Quick Response Content based Image Retrieval (QR-CBIR) using Hybrid Feature Descriptor

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Abstract: The quick response content based image retrieval (QR-CBIR) systems using hybrid features descriptor are utilized to discover the matching images in comparison to the query image. The CBIR models are designed by using the combination of the feature descriptor with classification algorithm, where the feature descriptor is used for deriving the visual or texture based features from the training and testing images, which is followed by the phase distance or probability based classification algorithm. In this paper, the hybrid feature descriptor has been proposed by combining the color and texture based feature descriptors, which are aimed to achieve the quick response feature descriptor model. The proposed model is aimed at resolving the issue of quick response CBIR models for the big image database querying. The performance of the proposed model will be estimated using the precision, recall and accuracy factors.

Keywords: Color and texture feature descriptors, Support Vector Machine (SVM), CBIR, Quick Response CBIR (QR-CBIR).

I. INTRODUCTION

In this computing age, just about all spheres of human life as well as commerce, government, academics, hospitals, crime interference, police work, engineering, design, journalism, fashion and graphic style, and historical analysis use pictures for economical services. An outsized assortment of pictures is remarked as image information. A picture information may be a system wherever image knowledge square measure integrated and keep [1]. Image knowledge embrace the raw pictures and data extracted from pictures by machine-controlled or laptop motor-assisted image analysis.

The police maintain image information of criminals, crime scenes, and taken things. Within the health profession, X-rays and scanned image information are unbroken for identification, monitoring, and analysis functions. In discipline and engineering style, image information exists for style comes, finished comes, and machine elements. In business and advertising, journalists produce image databases for varied events and activities resembling sports, buildings, personalities, national and international events, and merchandise advertisements. In historical analysis, image databases square measure created for archives in areas that embrace arts, sociology, and drugs. During a little assortment of pictures, straightforward browsing will determine a picture. This can be not the case for giant and varied assortment of pictures, wherever the user encounters the image retrieval drawback. A picture retrieval drawback is that the drawback encountered once looking out and retrieving pictures that square measure relevant to a user’s request from a information, to unravel this drawback, text-based and content-based are the two techniques adopted for search and retrieval in a picture information.

II. LITERATURE REVIEW

Zheng, Liang et. al. [1] has worked on the fast image retrieval: query pruning and early termination. This paper is based upon the efficiency of the image retrieval methods. For this pragmatic issue, this paper proposes a fast image retrieval framework to speed up the online retrieval process. To this end, an impact score for local features is proposed in the first place, which considers multiple properties of a local feature, including TF-IDF, scale, saliency, and ambiguity. Then, to decrease memory consumption, the impact score is quantized to an integer, which leads to a novel inverted index organization, called Q-Index. Importantly, based on the impact score, two closely complementary strategies are introduced: query pruning and early termination. On one hand, query pruning discards less important features in the query. On the other hand, early termination visits indexed features only with high impact scores, resulting in the partial traversing of the inverted index. Ren et al. [2] suggested that similar secure per-file index, where an index including trapdoors of all unique words is constructed for each file. Here, the author’s outline several critical securities challenges and motivate further investigation of security solution for a trustworthy public cloud environment. Penatti, Otávio AB et. [3] al. has performed a comparative study of global color and texture descriptors for web image retrieval.
This paper presents a comparative study of color and texture descriptors considering the Web as the environment of use. The authors have taken into account the diversity and large-scale aspects of the Web considering a large number of descriptors (24 color and 28 texture descriptors, including both traditional and recently proposed ones). The evaluation is made on two levels: a theoretical analysis in terms of algorithms complexities and an experimental comparison considering efficiency and effectiveness aspects. The experimental comparison contrasts the performances of the descriptors in small-scale datasets and in a large heterogeneous database containing more than 230 thousand images. Although there is a significant correlation between descriptors performances in the two settings, there are notable deviations, which must be taken into account when selecting the descriptors for large-scale tasks. Ibrahim et al. [4] concluded that to protect the privacy, users have to encrypt their sensitive data before outsourcing it to the cloud. However, the traditional encryption schemes are inadequate since they make the application of indexing and searching operations more challenging tasks. Accordingly, searchable encryption systems are developed to conduct search operations over a set of encrypted data. Unfortunately, these systems only allow their clients to perform an exact search but not approximate search, an important need for all the current information retrieval systems. Recently, an increased attention has been paid to the approximate searchable encryption systems to find keywords that match the submitted queries approximately. Our work focuses on constructing a flexible secure index that allows the cloud server to perform the approximate search operations without revealing the content of the query trapdoor or the index content. Specifically, the most recently cryptographic primitive, order preserving symmetric encryption (OPSE), has been employed to protect our keywords. Xia et al.[5] described that the results could return not only the exactly matched files, but also the files including the terms semantically related to the query keyword. In the proposed scheme, a corresponding file metadata is constructed for each file. Then both the encrypted metadata set and file collection are uploaded to the cloud server. With the metadata set, the cloud server builds the inverted index and constructs semantic relationship library (SRL) for the keywords set. After receiving a query request, the cloud server first finds out the keywords that are semantically related to the query keyword according to SRL. Then both the query keyword and the extensional words are used to retrieve the files. Cao et al. and Yang et al. [6] proposed that scheme for multi-keyword ranked search, where “Inner product similarity” is used for result ranking. This paper for the first time defines and solves the challenging problem of privacy preserving multi-keyword ranked search over encrypted cloud data. Ahmad et al. [7] described the detailed view of texture, color and shape descriptors for CBIR. A comparison of different challenges in this field is discussed. There is an exponential growth of images around and the information which they carry needs to be effectively utilized. So the authors have extracted the low level features from the image such as texture, shape and color.

III. FINDINGS OF LITERATURE REVIEW

The existing model utilizes the early rejection model, which utilizes the term frequency based methodology along with other features descriptors. The term frequency is the method to compute the repetitiveness of the objects within the given data and uses the high priority object selection based procedure, which is prone to the elimination of the useful features due to the lower frequency. Also the feature in the existing model is based upon the tamura texture features, which extracted the feature vector based upon the texture features only. The image data can be effectively matched using the color and low level features, which may be obtained using the specific color based feature descriptor such as histogram of gradients (HoG), principle component analysis (PCA), etc. For the low level features, the matrix decomposition based many feature descriptors are utilizes such as the scale invariant feature descriptor (SIFT), speeded up robust features (SURF), etc. The use of these components may improve the overall performance of the existing model.

IV. FEATURE DESCRIPTION MODELS

Compressed Histogram of Gradients: The features are usually compressed to realize the quick response systems for information retrieval. The feature compression can be done by compression algorithm, sub-feature selection, standard deviation, mean factor, median factor and many other systematic approaches. In the existing model, the histogram of the gradients (HoG) has been utilized after applying the term frequency–inverse document frequency (TF-IDF) over the obtained HoG Features. The TF-IDF algorithm is known to return the important values out of the input vector and usually applied over the text data for quick response CBIR systems. According to our evaluation, we have found that the
existing model is not capable of detecting the correct results after the application of TF-IDF.

In our research model, instead of the TF-IDF, we have utilized the threshold based feature elimination over the histogram of gradients. The OTSU method has been utilized to calculate the weighted threshold over the data vector obtained after the HoG method over the given image. The HoG values lower than the calculated threshold has been obtained as the compressed feature. Nearly 65% compression has been achieved with the prominent features kept in the data matrix. The TF-IDF features are least informative when compared to the proposed model features obtained from the HoG after early elimination. The following table shows the quality of the existing HoG features with TF-IDF and the proposed OTSU based compressed HoG model.

<table>
<thead>
<tr>
<th>Comparative Factor</th>
<th>Standard HOG</th>
<th>Existing HOG</th>
<th>Proposed HOG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Deviation</td>
<td>0.0021</td>
<td>0.1011</td>
<td>0.00018</td>
</tr>
</tbody>
</table>

Table: Comparison of feature vector with compressed HoG against the existing HoG feature vectors

The lower HoG value than the even the standard HoG feature shows the high significance of the proposed model, whereas the existing HoG has been recorded with the way higher value, which shows the significant inefficiency of the existing model[8].

Null Eliminated Scale Invariant Feature Transform: The scale invariant feature transform feature descriptor utilizes the difference of Gaussians for the purpose of feature vector construction from the input image matrix. The SIFT features includes the null values which effect the overall matching of the features obtained from two input image objects.

The similarity evaluation between the two features has been calculated over the two features which has been recorded nearly at 48.52%, which reveals the null value problem in the SIFT feature vectors. The null values must be eliminated for the betterment of the results between the two images. For the null value elimination the following factoring has been utilized for the compatibility indexing calculation of the SIFT features:

\[ \text{Compatibility Index} = (\text{Count of Null Values}) - (\text{Standard Deviation}) \]

The Compatibility index for each feature vector in the feature vector matrix is calculated and then the feature selection threshold is calculated though using the following equation:

\[ \text{Threshold} = (\frac{\text{Mean(Compatibility Index)}}{2} + \text{Median(Compatibility Index)}) \]

All of the features with the threshold lower than the calculation Threshold are kept for the matching and others are eliminated to enhance the overall accuracy of the feature matching.

Tamura Texture Features: The process can be started with key point detection. For this, a Difference of Gaussians pyramid can be constructed by subtracted Gauss-filtered images where the standard deviation \( \sigma \) differs by factor \( k \):

\[ D(x,y) = L(x,y,k\sigma) - L(x,y,\sigma) \]

Next, extreme can be detected in DoG images which is compared each pixel to 8 neighboring pixels and nine pixels in the scales above and below. If a pixel value is larger or smaller than all of its neighbors, it is accepted as a preliminary key point candidate.

Algorithm 1: Tamura Feature Descriptors (TFD)

1: \( I(\theta,\phi) \leftarrow \text{omnidirectional input image mapped on } S2 \)
2: Compute spherical scale-space representation of \( I(\theta,\phi) \)
3: Compute spherical DoG
4: \( E \leftarrow \text{Local extrema of spherical DoG} \)
5: for each \( Ei \in E \) do
6: Compute LSD and/or LPD of \( Ei \)
7: end for

The workflow of spherical Tamura algorithm can be summarized in Algorithm 1. Each one of the steps is defined in details in following sections. In this paper, spherical image
can be defined in a \((\theta, \phi)\)-grid where columns are points of constant longitude, \(\phi \in [0, 2\pi]\), and rows are points of constant latitude, \(\theta \in [0, \pi]\).

V. BACKGROUND OBJECT FEATURE ESTIMATION

The feature extraction and classification has been performed by using the following methodology. The following

\[
\begin{array}{cccccccc}
0.832438 & 0.604312 & 0.850893 & 0.453022 & 0.741072 & 0.858625 & 0.122915 & 0.327249 & 0.948102 \\
0.31688 & 0.298704 & 0.800326 & 0.71467 & 0.569842 & 0.599861 & 0.003673 & 0.518143 & 0.15778 \\
\end{array}
\]

Table-a

The normal value features obtained from object 1 are listed in the vector Table c:

\[
\begin{array}{cccccccc}
0 & 0 & 0 & 0 & 0 & 0 & 0.122915 & 0.327249 & 0.948102 \\
\end{array}
\]

Table c

The similar feature vector has been also obtained from the object 2, which are listed herein the vector Table d:

\[
\begin{array}{cccccccc}
0 & 0 & 0 & 0 & 0 & 0 & 0.003673 & 0.518143 & 0.15778 \\
\end{array}
\]

Table d

methodology has been defined for the extraction of the features from the dataset images\[8\]. The content based image retrieval program utilizes the extracted features for the feature classification purposes to calculate the similarity of the images to create the semantic ranking. The feature extraction algorithm works in the following manner:

Figure 1: Flowchart of Tamura based feature classification
Algorithm 2: Object Feature Estimation

1. Load the image into the memory, which is a 3-D matrix containing the color planes or Red, Green and Blue and denoted as $I_m$.
2. Apply the Greyscale conversion method on the 3-D image matrix and denoted as $I_g$.
3. Define the Gaussian filter with the essential parameters and denoted as $G$.
4. The Gaussian filter $G$ is applied over the Greyscale image $I_g$ to create the $I_{gf}$.
5. Estimate the front-ground by using the pre-defined features to create $F_I$.
6. Define the dilation object with appropriate size and shape $D_f$.
7. Apply the image dilation over the $F_I$ with filter $D_f$ to produce the $A_f$.
8. Apply the mathematical morphological operation on the image object to detect and shortlist the feature and denoted as $A_i$.
9. Perform the subtraction operation to subtract the $A_i$ from $F_I$ to produce the $B_Gi$.
10. Return the $B_Gi$.

Training

Algorithm 3.2: SVM classification with the background feature extractor CBIR

1. Read the query image and load in the memory as the 3-D image matrix and convert it to the greyscale to produce the 2-D image matrix.
2. The pre-processing methods are applied to remove/reduce the noise in the image.
3. Perform the feature extraction over the query image to fetch the known features form the image matrix.
4. Reshape the feature descriptor data for the validation of the training set containing the feature descriptors.
5. Create the group matrix with the appropriate group ids denoted to the training samples.
6. Run the SVM over the training dataset to match the testing set to obtain the training matrix in the form of similarity and bias.
7. Then the SVM classifier is applied over the SVM training data to classify the given sample.
8. Return the matching sample one the basis of SVM classification information in the classification matrix.
9. Return the decision logic.

VI. CONCLUSION

In this project, as the initial try, a secure linguistics enlargement primarily based similar search theme over encrypted cloud knowledge is planned. The question is submitted victimization single keyword search. The planned theme may come not solely the specifically matched files, however additionally the files as well as the terms semantically regarding the question keyword. The encrypted files and data set are outsourced to the server by the owner. With the file data, the cloud builds the inverted index and constructs linguistics relationship library (SRL) for the keywords. The co-occurrence of terms is employed to capture the linguistics relationship of keywords within the lexicon, which offers acceptable linguistics distance between terms to accomplish the question keyword extension, so as to possess higher results, user will discard the unwanted results for future, which can never be shown. For this purpose fuzzy linguistics connection matrix is employed. The rule is analogous and comparable to the expert mechanism of human brain based neural network computing and has an initial learning mechanism.

REFERENCES

[8]. http://www.scholarpedia.org/article/Scale_Invariant_Feature_Transform