Spectral Correlation & Combined Moments Framework for Application of CBIR at Biomedical Database

Shahin Shafei[1], Hamid Vahdati[1], Tohid Sedghi[2*], Asghar Charmin[1]
[1]Department of Electrical Engineering, Ahar Branch, Islamic Azad University, Ahar, Iran
[2]Department of Electrical Engineering, Urmia Branch, Islamic Azad University, Urmia, Iran
[*]Sedghi.tohid@gmail.com, t.sedghi@iaurmia.ac.ir

Abstract

A new feature extraction technique for Content based retina biomedical image retrieval is proposed. This method is based on spectral correlation that provides description in the frequency domain. The image is partitioned into non-overlapping tiles. The features drawn from transferred image with proposed new features Spectral correlation using moments between the image tiles, serve as local descriptors. Shape information is captured in terms of edge images computed using combined moments. The combination of the texture features between image and the shape features provide a robust feature set for biomedical retina image retrieval. The experimental results show the efficacy of the method. For matching the biomedical retina images an integrated matching, based on similar highest is provided. The experimental results are compared and found to be encouraging.

Keywords: Spectral correlation, Spectral Analysis, Feature generation, Moments.

1. Introduction

Precise image segmentation has still been an open area of research for example the integrated region matching algorithm [1-2] proposes an image similarity combining all the regions. In [3], every region is assigned significance worth its size in the image, in [4] method is similar to integrated, but so simple and less time consumer, this property makes to time consumption and in Any retrieval system, fast retrieval is main goal. Texture is a key component of human visual perception. Everyone can recognize texture, but it is more difficult to define. It has qualities such as periodicity and scale; it can be described in terms of direction, coarseness, contrast. It makes texture a particularly interesting facet of images and results in a plethora of ways of extracting texture features. To enable us to explore different approaches for computing texture feature: in this manuscript we propose a novel textural feature extraction based on cyclostationary analysis. One of the best benefits of using cyclostationary analysis is the simplicity. The spectral correlation, which is the cross spectral of a signal and a frequency shifted version of itself, provides a second-order statistical description in the frequency domain of such signals. The basic time-smoothing and frequency-smoothing methods of spectral correlation analysis were introduced in [2]. Shape feature has been extensively used for retrieval systems [3].

In [4], features are used to capture the shape information. Shape signatures are computed from biomedical images and invariant moments are computed as shape descriptors.

The retrieval performance is shown to be better than previous systems such as [3-4]. In

retrieval system, local features play a significant role in determining the similarity of biomedical retina images along with the shape information of the objects so this reason encourage researchers to apply local features.in this study, we introduce our efficient and simple modified system operation. At First step, biomedical retina image is partitioned into different sized non-overlapping tiles. The proposed features computed on these tiles serve as texture local descriptors. An integrated matching method based on Minkowski graph is provided, similar to the one discussed in [2], yielding image similarity. Then invariant moments of the same retina biomedical image is calculated, then invariant moments are generated. Distance with Minkowski from shape comparison between query image and dataset image is calculated, computed by integrating matching method. The final distance is kept in system for retrieval. Beside that this process is done between biomedical retina images database and query image then Minkowski distance used to retrieval from retina biomedical database.

2. Proposed Method

Biomedical retina database to explore the performance of our system downloaded from ist.psu.edu/docs/related. The retina image set comprises 400 images in four classes. The some randomly selected biomedical retina images are shown in Fig. 1. An image is partitioned into nine tiles as shown in Fig.2. Features drawn from transformed image tiles are used for texture similarity.

Retina biomedical database used for experimentation with 9 partitions. We have supposed that, the most important part of image is center of it, beside that the center contains the most valuable information respect to side tiles. So we apply partitioning process in a way that image center to be in a large tile and side of image in small tiles (see Fig.2). Then spectral & shape features are extracted.

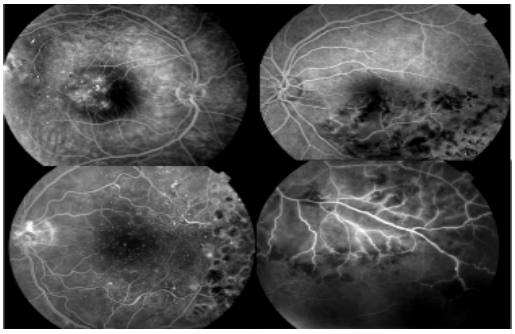

Fig.1 Sample images from Retina biomedical database

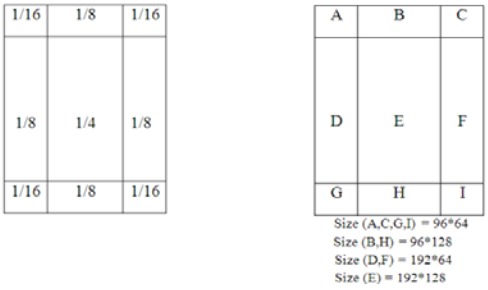

Fig. 2: Image partitioning for extracting textural features

3. Feature Extractions with Spectral Correlation & Shape

The Spectral Correlation for *x[n]* is defined as the Fourier transform of the cyclic correlation $R_x^{\alpha}(k)$,

$$R_x^{\alpha}(k) = \lim_{N\to\infty} \frac{1}{2N+1}.$$

$$\sum_{n=-N}^{N} [x(n+k)e^{-j\pi\alpha(n+k)}].[x(n)e^{j\pi\alpha n}]^{*} \qquad (1)$$

the cross spectrum of the pair of complex valued frequency-shifted signals $x(n)\ e^{-j\pi\alpha n}$ and $x(n)\ e^{j\pi\alpha n}$ where f is the cross spectrum frequency variable and the parameter α , called the cyclic frequency, is the relative frequency shift. If the signal has finite average power then there are at most a countable number of values of α .

$$S_x(f) = S_x^0 = \sum_k R_x^0(k) e^{-j2\pi fk} \qquad (2)$$

First we partition an image into nine regions. Two, one dimensional signals are obtained from each of partition of partitioned biomedical retina image by ordering of pixels row by column. For constructing the feature vector, the Norm-1 and Energy are computed separately on each region of cross spectrum of from each signal and then vector is formed using these two parameter values. The basic assumption of using energy as a feature for texture discrimination is that the energy distribution in the frequency-domain identifies a textural information of an retina biomedical image. Resulting feature vectors are:

$$\overline{f_j} = [E_{11_j},...,E_{1N_j}; E_{21_j},...,E_{2N_j}; \qquad (3)$$

$$\sigma_{11_j},...,\sigma_{1N_j}; \sigma_{21_j},...,\sigma_{2N_j}] \qquad (4)$$

Respectively, Ein_j , and σ_{in_j} , *are* the Norm-1 and energy at the cross spectrum of amplitude that are calculated for the signal at the nth region:

$$E_{norm1} = \frac{1}{Q} \sum_{\alpha \& f \in D} \left| S_x^{\alpha}(f) \right| \qquad (5)$$

Where Q and $\overline{S}_x^{\alpha}(f)$ are the number of estimate points and the mean of spectral correlation at corresponding regions. Finally, for producing the main feature vector, we combine nine feature vector of each partition as follows to get the main feature vector:

$$F = (1/16)f_1 + (1/18)f_2 + (1/16)f_3 + (1/8)f_4 + (1/4)f_5 + (1/8)f_6 + (1/16)f_7 + (1/8)f_8 + (1/16)f \qquad (6)$$

The size of the feature vector will be equal to 32. Combined moment are nonlinear set, which are invariant to scale & translation. Since the higher order moment invariants have resulted higher sensitivity, a set of four invariants moment limited by order less than or equal to four seems to be proper in retrieval systems. Central invariant moments can be:

$$\begin{aligned} \varphi_1 &= \eta_{20} + \eta_{02} \\ \varphi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\ \varphi_3 &= (\eta_{30} - 3\eta_{12}) + (3\eta_{21} - \eta_{03})^2 \\ \varphi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \end{aligned} \qquad (7)$$

Feature vector will be add to previous textural features.

4. Experimental result on Retina Biomedical Database

The comparison of proposed method with other systems reported in [1-3] is presented in Table 1. Since in previous methods, textured and non textured regions are treated differently with different feature sets, their results are claimed to be better than histogram based method. Further, proposed system is better than [1] & [2]. In comparison between our method and [3] in all of classes of the categories our method has performed better than other systems. It is

obvious that presented method has obtained a good average precision of various biomedical Retina images than the other methods. Besides, the precision results of the various biomedical retina images with the number of returned images, is shown in Fig. 2. The experimental results clearly reveal that for the returned images biomedical image database, the present method is significantly superior to the methods of [1-3]. The present method is more superior to the methods of [1-3]. The computational complexity of our method was measured using Retina database. Table 2 presents the computing time of the feature extraction and retrieval time. The computing time of method is compared to [1] & [2] The computation was made using MatLab Software 2020 on a PC with Corei7 CPU and 8 GB memory. Table 2 shows that there is a significant difference between the computational cost of the introduced system and other algorithms. The reason is that other systems are iterative algorithms, which makes it heavy, especially in the case of large-scale biomedical databases.

Table 1: Comparison of precision with proposed method and other systems

Class	[1]	[2]	[3]	Present Method
Class#1	75%	82%	85%	88%
Class#2	70%	86%	80%	89%
Class#3	75%	88%	85%	89%
Class#4	75%	82%	85%	91%

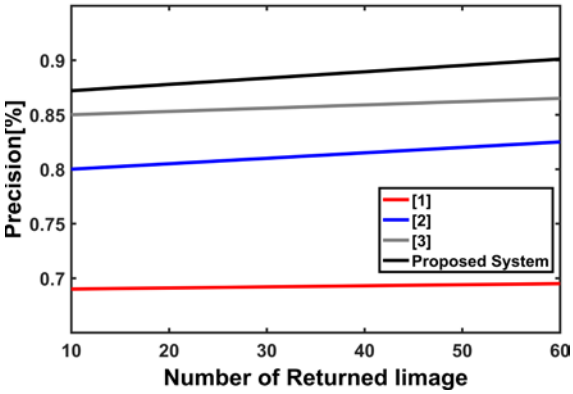

Fig.3. precision of different methods on Retina Biomedical image database

Table 2: Computing time process

	Feature Extraction time for 1 image [millisecond]	Retrieval of 50 image [Second]
[1]	2	3
[2]	3	4
Present method	1	2

Conclusion

For Retina Biomedical image retrieval using texture & shape features in transformed domain a new algorithm is proposed. The Retina Biomedical images are partitioned into different tiles. Features drawn transformed image using Spectral correlation from each of tiles computed Norm-1 and energy. A matching method based on most significant highest priority, is implemented for image similarity. Combined moments are used to describe the shape features. A combination of these features provides an outstanding feature set for retina biomedical image retrieval. The experiments using the biomedical database shows the efficacy in comparison with the previous papers.

References

[1] S.Shafei, H.Vahdati, T. Sedghi, and A. Charmin, “Novel high level retrieval system based on mathematic algorithm & technique for RETINAI medical imaging and classification, ”Journal of Instrumentation.,vol. 16, no. 7, pp. 1-14, July. 2021.

[2] T. Sedghi, “A Fast and Effective Model for Cyclic Analysis and Its Application in Classification, ” Arab Journal Sci.Eng, vol.3, pp.927–935, Sep. 2013.

[3] F .Baig, Z .Mehmood, M .Rashid, M. Arshad. Javid, A .Rehman, T. Saba, and A. Adnan, “Boosting the Performance of the BoVW Model Using SURF–CoHOG-Based Sparse Features with Relevance Feedback for CBIR, ” Iranian Journal of Science and Technology Transactions of Electrical Engineering, vol. 44, p.p 99–118, Aug 2020.

[4] M.h.Hajigholam, A.A.Raie, and K. Faez, “Using Sparse Representation Classifier (SRC) to Calculate Dynamic Coefficients for Multitask Joint Spatial Pyramid, ” Matchingranian Journal of Science and Technology Transactions of Electrical Engineering, vol. 45, pp. 295–307, 2021.

[5] F.Rahdari, E.Rashedi, M.Eftekhari, “ A Multimodal Emotion Recognition System Using Facial Landmark Analysis , ” Iranian Journal of Science and Technology Transactions of Electrical Engineering, ” vol. 43, pp. 171–189, Sep. 2019