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# Approaches and Trends in Content Based Image Retrieval System

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**ABSTRACT**
*Content-based image retrieval (CBIR) has been more and more important in the last decade. Visual information systems are radically different from conventional information systems. Many novel issues need to be addressed. A visual information system should be capable of providing access to the content of image. Where symbolic and numerical information are identical in content and form, images require a delicate treatment to approach their content. To search and retrieve items on the basis of their content requires a new visual way of specifying the query, new indices to order the data and new ways to establish similarity between the query and the target. In this paper, we discuss some of the key contributions in the current decade related to image retrieval and automated image annotation. We also discuss some of the key challenges involved in the benchmark datasets and adaptation of existing image retrieval techniques to build useful systems.*
**Keywords:** *Annotation, Content-based image retrieval (CBIR), Feature Extraction, Query learning, Support vector machines (SVM).*

## 1. INTRODUCTION

Content- based means that the search will analyze the actual contents of the image. The term 'content' in this context might refer colors, shapes, textures, or any other information that can be derived from the image itself. Without the ability to examine image content, searches must rely on metadata such as captions or keywords. Such metadata must be generated by a human and stored alongside each image in the database.

Various Comprehensive surveys exist on the topic of content-based image retrieval (CBIR) , some of which are primarily on publications prior to the year 2005. Surveys also exist on closely related topics such as relevance feedback, high dimensional indexing of multimedia data, applications of content-based image retrieval to medicine, and applications to art and cultural imaging. One of the reasons for writing this survey is that the field has grown tremendously after 2005, not just in terms of size,but also in the number of new directions explored. To validate this, we conducted a simple test. 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, growth patterns in both these fields are somewhat similar, although SVMs have had a faster growth rate. A precise comment on the growth is not possible using the plots, since there are many implicit assumptions. We also note that growth in the field has been particularly strong over the last five years, spanning new techniques, new support systems, and diverse application domains. Yet, a brief scanning of about 300-400 relevant papers published in the last five years revealed that less than 25% were concerned with applications or real-world systems. This may not be a cause for concern, since the theoretical foundation behind how we humans interpret images is still an open problem. But then, with hundreds of different approaches proposed so far, and no consensus reached on any, it is rather optimistic to believe that we will chance upon a reliable one in the near future. Instead, it may make more sense to build systems that are useful, even if their use is limited to specific domains. A way to see this is that natural language interpretation is an unsolved problem, yet text-based search engines have proved very useful.

A major problem stems from the fact that an interpretation of an image has no unique meaning. The gap between high-level semantic concepts and low-level visual features hinders further performance improvement. The problem of online feature selection is critical to really bridge this gap. Wei et al. proposed a similarity based online feature selection in Content-based image Retrieval system. An investigation is based on online feature selection in the relevance feedback learning process to improve the retrieval performance of the region-based image retrieval system. The contributions are mainly in three areas.

1) A novel feature selection criterion is proposed, which is based on the psychological similarity between the positive and negative training sets.

2) An effective online feature selection algorithm is implemented in a boosting manner to select the most representative features for the current query concept and combine classifiers constructed over the selected features to retrieve images.

3) To apply the proposed feature selection method in region-based image retrieval systems

Wei Jiang and Q. Da propose a novel region-based representation to describe images in a uniform feature space with real-valued fuzzy features. The system is suitable for online relevance feedback learning in CBIR by meeting the three requirements: learning with small size training set, the intrinsic asymmetry property of training samples, and the fast response requirement .Extensive experiments, including comparisons with many state-of-the-arts, show the effectiveness of algorithm in improving the retrieval performance and saving the processing time.

Local image descriptors are employed in many real world applications like object detection and view matching using local invariant features, texture classification using micro textons , face detection and recognizing using local features, etc. Every image descriptors attempt to describe the image robustly in adverse imaging condition like lighting variation, changed view point, alteration due to rotation, zooming etc. Descriptors found in literature can be classified into two groups: sparse descriptor and dense descriptor. The sparse first detects the interest points from a given image for sampling local image patch around detected interest points then it generates a feature vector capable to describe the patch. On the other hand, the dense descriptors extract local image features pixel by pixel over the whole input image without identify the interest points.

In various computer vision applications widely used is the process of retrieving desired images from a large collection on the basis of features that can be automatically extracted from the images themselves. These systems called CBIR (Content- Based Image Retrieval) have received intensive attention in the literature of image information retrieval since this area was started years ago, and consequently a broad range of techniques has been proposed.

## 2. GENERAL FRAMEWORK FOR CONTENT-BASED IMAGE RETRIEVAL SYSTEM

Content-based image retrieval (CBIR) is any technology that in principle helps organize digital picture archives by their visual content. CBIR Systems are applied in the context of huge databases where the question arising is how to find the right image. This difficulty is increased when dealing with images having a multidimensional and subjective nature as it is the case in the context of industrial design. User queries are based on various types of queries: query by example, query by region of interest, query by concept with the problem of semantic gap, and query by sketch which is similar in principle to query by example.

The search process consists of query formulation, specification of which images to retrieve by the system from the database by various ways: one by one browsing, keywords or image features specification, or automatic image features extraction, or finally providing first an example or sketch from which features will be compared by similarity to those of the images. The technologies used come from a range of scientific knowledge bases from artificial intelligence and computer vision applications, including statistics, pattern recognition, and signal processing. Content means any information that can be derived from the image itself: colors, shapes, or textures. Searches must rely on metadata such as captions or keywords. These keywords can be generated by a human or automatically extracted from the web.

For specialized tasks, such as finding images that show certain objects, better methods exist today that can learn models of particular objects from a set of training data. However, these approaches are computationally far more expensive and always require relatively large amounts of training data. Although the selection of features tested was not completely exhaustive, the selection was wide and the methods presented can easily be applied to other features to compare them to the features presented here.

Furthermore, it has been shown that, despite more than 30 years in research on texture descriptors, still none of the texture features presented can convey a complete description of the texture properties of an image. Therefore a combination of different texture features will usually lead to best results.

## 3. FEATURES USED IN CBIR SYSTEM

The feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed such that it quantifies some significant characteristics of the object. The various features currently employed as follows:

### 3.1. Color

The color feature is one of the most widely used visual features in image retrieval. Images characterized by color features have many advantages:

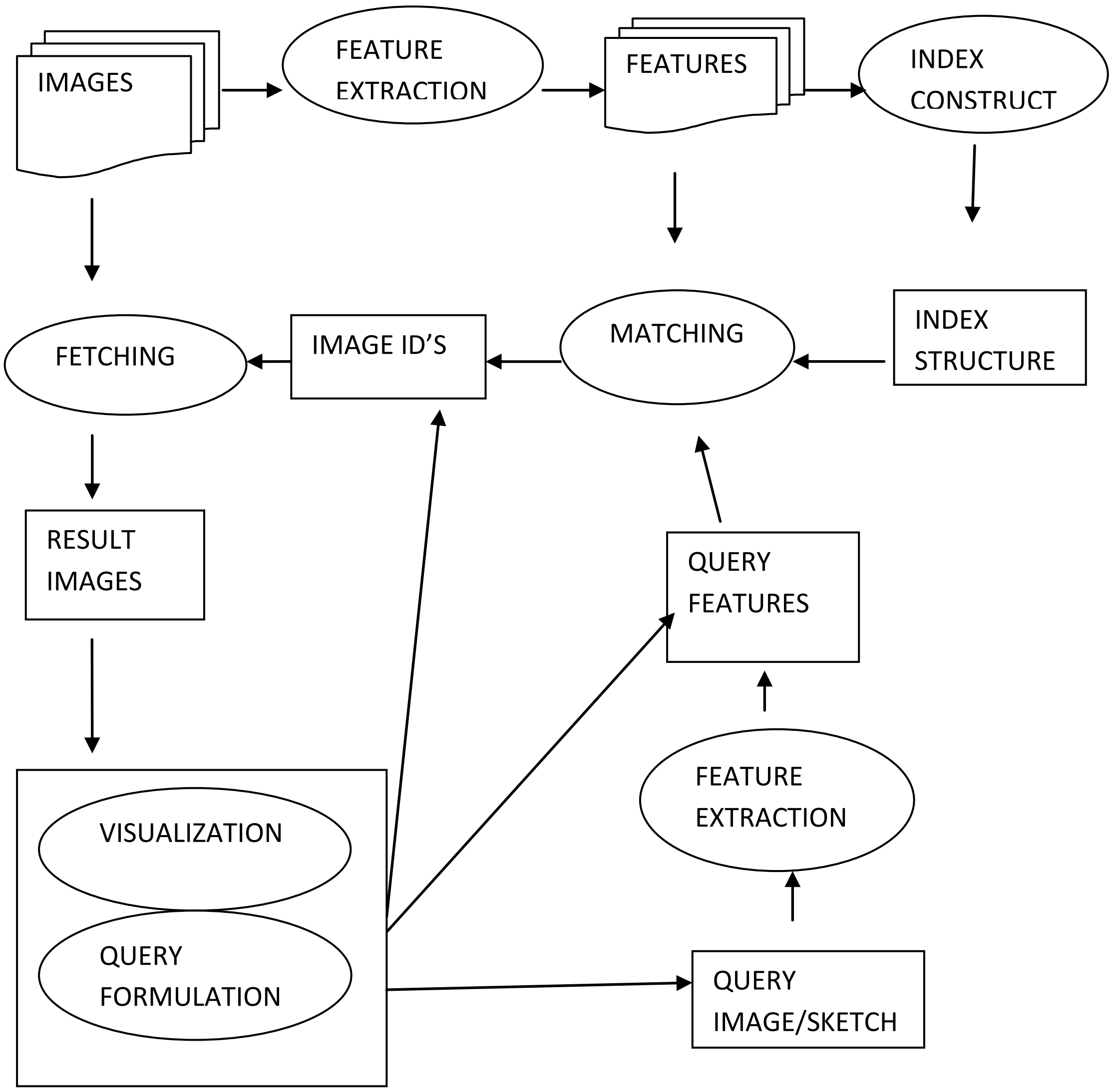


**Fig.1:** Framework for CBIR System

- **Robustness:** The color histogram is invariant to rotation of the image on the view axis, and changes in small steps when rotated otherwise or scaled. It is also insensitive to changes in image and histogram resolution and occlusion.
- **Effectiveness:** There is high percentage of relevance between the query image and the extracted matching images.
- **Implementation simplicity:** The construction of the color histogram is a straightforward process, including scanning the image, assigning color values to the resolution of the histogram, and building the histogram using color components as indices.
- **Computational simplicity:** The histogram computation has O(X, Y) complexity for images of size X×Y . The complexity for a single image match is linear; O (n), where n represents the number of different colors, or resolution of the histogram.
- **Low storage requirements:** The color histogram size is significantly smaller than the image itself, assuming color quantization. Typically, the color of an image is represented through some color model.

The color of an image is represented through some color model. There exist various color model to describe color information. A color model is specified in terms of 3-D coordinate system and a subspace within that system where each color is represented by a single point. The more commonly used color models are RGB (red, green, blue), HSV (hue, saturation, value) and Y, $C_b$ , $C_r$ (luminance and chrominance). Thus the color content is characterized by 3-channels from some color model. One representation of color content of the image is by using color histogram. Statistically, it denotes the joint probability of the intensities of the three color channels.

Color is perceived by humans as a combination of three color stimuli: Red, Green, Blue, which forms a color space.RGB colors are called primary colors and are additive. By varying their combinations, other colors can be obtained. The representation of the HSV space is derived from the RGB space cube, with the main diagonal of the RGB model, as the vertical axis in Hue, Saturation, Value (HSV) or Hue, Saturation, Intensity (HSI). As saturation varies from 0.0 to 1.0, the colors vary from unsaturated (gray) to saturated (no white component). Hue ranges from 0 to 360 degrees, with variation beginning with red, going through yellow, green, cyan, blue and magenta and back to red. These color spaces are intuitively corresponding to the RGB model from which they can be derived through linear or non-linear transformations. The HSI or, HSV space is obtained by non-linear transformation of the RGB space. The HSV or HSI representation is defined by equation (1).

$$H = \cos^{-1}\left\{\frac{\frac{1}{2}[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-G)(R-B)}}\right\}$$

$$S = 1- \frac{3[\min(R,G,B)]}{V} \qquad (1)$$

$$V = \frac{1}{3}(R+G+B)$$

The Y, $C_b$, $C_r$ color space is used in the JPEG and MPEG international coding standards. In JPEG, Y $C_b$ $C_r$ the color space is defined by equation (2).

$$\begin{aligned} Y &= 0.257R + 0.504G + 0.098B + 16 \\ C_b &= -0.148R - 0.291G + 0.439B + 128 \qquad (2) \\ C_r &= 0.439R - 0.368G - 0.071B + 128 \end{aligned}$$

In MPEG-7 the $YC_bC_r$ color space is defined by equation (3).

$$\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ C_b &= -0.169R - 0.331G + 0.500B \qquad (3) \\ C_r &= 0.500R - 0.419G - 0.081B \end{aligned}$$

### 3.1.1. Color Histograms

Color histograms are among the most basic approaches and widely used in image retrieval. To show performance improvements in image retrieval systems, systems using only color histograms are often used as a baseline. The color space is partitioned and for each partition the pixels with a color within its range are counted, resulting in a representation of the relative frequencies of the occurring colors. And use the RGB color space for the histograms.

### 3.1.2. MPEG-7 Features

Sikora et.al describes MPEG-7 features. The Moving Picture Experts Group (MPEG) has defined several visual descriptors in their standard referred to as MPEG-7 standard. The MPEG initiative focuses strongly on features that are computationally inexpensive to obtain and to compare and also strongly optimizes the features with respect to the required memory for storage. The feature types are briefly described as:

MPEG 7: Scalable Color Descriptor

The scalable color descriptor is a color histogram in the HSV color space that is encoded by a Haar transform. Its binary representation is scalable in terms of bit numbers and bit representation accuracy over a broad range of data rates. Retrieval accuracy increases with the number of bits used in the representation.

MPEG 7: Color Layout Descriptor

This descriptor effectively represents the spatial distribution of the color of visual signals in a very compact form. This compactness allows visual signal matching functionality with high retrieval efficiency at very small computational costs. It allows for query-by-sketch queries because the descriptor captures the layout information of color features. This is a clear advantage over other color descriptors. This approach closely resembles the use of very small thumbnails of the images with a quantization of the colors used.

MPEG 7: Edge Histogram

The edge histogram descriptor represents the spatial distribution of five types of edges, namely four directional edges and one non-directional edge. According to the MPEG-7 standard, the image retrieval performance can be significantly improved if the edge histogram descriptor is combined with other descriptors such as the color histogram descriptor. The descriptor is scale invariant and supports rotation invariant and rotation sensitive matching operations.

### 3.2. Texture

Texture is another important property of images. Texture is a powerful regional descriptor that helps in the retrieval process. Texture, on its own does not have the capability of finding similar images, but it can be used to classify textured images from non-textured ones and then be combined with another visual attribute like color to make the retrieval more effective. Texture has been one of the most important characteristic which has been used to classify and recognize objects and have been used in finding similarities between images in multimedia data bases. Basically, texture representation methods can be classified into two categories: structural; and statistical. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura features, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform, characterize texture by the statistical distribution of the image intensity.

### 3.2.1. Local Directional Pattern (LDP)

Chae et. al. describes a novel local descriptor for describing local image features, called Local Directional Pattern(LDP).A LDP feature is obtained by computing the edge response values generating a code from the relative strength magnitude. Each bit of code sequence is determined by considering a local neighborhood and becomes robust in noisy situation. Finally an image descriptor is formed to describe the image by accumulating the occurrence of LDP feature over the whole input image.

### 3.2.2. Haralick Texture Features

Robert M. Haralick described a technique for computing texture features based on gray-level spatial dependencies using a Gray Level Co-occurrence Matrix (GLCM). The traditional GLCM process quantizes a grayscale image into a small number of discrete gray-level bins. The number and arrangement of spatially co-occurring gray-levels in an image is then statistically analyzed. The output of the traditional GLCM process is a gray-scale image with values corresponding to the intensity of the statistical measure.

**Table 1:** Features calculated from the normalized co-occurrence matrix $P(i, j)$

| Feature | Formula |
|---|---|
| Energy | $\sum_i \sum_j P^2(i, j)$ |
| Entropy $\sum_i \sum_j P(i,j) \log P(i,j)$ | |
| Contrast | $\sum_i \sum_j (i-j)^2 P(i, j)$ |
| Homogeneity | $\sum_i \sum_j \frac{P(i,j)}{1+\langle \lvert i-j \rvert \rangle}$ |

### 3.2.3. Gabor Features

One of the most popular signal processing based approaches for texture feature extraction has been the use of Gabor filters. These enable filtering in the frequency and spatial domain. It has been proposed that Gabor filters can be used to model the responses of the human visual system. Turner first implemented this by using a bank of Gabor filters to analyses texture. A bank of filters at different scales and orientations allows multichannel filtering of an image to extract frequency and orientation information. This can then be used to decompose the image into texture features. The feature is computed by filtering the image with a bank of orientation and scale sensitive filters and computing the mean and standard deviation of the output in the frequency domain.

Filtering an image $I(x, y)$ with Gabor filters $g_{mn}$in its Gabor wavelet transform:

$W_{mn}(x,y) = \int I(x,y)\, g^*_{mn}(x - x_1, y - y_1) dx_1 dy_1$ (4)

The mean and standard deviation of the magnitude $|W_{mn}|$ are used for the feature vector. The outputs of filters at different scales will be over differing ranges. For this reason each element of the feature vector is normalized using the standard deviation of that element across the entire database.

### 3.2.4. Global Texture Descriptor

Deselaers describe texture feature consisting of several parts: Fractal dimension measures the roughness of a surface. The fractal dimension is calculated using the reticular cell counting method. Coarseness characterizes the grain size of an image. It is calculated depending on the variance of the image. Entropy of pixel values is used as a measure of disorderedness in an image. The spatial gray-level difference statistics describe the brightness relationship of pixels within neighborhoods. It is also known as co-occurrence matrix analysis. The circular Moran autocorrelation function measures the roughness of the texture. For the calculation a set of autocorrelation functions is used. From these,43 dimensional vector is obtained consisting of one value for the fractal dimension, one value for the coarseness, one value for the entropy and 32 values for the difference statistics, and 8 values for the circular Moran autocorrelation function. This descriptor has been successfully used for medical images.

### 3.2.5. Appearance-based Image Features

The most straight-forward approach is to directly use the pixel values of the images as features: the images are scaled to a common size and compared using the Euclidean distance. A 32×32 down-sampled representation of the images has been taken and compared using the Euclidean distance. It has been observed that for classification and retrieval of medical radiographs, this method serves as a reasonable baseline. Deselaers et. al proposed different methods to directly compare images accounting for local deformations. The proposed image distortion model (IDM) is shown to be a very effective means of comparing images with reasonable computing time. IDM clearly outperforms the Euclidean distance for optical character recognition and medical radiographs. The Image Distortion Model is a non-linear deformation model, it was also successfully used to compare general photographs and for sign language and gesture recognition. In this work it is used as a second comparison measure to compare images directly. Therefore the images are scaled to have a common width of 32 pixels while keeping the aspect ratio constant, i.e. the images may be of different heights.

### 3.3. Shape

Shape based image retrieval is the measuring of similarity between shapes represented by their features. Shape is an important visual feature and it is one of the primitive features for image content description. Shape content description is difficult to define because measuring the similarity between shapes is difficult. Therefore, two steps are essential in shape based image retrieval, they are: feature extraction and similarity measurement between the extracted features. Shape descriptors can be divided into two main categories: region-based and contour-based methods. Region-based methods use the whole area of an object for shape description, while contour-based methods use only the information present in the contour of an object.

The use of object shape is one of the most challenging problems in creating efficient CBIR. The object's shape plays a critical role in searching for similar image object. In image retrieval, one expects that the shape description is invariant to scaling, rotation, and translation of the object and is naturally either 2D or 3D depending on the object.

Shape features are less developed than their color and texture counterparts because of the inherent complexity of representing shapes. In particular, image regions occupied by an object have to be found in order to describe its shape, and a number of known segmentation techniques combine the detection of low-level color and texture features with region-growing or split-and-merge processes. But generally it is hardly possible to precisely segment an image into meaningful regions using low-level features due to the variety of possible projections of a 3D object into 2D shapes, the complexity of each individual object shape, the presence of shadows, occlusions, non-uniform illumination, varying surface reflectivity, and so on. After segmenting objects, their shapes have to be described, indexed, and compared. However no mathematical description is able to fully capture all aspects of visually perceived shapes as well as shape comparison is also a very difficult problem. The elusive nature of shape hinders any formal analysis of a trade-off between the complexity of shape description and its ability to describe and compare shapes of interest. At present CBIR exploits two large groups of 2D shape descriptors, namely, contour-based and region-based, representing either an outer boundary (or contour) or an entire region. These representations can also be combined together.

Both boundary-based and region-based descriptions are perceptually meaningful and interchangeable in the sense that each one can be used as a basis to compute the other. But the explicit shape features available in each type of description are quite different, so that an ideal description should include both boundaries and regions in order to obtain more efficient retrieval.

#### 3.3.1. Boundary-based Representation

Boundary representation describes the closed curve surrounding the shape. The curve can be specified in numerous ways, e.g., by chain codes, polygons, circular arcs, splines, or boundary Fourier descriptors.

The boundary features such as an ordered polygonal approximation allow for a user query formulated as a sketch. Generally, the sketch is deformed to adjust to the shape of target models, and the amount of deformation, e.g. the energy for an elastic deformation model. Such a deformable template represents shape variability by allowable transformations of a template.

#### 3.3.2. Region-based Representation

Region-based or interior descriptions of shape specify the object's "body" within the closed boundary. Such a shape is represented with moment invariants, or a collection of primitives such as rectangles, disks, quadrics, etc., deformable templates, skeletons, or simply a set of points.

A skelton represents each shape with the axis of symmetry between a pair of boundaries. The simplest skeleton is given by the medial axis defined as the trace of a locus of inscribed maximum-size circles. The skeleton is usually represented by a graph.

A shock set created by propagation from boundaries is another variant of the medial axis. Shocks are singularities formed from the collisions of propagating fronts. By adding shock dynamics to each point and grouping the monotonically flowing shocks into branches, a shock graph is formed.

Because shape is also defined in terms of presence and distribution of oriented parts, the quantitative characteristics of objects' orientation within an image, for instance, angular spectral of image components or edge directionality, may serve as global shape descriptors. In particular, the blob world model efficiently describes objects separated from the background by replacing each object with a “blob”, or an ellipse identified by the centroid and the scatter matrix. The blob is characterized also with the mean texture and the two dominant colors.

## 4. ANNOTATION

While image retrieval has been active over the years, an emerging new and possibly more challenging field is automatic concept recognition from visual features of images. The challenge is primarily due to the semantic gap that exists between low level visual features and high level concepts. The primary purpose of a practical content-based image retrieval system is to discover images pertaining to a given concept in the absence of reliable meta-data. All attempts at automated concept discovery, annotation, or linguistic indexing essentially adhere to that objective more closely than do systems which return an ordered set of similar images. Of course, ranked results have their own role to play, e.g. visualization of search results, retrieval of specific instances within a semantic class of images etc..Annotation, on the other hand, allows for image search through the use of text. For this purpose, automated annotation tends to be more practical for large data sets than a manual process. If the resultant automated mapping between images and words can be trusted, then text-based image searching can be semantically more meaningful than CBIR. Image understanding has been attempted through automated concept detection. The annotation process can be thought of as a subset of concept detection, i.e., images pertaining to the same concept can be described linguistically in different ways based on the specific instance of the concept.

### 4.1 Search by text

Major Web image search engines (Google, Yahoo) process the search from keywords and display images with the words corresponding to the textual description of the images. These images are manually indexed before to be entered in the database or, as it is the case for web grabbing, text information is extracted from the document where the image is cited. The limits of search by text occur when text annotations are nonexistent or incomplete. In this case content based image retrieval turns out to be more appropriate.

### 4.2. Image search

Image search enables to find images in databases not by keywords but by visual and semantic content. In this case each image is represented by a set of features. To find images similar to a given query image, the features of the images in the database are compared to those of the query image. Even if similarity by visual content alone is very useful, users often prefer to keep both possibilities (text and content).Various categorization systems are used for the definition of images features. Colour is the most frequently used feature for images classification, together with texture and shape. Major colour systems used as basis for image classification are systems Red Green Blue (RGB), Munsell Hue, value and chroma (HVC), CIE Lab, and Natural Colour System (NCS). A huge research body exists for extracting image signatures according to different colour space representations. Texture characteristics, although not as well defined as colour, are esential to retrieval accuracy. Several features describe the global texture of images, like Tamura features, the repartition of the power spectral density of images and Fourier Transform histograms. Texture histograms are also used in addition to traditional texure models, such as Gaussian of Markov features, or recently new texture features based on Radon transform orientation. Shape is most of the time a well defined characteristic. Traditional shape features include geometric characteristics like ratio and circularity, also Fourier descriptors, edge orientation histogram and region contours, turning angle functions, deformable templates, algebraic moments and descriptors based Hough Transform.In addition combinations of these descriptors and weighted signatures have been considered. In contrast to the global description, local descriptors try to give a detailed description of the visual content focused on salient parts of the images.

## 5. RELEVANCE FEEDBACK AND LEARNIN

Relevance feedback (RF) is a query modification technique, originating in information retrieval, that attempts to capture the user's precise needs through iterative feedback and query refinement. Ever since its inception in the image retrieval community, a great deal of interest has been generated. In the absence of a reliable framework for characterizing high-level semantics of images and human subjectivity of perception, the user's feedback provides a way to learn case-specific query semantics. We present short overview of recent progress in RF. Normally, user's RF results in only a small numberof labeled images pertaining to each high level concept. Learning based approaches are typically used to appropriately modify the feature set or the similarity measure. To circumvent the problem of learning from small training sets, a discriminant-EM algorithm has been proposed to make use of unlabeled images in the database for selecting more discriminating features.One problem with RF is that after every round of user interaction, usually the top results with respect to the query have to be recomputed using a modified similarity measure. A way to speed up this nearest-neighbor search has been proposed. Another issue is the user's patience in supporting multiround feedbacks. A way to reduce the user's interaction is to incorporate logged feedback history into the current query. History of usage can also help in capturing the relationship between high level semantics and low level features.We can also view RF as an active learning process, where the learner chooses an appropriate subset for feedback from the user in each round based on her previous rounds of feedback, instead of choosing a random subset. Active learning using SVMs was introduced into the field of image retrieval.Extensions to the active learning process have also been proposed, With the increase in popularity of region-based image retrieval, attempts have been made to incorporate the region factor into RF using query point movement and support vector machines. A tree-structured self organizing map has been used as an underlying technique for RF in a content-based image retrieval system.

A clustering based approach to RF incorporating the user's perception in case of complex queries has been studied. In, manifold learning on the user's feedback based on geometric intuitions about the underlying feature space is proposed. While most RF algorithms proposed deal with a two-class problem, i.e., relevant or irrelevant images, another way of looking at RF is to consider multiple relevant and irrelevant groups of images using an appropriate user interface.

## 6. CONCLUSION

We have presented a brief survey on work related to the young and exciting fields of content-based image retrieval and automated image annotation.We believe that the field will experience a paradigm shift in the foreseeable future, with the focus being more on application-oriented, domain-specific work, generating considerable impact in day-to-day life. We have laid out some guidelines for building practical, real-world systems that we perceived during our own impleme-ntation experiences. Finally, we have compiled research trends in CBIR and automated annotation. The trends indicate that while systems, feature extraction, and relevance feedback have received a lot of attention, application-oriented aspects such as interface, visualization, scalability, and evaluation have traditionally received lesser consideration. We feel that for all practical purposes, these aspects should also be considered equally important. Meanwhile, the quest for robust and reliable image understanding technology needs to continue as well. The future of this field depends on the collective focus and overall progress in each aspect of image retrieval, and how much the ordinary individual stands to benefit from it.

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