Intergrating Salient Regions with New Perceptual Texture Features Based on Wavelet Transform for Image Retrieval

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***Abstract*—In content-based image retrieval, the representation of local properties in an image is one of the most active research issues. This paper introduces a salient region detector based on wavelet transform. The detector can extract the visually meaningful regions on an image and reflect local characteristics. An annular segmentation algorithm based on the distribution of salient regions is designed. It takes not only local image features into account, but also the spatial distribution information of the salient regions. Then, Color moments and the introduced visual perception texture features of the regions around the salient points were computed as a features vector used for indexing the image. We tested the proposed scheme using a wide range image samples from the Corel Image Library, the experimental results indicating that the method has produced promising results.**

***Index Terms*—Content-Based Image Retrieval, visual Perception Texture Features, Wavelet Transform, Salient regions, Spatial Distribution Information**

I. INTRODUCTION

With the rapid development of internet and increase of the volume of digital image collections, content-based image retrieval (CBIR) is becoming one of the active research areas [1, 15, 16]. Content-based image retrieval systems normally return the retrieval results according to the similarity between features extracted from the query image and candidate images. The most common approach of the CBIR, known as querying images by examples (Query-By-Example), searches for the most similar images to the given example among a number of candidate images. Usually, content-based image retrieval searches the image database by visual content, such as color, texture or shape. The pre-process of images mainly focuses on extracting features that can be used to represent the relevant visual content. When users perform retrieval, features of the sample and candidate images are compared. Those images that have the most similar features are retrieved. However, the retrieval systems based on global visual content features usually cannot represent all the characteristics of the image, for a typical query image also includes local features which are normally associated with certain objects or different parts. Obviously, these local features are particularly important to characterize an image.

Thus, in order to avoid using global features, corner detectors were introduced to represent local properties of images in image retrieval systems [2, 3]. Corner detectors were initially designed for shape and robotics recognition. These detectors can extract visual corners of the image based on local derivatives in multiple orientations [4]. While there are two main drawbacks when corner detectors were applied to various natural images in content-based image retrieval. One is that the points extracted by the corner detectors are the visual focus ones, so visual meaningful points are not necessarily located in the corner points and the corner points may be redundant. Second, corner may gather in small regions so they cannot represent all parts' properties of an image. For the above reasons, corner points may not be indexing an image effectively.

In accordance with theory of wavelet transform, a local absolute maximum value of the wavelet coefficients at a coarse resolution corresponds to a region with high global variations and reflects the singularity point of a signal. So salient points detector based on wavelet transform, which expresses image variations at different resolutions, was designed to extract the visual meaningful points, namely, salient points[5][6]. However, because the human eye's capacity of resolving power is limited, people usually focus on the visual meaningful regions of the image .In order to reflect the local characteristics of these regions, in this paper, we propose an salient regions

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detector based on wavelet transform which can extract the visual meaningful regions of the image and reflect the image's local characteristics. Aim to achieving optimum retrieval performance, an annular segmentation algorithm based on salient regions spatial distribution is designed, which take not only the local image features into account, but also the spatial distribution information of the salient regions.

As is known, texture can describe a wide variety of surface characteristics and a key component for human visual perception and plays an important role in image-related applications. In the past, textures have attracted attention from both the Computer Graphics and Computer Vision communities. In a certain sense, an image can be considered as the composition of different texture regions. This makes texture an essential feature of images. Accordingly, texture features have been extensively studied in the research area of content-based image retrieval, image classification, image segmentation, as well as other pattern analysis fields. In the real world, Texture can describe a wide variety of surface characteristics of image. Perceiving texture is a ubiquitous visual experience; it can be recognized when we see it. However, a precise and general definition of texture is still not available. Modeling texture is not an easy task and it is usually characterized by the two-dimensional variations in the intensities or the spatial distribution of gray values in the image. Many researchers from different communities have paid attention to this issue. Traditionally, how to represent a texture can be simply classified into three categories, namely structural, statistical and multi-resolution filtering methods. Typical structure based methods include morphological and graph techniques, which describe texture using structural primitives and layout [1]. Statistical methods are commonly used and proved to be effective in texture analysis [7, 8, 9], For example, Haralick [10] suggested gray level co-occurrence matrices (GLCM) can be used to estimates image properties related to second-order statistics, which have become one of the most well-known and widely used texture features. Methods based on Multi-resolution decompose a texture image into different scales, from which statistics can be extracted and used to describe texture features [11, 12]. Typical approaches include wavelet transform, which produces subbands' statistics (such as mean and standard deviation) and can be used as feature vectors [11, 12].

Psychophysical investigation has shown that the Human Visual System (HVS) does a frequency analysis when we see images [21, 22, 23]. Texture is especially suited for this type of analysis for its intrinsic properties. In this paper, we focus on studying new features that are based on wavelet transform and can agree with human visual perception. We propose three perceptual features, namely directionality, contrast and coarseness, which are proved to be in accordance with human visual perception in image retrieval experiments.

The rest of the paper is organized as follows. In section 2, we introduce the salient regions detection algorithm. Section 3 presents an annular segmentation algorithm based on salient regions which is designed to take the local image features and the space distribution information of the salient regions into account. Section 4 presents visual perception texture features based on wavelet transform. Experimental results are presented in section 5. Finally, we conclude the paper in section 6.

II. Salient Regions Detection based on Wavelet Transform

A. Wavelet Transform

Wavelet transform is a multi-resolution analysis that represents image variations at different scales [13, 14]. A wavelet is an oscillating and attenuated function and its integral equals to zero. Given $f(x)$ is a one-dimensional input signal, a 1-Ddiscrete wavelet transform is defined as:

$$\phi_{jk}(x) = 2^{-j/2}\phi(2^{-j}x - k),$$

$$\psi_{jk}(x) = 2^{-j/2}\psi(2^{-j}x - k),$$

Where $\phi(x)$ and $\psi(x)$ are the scaling function and wavelet function respectively, $\{\phi_{jk}(x)\}$ and $\{\psi_{jk}(x)\}$ are the two orthogonal function basis sets.

Define $P_0f=f$, a 1-D discrete wavelet transform at the scale j decomposed $P_{j-1}f$ through orthogonal projection P_jf and Q_jf as follows :

$$P_{j-1}f = P_j f + Q_j f = \sum_k c_k^j \phi_{jk} + \sum_k d_k^j \psi_{jk},$$

and

$$c_k^j = \sum_{n=0}^{p-1} h(n) c_{2k+n}^{j-1},$$

$$d_k^j = \sum_{n=0}^{p-1} g(n) c_{2k+n}^{j-1},$$

$$(j = 1,2,...,L, k = 0,1,..., N/2^j - 1),$$

Where $\{h(n)\}$ and $\{g(n)\}$ low pass filter and high pass filter, respectively.

$\{C_n^0\}$ is the input signal, N is the length of the input signal, L is the necessary progression.

The computation of wavelet transform of a 2-D image involves recursive filtering and sub-sampling. At each level, there are three detail images. Following [1], we denote these detail images as LH (containing horizontal information in high frequency), HL (containing vertical information in high frequency), and HH (containing diagonal information in high frequency). The decomposition also produces one approximation image, denoted by LL, which contains the low frequency information. The wavelet transform can recursively decompose the LL band. Since two level wavelet decomposition yields 6 detail images, we use LH1, HL1, HH1, LH2, HL2, HH2, and an additional approximation image LL2 to denote all the subband images.

B. Improved Salient Points Detector Based on Wavelet Transform

Here we only consider orthogonal wavelets with a compact support, which lead to a non-redundant and complete representation of the signal. As the orthogonal wavelets have a characteristic that from which signal points each wavelet coefficient at the scale 2^j was computed. The wavelet transform provides information about the variations in the signal at different scales. A local absolute maximum value of the wavelet coefficients at a coarse resolution corresponds to a region with high global variation of a signal. So salient points can be detected through finding a relevant point to represent this global variation by looking at coefficients at finer resolutions.

Assume a wavelet with a compact support; we know that each wavelet coefficient $W_{2^j} f(n)$ at the scale 2^j is computed with $2^{-j} p$ signal points, where p is the wavelet regularity. we can further investigate the wavelet coefficient at the finer scale 2^{j+1}. At the scale 2^{j+1}, there is a set of coefficient computed with the same points as a coefficient at the scale 2^j. We call these coefficients $C(W_{2^j} f(n))$ the children of the coefficient $W_{2^j} f(n)$, and they have relationship as follows:

$$C(W_{2^j} f(n)) = \{W_{2^{j+1}} f(k), 2n \le k \le 2n + 2p - 1\}$$

Where $0 \le n \le 2^j N$ and N is the length of the signal. The children coefficients $C(W_{2^j} f(n))$ reflect the variations of the $2^j p$ signal points, and the most salient one is the wavelet coefficient with the highest absolute values. Salient point can be detected to consider this maximum and look at its highest child. Applying this process recursively, we can extract the salient point. Loupias and Sebe etc. used the following formula which called saliency value to detect the salient point [5, 6]:

$$saliency = \sum_{k=1}^{-j} | C^{(k)} (W_{2^j} f(n)) |, 0 \le n \le 2^j N, -\log_2 N \le j \le -1$$

However, the highest absolute values of the wavelet coefficient at the different scales have different means and varying scope .From Table 1 we can see that the set of maximum wavelet coefficients at the first level is larger than that at the second level, and the set of maximum wavelet coefficients at the second level is larger than that at the third level too. This result accords with the wavelet transform theory .In order to extract the salient points more exactly, we propose an improved salient points detector:

$$saliency = \sum_{k=1}^{-j} | w(k) C^{(k)} (W_{2^j} f(n)) |, 0 \le n \le 2^j N$$

$$-\log_2 N \le j \le -1,$$

Where *w(k)* is the weight of the maximum wavelet coefficients at different scales. The weight *w(k)* is the reciprocal of the standard deviation which is defined as:

$$\mu_k = \frac{1}{S} \sum_{z=1}^{S} | W_{2^k} f(z) | \quad ;$$

$$\sigma_k = \frac{1}{S} \sum_{z=1}^{S} ([W_{2^k} f(z) - \mu_k]^2)^{\frac{1}{2}} \quad ;$$

$$w(k) = 1/\sigma_k \quad ;$$

Where: $W_{2^k} f(z)$ is one of the elements of wavelet decomposition in the maximum coefficients set ; $0 \le z \le S$, S is the number of the set of maximum wavelet coefficients at k level.

In practice, if M salient points extracted in the image retrieval application, we can set: *S=1.5M.*

III. ANNULAR SEGMENT DOMAINS BASED ON SALIENT REGIONS DISTRIBUTION

In order to combine the spatial distribution characteristic of the salient region, an annular segmentation algorithm based on salient regions distribution is designed, which takes not only the local image features into account, but also the space distribution information of the salient regions.

Let M salient regions be extracted in an image, given $point = \{(x, y) / (x, y) \in \text{ a salient region}\}$ is the set of salient regions, where $1 \le i \le M$.

Let *Cen*=(*x'*, *y'*) be the centroid of the salient regions, and *x'* and *y'* are defined as :

$$x' = \frac{1}{M} \sum_{(x,y) \in point} x \quad ;$$

$$y' = \frac{1}{M} \sum_{(x,y) \in point} y \quad .$$

Set the centroid *Cen* as the center of salient regions, Let R be the maxmium radius with the *Cen* as the center of a circle:

$$R = \max_{(x,y)\in point} [(x-x')^2 + (y-y')^2]^{\frac{1}{2}} .$$

The M salient regions in an image can be segmented into a serial annular with radius KR/N ($1 \le K \le N$) and with the Cen as the center.
From the center to the outside, a salient region set in an annular is:

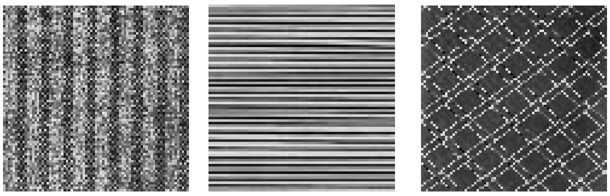
$$\{(x,y) / \frac{(K-1)}{N} \le [(x-x')^2 + (y-y')^2]^{\frac{1}{2}} < \frac{K}{N}, (x,y) \in point\}$$

The salient regions in every annular region were computed as a features vector for indexing the image.
More details about the salient regions and annular segment domains based on salient regions distribution can be seen in [16].

IV. VISUAL PERCEPTION TEXTURE FEATURES

A. *Directionality*

Directionality is an important characteristic for texture images. For example, from human perception's viewpoint, we perceive the D11 texture in Figure 1 as a "vertical" texture, D49 as a "horizontal" one and D47 as "diagonal". Instead of computing a vague value of directionality, we introduce three different directionalities, namely "the vertical directionality", "the horizontal directionality" and "the diagonal directionality", to represent the directional information of a texture image.



D11 D49 D47

Fig.1 Three textures from Brodatz database.

A.1. The Horizontal Directionality

In allusion to every HL (contains the high vertical frequency information) subband of wavelet decomposition, we compute the horizontal directionality. Let M, N be the sizes of HL subband, and $x(j,k)$ be the subband's coefficient of wavelet decomposition, where j and k represent the row and column values of the subband images respectively. Firstly, the subband image is convoluted with a template $\begin{pmatrix} 1\ 0\ 1 \\ 1\ 0\ 1 \\ 1\ 0\ 1 \end{pmatrix}$ at each wavelet decomposition coefficient in order to enhance the direction contrast. Let $h(j,k)$ represent the result of convolution. For every row, the normalized convolution result is computed as:

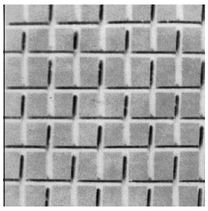
$$p_{jk} = \frac{|h(j,k)|}{\sum_{k=1}^{N} |h(j,k)|} ;$$

The horizontal directionality is then defined as :

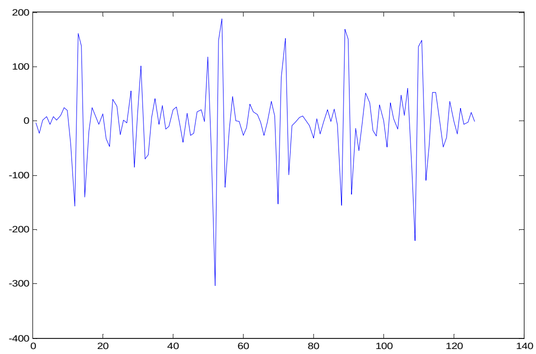
$$Dir_H = \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} p_{jk}{}^2 ,$$

Where, M and N are the sizes of HL subband.

Fig. 2 (a) is the D1 texture from the Brodatz database and (b) shows the 10th row's coefficient convolution result of HL1 subband , which comes from .



(a)



(b)

Fig.2 (a) The D1 texture from Brodatz database.
(b). The coefficient convolution result of the 10th row's HL1 subband .

A.2. The Vertical Directionality

Similar to the definition of the horizontal directionality, the LH subband is convoluted with a different template $\begin{pmatrix} 1\ 1\ 1 \\ 0\ 0\ 0 \\ 1\ 1\ 1 \end{pmatrix}$ for each coefficient produced by wavelet decomposition. Let $v(j,k)$ represent the result of convolution; j and k represent the row and column values of the subband. Then for every column, normalized coefficient convolution result is computed as:

$$q_{jk} = \frac{|v(j,k)|}{\sum_{j=1}^{M} |v(j,k)|};$$

The vertical directionality is defined as :

$$Dir_V = \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} q_{jk}^{2},$$

Where: M, N is the size of HL subband.

A.3. The Diagonal Directionality

Compared to the horizontal and vertical directionality, the computation of the diagonal directionality is more complex. We should take two diagonal directions into account, namely, $\pi/4$ and $3\pi/4$.

When we consider the diagonal directionality of $\pi/4$, convolution is performed with a template $\begin{pmatrix} 0\,0\,1 \\ 0\,1\,0 \\ 1\,0\,0 \end{pmatrix}$ at the HH subband. Similarly, when the diagonal directionality of $3\pi/4$ is considered, convolution is computed with a template $\begin{pmatrix} 1\,0\,0 \\ 0\,1\,0 \\ 0\,0\,1 \end{pmatrix}$. Then we sample $\pi/4$ diagonals and $3\pi/4$ diagonals for computing the diagonal directionality. The calculation process is the same as the horizontal and vertical directionality. The diagonal directionality in the same wavelet decomposition level is defined as the average of the diagonal directionality of $\pi/4$ and $3\pi/4$:

$$Dir_D = \frac{1}{2}(Dir_{D1} + Dir_{D2}),$$

Where Dir_{D1} represents the Diagonal Directionality of $\pi/4$ and Dir_{D2} represents the Diagonal Directionality of $3\pi/4$, respectively.

B. Contrast

For the purpose of denoting the change of grey levels in a texture, contrast is commonly defined for each pixel as an estimate of the local variation in a neighborhood. The calculation of the contrast is implemented in the wavelet decompose approximation subband, denoted as LL, which contains the low frequency and reflecting the global information of the texture.

Given $x(j,k)$ as the coefficient of LL subband, where j and k represent the row and column values of the subband images, respectively, let the pixel at the point (j, k) be $x(j,k)$ and the neighborhood of size $W \times W$ be a mask of the pixel. Then local contrast is computed as:

$$l\_con(i,j) = \frac{\max_{x \in W \times W}(x) - \min_{x \in W \times W}(x)}{\max_{x \in W \times W}(x) + \min_{x \in W \times W}(x)}.$$

The global contrast is defined as the mean of all the local contrast values:

$$Con = \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} l\_con(i,j).$$

Since the wavelet decomposition results in a smaller size for the approximation subband compared with that of the original texture's size, we recommend a neighborhood window with a size of 3x3, instead of using the size 7x7 as introduced in [8].

C. Coarseness

Coarseness is the granularity measurement of texture and the most fundamental texture feature. Researchers usually identify the texture by “coarseness”. The coarseness defined by Tamura etc. in [7] coincides well with the psychological measurements for human perception, so we also use it in the wavelet decompose approximation subband to calculate the granularity of texture. The computational definition of coarseness is briefly described as follows:

The moving average $A_Z(s,t)$ over the neighborhood of size $2^z \times 2^z$ (z=0, 1, 2, 3, 4, 5) at the point *(s, t)* is

$$A_Z(s,t) = \sum_{j=s-2^{z-1}}^{j=s+2^{z-1}} \sum_{k=t-2^{z-1}}^{k=t+2^{z-1}} x(j,k) \Big/ 2^{2z}.$$

Where $x(j,k)$ is the coefficient of the LL subband at *(j, k).*
Then, the differences between pairs of non-overlapping moving averages in the horizontal and vertical directions for each pixel are computed,

$$E_{Z,h}(s,t) = |A_Z(s + 2^{Z-1}, t) - A_Z(s - 2^{Z-1}, t)|;$$

$$E_{Z,v}(s,t) = |A_Z(s, t + 2^{Z-1}) - A_Z(s, t - 2^{Z-1})|.$$

At each point, the value of Z that maximizes E in either direction is used to set the best size:

$$S_{best}(s,t) = 2^Z;$$

The global coarseness is calculated by averaging S_{best} over the entire LL subband:

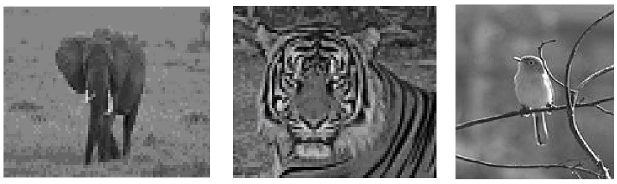
$$Conse = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N} S_{best}(j,k)$$

More details on the Visual Perception Texture Features can be found in [17, 18].

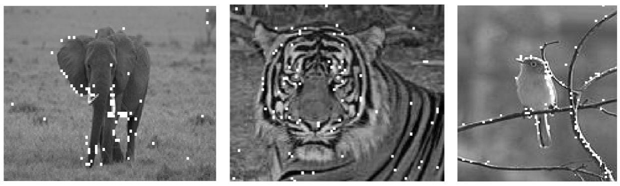
V. Experimental Results

The salient region detector aims to extract visually meaningful regions in an image. Fig.2 is an example of salient regions exacted using Haar and db4 wavelet. In our experiment, sixty salient regions were extracted. From Fig.2 we can see that the salient regions detector can extract the visually meaningful regions in the image exactly, such as the regions around the eyes and mouth of the tiger.

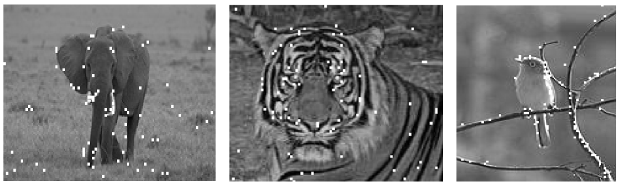
In order to verify the effectiveness of our proposed scheme, many experiments were performed. In our experiment, sixty salient regions are extracted. The retrieval performance is tested using a wide range image samples from the Corel Image Library database [19]. We selected images that contain significant natural features, such as Bighorn Sheep, African Elephant, Brown Bear, Cheetah, Sumatran Tiger and Yellow-bellied Marmot, etc., including 40 species ,1880 images in total. In our experiments, all images are pre-processed using 3-level wavelet decomposition [7], then sixty salient regions are extracted. The salient regions in an image can be segmented into six annular with radius KR/N ($1 \le K \le 6$). For feature extraction, the regions in a 6×6 neighborhood region around the salient regions are considered, Color moments and the introduced visual perception texture features [17, 18] of the regions were computed as a features vector used for indexing the image. Then, the features of the salient regions in every annular zone are averaged to form a feature vector for indexing the image. As a contrast, the retrieval experiments based on the salient regions without the annular segmentation algorithm and the global features were performed.



(a)Original images.



(b)Salient regions exacted using Haar wavelet.



(c)Salient regions exacted using db4 wavelet.

Fig. 2. Salient regions exacted by Haar and db4 wavelet.

Precision-recall graph was used to evaluate the retrieval performance. For a query image, n most similar images in the database are returned by computing the feature vectors between the query image and all the images in the database. The average precision-recall graph (Fig. 3) is given by computing different numbers of return images n.

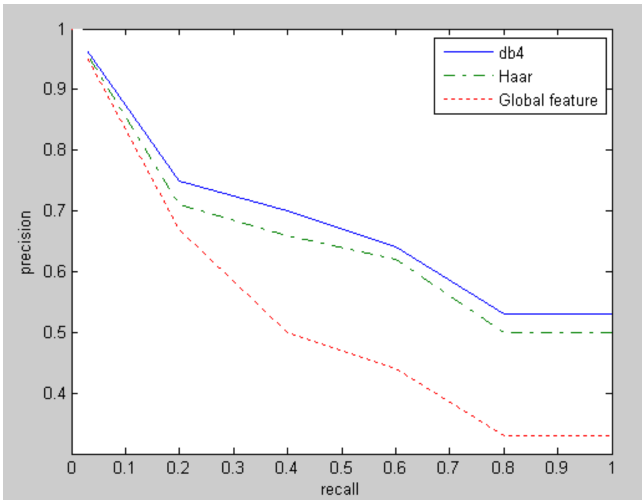


Fig. 3. Average precision-recall graph.

As Fig.3 shows, the performance based on salient region is much better than the global features, for the salient regions detector can accurately extract the visually meaningful regions of the image and can index an image effectively. Furthermore, the salient regions can represent the local features of image, whereas the global features contain features of irrelevant image areas (such as the background). In addition, the performance based on salient regions and the annular segmentation algorithm is best, for the scheme can take the local image features and the spatial distribution information of salient regions into account. Meanwhile, Db4 wavelet has a better performance than Haar wavelet, because the Db4 wavelet is an overlapping wavelet, whereas the Haar wavelet is not. However, the computation for the former is more expensive than that for the latter, for the wavelet regularity p of Db4 is larger than that of the Haar's.

VI. CONCLUSION AND DISCUSSION

In this paper, we introduce a salient region detector with the aim to extract visually meaningful regions in an image. Then, an annular segmentation algorithm based on salient regions' distribution is designed and it can take not only the local image features into account, but also concern the space distribution information of the salient regions for content-based image retrieval. Then, with the proposed scheme, we combing the salient regions and visual perception texture features during the image retrieval. Many experiments have tested the effectiveness of the proposed scheme.

At the same time, we should know that the proposed method may be further improved by combining more complex similarity metrics, such as EMD metric. Furthermore, more experiments based on different image database will be tested in the future.

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