Image Retrieval Based on Edge Detection and Histogram

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Abstract. Based on the existing algorithm, improved mathematical morphology for image retrieval, a new method, using the combination of edge magnitude histogram and edge angular histogram, was proposed in this paper. Analysis and experimental results reveal that the proposed algorithm has a superior image retrieving performance.

1. Introduction

With high speed multimedia and network technology development, the number of digital images is also an alarming rate, how to effectively manage these images is a serious problem. As one solution, content-based image retrieval [1] become a hot research.

With the distance between the feature vector size to reflect the degree of similarity between images. Currently, the often used features colored, texture and shape[2], these features can be more effective to characterize the image content, in practice there are good results, but overall performance is still to be improved.

Mathematical morphology is a new mathematical theory which can be used to process and analyze the images. It provides an alternative approach to image processing based on shape concept stemmed from set theory, not on traditional mathematical modeling and analysis. Image processing problem such as edge detection, noise restrain, feature extraction and image partition are usually adopt the Mathematical morphology method. MPEG-7 standard defines an edge histogram descriptor (Edge Histogram Descriptor, EHD) [4]. The descriptor can be more efficiently extract the edge information, but there are some drawbacks.

To make up for EHD these shortcomings, many researchers have proposed their own solution. Wan Hualin [5] proposed a fixed-size sub-image method, eliminating the second disadvantage of EHD; Park [4] According to the results of EHD, export of several global and semi-global edge descriptors, the first to solve the EHD three shortcomings; Wei Hai, etc. [3] from another point of view, presents a histogram based on the direction of the gradient phase angle CBIR algorithm, which does not have EHD few shortcomings, but there are still some for improvement.

This paper presents a comprehensive utilization of the edge angle and amplitude information of the image retrieval algorithm, experimental results show that the algorithm can effectively improve the precision of retrieval algorithms, to improve the retrieval performance of great importance.

2. Concept of Mathematical Morphological Theory

2.1. Basic Mathematical Morphology Theory

Mathematical morphology [6] is a powerful tool for dealing with various problems in image processing and computer vision. It is developed from set theory. The image which will be processed by mathematical morphology theory must been changed into set and mathematical morphology operation must be defined by set arithmetic.
The basic morphological operations [7] are erosion, dilation, opening, closing, and they are used for detection, modifying, manipulation the features present in the image based on their shapes. The shape and the size of structure elements (SE) play crucial roles in such type of processing and are therefore chosen according to the need and purpose of the associated application. Let \( X \) denote image sets. \( B \) denote a SE. It is also a set. \( B \), denote the centre of \( B \) locate at \( X \). Through Moving \( B \) in \( X \), \( B \), have three state.

The first relation denote \( SE \) and \( X \) have the most correlativity. The second relation denote \( SE \) and \( X \) have no correlativity. The third relation denote \( SE \) and \( X \) have partly correlativity. Mathematical morphological define the erosion and dilation operator as follow:

\[
F \ominus B = \{x \in X : B \subseteq X - x\} 
\]

\[
F \oplus B = \{x \in X : B \cap X \neq \emptyset\} 
\]

2.2. The Mathematical Morphology Edge Detection Algorithm

Firstly, we introduce some basic mathematical morphological operators of gray-scale images. In the two-dimensional Euclidean space \( \mathbb{Z}^2 \), Let \( F(x, y) \) denote a gray-scale two dimensional image, \( B \) denote \( SE \). Dilation of a gray-scale image \( F(x, y) \) by a gray-scale \( SE \), \( B(s, t) \) is denoted by

\[
(F \oplus B)(x, y) = \max\{F(x - s, y - t) + B(s, t)\} 
\]

Erosion of gray-scale image \( F(x, y) \) by gray-scale \( SE \), \( B(s, t) \) is denoted by

\[
(F \ominus B)(x, y) = \min\{F(x + s, y + t) - B(s, t)\} 
\]

Erosion is a transformation of shrinking, which decreases the gray-scale value of the image, while dilation is a transformation of expanding, which increases the gray-scale value of the image. But both of them are sensitive to the image edge whose gray-scale value changes obviously. Erosion filters the inner image while dilation filters the outer image.

The edge of image \( F \), which is denoted by \( E_d(F) \), is defined as the difference set of dilation domain of \( F \) and the domain of \( F \). This is also known as dilation residue edge detector:

\[
E_d(F) = (F \oplus B) - F 
\]

Accordingly, the edge of image \( F \), which is denoted by \( E_e(F) \), can also be defined as the difference set of the domain of \( F \) and the erosion domain of \( F \). This is also known as erosion residue edge detector:

\[
E_e(F) = (F \ominus B) - (F \ominus B) 
\]

The dilation and erosion often are used to compute the morphological gradient of image \( F \), denoted by \( E(F) \). The morphological gradient highlights sharp gray-level transition in the input image, and therefore, it is often used as edge detector. Experiment result is shows in Figure 1.

3. The Image Retrieval Algorithm Based on Edge Angle and Amplitude

There are a number of ways to get the local edge directional information, such edge direction histogram, directional fields [8] etc. We have implemented the fast intra mode prediction algorithm based on both the edge direction histogram and directional fields. We concluded that the scheme based on edge direction histogram gives better performance.
In order to obtain the edge information, we first apply the Sobel edge operators [7] to the intra image to generate the edge map. Each pixel in the intra image will then be associated with an element in the edge map, which is the edge vector containing its edge direction and amplitude.

Sobel operator has two convolution kernels. Each pixel in the image is convolved with both kernels. One responds to degree of difference in vertical direction and the other in horizontal.

For a pixel $p_{i,j}$, in a luminance (or chrominance) picture, we define the corresponding edge vector, $\vec{d}_{i,j} = \{dx_{i,j}, dy_{i,j}\}$, as,

$$
\begin{align*}
 dx_{i,j} &= p_{i-1,j+1} + 2p_{i,j+1} + p_{i+1,j+1} - p_{i-1,j-1} - 2p_{i,j-1} - p_{i+1,j-1} \\
 dy_{i,j} &= p_{i+1,j+1} + 2p_{i+1,j+1} + p_{i+1,j+1} - p_{i+1,j-1} - 2p_{i+1,j-1} - p_{i+1,j+1} 
\end{align*}
$$

(7)

Where $dx_{i,j}$ and $dy_{i,j}$ represent the degree of difference in vertical and horizontal directions respectively. Therefore, the amplitude of the edge vector can be decided by,

$$
\text{Amp}(\vec{d}_{i,j}) = |dx_{i,j}| + |dy_{i,j}| = \omega_m * d_m(x,y) + \omega_a * d_a(x,y)
$$

(8)

(9)

Where $\omega_m$ and $\omega_a$ is a constant. $\omega_m + \omega_a = 1$

Here, the histogram for the angle and amplitude histograms two features are the use of $d(x,y)$ as the distance between the image $x$ and $y$.

$$
d(x,y) = \sum_{i=1}^{n} |p(x, y) - p(y, y)|
$$

(10)

Where $p(x)$ represent of the $i$ components of $x$ feature vectors in the image, $n$ is the dimension. The smaller the distance $d_s(x,y)$ between two images, indicating their contents closer. Calculating the mean of this series the distance $\mu$ and standard deviation $\sigma$:

$$
d_s(x,y) = \frac{d_s(x,y) - \mu}{3\sigma} + 1
$$

(11)

Here the normalized angle histogram distance as an example, the normalized specific approach. For a one query image $x$, the calculation of the image and image database, each pair of images $y$, distance $d_s(x,y)$, calculate the number of columns from the mean and standard deviation, Then the following formula series the distance each value is normalized to $[0, 1]$.

4. Experimental Results and Analysis

As mentioned above, the angle and amplitude histogram can reflect different aspects of image features, and can complement each other in some respects, in order to improve the efficiency of retrieval, the two features combine to retrieve. The article proposed algorithm was tested verified. First, select a picture from the 1000 composition of the image library, which includes 10 categories of images (cars, flowers, life in Africa, etc.), each 100 of each type of picture. Evaluation of retrieval performance is generally based on two indicators, namely, precision ratio (Precision) and recall (recall).
Table 1  Several algorithms performance comparison

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Precision rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Based on angle histogram</td>
<td>43.3%</td>
</tr>
<tr>
<td>Based on margin histogram</td>
<td>37.8%</td>
</tr>
<tr>
<td>Based on angle and margin histogram ( (\omega_a = 0.2, \omega_p = 0.8) )</td>
<td>48.6%</td>
</tr>
</tbody>
</table>

Here is the relevant images belong to the same class of images, as in the experiment, the total number of images for each type of image (100) and each time the total number of retrieved images (20) is fixed, so the following only to compare the precision rate the performance of different algorithms (Table 1).

5. Conclusions

The article improved algorithm to distinguish the strength of the edge, combined with amplitude information retrieval, to get better results. As the test results shows, relying solely on the side edge information retrieval accuracy is limited, but also integrated color, texture and shape information, and through relevance feedback, the dynamic similarity model parameters adjusted to more effectively express the user's query requirements to improve retrieval accuracy, which is the focus of future work.

References


