Performance Evaluation of Content Based Image Retrieval Algorithms using Statistics Based Transforms

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Abstract-In this paper we use statistics based transforms for Content Based Image Retrieval (CBIR). Image signature computed using the Singular Value Decomposition (SVD), Schur algorithm and K-L Transform (KLT). Singular values used as feature are obtained from SVD of an image. Schur algorithm is a fast procedure for the Cholesky factorization of positive-definite structured matrices. KLT analyzes a set of vectors or images, into basis functions of images where the choice of the basis set depends on the statistics of the image. By using these three transforms similarity between the query image and database image measured here by using simple Euclidean distance (ED). Thus by these statistical transforms we retrieve the relevant image.

Keywords-CBIR; SVD; KLT; Schur; RGB; Lab; Euclidean Distance

INTRODUCTION

In recent years, the real world applications, implications and constraints of the technology are being understood by keeping the significant effort. We try to understand image retrieval in the real world by designing a real-world image search engine capable of serving all categories of users requires understanding and characterizing user-system interaction and image search, from both system points-of-view and user. The image collections are not made easier by the process of digitization. Some form of cataloguing and indexing is still necessary the only difference being that the required information can now potentially be derived automatically from the images themselves.

The semantic information which is associated with an image will not be carried by an image which is represented simply as a collection of gray or colored pixel values in the digital form. However when talking about similarity, we might refer to the similarities in its appearance or in semantics. For example for us a picture of a tiger on grass or snow is similar although its information regarding the color may be quite different. As we have the semantic knowledge of it being associated to the person is there with us so the image of the person young and old appears to be same for us. It is difficult and sometimes even impossible in absence of additional information to infer semantic deductions from the set of pixels. Every CBIR system is completely described by answering the two questions: (a) how to describe an image mathematically (computing the image signature or feature vector) and (b) how to assess the similarity (similarity metric).

The typical CBIR system performs two major tasks. The first one is extraction of features (Feature Extraction (FE)), where a set of features, called feature vector, represents the content of each image in the database accurately. The second task is to measure the similarity (similarity measurement (SM)), where a distance between the query image and each image in the database using their feature vectors is measured and it is used to retrieve the top “closest” images. For feature extraction in CBIR there are mainly two approaches: feature extraction in transform domain and feature extraction in spatial domain.

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision to the image retrieval problem, that is, the images from the large databases cannot be easily retrieved. “Content- based” means the actual contents of image will be analyzed the search. The term 'content' in this context it might refer to any other information that can be derived from the image itself like colors, shapes, textures. Without the ability to examine image content, searches must rely on metadata such as keywords or captions, which may be laborious or expensive to produce. The need to find a desired image from a collection is shared by many art historians, professional groups, including journalists and design engineers.

The term CBIR seems to be used by T. Kato in 1992, to describe experiments into automatic retrieval of images from a database, based on the shapes and colors present. Since then, the term has been used to describe the process of retrieving desired images from a large collection on the basis of syntactical image features. The algorithms, techniques and tools that are used originate from fields such as pattern recognition, signal processing, computer vision and
current indexing practice for images relies largely on classification codes or text descriptors, supported in some cases by text retrieval packages designed or adapted specially to handle images. Again, remarkably little evidence on the effectiveness of such systems has been published. Considerably depending on the user satisfaction such systems appears to vary. Manual annotation for every image is required for text based image retrieval. Using the text string is very time consuming task for describing every image. The content of an image that is dependent on the user is described by the text string.

The feature vector is calculated by using SVD, KL Transform and Schur algorithm individually for the query image and the database images.

Now the second task is to calculate the distance metric using Euclidean distance for query and the database images. Then the images which are having the minimum distance are retrieved depending on the feature vector. Based on the results the best transform is suggested.

COLOR PLANE CONSIDER FOR THE PROPOSED METHOD

In this paper we use Lab color plane and then we apply SVD, KL Transform and Schur Transform for calculating the features for the query and the database.

Lab color plane:

Lab color plane is denoted by the equation

\[
\begin{bmatrix}
X \\
Y \\
Z
\end{bmatrix} = \begin{bmatrix}
0.4124 & 0.3575 & 0.1804 \\
0.2126 & 0.7151 & 0.0721 \\
0.0193 & 0.1191 & 0.9502
\end{bmatrix} \begin{bmatrix}
R \\
G \\
B
\end{bmatrix}
\]

\[L = 116 * (Y / Y_n)^{1/3} - 16 \text{ For } Y / Y_n > 0.008856 \]
\[a = 500 * (f(X / X_n) - f(Y / Y_n)) \]
\[b = 200 * (f(Y / Y_n) - f(Z / Z_n)) \]

Where,
\[f(t) = t^{4/3} \text{ for } t<0.00885 \]
\[f(t) = 7.787^{t+16/116} \text{ otherwise} \]

For the reference white color Xn, Yn, Zn are the tristimulus values

KARHUNEN-LOEVE TRANSFORM (KLT)

KL Transform is also known as Hotelling transform or Eigen vector transform. This transform is used in many fields for data analysis and it is also related to the principal component analysis (PCA). This transform mainly reduces the total mean squared error.

Let \( \phi_k \) is the Eigen vector which corresponds to the kth Eigen value \( \lambda_k \) of the covariance matrix \[ \sum_x \] that is

\[ \sum_x \phi_k = \lambda_k \phi_k \]

Where,

\[ K=1, 2, 3, \ldots, N \]

This can be represented in the form of matrix as

\[
\begin{bmatrix}
\sigma_{ij} & \ldots & \sigma_{ij} \\
\vdots & \ddots & \vdots \\
\sigma_{ij} & \ldots & \sigma_{ij}
\end{bmatrix}
\begin{bmatrix}
\phi_1 \\
\vdots \\
\phi_N
\end{bmatrix} = \lambda_k \begin{bmatrix}
\phi_1 \\
\vdots \\
\phi_N
\end{bmatrix}
\]

Where,

\[ K=1, 2, 3, \ldots, N \]

The co-variance matrix \( \sum_x = \sum_{x} \cdot \) is Hemirtian i.e. symmetric if X is real and its Eigen vectors \( \phi_i \)'s are orthogonal

\[ \langle \phi_i, \phi_j \rangle = \phi_i^T \phi_j = \begin{cases} 1 & \text{for } i = j \\ 0 & \text{for } i \neq j \end{cases} \]

an unitary matrix of dimensions \( N \times N \) size ' \( \phi \) ' is constructed it is orthogonal if X is real

\[ \phi \square \begin{bmatrix}
\phi_1, \ldots, \phi_N
\end{bmatrix} \]

this satisfies the equations

\[ \phi^T \phi = I \text{ i.e. } \phi^{-1} = \phi^T \]

the above N equations are combined and expressed as

\[ \sum_{x} \phi = \phi \Lambda \]

it is expressed in the matrix form as

\[
\begin{bmatrix}
\sigma_{ij} & \ldots & \sigma_{ij} \\
\vdots & \ddots & \vdots \\
\sigma_{ij} & \ldots & \sigma_{ij}
\end{bmatrix}
\begin{bmatrix}
\phi_1 \\
\vdots \\
\phi_N
\end{bmatrix} = \begin{bmatrix}
\lambda_1 & \ldots & 0 \\
\vdots & \ddots & \vdots \\
0 & \ldots & \lambda_N
\end{bmatrix}
\]

Where,
\[ \phi^T = \phi^{-1} \]

On left multiplying the above equation on both sides with covariance matrix \( \sum_x \) that can be diagonalized:

\[ \phi^T \sum_x \phi = \phi^{-1} \sum_x \phi = \phi^{-1} \phi \Lambda = \Lambda \]

Now, \( X \) can define the unitary matrix then the KL Transform of \( X \) is

\[ y = \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \phi^T X = \begin{bmatrix} \phi_1^T \\ \vdots \\ \phi_N^T \end{bmatrix} \begin{bmatrix} X_1 \\ \vdots \\ X_N \end{bmatrix} \]

The \( i^{th} \) component \( y_i \) of the transform vector is the projection of \( X \) onto \( \phi_i \)

\[ y_i = \phi_i^T X = \phi_i^T X \]

Here as

\[ \phi = \left( \phi \phi^T \right)^{-1} \]

Left multiplying the above equation on both sides of the transform \( y = \phi^T X \), we get the inverse transform

\[ X = \phi^T y = \begin{bmatrix} \phi_1, \ldots, \phi_N \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \sum_{i=1}^{N} y_i \phi_i \]

Now the original vector \( X \) is obtained which is expressed in \( N \)-dimension spaced spanned by the \( N \) Eigen vectors \( \phi_i \) (i=1,2,\ldots,N) as the basis vectors of the space.

**Properties of KL Transform:**
- KL Transform de correlates particular process.
- The total mean square error is minimized.

**Applications of KL Transform:**
- Used for image compression.
- Used for signal estimation & detection.
- Signal detection for colored noise.

**SCHUR TRANSFORM**

Schur transform is a matrix decomposition. In the decomposition of Schur if \( A \) is a matrix of size \( n \times n \) which has complex entries also then the matrix \( A \) can be expressed as

\[ A = QUQ^{-1} \]

Where,
- \( Q \) is a unitary matrix and its inverse \( Q^{-1} \) is also the conjugate transpose \( Q^* \) of \( Q \).
- \( U \) denotes upper triangular matrix.

The above equation indicates the Schur form of \( A \).

**Properties of Schur transform:**
- Decomposition of matrices.
- Transformation of images.

**Applications of Schur transform:**
- It is used for the watermarking.
- Used for image compression.
- Used for enhancement.

**SINGULAR VALUE DECOMPOSITION (SVD)**

Computation of singular value decomposition of a matrix \( A \) is the factorization of \( A \). The matrix \( A \) is a \( m \times n \) matrix. The factorization is the product of three matrices which means the decomposition of \( A \) into \( U \), \( D \) and \( V^T \)

\[ A = UDV^T \]

Where,
- \( U \) and \( V \) denotes orthogonal matrices and the \( D \) is the diagonal matrix with positive real entries.
- \( \sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_n \geq 0 \) are the singular values that appears in the descending order along with the main diagonal of \( D \).

By taking square root of the Eigen values of \( A^TA \) and \( AA^T \) we can get the singular values.

The equation \( A = UDV^T \) can be expanded as

\[ A = \begin{bmatrix} u_1, u_2, \ldots, u_n \end{bmatrix} \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ \vdots & \vdots & \ddots \end{bmatrix} \begin{bmatrix} v_1^T \\ \vdots \\ v_n^T \end{bmatrix} \]

The relation between SVD and Eigen vectors can be given as
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\[ AA^T = UDV^T (UDV^T)^T = UDV^T VDU^T = UD^2 U^T \]
\[ A^T A = (UDV^T)^T UDV^T = VDU^T UDV^T = VD^2 V^T \]

\( AA^T \) and \( A^T A \) are having the Eigen vectors as \( U \) and \( V \) respectively are calculated. The matrix \( D \) is having singular values along its diagonal which are obtained from the square root of the Eigen values. If the matrix \( A \) is real then the singular values are always real and the matrices \( U \) and \( V \) are also real.

**Properties that are exhibited by SVD:**

- The matrices \( U \) and \( V \) are not unique where the singular values such as \( \sigma_1, \sigma_2, \ldots, \sigma_n \) are unique.
- The Eigen vectors of \( A^T A \) are used to compute the matrix \( U \).
- The number of non-zero singular values is equal to the rank of the matrix \( A \).

**Applications of SVD:**

- SVT can be used for watermarking.
- It is used for the image compression.
- Used for face identification.
- Used for the texture classification.

**ALGORITHM**

- In this paper we use mainly three statistics based transforms (svd, schur, kl) for CBIR.
- Convert raw RGB plane of an image to Lab plane.
- First we convert the query image and the all database images into Lab plane.
- Now we apply SVD, KLT and Schur for the query and the database images individually.
- Apply the Euclidean distance between the query image and the database images for the three statistical transforms individually.
- The distance between the query image and the database image is less is taken as the final retrieved image.
- Here the distance is being found by this transforms and the performance of each transform is estimated.

**EXPERIMENTAL RESULTS**

Retrieval performance of the proposed CBIR is verified by conducting experiments on coil-100 database using statistical transforms.

Coil-100 is a database of RGB images of 100 classes per objects. The objects are oriented in 360 degrees to vary their object pose with respect to the fixed camera. Images are rotated at an angle of 5 degree for each pose. This corresponds to 72 subjects per images per class per object resulting in a total of 7200 images.

All the images in the database are converted from RGB to Lab color model. Feature vector for the database are obtained by using statistical transforms. Now Euclidean distance is calculated for the database images and the query depending on feature vector of each transform individually. The corresponding class images are retrieved finally.

**Average retrieval efficiency:**

The superiority of the algorithm is observed in terms of percentage average retrieval efficiency, when the Euclidean distance is considered. Thereby, in subsequent experiment, this distance measure is considered. The numbers of top retrieved images considered in this experiment are 1, 20, 40, 50, 60, 72 for coil-100 color database. The retrieval efficiencies are represented in the table.

Comparative average retrieval efficiency on COIL-100 color database:

<table>
<thead>
<tr>
<th>TRANSFORMATION METHODS</th>
<th>Number of top retrieved images</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Karhunen-Loeve</td>
<td>1.0</td>
</tr>
<tr>
<td>Schur</td>
<td>1.0</td>
</tr>
<tr>
<td>Singular value</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Comparative percentage average retrieval efficiency on statistical transforms.

**CONCLUSION**

The performance of a CBIR system in terms of average retrieval efficiency depends on the feature...
vector representing the image in the database. The perturbation theory of singular values is explored in obtaining improved by using Euclidean distance measure for statistics based transforms (SVD, Schur, KL).

From the experimental results, it is perceived that the average retrieval efficiency is more for SVD compared to KL and Schur transforms.

REFERENCES


Authors Profile

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