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Content Base Image Retrieval using Combination of Color, Shape and Texture Features

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Abstract

Image retrieval based on color, texture and shape is an emerging and wide area of research scope. In this paper we present a novel framework for combining all the three i.e. color, texture and shape information, and achieve higher retrieval efficiency using dominant color feature. The image and its complement are partitioned into non-overlapping tiles of equal size. The features drawn from conditional co-occurrence histograms between the image tiles and corresponding complement tiles, in RGB color space, serve as local descriptors of color, shape and texture. We apply the integration of the above combination, then we cluster based on alike properties. Based on five dominant colors we retrieve the similar images. We also create the histogram of edges. Image information is captured in terms of edge images computed using Gradient Vector Flow fields. Invariant moments are then used to record the shape features. The combination of the color, shape and texture features between image and its complement in conjunction with the shape features provide a robust feature set for image retrieval. The experimental results demonstrate the efficacy of the method.

Keywords

CBIR, Image Retrieval, Cluster, Dominat Color

1. Introduction

In this computer age, virtually all spheres of human life including commerce, government, academics, hospitals, crime prevention, surveillance, engineering, architecture, journalism, fashion and graphic design, and historical research use images for efficient services. A large collection of images is referred to as image database. An image database is a system where image data are integrated and stored [1]. Image data include the raw images and information extracted from images by automated or computer assisted image analysis.

In text-based retrieval, images are indexed using keywords, subject headings, or classification codes, which in turn are used as retrieval keys during search and retrieval [2]. Text-based retrieval is non-standardized because different users employ different keywords for annotation. Text descriptions are sometimes subjective and incomplete because they cannot depict complicated image features very well. Examples are texture images that cannot be described by text. Textual information about images can be easily searched using existing technology, but requires humans to personally describe every image in the database. This is impractical for very large databases, or for images that are generated automatically, e.g. from surveillance cameras. It is also possible to miss images that use different synonyms in their descriptions. Systems based on categorizing images in semantic classes like "cat" as a subclass of "animal" avoid this problem, but still face the same scaling issues [3].

The Content Based Image Retrieval (CBIR) technique uses image content to search and retrieve digital images. Content-based image retrieval systems were introduced to address the problems associated with text-based image retrieval. Content based image retrieval is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features [4]. The main goal of CBIR is efficiency during image indexing and retrieval, thereby reducing the need for human intervention in the indexing process[5]. The computer must be able to retrieve images from a database without any human assumption on specific domain.

We provide here an overview of Image Compression Technique. The rest of this paper is arranged as follows: Section 2 introduces Image Retrieval; Section 3 describes about Recent Scenario; section 4 shows the problem domain. Section 5 shows the proposed approach; Section 6 describes Conclusion and outlook.

2. Image Retrieval

Image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital libraries. The use of Metadata such as captioning, keywords or descriptions to the images stored in the database along with the images or the low level feature extracted from the image like shape, color, texture etc. have been used till now for the image retrieval from the existing search engine. A user formulating a query usually has in mind just one topic, while the results produced to satisfy this query may belong to different topics. Therefore only parts of the search results are relevant for a user.

Requirements for a good image retrieval system:
It should have less response time
It should be accurate
Querying for image retrieval should be easy

General Techniques for image retrieval:
There are several existing techniques for image retrieval. Some of the important of these techniques are discussed below
Text based Image Retrieval
Content Based Image Retrieval
Region based image retrieval
Context based image retrieval

Text based image Retrieval
TBIR store text in the form of keywords together with the image. Some TBIR uses Surrounding text of the image to search the keywords which are physically close to the image. This technique relies on the assumption that the surrounding text describes the image. Search Engines that uses this technique are Google, yahoo & AltaVista.

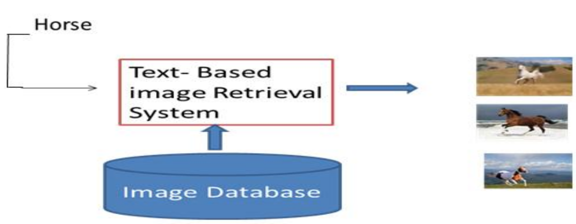

Figure 1: Text based Image retrieval

Advantages of TBIR
- Easy to construct queries. There is no need of drawing, example image or other advanced tools of constructing queries.
- Image retrieval is fast.
- String Matching is a relatively resource – friendly task.

Disadvantages of TBIR
- A relevant image might be left out due to lack of specific keyword in the query.
- It may return irrelevant results when there is no relevant text surrounding the picture.
- Image annotation is very time consuming process and it is often manual.
- Retrieval depends on the image annotator and retriever sharing some common vocabulary or language.
- Use of synonyms would result in missed result
- Single word can mean radically different things.
- If the Query string is misspelled there are no results returned.

Content Based Image Search (CBIR)
CBIR system makes direct use of content of the image rather than relying on the human annotation of metadata with the keywords. Current CBIR make use of low level features like shapes, color and texture to retrieve desired images from database. To have efficient image retrieval, tools like pattern recognition and statistics are well used Different implementation of CBIR make use of different types of queries.

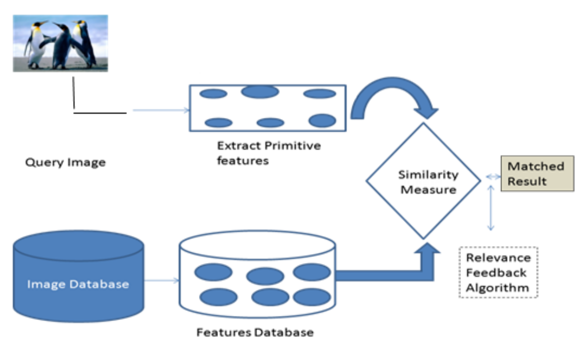

Figure 2: Content Based image Search

Query Techniques of CBIR
Query By example is a query technique that involves providing the CBIR system with an example image that it will then base its search upon. The underlying search algorithm may vary depending upon the application, but the result images should all share common elements with the provided example

User can draw Rough images, sketches or drawing to find matching images. Comparison using image distance measure: An image distance measure compares the similarity of two images in various dimensions such as color, texture, shape and other.

Content Other query method include browsing for example image navigation, customized/ hierarchical categories, querying by image region, image feature and multimodal queries(e.g. combining touch, voice etc. Relevance feedback is also used for refining queries.

Advantages of CBIR

This technique removes the difficulty that can arise upon trying to describe images with words. It does not depend upon image size or orientation for searching.

Disadvantages of CBIR

Indexing of large image repositories is time and resource consuming .A major limitation of CBIR system is that they are limited to relatively small databases.

It is not possible to search for the semantic of the images.

Tools to construct query image may be complicated to use.

Due to semantic gap between low level features and high level features of the image Sometimes CBIR returns irrelevant result.

Region Based Image Retrieval

RBIR is an extension of content based image retrieval techniques. Region based image retrieval system provide new query types to search for objects embedded in an arbitrary environment. An RBIR system automatically segments images in to a variable number of region, and uses a segmentation algorithm to extract a set of features(like colors, shapes and sketches) for each region. A function determines the differences between the database image and a set of reference region. Systems that use region based image retrieval are Blob world, Walrus and Simplicity.

Advantages of region based image search:

It can correctly separate the regions that have the same properties that we define. Region growing methods can provide the original images which have clear edges and the good segmentation results.

We can choose the multiple criteria at the same point.

Disadvantages of RBIR

This computation is consuming more time and power.

Noise or variation of intensity may result in over segmentation.

This method may not distinguish the shading of real images.

Context based/Semantic Image Retrieval

This is a comparatively new approach of image retrieval. Context is any information that can be used to characterize the situation of an entity. Context is the where, who, what and when of an object. if a piece of information can be used to characterize the situation of a participant in an interaction or conversation, this information is context. An image can have two type of context associated with it.

Static Context

Static context often refers to the context that can be measured by hardware sensors e.g. location, time, light, sound, movement touch, temperature, humidity and air pressure. Static context is information added to the image when the image is captured or created. This context never changes in time. Because of static nature of context; Image retrieval based on static information is relatively easy.

Dynamic context

this context is added after the image is taken and can change in time, situation and it is dependent of who the viewer is. The same image can be interpreted differently by different viewer.

The context based search engine can automatically select relevant image based on the description given in textual passage. Context based search uses semantic role labelling and Concept net technique for retrieval of image using textual passage.

Advantages of Context Based search

1. This is fully automated and requires lesshuman interaction for querying.
2. It can lessen the semantic gap problem in searching of relevant images.
3. User can make a query to the search engine easily either in image or text forms.

Disadvantages

1. Such type of search engine is very difficult to implement because it require machine intelligence.
2. It may be very complex and time consuming to search images using context because context may change with time.

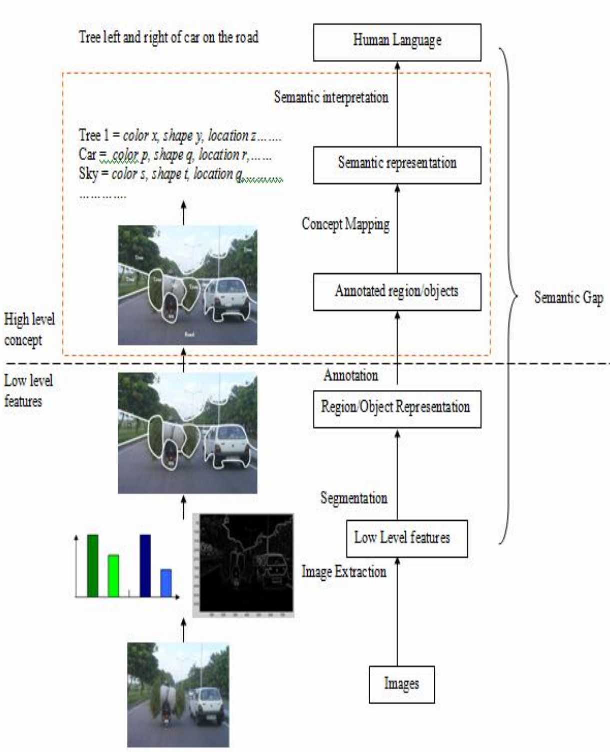

Figure 3: Bridging the gap: The semantic extraction and representation of images Conclusion

3. Literature Review

In 2005, Xiaojun Qi et al. [6] propose a novel fusion approach to content-based image retrieval. In their retrieval system, an image is represented by a set of color -clustering-based segmented regions and global/semi-global edge histogram descriptors (EHDs). As a result, the resemblance of two images is measured by an overall similarity fusing both region-based and global/semi-global-based image level similarities. In their approach, each segmented region corresponds to an object or parts of an object and is represented by two sets of fuzzified color and texture features. A fuzzy region matching scheme, which allows one region to match several regions, is then incorporated to address the issues associated with the color/texture inaccuracies and segmentation uncertainties. The matched regions, together with the simple semantics for determining the relative importance of each region, are further used to calculate the region-based image level similarity. The global/semi-global EHDs are also incorporated into our retrieval system since they do not depend on the segmentation results. These EHDs not only decrease the impact of inaccurate segmentation and but also reduce the possible retrieval accuracy degradation after applying the fuzzy approach to the accurate segmentation for images with distinctive and relevant scenes. The Manhattan distance is used to measure the global/semi-global image level similarity.

In 2008, N. S. Vassilieva [7] presents a survey of common feature extraction and representation techniques and metrics of the corresponding feature spaces. Color, texture, and shape features are considered. A detailed classification of the currently known features' representations is given. Experimental results on efficiency comparison of various methods for representing and comparing image content as applied to the retrieval and classification tasks are presented by the author.

In 2011, Chandan Singh et al. [8] proposed a novel solution to content based image retrieval system. Local features extraction is done by computing histograms of distances from edge lines to the centroid of edge image, where edge lines are detected using Hough transform. It is a robust and effective method according to the authors. It provides association among adjacent edge points, which representtheirlinearrelationshipwitheachother.Zernike momentsareused to describe the global features. They have applied algorithms for the fast computation of Hough transform and Zernike moments to make our system fast and efficient. Bray–Curtis similarity measure is applied to compute the similarity among images. A large number of experiments is carried out to evaluate the system performance over six standard databases, which represent various kinds of images.

In 2011, Daniel Carlos et al. [9] present the Distance Optimization Algorithm (DOA), aiming to improve the effectiveness of Content-Based Image Retrieval (CBIR) systems. DOA Considers an iterative clustering approach based on distances correlation and on the similarity of ranked lists. Their algorithm explores the fact that if two images are similar, their distances to other images and therefore their ranked lists should be similar as well.

In 2011, Xiang-Yang Wang [10] proposed effective and novel color image retrieval based on color, texture and shape. They firstly apply quantization algorithm for cluster merging. Second the spatial texture features are extracted using steerable filter decomposition. Finally they apply pseudo-zernike moments of an image for the shape descriptor. According to the author they provide an efficient and robust capability of image retrieval after applying the above techniques.

4. Problem Domain

There are several problems of image annotation like large volumes of databases Valid only for one language with image retrieval this limitation should not exist. Text based retrieval is oriented with several language, so there is the need of language independent retrieval. Problem of human perception Subjectivity of human perception. Too much responsibility on the end-user. There is also the problem of deeper (abstract) needs. Queries that cannot be described at all, but tap into the visual features of images. The previous work by the researchers of image retrieval, images was manually annotated. It was costly; this was affordable for only large organizations. Content Based Image Retrieval (CBIR) [11] systems have shown ample promise for querying-by-example, but the image matching techniques are often computationally intensive and thus time consuming. Transcriptions of images through object recognition, scene analysis, etc. have not been effective, partly due to the restricted applicability of present day recognition techniques [12].

5. Proposed Approach

In many texture analysis applications it is desirable to have features that are invariant or robust to rotations of the input image. As the LBPP,R patterns are obtained by circularly sampling around the center pixel, rotation of the input image has two effects: each local neighborhood is rotated into other pixel location, and within each neighborhood, the sampling points on the circle surrounding the center point are rotated into a different orientation.

In this paper we propose a combination of color, texture and shape based approach. The basic local binary pattern operator, introduced by Ojala et al. [13], was based on the assumption that texture has locally two complementary aspects, a pattern and its strength. In that work, the LBP was proposed as a two-level version of the texture unit [14] to describe the local textural patterns.

The original version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are thresholded by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighborhood consists of 8 pixels, a total of 28 = 256 different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood. Our approach is shown in figure 4 and Figure 5.

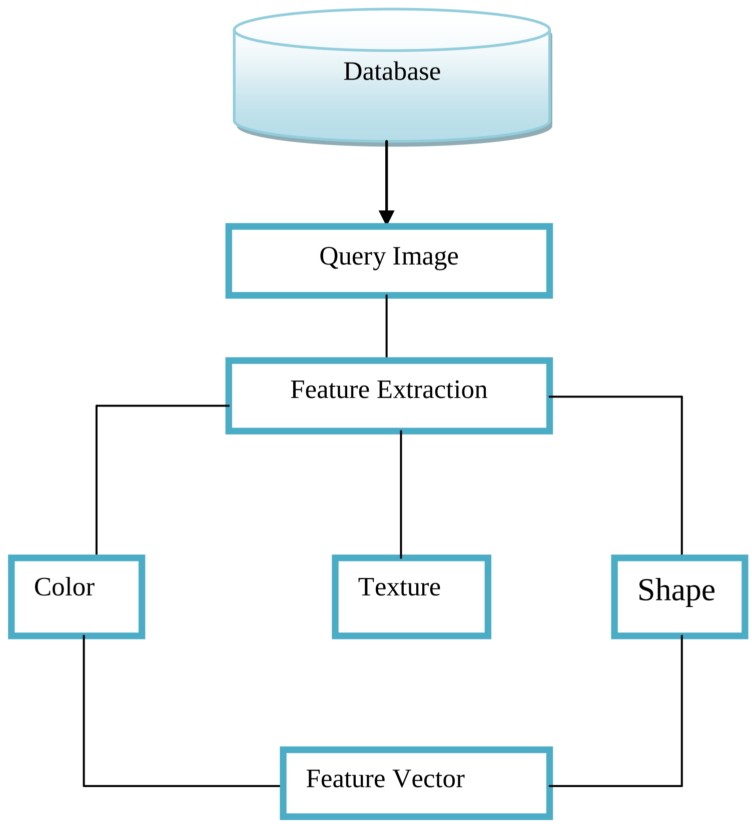

Figure 4: Indexing

In our approach Query Image is retrieved for feature extraction. Based on the dominant color we extract the features which are the combination or clusters of combinations of color fetched. Before extracting the color feature of an image, all pixels on database images are categorized into similar types of groups according to the similarity of their colors. All images are quantized to these similar colors in RGB color space. A color will be selected from predefined colors which are very near to image pixel color and it will be stored as new color pixel in the image. Color distance C_D is calculated using Euclidean distance formula, as specified below:

$$C_D = \min(\sqrt{(R_P - R_{iT})^2 + (G_P - G_{iT}) + (B_P - B_{iT})^2})$$

I = 1…….K

Using R_P, G_P, B_P as red, green, and blue components of intensity values of the pixel and R_{iT} , G_{iT}, B_{iT} are the corresponding values of the color entry in the table.The color having highest percentage is determined as dominant color of the block. Three dimensional Dominant color together with its percentage is stored as a color feature.

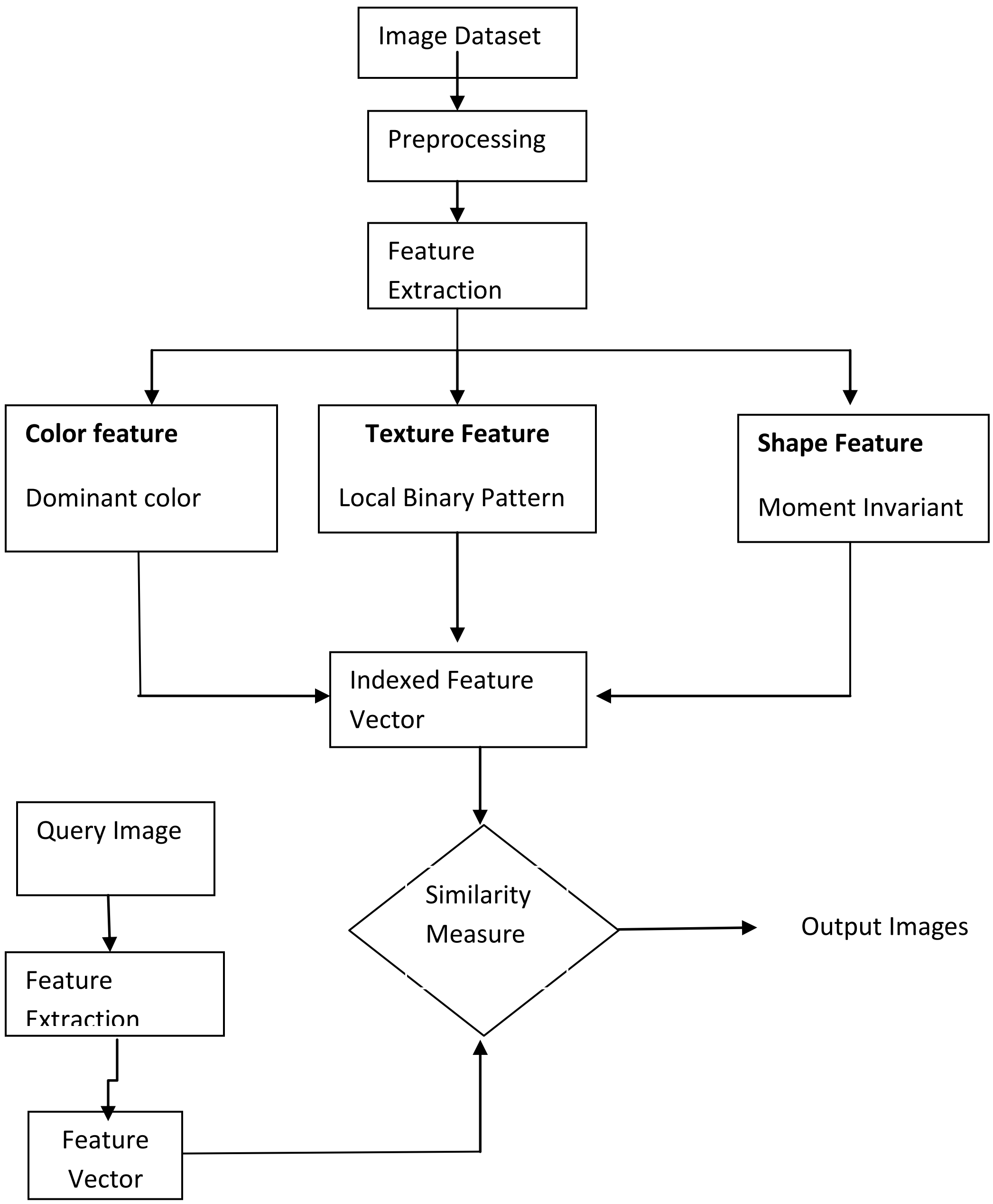

Figure 5: Working Procedure

For similarity comparison, we have used Euclidean distance, *d* using equation below.

$$d = \sqrt{\left(F_Q[i] - F_{DB}[i]\right)^2}$$

Where $F_Q[i]$ is the i^{th} query image feature and F_{DB} [i] is the corresponding feature in the feature vector database. Here, *N* refers to the number of images in the database.

In many texture analysis applications it is desirable to have features that are invariant or robust to rotations of the input image. As the Local Binary pattern are obtained by simply integrating with the dominant colors and the effects will be sampled based on similarity measures given by the above equation. RGB is of 8 bit, so the combination is of 2^{24}. The combination of each color is repented in the combination and the feature extracted based on the dominant color. Color is chosen or selected in such manner so that their percentage is color features, which are based on the 5 dominant colors. In our approach we reduce the number of colors in the five color combination, which is the centroid of the combination of the five clusters. We use the histogram of edges. n = histc(x,edges) counts the number of values in vector x that fall between the elements in the edges vector (which must contain monotonically nondecreasing values). n is a length(edges) vector containing these counts. No elements of x can be complex.n(k) counts the value x(i) if edges(k) <= x(i) < edges(k+1). The last bin counts any values of x that match edges(end). Values outside the values in edges are not counted. Use -inf and inf in edges to include all non-NaN values.

For matrices, histc(x,edges) returns a matrix of column histogram counts. For N-D arrays, histc(x,edges) operates along the first nonsingleton dimension. n = histc(x,edges,dim) operates along the dimension dim.

[n,bin] = histc(...) also returns an index matrix bin. If x is a vector, n(k) = sum(bin==k). bin is zero for out of range values. If x is an M-by-N matrix, then

```
for j=1:N,
n(k,j) = sum(bin(:,j)==k);
end
```

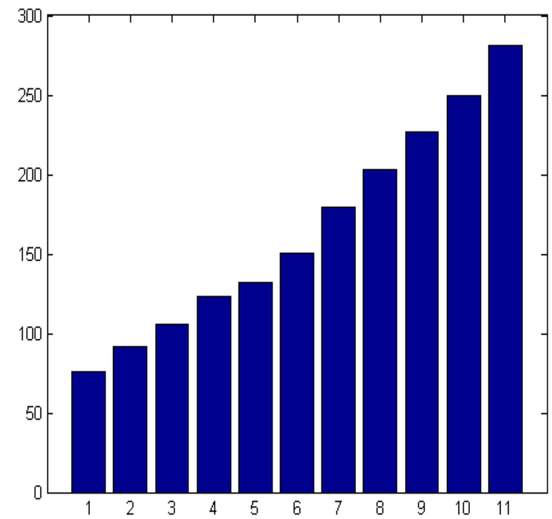

Figure 6: Single Data Histogram

Finally by the above approach we find better retrieval in comparison to the traditional approach.

6. Conclusion

Users needing to retrieve images from a collection come from a variety of domains, including crime prevention, medicine, architecture, fashion and publishing. Remarkably little has yet been published on the way such users search for and use images, though attempts are being made to categorize users' behaviour in the hope that this will enable their needs to be better met in the future. So in our paper we present an efficient way of image retrieval based on the combination of color, texture and shape.

References

[1] H. Tamura, and N. Yokoya, "Image Database Systems: A Survey," Pattern Recognition, vol. 17, no 1, pp.29–49, Sep. 1984.

[2] S. Gerard, C. Buckely, "Term-Weighting Approaches in Automatic Text Retrieval," Information Processing and Management, vol. 24, no.5, pp. 513-523, Jan. 1988.

[3] Y. Chen, J. Wang, "Image Categorization by Learning and Reasoning with Regions," Journal of Machine Learning Research, vol. 5, pp. 913–939, May 2004.

[4] F. Long, H. Zhang, H. Dagan, and D. Feng, "Fundamentals of content based image retrieval," in D. Feng, W. Siu, H. Zhang (Eds.): "Multimedia Information Retrieval and

Management. Technological Fundamentals and Applications,"Multimedia Signal Processing Book, Chapter 1, Springer-Verlag, Berlin Heidelberg New York, 2003, pp.1-26.
[5] M. Kherfi, D. Ziou, and A. Bernardi, " Image Retrieval From the World Wide Web: Issues, Techniques, and Systems," ACM Computing Surveys, vol. 36, no. 1, pp. 35–67, March 2004.
[6] Xiaojun Qi,Yutao Han," Anovel fusion approach to content-based image retrieval", Pattern Recognition Society. Published by Elsevier Ltd., 2005.
[7] N. S. Vassilieva," Content-based Image Retrieval Methods", Programming and Computer Software, 2009, Vol. 35, No. 3, pp. 158–180. Pleiades Publishing, Ltd., 2009.
[8] Chandan Singh, Pooja, "Improving image retrieval using combined features of Hough transform and Zernike moments", Elsevier 2011.
[9] Daniel CarlosGuimar~aes Pedronette n, Ricardoda S.Torres," Exploiting Clustering approaches for image re-ranking", Elsevier Ltd 2011.
[10] Xiang-Yang Wang,Yong Jian Yu and Hong-ying Yang,"An effective image retrieval scheme using color texture and shape features", Elsevier Ltd 2011.
[11] A. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain.Content-based image retrieval at the end of the early years.IEEE PAMI, 22(12):1348, 2000.
[12] Pramod Sankar K., C. V. Jawahar," Probabilistic Reverse Annotation for Large Scale Image Retrieval",IEEE 2007.
[13] Ojala, T., Pietikäinen, M., Harwood, D.: A comparative study of texture measures with classification based on feature distributions. Pattern Recognit. **29**(1), 51–59 (1996).
[14] Wang, L., He, D.C.: Texture classification using texture spectrum. Pattern Recognit. **23**, 905–910 (1990).

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