Trademark Image Retrieval Based On Improved Distance Measure of Moments

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Abstract. Zernike moments and Pseudo-Zernike moments are widely used as shape descriptors in trademark image retrieval. One moment is a complex number that contains magnitude and phase. In a classical way, Euclidean distance is used for computing distance between two moments, only taking the magnitude information into consideration. When retrieving binary trademark image, this paper conducts a comparison between the classical and the improved distance measure of Zernike moments and Pseudo-Zernike moments. With the demonstration of two experiments, it proposes to apply the improved distance measure of Pseudo-Zernike moments to binary trademark image retrieval in that the improved one takes both magnitude and phase information into account and achieves more accuracy than the classical one.

Keywords: Moments, Distance measure, Retrieval, Phase.

1 Introduction

As a sign of a corporation, trademark plays an important part in industry and commerce. Not only does it identify the producer of commodity and service, but also represents the reputation of the corporation for its quality and reliability [1]. With the rapid increasing number of registered trademarks, it is urgently necessary to establish an accurate and efficient trademark image retrieval system, which is used to avoid similar trademarks registered repeatedly and spitefully.

Since first introduced by Teague [2] and Teh [3], Zernike moments and Pseudo-Zernike moments have been extensively studied and widely used in pattern recognition and image analysis as global feature descriptions due to the advantages of rotation invariance and robustness to deformations [3-8]. Recently, efforts have been devoted to improve the computation time and accuracy of the moments [9-13].

One moment is a complex number that contains magnitude and phase. But the classical way and all the modified way mentioned above to measure the distance of two moments only take into account the moment magnitude. Though losing the phase information allows the invariance to rotation, it also limits the ability of retrieving the rotation angle between two similar images and the accuracy of image retrieval.

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To compensate for this shortage, Jerome Revaud proposes a new distance measure of Zernike moments which takes both magnitude and phase into consideration [14]. With reference to Revaud's improvement idea, this paper will improve the distance measure of Pseudo-Zernike moments through the calculation of both magnitude and phase and propose a new method for binary trademark image retrieval.

2 Improved Distance Measure of Zernike Moments

2.1 Zernike Moments

In recent years, Zernike moment has been used widely in pattern recognition and image analysis as a shape descriptor. Zernike moments of a given image are calculated as correlation values of the image with a set of orthogonal Zernike basis functions mapped over a unit circle.

A basis function for Zernike moments is defined with the order of Zernike moments n and a repetition m constrained by n with the following condition: $D = \{(n, m) \mid n \geq 0, n > |m|, n - |m| \ is \ \ even\}$. In Eq. (1), (x, y) is the pixel value of the image and (r, θ) is the polar coordinate position.

$$V_{nm}(x, y) = V_{nm}(r, \theta) = R_{nm}(r)\exp(im\theta) \tag{1}$$

and

$$R_{nm}(r) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s!\times\left(\frac{n+|m|}{2}-s\right)!\times\left(\frac{n-|m|}{2}-s\right)!} r^{n-2s} \tag{2}$$

Then a Zernike moment can be expressed as:

$$Z_{nm} = \frac{n+1}{\pi}\int_0^{2\pi}\int_0^1 f(r, \theta)R_{nm}(r)\exp(-im\theta)rdrd\theta \tag{3}$$

2.2 Distance Measure of Zernike Moments[14]

Apparently, Z_{nm} is a complex number. In a classical way, Euclidean distance is used for computing distance between two Zernike moments, only taking the magnitude information into consideration without the phase information. Let I and J be two different images and Z_{nm}^I and Z_{nm}^J represent Zernike moments of image *I* and *J*, the classical distance measure can be simply expressed as:

$$d_{ZMs}{}^2 = \sum\sum\left(\left|Z_{nm}^I\right| - \left|Z_{nm}^J\right|\right)^2, \qquad (n, m) \in D \tag{4}$$

Though losing the phase information can allows the invariance to rotation, it also makes a negative impact on estimating the degree of similarity between two images. In order to ameliorate this situation, an improved distance measure of Zernike moments is proposed by Jerome Revaud. The improved method takes both magnitude and phase into account.

We express J image rotated by φ as $(J * R_\varphi)$ and define the distance between I and $(J * R_\varphi)$ as Eq. (5), where Z^I_{nm} and Z^J_{nm} represent Zernike moments of image I and J.

$$d^2(\varphi) = \sum\sum \frac{\pi}{n+1}\left[\left|Z^I_{nm}\right|^2 + \left|Z^J_{nm}\right|^2 - 2\left|Z^I_{nm}Z^J_{nm}\right| \cdot \cos(m\varphi + [Z^J_{nm}] - [Z^I_{nm}])\right], \quad x^2 + y^2 \le 1 \quad and \quad (n, m) \in D \tag{5}$$

Then, we can get the minimize distance between I and J by finding an optimal angle φ to minimize the expression mentioned above. We can simplify the process of computing $d^2(\varphi)$ by removing the constant part. The left part can be equivalently expressed as a sum of n cosines by aggregating the cosine terms that own the same frequency. After the pretreatment, the problem can be turned to finding out the minimum of a 2π - periodic function. As usual, we would use gradient descent to get the extremum. In order to extract the global minimum of Eq. (5) efficiently, we would use Nyquist-Shannon sampling theorem to restrict the search.

After all, the minimum of the expression is just the minimal distance between two images and the corresponding φ is just the optimal angle to make two images most similar. Then the improved distance measure of Zernike Moments can be simply expressed as:

$$d_{ZMs}{}^2 = \min\left(d^2(\varphi)\right), \qquad (n, m) \in D \tag{6}$$

3 Improved Distance Measure of Pseudo-Zernike Moments

3.1 Pseudo-Zernike Moments

Be similar to Zernike moments, the kernel of Pseudo-Zernike moments is a set of orthogonal Pseudo-Zernike polynomials which have properties analogous to those of Zernike polynomials. These polynomials have the form of Eq. (1) and are defined over the polar coordinate space inside a unit circle, too. Yet, the distinction is that Zernike radial polynomials are replaced by Pseudo-Zernike radial polynomials as follows:

$$R'_{nm}(r) = \sum_{s=0}^{n-|m|}(-1)^s \frac{(2n+1-s)!}{s!\times(n-|m|-s)!\times(n+|m|+1-s)!} r^{n-s}, \quad n > |m| \ge 0 \tag{7}$$

The Zernike moment Z_{nm} in Eq. (3) becomes Pseudo-Zernike moment P_{nm} if the radial polynomial in Eq. (7) is used to compute the polynomial with the condition, n-|m|= even, eliminated. So P_{nm} can be expressed as:

$$P_{nm} = \frac{n+1}{\pi} \int_0^{2\pi} \int_0^1 f(r,\theta) R'_{nm}(r) \exp(-im\theta) r dr d\theta \tag{8}$$

3.2 Distance Measure of Pseudo-Zernike Moments

In the classical way to measure the similarity of two Pseudo-Zernike moments, just like Eq. (9), Euclidean distance also only takes the moment magnitude information into account. P^I_{nm} and P^J_{nm} represent Pseudo-Zernike moments of two different images I and J.

$$d_{PZMs}{}^2 = \sum\sum \left(\left|P^I_{nm}\right| - \left|P^J_{nm}\right| \right)^2, \qquad (n,m) \in D \tag{9}$$

Since the Pseudo-Zernike polynomials are also a complete set of functions orthogonal on the unit disk, Revaud's improvement idea of calculating both magnitude and phase is also applicable to improve the distance measure of Pseudo-Zernike moments. We can describe the minimum distance between image I and J using the following expression:

$$d_{PZMs}{}^2 = \min\left(d^2(\varphi) \right), \qquad (n,m) \in D \tag{10}$$

where $d^2(\varphi)$ is computed as:

$$d^2(\varphi) = \sum\sum \frac{\pi}{n+1} \left[\left|P^I_{nm}\right|^2 + \left|P^J_{nm}\right|^2 - 2\left|P^I_{nm} P^J_{nm}\right| \cdot \cos(m\varphi + [P^J_{nm}] - [P^I_{nm}]) \right], \quad x^2 + y^2 \le 1 \quad and \quad (n,m) \in D \tag{11}$$

4 Experiments

In this section, we will use a trademark database including 1500 binary trademark images of BMP format with 111 × 111 resolution, of which 100 images are generated via 10 kinds of deformation of 10 images in the database. The 100 deformed images and their original images are shown in Fig. 1[15].

We will do two experiments to compare the trademark retrieval performance between the classical and the improved distance measure of Zernike moments and Pseudo-Zernike moments.

- One of the experiments is to proof-test the ability of finding original images through using the 100 deformed images as query images.
- The other experiment is to use 10 original images to retrieve their deformed images in the database.

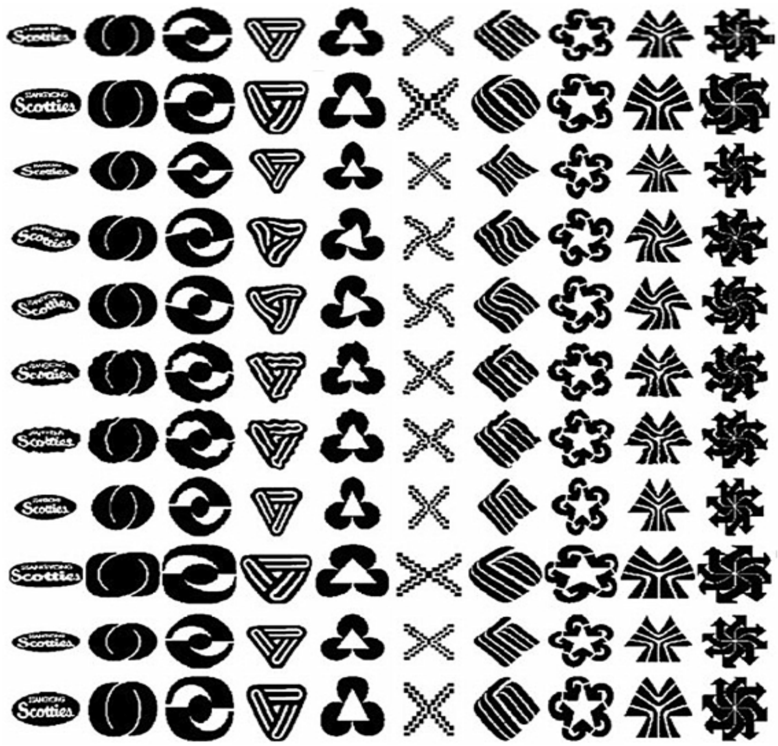

Fig. 1. 10 trademark images (in Line 1) and the corresponding 10 deformed images for each

4.1 Experiment I

With the increase of matrix order and feature dimension, the descriptive power of the image will enhance, which, yet, also results in information redundancy and dimension curse. Therefore, in this experiment, 100 deformed images are set as query images. Then, in different dimensions, improved and classical distance measure are carried on respectively to examine the ability of each measure to retrieve original images of these 100 deformed images during the other 1400 images in the database. The retrieval performance is measured using Accumulative frequency (AF) [15] as follows and higher value of AF means better retrieval performance.

$$AF(n) = \frac{original\ images\ \ within\ n\ positions}{N} \times 100\% \tag{12}$$

where N=100 is the number of query images.

The retrieval results of the two measures of Zernike moments (ZMs) and Pseudo-Zernike moments (PZMs) are listed in Table 1. The results indicate that, using Zernike moments as a shape descriptor, the retrieval in 36 dimensions of the feature matrix is better enhanced than that in 30 dimensions, whereas 42 dimensions involves much more calculation yet without significant enhancement. Using Pseudo-Zernike moments, the amount of computation in 36 dimensions is less than that in 45 dimensions and 55 dimensions, but the retrieval precision is similar to that in 45 dimensions and 55 dimensions. Thus, both for Zernike moments and for Pseudo-Zernike moments, the retrieval in 36 dimensions achieves the best overall performance. What's more, in these three feature dimensions in this experiment, the retrievals of the improved distance measure are better than those of the classical one, especially, the capability to retrieve the original image as the most similar one. The last, of the four methods, we can clearly figure out the improved distance measure of Pseudo-Zernike moments performs best.

Table 1. The retrieval results of the classical and the improved distance measure of Zernike moments and Pseudo-Zernike moments with different n

AF(n) / method		n=1	n=2	n=3	n=5	n=8	n=10
Classical Distance Measure of ZMs in Eq. (4)	30 dimensions	63%	69%	73%	79%	83%	87%
	36 dimensions	66%	75%	79%	82%	87%	89%
	42 dimensions	67%	76%	80%	85%	89%	90%
Improved Distance Measure of ZMs in Eq. (6)	30 dimensions	68%	77%	81%	85%	88%	90%
	36 dimensions	72%	77%	83%	86%	90%	90%
	42 dimensions	76%	84%	87%	91%	92%	92%
Classical Distance Measure of PZMs in Eq. (9)	36 dimensions	72%	80%	82%	86%	91%	92%
	45 dimensions	74%	82%	83%	87%	92%	93%
	55 dimensions	73%	83%	86%	90%	92%	93%
Improved Distance Measure of PZMs in Eq. (10)	36 dimensions	77%	85%	89%	92%	93%	93%
	45 dimensions	80%	84%	87%	92%	94%	94%
	55 dimensions	82%	86%	88%	92%	93%	94%

4.2 Experiment II

In this experiment, we use the 10 original images shown in the first line of Fig. 1 as query images. For each query image, the 10 deformed images listed below it in Fig. 1

are regarded as its highly similar images. Furthermore, for each query image, our aim is to retrieve as many deformed images as possible from the other 1499 images.

Just as is illustrated in Experiment I, the overall performance of both Zernike moments and Pseudo-Zernike moments in 36 dimensions is the best; therefore, in Experiment II, the comparison is conducted in 36 dimensions. First, we compute Zernike moments and Pseudo-Zernike moments of each image. Then, classical and improved way to measure similarity of these moments are respectively carried on between every query image and the other 1499 images in the database. At last, the mean Recall Ratio of each method is calculated for the final comparison of retrieval capabilities. From the retrieval results, the most similar K images to the query image are selected. In this experiment, we assign 16 to K. Parts of the results are illustrated in Fig. 2.

Fig. 2 shows that being used in binary trademark image retrieval, just like classical way to measure the similarity of moments, the improved one also has rotation invariance and can well retrieve images after rotation. However, for other geometrical deformation, the retrieval capability of the improved distance measure is much better than the classical one. Moreover, the arrangement sequence of the retrieved similar images basically satisfies human vision.

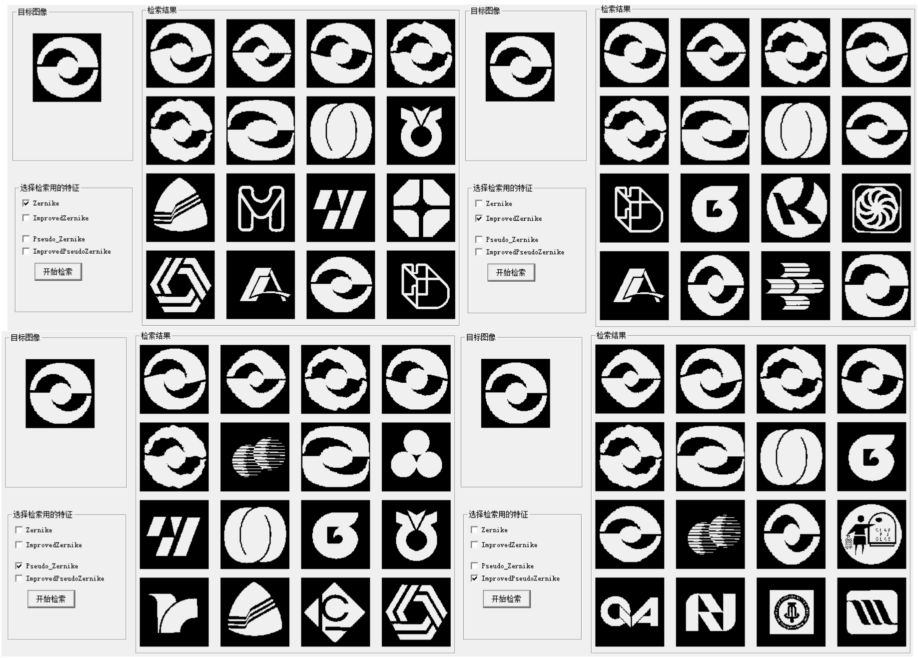

Fig. 2. The figure shows the retrieval results of the classical way and the improved way to measure similarity of Zernike moments and Pseudo-Zernike moments. The 16 best retrievals for the query image are displayed, which are ordered by distance measure.

Table 2. MR of each method

method	Classical Distance measure of ZMs	Improved Distance measure of ZMs	Classical Distance measure of PZMs	Improved Similarity Measure of PZMs
MR	77%	79%	79%	82%

In the application of trademark image retrieval, we usually use the Recall Ratio of the retrieval to present the capability of every retrieval method. Higher value of R means better performance. Since single image retrieval result is insufficient to prove the performance of the retrieval method, hence, we will respectively calculate the Recall Ratio for each query image and then average the results. The performance measure used in the experiment is expressed as:

$$MR = \frac{sum\ of\ similar\ images\ retrieved}{M \times K} \times 100\% \tag{13}$$

where M=10 is the number of query images and K=10 is the number of similar images for each query image. The calculation results are listed in Table 2.

This experiment also proves that the performance of the improved distance measure of moments is better than the classical one. And of all, the improved measure of Pseudo-Zernike moments has the highest retrieval precision.

5 Conclusion

In this paper, based on the comparison of the classical and the improved distance measure of Zernike moments and Pseudo-Zernike moments, a new method for binary trademark retrieval is proposed, that is, the improved measure of Pseudo-Zernike moments. Just as is illustrated in the two experiments, the new method can achieve more accuracy than the other three methods. Yet, the new trademark retrieval can be further polished up. For instance, in the future, it can be combined with Multi-Feature extraction to achieve a better result.

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