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Image Database Search by Similarly Index Matching of HSV Content using 3D Histogram

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Abstract: The retrieval principle of CBIR systems is based on visual features such as colour, texture, and shape or the semantic meaning of the images. To enhance the retrieval speed, most CBIR systems pre-process the images stored in the database. This is because feature extraction algorithms are often computationally expensive. If images are to be retrieved from the World-Wide-Web (WWW), the raw images have to be downloaded and processed in real time. In this case, the feature extraction speed becomes crucial. Ideally, systems should only use those feature extraction algorithms that are most suited for analyzing the visual features that capture the common relationship between the images in hand. In this thesis, a statistical discriminate analysis based feature selection framework is proposed. Such a framework is able to select the most appropriate visual feature extraction algorithms by using relevance feedback only on the user labelled samples. The idea is that a smaller image sample group is used to analyze the appropriateness of each visual feature, and only the selected features will be used for image comparison and ranking. As the number of features is less, an improvement in the speed of retrieval is achieved.

1. Introduction:

Content-based image retrieval (CBIR), as we see it today, is any technology that in principle helps to organize digital picture archives by their visual content. By this definition, anything ranging from an image similarity function to a robust image annotation engine falls under the purview of CBIR. This characterization of CBIR as a field of study places it at a unique juncture within the scientific community. While we witness continued effort in solving the fundamental open problem of robust image understanding, we also see people from different fields, such as, computer vision, machine learning, information retrieval, human-computer interaction, database systems, Web and data mining, information theory, statistics, and psychology contributing and becoming part of the CBIR community [1]. Moreover, a lateral bridging of gaps between some of these research communities is being gradually brought about as a by-product of such contributions, the impact of which can potentially go beyond CBIR. Again, what we see today as a few cross-field publications may very well spring into new fields of study in the foreseeable future.

Amidst such marriages of fields, it is important to recognize the shortcomings of CBIR as a real-world technology. One problem with all current approaches is the reliance on visual similarity for judging semantic similarity, which may be problematic due to the semantic gap [2] between low-level content and higher-level concepts. While this intrinsic difficulty in solving the core problem cannot be denied, we believe that the current state-of-the-art in CBIR holds enough promise and maturity to be useful for real-world applications if aggressive attempts are made.

For the purpose of completeness, and better readability for the uninitiated, we have introduced key contributions of the earlier years in Section 1. Image retrieval purely on the basis of textual metadata, Web link structures, or linguistic tags is excluded. The rest of this article is arranged as follows: For a CBIR systems to be useful in the real world, a number of issues need to be taken care of. Hence, the desiderate of real-world image retrieval systems, including various critical aspects of their design, are discussed. Core research in CBIR has given birth to new problems, which we refer to here as CBIR offshoots. When distinct solutions to a problem as open-ended as CBIR are proposed, a natural question that arises is how to make a fair comparison among them.

2. Related Work:

GoogleTM and Yahoo!® are household names today primarily due to the benefits reaped through their use, despite the fact that robust text understanding is still an open problem.

Online photo-sharing has become extremely popular with [3], which hosts hundreds of millions of pictures with diverse content.

The video-sharing and distribution forum YouTube has also brought in a new revolution in multimedia usage. Of late, there is renewed interest in the media about potential real-world applications of CBIR and image analysis technologies, as evidenced by publications in Scintific American [4], Discovery News [5] and on [6].

We envision that image retrieval will enjoy a success story in the coming years. We also sense a paradigm shift in the

goals of the next-generation CBIR researchers. The need of the hour is to establish how this technology can reach out to the common man in the way text retrieval techniques have. Methods for visual similarity, or even semantic similarity (if ever perfected), will remain techniques for building systems. What the average end-user can hope to gain from using such a system is a different question altogether.
Comprehensive surveys exist on the topic of CBIR [7, 8, 9], all of which deal primarily with work prior to the year 2000. Surveys also exist on closely related topics such as relevance feedback [10], high-dimensional indexing of multimedia data [11], face recognition [10] (useful for face-based image retrieval), applications of CBIR to medicine, and applications to art and cultural imaging [12]. In our current survey, we restrict the discussion to image-related research only.
One of the reasons for writing this survey is that CBIR, as a field, has grown tremendously after the year 2000 in terms of the people involved and the papers published. Lateral growth has also occurred in terms of the associated research questions addressed, spanning various fields. To validate the hypothesis about growth in publications, we conducted a simple exercise. We searched for publications containing the phrases "Image Retrieval" using Google Scholar [l3] and the digital libraries of ACM, IEEE, and Springer, within each year from 1995 to 2005. In order to account for: (a) the growth of research in computer science as a whole, and (b) Google's yearly variations in indexing publications, the Google Scholar results were normalized using the publication count for the word "computer" for that year. A plot on another young and fast-growing field within pattern recognition, support vector machines (SVMs), was generated in a similar manner for comparison. Not surprisingly, the graph indicates similar growth patterns for both fields, although SVM has had faster growth. These trends indicate, given the implicit assumptions, a roughly exponential growth in interest in image retrieval and closely related topics. We also observe particularly strong growth over the last five years, spanning new techniques, support systems, and application domains.
In this chapter, we comprehensively survey, analyze, and quantify current progress and future prospects of image retrieval. A possible organization of the various facets of image retrieval as a field. Our article follows a similar structure. Note that the treatment is limited to progress mainly in the current decade, and only includes work that involves visual analysis in part or full.

3. Methodology:

To retrieve an image form the database, we first analyze the sample image inputted by the user using the above analysis and form the sample index. Then we read data from the index file and calculate the similarity value between the stored image and the input image based on absolute difference or generalized similarity matrix. The image with the highest similarity is then selected.

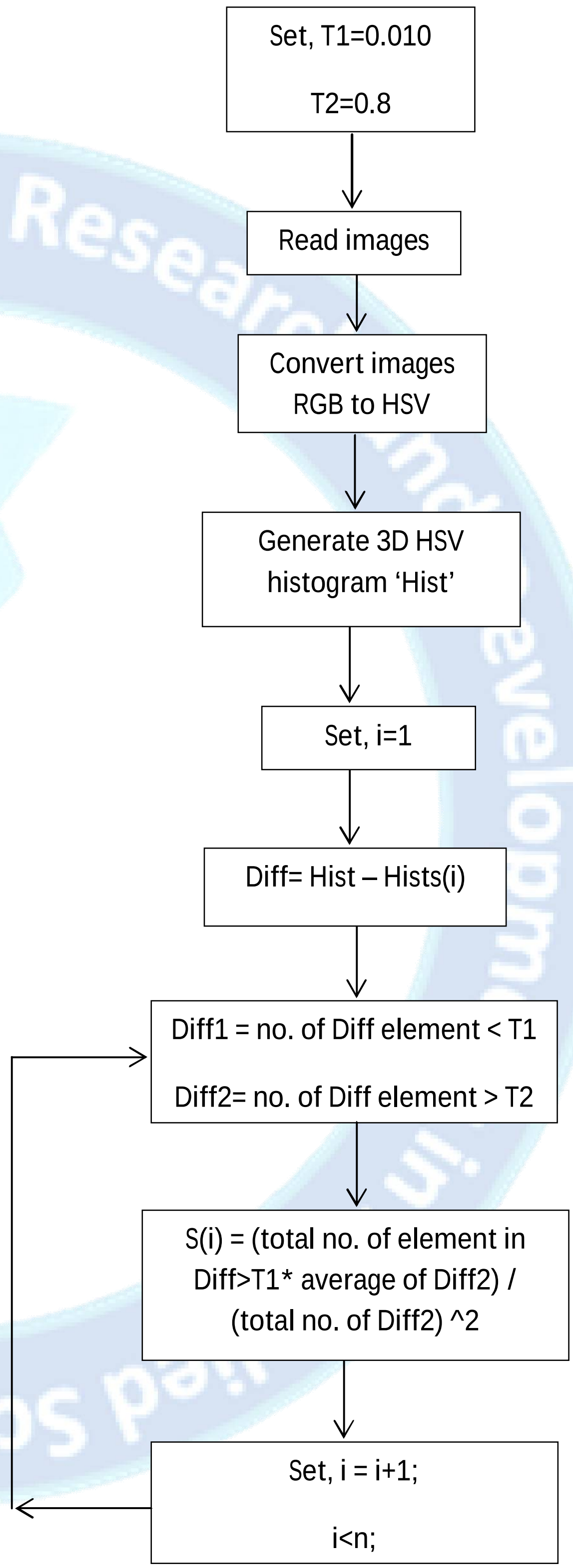

Fig. 1. Flow chart for Image Retrieval Algorithm.

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3.1 Absolute Difference

This is the most straightforward method. To compare two images, we compute the similarity value S_D as follows

$$S_D(X,Y) = \sum_{k=1}^{N} |X_k - Y_k|$$

where Xk and Yk are the percentage of pixels of the corresponding color/edge bin k in image X: and image Y respectively. N denotes the number of colour/edge bins. Obviously the larger the value of &(X, Y), the less similar the two images.

3.2 Generalized Similarity Matrix:

The absolute difference method does not cater the relationship among different color bins. If two colors which look similar perceptually but fall into different color bins, they will be considered as totally different in the calculation of the similarity value. Consequently the retrieval result will be worse than expected. To overcome this weakness the similarity matrix A = [a(i, j)] is introduced. The values assigned in A specify the weighting relationship among different color bins and are calculated as follows:

$$a(i,j) = 1 - d(i,j)/d_{max}$$

where d(i, j) is the Eluclidean Distance between color/edge bins i and j, and dmax is the maximum distance.

Then the similarity value S_M is calculated as follows:

$$S_M(X,Y) = Z^t\, A\, Z$$

where matrix Z = [z(k)] is the bin by bin difference between image X and Y and

$$z(k) = X_k - Y_k\,,\quad k = 1, 2, \ldots, N$$

Z^t is the transpose of Z.

4. Result and Discussion:

In this paper an integrated approach combing color, HSV features and symmetry analysis for image retrieval has been designed and implemented. Various experiments have been carried out to evaluate the performance of this integrated approach. An image database of 654 JPEG format image is taken with different types of object in different image size. Results are obtained by taking a query image is given to the CBIR system and as an output we get images from image database with minimum distance with the query image.

Some of the results are shown below first of all the query image is shown then 8 image similar to query image returned by CBIR calculation are shown. After the displaying of retrieved image how many images are perceptually similar out of 8 images is discussed and collective results for all the experiments are tabulated at the last. Image ‘glasgow3.jpg’ is shown in Fig 2.This is a coloured image and its RGB planes are shown in Fig 3(a) and there respective histograms are shown in Fig 3(b).

Fig 2. Image of Glasgow.jpg

Fig 3(a) Gray level image of ‘glasgow3.jpg’ showing intensity in RGB planes (from left to right).

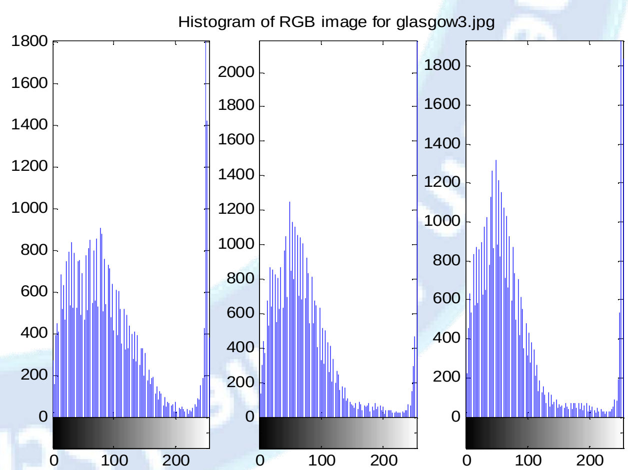

Fig 3(b) Image histograms of images of RGB plane shown in Fig 4.2(a) for 100 bins.

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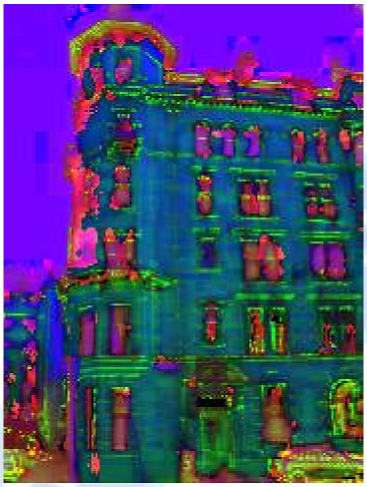

Fig 4(a).HSV image based on hue saturation and value of RGB image 'glasgow3.jpg'

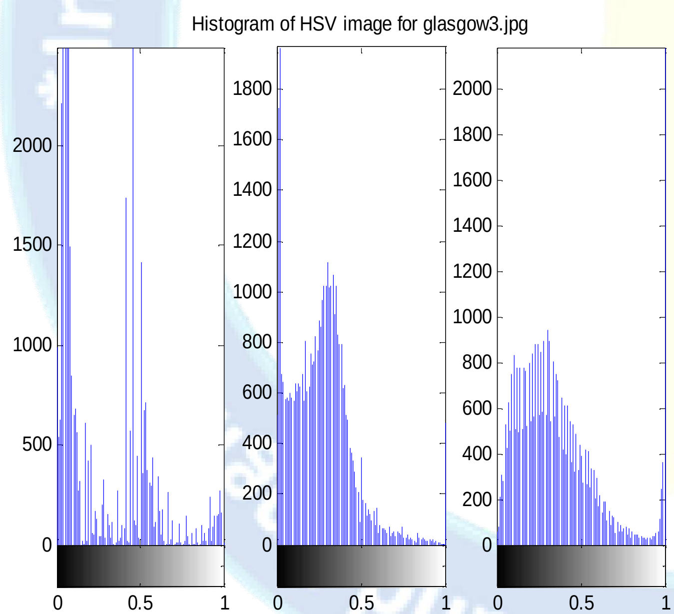

Fig 4(b) Image histograms of images of HSV plane shown in Fig 4. 3(a) for 100 bins.

5. Conclusion:

In this work, image retrieval methods based on color, shape and spatial analysis are investigated. We have designed and implemented a prototype to retrieve a particular image from an image database. We have designed an indexing methods based on different criteria. We introduce an integrated method that calculates the similarity value between two images. We then evaluate the performance and compare the characteristic of each image retrieval approach.

Many existing world wide image retrieval systems, for example Google and WebSeer are based on the WWW. In contrast to the retrieval based on text annotations, the queries of a CBIR system are made on the image content itself. Most existing CBIR systems run in a centralized manner, which cannot accommodate the dramatically increasing number of digital images in the world .In this work we attempt to open a way for research to construct an efficient and easy-used P2P application for image sharing. In addition to just retrieving the raw files by their names or IDs, a user can interactively search the interesting images by their content. A few CBIR systems in the P2P network have been proposed. Recent approaches which employs k-means clustering on the images or clusters the peers according to the similarity defined by the vectors of their Gaussian parameters operate only in the high dimensional feature space, which may require large amount of computing time and memory space. Without hierarchical searching mechanism, the information lookup in large networks becomes infeasible. Furthermore, only a single feature is supported by these systems. We briefly reviewed the essence of PicSOM, a centralized interactive content based image retrieval system using the Self-Organizing Maps, and proposed a preliminary design of its extension for the peer-to-peer network.

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