benchmark platform. The experimental result confirms the effectiveness of the proposed method for static shots. On the other hand, since this kernel can be computed in parallel [36], it is significant in real time systems.

VIII. FUTURE WORKS

The proposed system has used color histogram to determine the similarity between shots. Meanwhile, other features of shots can be used in this system. The inputs of the non-square determinant kernel are feature matrices, regardless how they have built. Also, the efficiency of the proposed kernel can be examined using other features.

The system can also be used for clustering shots by making a similarity matrix. The shot's can be grouped by using a suitable way, then for each cluster a header can be selected. However, the search speed increases but, the quality and efficiency of the method can also be investigated.

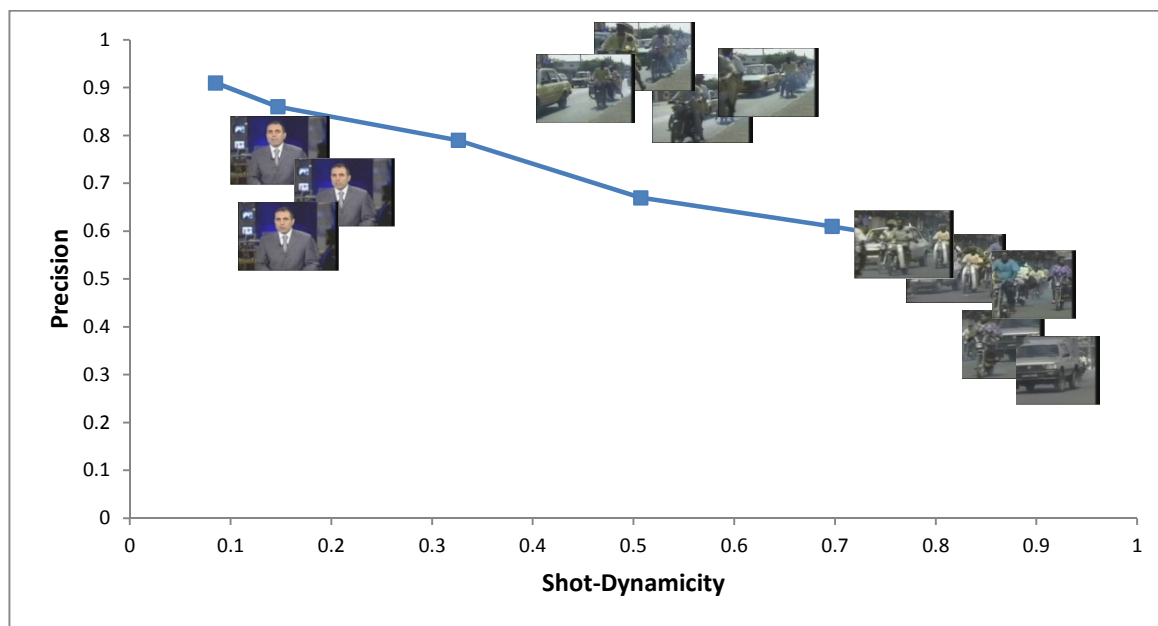


Figure 4. The precision of 600 shot queries with different dynamicity.

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