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A Novel Signature Histogram Based Indexing For CBIR System

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ABSTRACT: Content Based Image Retrieval (CBIR) is a technique used for retrieving similar images for given input image from an image database. CBIR aims to retrieve the images based on the content of a given image rather than textual information of a file name. CBIR uses the various features such as color, texture, shape etc.The shape is independent of transformations like scaling, translation, rotation and flip. A good shape representation method retrieve similar images irrespective of the transformation performed on a shape. The known shape representation called "centroid contour distance (CCD) signature" is invariant to translation, scale but not to rotation and flip. The CCD signature quantize into signature histogram which is invariance to rotation and flip. It has a drawback namely number of false positives will increase i.e. many different shapes can have a "similar signature histogram". This problem can be solved with augmented signature histogram with information present at the boundary of object. Images are presented to a user calculating Euclidian distance matching with every shape descriptor is a computational expensive problem. With large database this process may take minutes, hours. So to reduce the computational requirement, the images are indexed based on Color, Medial Axis, Area, Eccentricity, and Euler number.These indexing parameters are bias. To overcome this problem the static parameter such as mean was calculated from the signature histogram. Based on mean value images are indexed. This reduces the search space in retrieval process. So that the performance is increased.Keywords: Signature histogram, centroid distance signature, shape signature, indexing.

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I. Introduction

Large growth in data storage and image acquisition technologies has enabled the creation of large image datasets. In order to deal with these data, it is necessary to develop suitable information systems to efficiently manage these collections. Image searching is one of the most important services that need to be supported by such systems. In general, two different approaches have been applied to allow searching on image collections: one based on image textual medatada and another based on image content information. The first retrieval approach is based on attaching textual meta data to each image and uses traditional database query techniques to retrieve them by keywords. However these systems require a previous annotation of the database images, which is a very laborious and time-consuming task. Furthermore, the annotation process is usually inefficient because users, generally, do not make the annotation in a systematic way. In fact, different users tend to use different words to describe a same image characteristic. The lack of systematization in the annotation process decreases the performance of the keyword-based image search.

These shortcomings have been addressed by the so-called *Content-Based Image Re-trieval (CBIR) systems.* In these systems, image processing algorithms (usually automatic) are used to extract feature vectors that represent image properties such as color, texture, and shape. In this approach, it is possible to retrieve images similar to one chosen by the user (*query-by-example*). One of the main advantages of this approach is the possibility of an automatic retrieval process, contrasting to the effort needed to annotate images.

The creation of CBIR systems involves research on databases and image processing, handling problems that vary from storage issues to friendly user interfaces. Images are particularly complex to manage – besides the volume they occupy, retrieval is an application-and-context-dependent task. It requires the translation of high-level user perceptions into low-level image features (this is the so-called "semantic gap" problem). More-over, image indexing is not just an issue of string processing (which is the case of standard textual databases). To index visual features, it is common to use numerical values for the *n* features and then to represent the image or object as a point in a *n-dimensional* space. Multi-dimensional indexing techniques and common similarity metrics are factors to be taken into account. In this context, the main challenges faced are the specification of indexing structures to speed up image retrieval and the query specification as a whole.

Shape is the main factor to differentiate visual objects. Based on the shape (saying that, "This is a dog, but that is a cat") a child can easily differentiate an object (like image of

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an animal). Shape has more abstract and untold meaning as well; recently, an action (in a video stream) of a human being is seen as a three dimensional (two are the space dimensions and one is the time dimension) space-time shape. Walking shape of a person is different from running shape of person in space-time. There is no exact definition for shape except concluding that it is independent (invariant) of scale (size), rotation, translation, flip (mirror-reflection), and for small deformations (affinely transformed shapes). Shape recognition has several applications, like content-based image retrieval, character recognition, object-classification where input is the object's image, online hand-drawn text or shape recognition, writer recognition, etc.

Generally, shape representation methods are categorized into two types. They are (i) contour-based methods, and (ii) region-based methods. In contour based methods only the boundary is considered but region based methods entire region is taken into account.

The two representation methods are further divided into global and structural approaches. In structural approach it shows the object as consisting of several parts along with their relationships, but in global approach the shape is represented as a whole. These approaches can be further divided into space domain and transform domain based on whether the image is transformed into another domain (e.g., by applying Fourier transformation, medial axis transformation, etc.) or not. Various shape representation methods are proposed in past include shape invariants, moments, shape signature, signature histogram, curvature, shape context, shape matrix, spectral features, etc. A detailed review of existing methods is given by Zhang et. al.

A good representation scheme requires to have the following properties.

1) It should be simple and compact. This will reduce the complexities while computing.

2) It should be possible to regenerate the shape correctly from its representation. That is, there should be a one-to-one mapping between representation and the corresponding object's shape. This will minimize the error-rate while recognizing a shape.

3) The representation should be useful and suitable for shape analysis and recognition. In the best of circumstances the representation should lead in a metric space where distance metrics can easily defined.

4) For healing form, a hierarchical coarse to fine representation is required .Conequence go off at a tangent the oppressive at head infancy uses coarser representations and it uses finer representations towards the end of the search. This minimizes the duration required to retrieve a desired shape from a large database.

II.STRUCTURE OF CBIR SYSTEM

Content Based Image Retrieval systems are used to search digital images in large databases and retrieve relevant ones based on the actual content of the image. Content can be in the form of low-level features or any other information from the images.

Content-Based Retrieval has been used by different communities for various applications like Medical Diagnosis, Intellectual Property, Broadcasting Archives, and Information Searching on Internet, Biomedicine, Crime Prevention, and in Personal photo albums such as Picasa and Flickr.

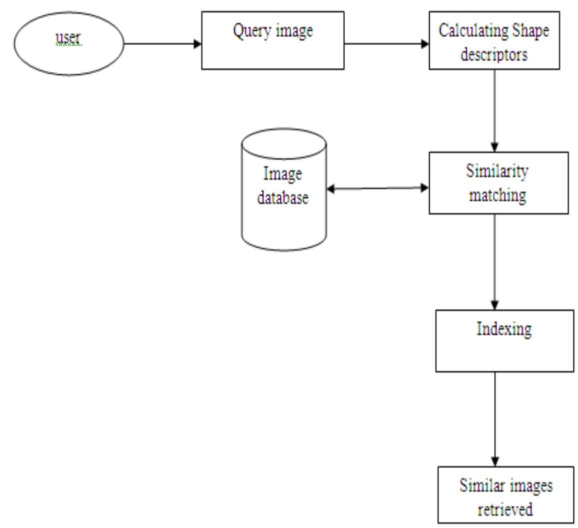

Figure1: Architecture of CBIR System

The retrieval process involves the following steps, as shown in fig. 1:

1) Receiving queries from the user in the form of image or sketch.

2) Extracting features of the query images and calculating shape descriptors and storing them in the feature database as feature vector/space.

3) Doing similarity matching with the features that are already stored in the feature database

3) Indexing the vectors for efficient retrieval.

4) Then sending back the retrieved images to the user.

A. *Queries*

Queries are given by the users. The queries are input images these can be in any form query-by-example, query-by-keyword, query-by-sketch.

B. *Calculating shape descriptors*

The feature extraction is used to measure some components of image contents using image processing. In most of the systems feature extraction is used as a preprocessing step. Typically, there are two types of visual features in CBIR: primitive features which include color, shape and texture, domain specific features. Feature extraction is concerned with capturing visual content of images for search and

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retrieval. Signature histogram is a frequencies of lengths in predefined length intervals are used. For the given input image signature histograms are calculated. These shape descriptors are used to calculate mean value based on mean value the image is searched in indexing module.

C. Feature Vector

Extracted features from images are stored as a feature vector or feature space in a feature database. The Feature database is a place where the extracted feature vector will be stored. Each feature vector is sorted in a specific order for the purpose of similarity matching.

D. Similarity Matching

This step consists of matching the query image to the most similar images in the database according to some image to image similarity measure. Images are said to be similar when the value of similarity measure is minimal for the feature vector. Most commonly used similarity function is Euclidean function.

E. Indexing and Retrieval

Indexing is a kind of sorting based on the value given to the image after finding the similarity of each images. It is used to accelerate the query performance in the search process and plays a main role in supporting effective retrieval of sequences of images. Proper indexing makes the search easy and efficient. In this paper the indexing is done based on the probability model mean.

III.CONTOUR BASD SHAPE REPRESENTATION METHODS

Contour based methods only the boundary of the object is considered but region based methods entire region is taken into account. The region information like texture etc. The boundary of an object can be seen as a number of parts collected as one which leads to structure based representation and there are numerous representation methods like chain code representation, polygon decomposition, smooth curve decomposition, etc. In syntactic approaches a language rules kind of representation (like regular expressions) can be used to signify the relationship among primitive parts of the border line.

The other approach is called global approach which generally represents the boundary in the form of a feature vector. In this case, well defined distance metrics can be used to compute similarity between shapes.

Various easy and regular global shape descriptors are area, circularity (ratio of squared perimeter and area), eccentricity(ratio of major axis' length and minor axis' length), major axis orientation, bending energy, etc. However, these are good to rapidly shrink the search space in the early stages of the search while retrieving the significant shapes, and if used alone, can give raise to several false-positives.

The other relevant global representation approaches are shape signatures, boundary-moments, etc.

Shape signature is a one dimensional function which correspond to the boundary points. Centroid to boundary distance as a function of angle is called centroid distance signature or centroid-contour distance (CCD) curve. Figure.2 illustrates this for a square. This representation is translation invariant.

two shapes to overcome the rotation problem, and reverse matching is needed to overcome the flip problem.

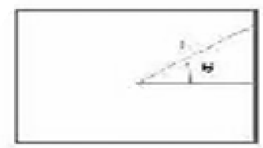

Fig (a) Square Shape

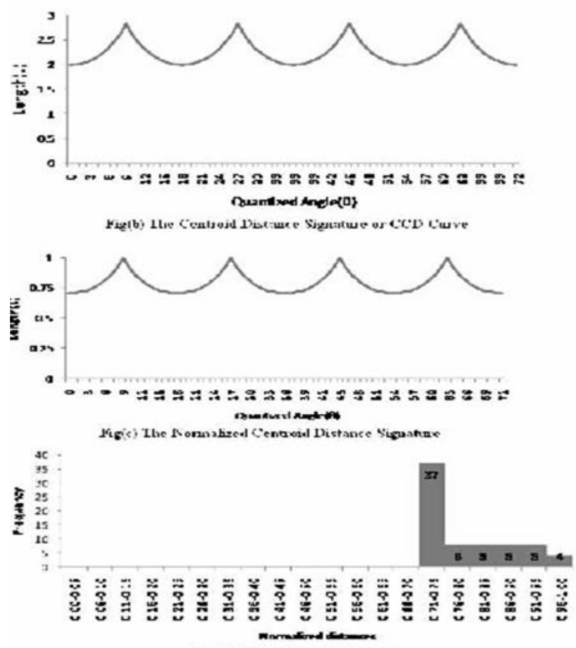

Figure 2 Centroid distance signature for a square, its normalized version and its histogram

A simple solution suggested is to quantize the signature into a signature histogram (where frequencies of lengths in predefined length intervals are used). While this achieves all properties required for the representation, it has a severe drawback, viz., many entirely different shapes can have same or similar signature histograms. This increases the number of false-positives in a retrieval system. Nevertheless

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this representation can be used to reduce the search space at initial stages of the search, because if the signature histograms did not match then one can conclude that they have different shapes, but even when signature histograms are matching one can not say that they are of the same shape. To overcome this problem, we augment the signature histogram with local information present at the contour.We proposed to use centroid distance signature (but they called it centroid-contour distance (CCD) curve).Normalized Centroid Contour Distance curve is translation and size invariant. But since this is not rotation invariant a shift matching method is applied to find similar shapes. Along with this angle code histogram (ACH) as proposed by Peng and Chen is used in order to preserve the local information, also eccentricity (ECC) is used.

IV.CENTROID DISTANCE SIGNATURE AND SIGNATURE HISTOGRAM

Centroid distance signature is a function s :[0, 2π] $\rightarrow R^+$ (here, R^+ is the set of positive real numbers which are less than a finite number) which is the distance from centroid to the boundary with respect to angle with a predefined axis (horizontal axis) taking centroid as the origin. Angles are measured in anti-clockwise direction from the horizontal axis. In Fig 2(a) the function values can be normalized by dividing each distance with the maximum distance, so that the distances are in the range [0, 1]. For theoretical purposes this function can be treated as a continuous one, but in practice this is a discrete one, where the function values are taken at discrete angle values like values in the set A = {ϵ, 2ϵ, 3ϵ ,...,Lϵ },where we assume that Mϵ =2π for some positive integer L. The quantizing factor is removed and the set A is represented{1, 2 , 3,...,L}. This is done to achieve notational simplicity. For example, in Figure 2, which is for a square image, A = {1, 2,...,72}. This means, for the example, ϵ= π/36.This function f : A →[0, 1], which is a quantized and normalized representation of the function s is called the normalized centroid distance signature. This is represented as a finite sequence $(f_1 ,f_2 ,...,f_L)$ where fi = f (j),for $1 \leq j \leq L$ .We say,f $=(f_1,f_2,...,f_L)$. Note, f is a function, since the domain of this function is a discrete one and also is an enumerated one, it is represented as a finite sequence. This kind of representation of a function, subsequently is adopted, to represent some other functions. Diagrammatically, for a geometric shape square, f is illustrated in Figure 2(c).

By rotation, we mean that the image of the object is rotated in anti-clockwise direction by an angle Θ such that Θ = rϵ for some integer r € {1, 2, 3,...,L}.By making arbitrarily small we can rotate the image by any arbitrary angle such that 0 <Θ = 2π. In this case, the normalized centroid distance signature will become (fr+1 ,fr+2 ,...,fL ,f1 ,f2 ,...,fr).This is nothing but circularly left shifted version of the original signature.

By flip (mirror-reflection), we mean that the normalized centroid distance signature is reversed in its order, i.e., it becomes $(f_L ,f_{L-1} ,...,f_1)$.The normalized centroid distance signature is invariant to translation and scale but the normalized centroid distance signature is not invariant to rotation and flip. A change of this representation called the signature histogram has all required properties, including, invariance to rotation and flip. For this purpose the range of f , i.e., [0, 1] is divided into equispaced intervals like $I_1 =[0,a),I_2 =[a, 2a),...,I_{n-1} =[(n-3)a,(n-2)a)$,In =[(n - 1)a, 1],where a =1/n. Let I = $\{I_1 ,I_2 ,...,In \}$.For a given f , its signature histogram is obtained from it, which is a function h : I → {0, 1, 2,...,L} such that h(Ij) is equal to the number of times "fx € Ij is true" while considering each fx in f only once. In other words, signature histogram gives the frequency of (number of) lengths in the normalized centroid distance signature that fall in predefined length intervals. Signature histogram is represented as a finite sequence h $=(h_1 ,h_2 ,...,h_n)$ where $h_i = h(I_i)$,for$1 \leq i \leq$n.Signature histogram is invariant to scale, translation, rotation and flip. Since normalized centroid distance signature is invariant to scale and translation, and since signature histogram is obtained from it, the signature histogram is also invariant to scale and translation.Even though, the signature histogram representation has all desired properties, it has a severe drawback, that the number of false-positives can be large. This happens because the histogram preserves number of centroid to contour distances in an interval, but can not preserve the order that is present between these distances. This paper proposes to preserve along with signature histogram some additional information regarding ordering of lengths. It is done in such a way that all desired properties like invariance to scale, translation, rotation and flip are preserved. The proposed representation scheme is called the k^{th} order augmented histogram,where $1 \leq k \leq M - 1$.

V.SIGNATURE HISTOGRAM BASED INDEXING FOR RETRIEVAL SYSTEM

Signature Histogram based Indexing image retrieval system, for a given input image of an object, images are retrieved from the database where the retrieved object's shape of images are similar to the given object's shape.

The database of images created by representing each images k^{th} order augmented histogram, where $1 \leq K \leq L-1$.

The kth order hierarchical retrieval system mechanism is as follows.

Let D be the database of images. For the given input image, signature histogram is calculated. The calculated signature histogram of input image is compared with the signature histograms of images present in the database. The distance gauge used is the L_1 distance. The images which are present within the threshold distance t0 those images are retrieved first. Let this subset of images be D_0. Then, the 1^{st} order difference histogram is used to retrieve from D_0, its subset

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D_1 by using a threshold distance t1. Here, the distances are found between 1st order difference histogram of the input image with 1st order difference histograms of the images in D_0 .Likewise the subsets, D_2 ,...,D_k are found. The relationship between these subsets is, D_k D_{k-1} ... D_0 D. Increasing the value of k can lead to a kind of over-fitting since eve a slight noise present at the contour of either input image or images stored in the database can affect the retrieval. To avoid this,it is found, based on experimental results that k=2 is enough to retrieve relevant shapes.t0 is fixed such that on average 25% of images are retained in D_0 , similarly t1 and t2 are chosen to retain 25% from their respective supersets. Then from D_2 most similar 5 images are presented to the user, if $D_2 \geq 5$.Otherwise, when $D_2 < 5$, from D1 ,the nearest 5 images are retrieved. So, always the top five retrieved images are presented to the user. This is done to simplify the experimentation process and the way in which the results can be presented as done by Wang et. al.

The Indexing uses the signature histogram values to calculate the mean value. Based on the mean value the images are indexed. The indexed images are stored in files. The files are indexed with mean value.

The each file will have some range i.e. 0-1, 1-2; 2-3 etc. This range represents the mean value. The indexing will reduce the search space to retrieve the images from large database.

In retrieval process the similarity between the query image and indexed images are evaluated. The similarity is calculated by using Euclidean distance between the shape descriptor(signature histogram) of query image and the database indexed image shape descriptors. The images which are having lowest distance values are sent to the user. This means that the highest similarity matching images are forwarded to the user.

VI.CONCLUSION

The proposed Novel Signature Histogram Based Indexing for CBIR System which improves the performance of image retrieval process. The mean value is calculated from the signature histograms. Based on the mean value the similar images are grouped under one Index. When the user request for similar images of query image, the mean value based indexes are preset as files .Therefore we can map the similar images based on the index files without searching the entire data base. This reduces the search space in retrieval of image from large image database and also increased the effectiveness of the CBIR system. From the mean value, calculating the variance from the signature histogram results will increase the hash indexing which can be applied to reduce the computational power. The different signature histogram can be calculated and also calculate the second level indexing parameter. Second level indexing is used for the larger databases.

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