Angular-Radial Decomposition Algorithm for Sketch-Based Image Retrieval

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ABSTRACT

This paper presents a novel algorithm for sketch-based image retrieval. The approach enables measuring the similarity between a full color multi-component model image and a black and white sketched query and needs no cost intensive image segmentation. Two different procedures, based on strong edges of the model image and thinned outline of the sketched image, are exploited to derive two abstract images. Angular-radial decomposition of pixels in the abstract images is used to extract new compact and effective features. A collection of paintings and sketches (ArT BANK) is used for testing the proposed method. Average Normalized Modified Retrieval Rank (ANMRR) is used for performance evaluation. The results are compared with three other well-known approaches. Experimental results show significant improvement in ANMRR factor using the proposed features.

Keywords: Sketch-Based Image Retrieval, Feature Extraction, and Invariant Features.

1. INTRODUCTION

In recent years, there has been an explosion of image databases resulted from advances in digital imaging devices such as scanners and digital cameras. Moreover, the advent of Internet gives more people the opportunity to access vast amount of multimedia information at their fingertips. Image retrieval from multimedia databases is still an open problem. Traditional textual methods have been inefficient and insufficient for searching through visual data. Consequently, image and video content-based indexing and retrieval methods have attracted many new researches [1, 2].

There are many popular image retrieval techniques currently being used with different technologies. Some of the representative content-based systems are Blobworld [3], QBIC [4], FourEyes [5], MetaSEEk and VisualSEEk [6, 7]. The MPEG-7 standard defines descriptors for three main image content features that are color, texture and shape [8, 9]. VisualSEEk is also using object layout as another content key.

In sketch-based image retrieval, where the query example is a rough and simple black and white hand-drawn sketch, color and texture lose their original abilities to serve as the content key. Visual shape descriptors are useful in sketch-based image retrieval only when the model and the query images contain one object in a plain background [10]. In multiple-object scenes, object layout is a powerful tool, but object extraction and segmentation costs together with rotation variance introduce major drawbacks.

We focus our discussion on the problem of finding image features invariant to scale, translation, and rotation, which can be used efficiently in sketch-based retrieval. We also eliminate any constraint regarding the number of objects and the existence of any background. In other words, the images may have several objects in an inhomogeneous background.

Related Work

A number of researchers have considered the problem of content-based image retrieval (CBIR) while a few have addressed sketch-based image retrieval (SBIR). The work of Hirata and Kato, Query by Visual Example (QVE) [11], focuses solely on this problem. IBM has adopted a modified version of the approach in its QBIC system [4]. In this approach the query and the target images are resized to 64×64 pixels and measuring the similarity is performed using a block correlation scheme. The approach does not allow indexing and is computationally expensive. Although the method can tolerate small local rotations, it is not rotation invariant and does not allow for large global rotations.

The edge histogram descriptor (EHD) was proposed in the visual part of the MPEG-7 standard [12, 13]. It originally consists of an 80-bin histogram. A given image is divided into 16 sub-images (4×4) first, local edge histograms are then computed for each sub-image based on the strength of five different edges (vertical, horizontal, $45°$ diagonal, $135°$ diagonal, and isotropic). S. Won *et al*. proposed the efficient use of the descriptor by extending the histogram to 150 bins [13]. The extended histograms are obtained by further grouping the image blocks into 13 clusters (4 vertical, 4 horizontal, and 5 square clusters). A 65-bin semi-global histogram and a 5-bin global histogram are added to make a 150-bin histogram. The EHD is basically intended for gray-image to gray-image matching but changing the internal parameter Th_{edge}, a threshold for edge extraction, could make it applicable for black and white queries in sketch-based retrieval.

The 2-D Fourier transform in polar coordinates is employed for shape description in [14]. Its supremacy over 1-D Fourier descriptors, curvature scale space descriptor (MPEG-7 contour-based shape descriptor) and Zernike moments (MPEG-7 region-based descriptor) has been shown in [15]. Polar Fourier descriptor (PFD) is extracted from frequency domain by exploiting two-dimensional Fourier transform on polar raster sampled image. It is able to capture image features in both radial and spiral directions [15].

Using histograms of edge directions for representing image information is one of the well-known methods in the image retrieval field. The feature is appropriate also for sketch-based image matching as it compares the distribution of edge points in the edge map of the query image with the corresponding information of the model image. Abdel-Mottaleb [16] uses the approach by applying the Canny edge operator to find strong edges in an image and then quantizes them into 4 directions. Jain and Vailaya [17] also propose edge directions as an image attribute for shape description and apply the method in a trademark registration process [18].

Edge Pixel Neighborhood Information (EPNI) method [19] is employing neighborhood structure of the edge pixels to make an extended feature vector . The vector is used efficiently for measuring the similarity between sketched queries and arbitrary model images. The semantic power of the method is examined in [20]. Although the method is scale and translation invariant it does not exhibit the rotation invariance property.

In this paper we present a novel analysis method for feature extraction. It is based on spatial decomposition of abstract images obtained from multi-component images without computationally expensive segmentation. Abstract images are derived from the full color model image and from the black and white query image by two different procedures. Angular-radial distribution of pixels in the abstract images is then employed as the key concept for feature extraction. The extracted features are scale, translation, and rotation invariant. The major contribution of the paper is in invariance properties. To our knowledge, there is no affine-transforms invariant approach dealing with arbitrary multi-component images in sketch-based retrieval in the current literature.

An art image experimental database, called ArT BANK, has been developed and employed for test in this study. The ArT BANK consists of two parts. The first part is a collection of artistic full color paintings and images (courtesy to World Art Kiosk at California State University). The second part contains several rough, black and white sketches similar to arbitrary candidates from the first part and their rotated versions. These are employed as sketched queries while the images in the first part are used as the image models. The proposed algorithm and three other well-known approaches are implemented and examined on the ArT BANK. Average Normalized Retrieval Rank (ANMRR) is used for retrieval performance evaluation. Experimental results show significant improvement in the ANMRR factor using the new approach.

The details of the proposed algorithm are discussed in the next section. Section 3 briefly explains similarity measurement and the ANMRR performance indicator. Section 4 exhibits experimental results and discussion. Section 5 concludes the paper and poses some new directions.

2. SPATIAL DECOMPOSITION OF ABSTRACT IMAGE (SDAI)

The main objective of the proposed approach is to transform the image data into a new structure that supports measuring the similarity between a full color image and a black and white hand-drawn simple sketch. The proposed algorithm is scale, translation and rotation invariant.

The edge map of an image carries the solid structure of the image independent of the color attributes. Its applicability is well known in computer vision, pattern recognition and image retrieval. Edges are also proven to be a fundamental primitive of an image for the preservation of both the semantics and the perceived attributes [21]. Furthermore, in sketch-based image retrieval, it is the most useful feature that can be employed for matching purposes [19, 10, 22].

According to the assumption that sketched queries are more similar to the edge maps which contain only the perceptive and vigorous edges, we obtain two abstract images through the strong edges of the model image and using the thinned version of the query image. The proposed features are then extracted from the derived abstract images.

Abstract Image

Two abstract images are obtained for the model image and for the sketched query by two different procedures. The full color model image is initially converted to a gray intensity image I, by eliminating the hue and saturation while retaining the luminance. The edges are then extracted using the Canny operator [23] with $\sigma = 1$ and Gaussian mask of size = 9 using the following procedure for depicting the most perceived edges.

The values of high and low thresholds for the magnitude of the potential edge points are automatically computed in such a way that only the strong edges remain. This improves the general resemblance of the resulted edge map and the hand drawn query. In order to depict strong edges, let G be the Gaussian 1-D filter and g be the derivative of the Gaussian used in the Canny edge operator. Then

$$H(k) = \sum_i G(i)g(k+1-i)$$

is the 1-D convolution of the Gaussian and its derivative.

$$X(u,v) = [\sum_{j=1}^{V} I'(u,j)H(v-j)]'$$

and

$$Y(u,v) = \sum_{i=1}^{U} I(i,v)H(u-i)$$

for $u = 1,2,3,\ldots U$ and $v = 1,2,3,\ldots V$, are the vertical and horizontal edge maps respectively. U is the number of rows and V is the number of columns in the image I. The $'$ notation indicates matrix transpose. The magnitude of the edge points is then obtained as

$$\Gamma(u,v) = \sqrt{X(u,v)^2 + Y(u,v)^2}$$

For efficient selection of the high and low thresholds, we then make a 64-bin cumulative histogram of the $\Gamma(u,v)$ values and find the minimum index ι in this cumulative histogram that is grater than $\alpha \cdot U \cdot V$, where α denotes the percentage of non-edge points in the image ($\alpha = 0.7$ is an adequate choice for many images). To retain strong edges of the image, $\beta \cdot \iota$ is selected as the high threshold value and $0.4\beta \cdot \iota$ is used for the low threshold value in the Canny edge operator. β is a parameter that controls the degree of the strength of the edge points. Higher β's lead to lower number of edge points but more perceptive ones. Consequently, the gray image I is converted to edge image P using the Canny edge operator exploiting the above automatic extracted thresholds.

For query images, the procedure of black and white morphological thinning [24] is applied to extract a thinned version of the sketched image. This image, namely Q, shows an outline of the query and contains the main structure of the user request. It contains the spatial distribution of pixels similar to the strong edge map of the model image P.

To eliminate the adverse effect of different directions of P and Q images the major axes direction is obtained, based on the algorithm given in [25], and the images are rotated so that the major axis becomes horizontal.

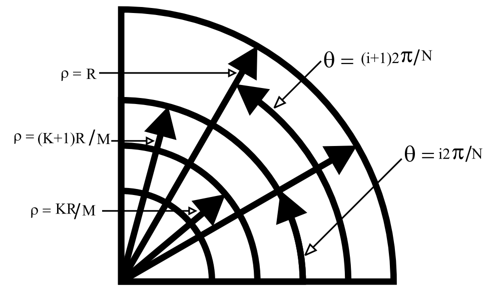

Fig. 1. Angular Radial Partitioning of an image to N angular and M radial sectors where $k = 0,1,2\ldots M-1$ and $i = 0,1,2\ldots N-1$

The bounding box of P and Q images are then normalized to $J \times J$ pixels, using nearest neighbor interpolation. The proposed normalization of P and Q images ensures the scale and translation invariant properties. The resulting images are called *abstract image* Ω and are used for the feature extraction scheme.

Angular-Radial Decomposition

Based on the fact that any rotation of a given image, with respect to its center, moves a pixel at (ρ,θ) to a new position at $(\rho,\theta+\tau)$, we define a set of adjacent sectors in the abstract image Ω. In the following, we consider pixels $\Omega(\rho,\theta)$ to be either equal to "1" for edge pixels or "0" for non-edge pixels.

The algorithm uses the surrounding circle of Ω for partitioning it to $M \times N$ sectors, where M is the number of radial partitions and N is the number of angular partitions. The angle between adjacent angular partitions is $\theta = 2\pi/N$ and the radius of successive concentric circles is $\rho = R/M$ where R is the radius of the surrounding circle of the image (see Fig. 1).

The number of edge points in each sector of I is chosen to represent the sector feature. The scale invariant image feature is then $\{f(k,i)\}$ where

$$f(k,i) = \sum_{\rho=\frac{kR}{M}}^{\frac{(k+1)R}{M}} \sum_{\theta=\frac{i2\pi}{N}}^{\frac{(i+1)2\pi}{N}} \Omega(\rho,\theta) \quad (1)$$

for $k = 0,1,2\ldots M-1$ and $i = 0,1,2\ldots N-1$. The features extracted above will be circularly shifted when the image Ω is rotated $\tau = l2\pi/N$ radians ($l = 0,1,2\ldots$). To show this, let Ω_τ denote the abstract image Ω after rotation by τ radians in counterclockwise direction:

$$\Omega_\tau(\rho,\theta) = \Omega(\rho,\theta-\tau). \quad (2)$$

Then,

$$f_\tau(k,i) = \sum_{\rho=\frac{kR}{M}}^{\frac{(k+1)R}{M}} \sum_{\theta=\frac{i2\pi}{N}}^{\frac{(i+1)2\pi}{N}} \Omega_\tau(\rho,\theta) \quad (3)$$

are the image feature elements for Ω_τ for the same k and i. We can express f_τ as

$$\begin{aligned} f_\tau(k,i) &= \sum_{\rho=\frac{kR}{M}}^{\frac{(k+1)R}{M}} \sum_{\theta=\frac{i2\pi}{N}}^{\frac{(i+1)2\pi}{N}} \Omega(\rho, \theta-\tau) \\ &= \sum_{\rho=\frac{kR}{M}}^{\frac{(k+1)R}{M}} \sum_{\theta=\frac{(i-l)2\pi}{N}}^{\frac{(i-l+1)2\pi}{N}} \Omega(\rho, \theta) \\ &= f(k, i-l) \end{aligned} \tag{4}$$

where $i-l$ is a modulo M subtraction. It means that there is a circular shift (for individual k's) in the image features $\{f_\tau(k,i)\}$ compared to the image features $\{f(k,i)\}$ representing Ω_τ and Ω respectively.

Using 1-D discrete Fourier transform of $f(k,i)$ and $f_\tau(k,i)$ for each k we obtain

$$\begin{aligned} F(k,u) &= \tfrac{1}{N}\textstyle\sum_{i=0}^{N-1} f(k,i)e^{-j2\pi ui/N} \\ F_\tau(k,u) &= \tfrac{1}{N}\textstyle\sum_{i=0}^{N-1} f_\tau(k,i)e^{-j2\pi ui/N} \\ &= \tfrac{1}{N}\textstyle\sum_{i=0}^{N-1} f(k,i-l)e^{-j2\pi ui/N} \\ &= \tfrac{1}{N}\textstyle\sum_{i=-l}^{N-1-l} f(k,i)e^{-j2\pi u(i+l)/N} \\ &= e^{-j2\pi ul/N}F(k,u). \end{aligned} \tag{5}$$

Because of the property $|F(k,u)| = |F_\tau(k,u)|$, the scale and rotation invariant image features are chosen as $\Upsilon = \{|F(k,u)|\}$ for $k = 0,1,2\ldots M-1$ and $u = 0,1,2\ldots N-1$.

Choosing a medium-sized sector (e.g. $M = 5$ and $N = 12$) makes the invariant image feature Υ to be robust to other small variations as well (i.e. translation, erosion and occlusion). This is based on the fact that the number of edge pixels in such sectors varies slowly with such variations. Fig. 2 shows an example of Ω image superimposed with angular-radial partitions.

Experimental results (Section 4) confirm the robustness and efficacy of the extracted features.

3. SIMILARITY MEASUREMENT AND EVALUATION METHOD

The similarity between images is measured by the ℓ_1 (Manhattan) distance between the two corresponding feature vectors. Suppose Υ_P and Υ_Q represent two different images P and Q respectively. The similarity between image P and Q is the inverse of their Manhattan distance calculated as:

$$d(P,Q) = \sum_k \sum_u |\Upsilon_P(k,u) - \Upsilon_Q(k,u)|.$$

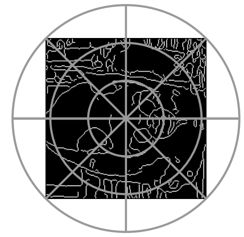

Fig. 2. An example of abstract image Ω and the Angular-radial partitions used for the feature extraction

Recall and Precision are well-known retrieval performance measures. They are basically "hit-and-miss" counters. In other words, the retrieval performance is based on the number of retrieved images, which have similarity measures that are greater than a given threshold. For more specific comparisons, however, we also need rank information among the retrieved images. Average Normalized Modified Retrieval Rank (ANMRR), which was developed during the MPEG-7 standardization activity, is a measure that exploits not only the recall and precision information but also the rank information among the retrieved images. It is defined in MPEG-7 standard [26, 13] as follows:

$$AVR(q) = \sum_{\kappa=1}^{NG(q)} \frac{Rank(\kappa)}{NG(q)}$$

$$MRR(q) = AVR(q) - 0.5 - \frac{NG(q)}{2}$$

$$NMRR(q) = \frac{MRR(q)}{K + 0.5 - 0.5 * NG(q)}$$

$$ANMRR = \frac{1}{Q_{tot}} \sum_{q=1}^{Q_{tot}} NMRR(q)$$

where $NG(q)$ is the number of ground truth images for a query q. K=min(4*NG(q),2*GTM), where GTM is max $\{NG(q)\}$ for all q's of a data set. $Rank(k)$ is the rank of the found ground truth images, counting the rank of the first retrieved image as one. A $Rank$ of $K+1$ is assigned to each of the ground truth images which are not in the first K retrievals. For example, suppose a given query q_i has 10 similar images in an image database ($NG = 10$). If an algorithm finds 6 of them in the top 20 retrievals ($K = 20$) in the ranks of 1,5,8,13,14 and 18, then the $AVR(q_i) = 14.3$, $MRR(q_i) = 8.8$ and $NMRR(q_i) = 0.5677$.

Note that NMRR and its average (ANMRR) will always be in the range of $[0, 1]$. Based on the definition of ANMRR, the smaller the ANMRR, the better the retrieval performance.

4. EXPERIMENTAL RESULTS

This section presents experimental results using the new proposed algorithm in comparison with three other methods known from the literature. We made a collection of different model and query images called ArT BANK. Currently, it contains 3600 full color images of various sizes in the model part and 220 sketches in its query part. Images in the model part are mostly art works obtained from the World Art Kiosk at California State University (450 images). Each image was rotated $45°$, $90°$, $135°$, $180°$, $225°$, $270°$ and $315°$ and put in the database. Images in the query part are black and white images which are draft sketches, drawn by different subjects similar to 55 arbitrary candidates from the model part and their rotated versions ($90°$, $180°$ and $270°$). This is to evaluate rotation invariance property and to simulate different vertical and horizontal directions when posing a sketched query to the retrieval system. Fig. 3 shows an example of a sketched image and the corresponding model image.

The ArT BANK was used as the test bed for the following four approaches: the proposed SDAI method (Section 2), the QVE approach, as used in the QBIC system [4], MPEG-7 edge histogram descriptor (EHD) [12, 13], and the polar Fourier descriptor (PFD) approach [15]. All methods were tested using the images in the query part as input queries while regarding the images in the model part as database entries.

In the SPAI method (Section 2), we applied $M = 5$, $N = 12$, $\beta = 3$, and $J = 129$ resulting in a 60-entry feature vector Υ. For the EHD method, *desired_num_of_blocks* was set to 1100 and Th_{edge} set to 11 (the default values) for the model images and Th_{edge} was set 0 for the queries since they are binary images. A 150-bin histogram was obtained in this approach employing local, semi-global and global histograms. We followed the algorithm given in [15] to obtain a 60-bin feature vector in PFD approach. The quantization stage in the EHD method was dropped to put all methods in a similar footing.

The ℓ_1 distance was used for measuring the similarity between image features of the MPEG-7 edge histogram descriptor (EHD) approach and of the proposed SDAI method. For the EHD method a weighting factor of 5 for global bins, as recommended in [13], was applied. Euclidian distance (ℓ_2) was exploited for measuring the similarity between PFD features [15] and global correlation factor was employed for measuring the similarity between images in the QVE method [4]. The generated vectors of SDAI, EHD, and PFD methods are used to represent the images.

We used ANMRR as retrieval performance measure. In our experiments the $NG(q) = 8$ for all q's, $K = 16$ and $Q_{tot} = 220$. Table 1 exhibits ANMRR for QVE, EHD, PFD, and SDAI methods. The retrieval performance of the proposed SDAI approach is the best (0.3307). PFD method's performance is better than EHD and QVE methods respectively (0.3935<0.4112<0.4918). It means the PFD approach is more robust than the other two approaches.

Fig. 3. An example of sketched image (left) and corresponding model image (right)

The QVE method exhibits lack of rotation invariance. This arises from the fact that the method looks only at local features and ignores global translation and rotation. Since SDAI, EHD, and PFD methods generate a feature vector for each image, they support indexing. On the other hand, the QVE approach ,which uses a correlation scheme for measuring the similarity between images, cannot be used to generate indices for the database.

Table 1. Retrieval performance of different methods

Method	QVE	EHD	PFD	SDAI
ANMRR	0.4918	0.4112	0.3935	0.3307

5. CONCLUSION

The image analyzing approach presented in this paper (SDAI) enables measuring the similarity between a full color multi-component model image and a black and white sketched query. The images are arbitrary and may contain several complex objects in inhomogeneous backgrounds. The approach deals directly with the whole image and needs no cost intensive image segmentation and object extraction. Two abstract images are defined, based on the strong edges of the model image and the thinned outline of the query image respectively, and are used for feature extraction. Angular-radial decomposition of the abstract images is used to extract features that are scale, translation, and rotation invariant. Experimental results, using SDAI approach and the ArT BANK, as the test bed, show significant improvement in the ANMRR measure over three other well-known approaches within the literature.

The decomposition scheme could be refined to improve retrieval performance. We also intend to investigate sketch-based object recognition using the SDAI approach.

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