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RGB_CMY HISTOGRAM BASED IMAGE RETRIEVAL BY PATTERN MATCHING

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The Image Retrieval from the database using Text comparison and the similarity of the images found using Threshold of Keywords matching. Here large no of keywords and descriptions about the image is stored with that image and the image comparison is done using Text Query with required also the Automated Annotations are now available to detect the objects in the image and automatically do the descriptions for that image. But the Automated Descriptions need extra computations and large amount of space rather than simple keywords that describe the image.

The Image Descriptions are given by the Users and Analyst who are interested in that Domain. The Image Descriptions are then converted into Text Patterns used for Faster Comparison.

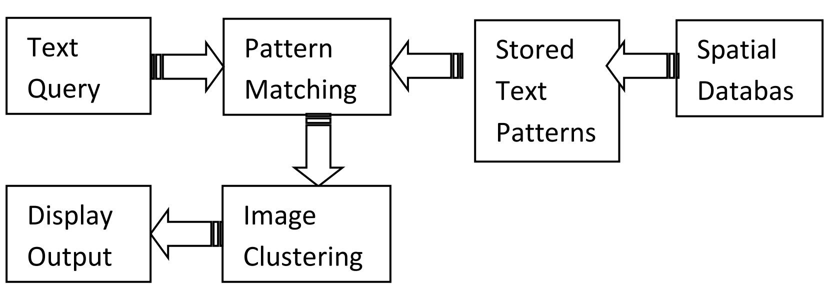
The Patterns contains the individual keywords extracted from the descriptions. Then the Text Patterns are Formatted and Indexed for Faster Accessing. Then All the Formatted and Indexed Patterns are now Stored into the Database with that Image.

The Input Text Query is given to the Pattern Matching System. The Pattern Matching System Matching System does the following,

- Extract Patterns from the Input Text Query and Format those Patterns.
- Get the Patterns of a Image From the Database and compare tho Formatted Patterns with that input patterns.
- If the patterns are matched as per the Threshold value then add that Corresponding image into Resulted set.
- Do the above until all the image patterns in the database are compared.

Now the Result set has matched patterns and the corresponding threshold values. Now we divide the result set into no of clusters using threshold ranges. Then finally display the output images according to the Clusters.

Here Clustering is done according to that Threshold value. The user must select the Threshold value and the range of thresholds to do the clustering. Each cluster contains images that have to be defined threshold range. Also how many no of ranges to be calculated also indicated by the user.



We overcome the disadvantage of user manually entering image descriptions using automated image annotations. In some areas the image source gives large no of images with higher size and we can't do the manual description for these images. For Example Consider, A Satellite gives some one million images of a planet in one minute. We can't do the manual descriptions here. We can either go to automatic annotations or Content Based Image Retrieval. But rather we use Automatic Annotations we can use Content based image Retrieval. Because content based image comparison has more efficiency.When the image comparison is needed by a small organization or any small purpose we can use the Text Based Image Retrieval using Automatic Annotations.

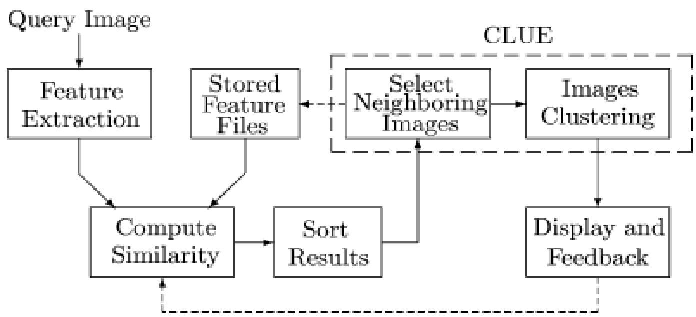


Figure : The Block Diagram for the General Approach to Content Based Image Retrieval with Clustering and Feedback.

Currently most widely used image search engineis GOOGLE. It provides its users with textualannotation. Not many images are annotated withproper description so many relevant images gounmatchedOur proposed system uses modified HED andcolor feature which overcomes above mentioned disadvantages. We also provide an interface where user can givequery images as input, automatically extracts thecolor feature and compared with the images in database, retrieve the matching image CHIR (color histogram based image retrieval) uses Euclidean Distance & Histogram Intersection.

In order to reflect the human perception precisely, there have been lots of image retrieval systems, which are based on the query-by-example scheme, including QBIC ,PhotoBook, VisualSEEK . Actually, low-level visual contents do not properly capture human perceptual concepts, so closing the gap between them is still one of the ongoing problems. However, a series of psychophysical experiments reported that there is a significant correlation between visual features and semantically relevant information . Based on these findings, many techniques have been introduced to improve the perceptual visual features and similarity measures, which enable to achieve semantically correct retrieval performances .

Among variety of visual features, color information is the most frequently used visual characteristic. Color histogram (or fixed-binning histogram) is widely employed as a color descriptor due to its simplicity of implementation and insensitivity to similarity transformation . Based on the psychophysical fact that at the first perception stage the human visual system identifies the dominant colors and cannot simultaneously perceive a large number of color, process.

This Color Histogram Bassed Image Retrieval research implements and tests simple color histogram based search and retrieve algorithm for images and finds the technique to be effective as shown by analysis using the Rank Power measurement. With the increasing popularity of image managementtools such as Google's image search applications in general social networking environment, the quest for practical, effective image search in the web context becomes ever more important.

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Once two sets of visual features, represented by a histogram or a signature, are given, we need to determine how similar one is from the other. A number of different similarity measures have been proposed in various areas of computer vision. Specifically for histograms, histogram intersection, and -statistics have been known to work successfully. However, these dissimilarity measures cannot be directly applied to signatures. As alternatives to these metrics, Euclidean distance are computationally more efficient .

Assumptions And Hypotheses To Be Tested:

Three differentimplementationsof thesimilarity computation were carried out.The first involveda Euclidean distancewhich computed differencesbetweenthenumberofacertain setofpixels foundinoneimageversusanotherforeach bininthe histogram. Thesecondutilizedahistogramintersection methodinwhichcolorsnotpresentin eitheroneof the images were not used to compare the images. The histogram valueswerenormalized bydividingthenumber ofpixelsineachhistogrambinby thenumberofpixel values usedin the comparison. This allowsimage.comparisonstobeunaffectedby transformationsof image size.

The developments in this field have been put forward in three levels.

Level one:-Atthis first stage, queries were tested in a limiteddatabase against images in the database that were different, duplicates, or transformations. The analysis was simply performed on whether or not the appropriate image was returned as the top most result. The algorithm performed as expected in that rotations, expansions and contractions do not affect the result of the query.Brightening and dimming do have an effect, althoughwhen the brightening or darkening is less than 15% the results are still accurate.Once the initial algorithm validation was completed,groups of images were added to the database. Then each query image was matched visually with groups of images from the database and the database images were rankedaccording to how similar they were perceived to be to thequery. These groups served as the expected relevant results during testing. This method is very subjective to the experimenter as it is difficult to visually compare images based solely on their color similarities.

Level two:As is apparent there is a fair degree of variation in the rank power of the results. However, the average demonstrates that the average rank with respect to the number of relevant images is fairly low using the traditional rank power methodology. The bounded representation, however, seems to provide mixed results. While the retrieval is not providing poor results, it is not providing consistently accurate results either. This is partially due to the presence of certain results that have extremely high traditional rank power values.The process of definingthese expected results is highly subjective and difficult as one must determine the visual similarity between images in the database with the query. These concernsled to the construction of a second stage database where images were taken from previous content based image retrieval platform databases. These images were already placed in groups by their similarity thus allowing the rank power analysis to be carried out much more efficiently.

REFERENCE

[1] James Z. Wang, "Integrated Region-Based Image Retrieval", Boston, Kluwer Academic Publishers, 2001

[2] J. R. Smith and S.-F. Chang. " Automated image retrieval using color and texture", Technical Report CU/CTR 408-95-14, Columbia University, July 1995.

[3] J. R. Smith and S.-F. Chang. " Tools and techniques for color image retrieval", In Symposium on Electronic Imaging: Science and Technology - Storage & Retrieval for Image and Video Databases IV, volume 2670, San Jose, CA, February 1996. IS&T/SPIE.

[4] M. J. Swain and D. H. Ballard. "Color indexing", International Journal of Computer Vision, 7:1 1991.

[5] J. R. Smith and S.-F. Chang. "VisualSEEk: a fully automated content-based image query system.", ACM Multimedia '96, November, 1996.

[6] James Hafner, HarpreetS.Sawhney, Will Equits, Myron Flickner and Wayne Niblack, "Efficient Color Histogram Indexing for Quadratic Form Distance Functions", IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 17, No. 7, July 1995