Linear Transformation Pre-Filtering with VGG Frame-work Based on ANN for CBMIR

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Abstract

*A comprehensive feature selection and weighting combination method with novel learning of ANN were introduced, for biomedical RETINA images retrieval. Modified Radon, and modified Hu Moments operators with weighting combinational methods were proposed for achieving higher percentage of retrieval. Besides that, these characteristics are re-composed for presenting outstanding statistic specification and spatial signals. This spatial and frequency information is obtained for all RETINA image dataset. Composition of shape & Textural features present robust vectors for retrieval of biomedical database. In addition, a ANN framework is proposed and applied to measure the similarity between the query and biomedical database. This novel scheme illustrates higher and better specialty in the RETINAI dataset. The results were compared and understood to be remarkab*le.

Keywords: Artificial Neural Networks, feature generation, retrieval, recall.

1. Introduction

The main problem in content based medical image retrieval (CBMIR) systems for RETINA images is the gap among the low-level data produced by the RETINAI systems and the high-level data understood by the operator [1-3]. The old feature extraction techniques works on low-level features to decrease the distance of the gap. Deep learning technique are strong for feature generation that can show data entirely and set the level of feature production at self-learning.

The oldest method of medical CBMIR utilize labels, or keywords, to biomedical images in way that retrieval process can be done based on feature descriptors .Manual labeling systems are toilsomeandtime-consumer[4-5]. Shape based medical image retrieval (SBMIR) systems illustrate the retrieving procedure of medical images from the datasets on the base of syntactical image features. The features are utilized, consist shape, texture, and multiresolution transformations like Gabor, wavelets or multiscale filtering [6].Section-to-section similar ity between the images of dataset are evaluated in [6-7] which the semethods are outdated. In [8],the matching of integrated section illustrates similarity of all regions. Each parts of region is given superiority worth on its window's size. In [9], to achieve the biomedical image descriptors are utilized fuzzy features .Shape features are generated from biomedical images and then some moments are utilized for shape attributes. Their retrieval performance are premier compared to other integrated region systems like [9-10]. To screen incoherent biomedical images of dataset, the preprocessing and classification are used in the first level of system. Previous research esdepict that combined generated features affect the characteristics of the similarity between biomedical images. Beside that these methods, uses the partitioning, which is not useful in shape specification. Search in spatial and local data of combined features is used in target-based retrieval, which more superior than partitioning methods[11-12].The present research is proposed to present a novel method to use improved Radon transformed (R-transform) with weighting composition in a deep leaning frame of ANN. Improved Hu operators is computed as shape descriptor, Also, a deep learning framework is utilized for retrieval. The deep learning with composition of features forms remarkable feature-vectors in retrieval process. Deep learning and weighted matrix method are used to improve the retrieval performance. The study are done with a total of 3064 RETINA image dataset that contain, three types of brain tumors (introduced in three different classes). The presented system has minimum preprocessing, and, less time consuming which can obtain a mean average 85% retrieval, and performs better on the CBMIR on the RETINA image database. Allprevious methods are complex because of using different kind algorithms which they are maximum processing. The results are compared with different algorithms.

2. Weighting of R-transform & Hu based features

Generation of Textural feature dataset on R-transform

A biomedical image of database can be shown by a various types of projections chosen at various kind of angles. Biomedical image analysis shows a binary planar shape for shape analysis. So, for improving the R-transform, It is better to consider in which the R-trans form functions substituted by a special form of function with $s_D(x,y)$:

$$s_D(x,y)=\begin{cases}1, & if\,(x,y)\in D\\ 0 & otherwise\end{cases} \quad (1)$$

The R-transform explains the intersection number of all the line of intensity with the above function .R-transform achieve a rectangular cellsarray.R-transform is variant to transformations so it can't present the shape features. In addition, One-dimensional information are produced from every sections ordered by row to row and column to column. The energy (E) and standard deviation (Ϭ) are calculated on one dimensional signals ofR-transform. These parameter values is fusionedto form initial feature vector. The utilization of energy as textural feature is that the parameter, indicates textural data of biomedical image. The feature vectors extracting from regions are expressed as:

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

$$=[f_{1_j},f_{2_j},...,f_{4N_j}]^T;\ j=1,2,\ldots 9;$$

where Ein_j, I *for* 1,2, n*for* 1,2,...,N and σ_{in_j}, i:1, 2, n :1,2,...,N, $j=1,2,..9$

N : the number of sections.

j : the number of partitions.

Ein_j :theR-transform amplitude Norm-1 parameter of energy.

σ_{in_j} :Deviationof standard calculatedat the nth sectionfor the jth signals:

$$E_{norm1} = \frac{1}{Q} \sum_{\alpha \& f \in D} \left| S_x^{\alpha}(f) \right| \quad (3)$$

$$\sigma = (\frac{1}{Q} \sum (S_x^{\alpha}(f) - \overline{S}_x^{\alpha}(f))^2)^{1/2} \quad (4)$$

In addition, R-transform can reduce the noise ratio, better than old filters such as Wavelet Transform& Spectral Coloration Function. The main signal connects to R-transform analyze, that is, mother R-transform signal makes basic zoom of signal. The generated features of the R-transform are utilized to study the textural descriptors. Improved function of R-transform is utilized to upper frequency data of biomedical image in very little resolution and lower the frequency data of the biomedical image in a large resolution. The refore, for extracting textural descriptors, coefficients are assigned to every signal section.

Weighting of texture, and shape descriptors makes, dataset of feature:

1-Discrete improved function R-transform.

2-Enhanced fast calculated Hu moments

Traditional Hu moments calculation are slower regard to R-transform. Also, R-transformgeneratedifferentsub-bands for different orientations. In addition, the R-transform allow terms decreasing which benefits shift invariance property. The R-transform is depicted in symmetric shape between different multi-resolution transform. The biomedical image of database are separated into different sub-bands utilizing-transformer.

The σ_l(standard deviation)and E_l(energy) are calculated for every sub-band of R-transform. At different biomedical image sub-band, the standard deviation and energy are achieved as:

$$\sigma_l = \sqrt{\frac{1}{MN} \sum_{k=1}^{M} \sum_{j=1}^{N} \left| M_l(k.j) - \mu_l \right|^2} \quad , \quad E_l = \frac{1}{MN} \sum_{k=1}^{M} \sum_{j=1}^{N} \left| M_l(k.j) \right|^2 \quad (5)$$

Thesub-band of R-transformis M_l(i,j), every sub-band window dimensionis M×N. frequency sub-bandthe mean value is μ_j. The dataset of main weighted feature is produced by the sub-bands of R-transformed data. A dataset ofbiomedical image featuresareobtained by σ &E of different sub-bands:

$$\overline{f}_{\sigma E}^{k} = [\sigma_1^k, \sigma_2^k, ..., \sigma_L^k, E_1^k, E_2^k, ..., E_L^k] \quad (6)$$

The generated feature size is 2Lin first level.

Shape Features Extraction

Hu is a set of non-linear moments withinvariant to orientation and translation property. A set of six moment invariants represent to be adequatefor all of applications.The upper order moment have deduced to upper sensitivity. All the moment are moralized to introduce central moments.Geometrical moment is computed as:

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x^p y^q f(x, y) \quad (7)$$

Image function is f(x, y).

Geometrical central moments can be calculated as:

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \overline{x})^p (y - \overline{y})^q f(x, y) \quad (8)$$

$\overline{x}$ and $\overline{y}$ are image gravity center and are computedas:

$$\overline{x} = \frac{m_{10}}{m_{00}}, \qquad \overline{y} = \frac{m_{01}}{m_{00}} \quad (9)$$

The Number of foreground pixels is $m_{00} = \mu_{00}$. This parameter has no major relation to scale, so central Hu moments can be normalized in scale with equation (10):

$$\eta_{pq} = \frac{\mu_{pq}}{m_{00}^{a}} \quad , \quad a = \frac{p+q}{2} + 1 \tag{10}$$

$$\begin{aligned}
\varphi_1 &= \eta_{20} + \eta_{02} \\
\varphi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\varphi_3 &= (\eta_{30} - 3\eta_{12}) + (3\eta_{21} - \eta_{03})^2 \\
\varphi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&+ (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{21})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned} \tag{11}$$

After computing Hu, Theywill be inserted to previous vectors.For extracting optimum features, LDA and PCA algorithms is applied to combined feature vector.

$$Combined \quad Feature \quad Vectore = [I_{fv}; HueFeatureVectore] \tag{12}$$

3. ANN Training Procedure

When one type of feature is generated from the biomedical image, large amount of information is lost. So, combination of extracted features are presented to enhance the accuracy of retrieval. Besides that, weighting of feature recombination produces a robust features. Using the weighting feature procedure combination produce good retrieval accuracy in compared with [1], and [6].This paper proposes CBMIR for retrieval similar biomedical images. For achieving better features and performance of ultimate system, beside the high level feature ,the VGG19 are used. ANN is used to meter the similarity among the generated features of the biomedical images database and the query. extracted features from VGG19 and are inserted into ANN. Features generated from the VGG19 upper levels, provide good consequence, since, upper levels in the VGG19are conveyed to the special features of the biomedical image learned layers. This learning method presented in [7],in which MLP-ANN were utilized as feature generators. The MLP-ANN learning method outset from the first input level to the ultimate layer in a back for ward mood. After that, error back propagation outset from the final level towards the first level. All weights in MLP-ANN in the levels are computed in the form of linear learning. The last level utilize rectangular window feature table and catch the average value of the square window. For data compression, the algorithm reduces the feature tableside. The ultimate layer calculates the retrieval expectancy of every classtype for detecting the type of image. Unknown weights of ANN are learned, with the back-propagation method. For minimizing the cost-function, gradient descent algorithm is applied over the MLP.

4. Evaluation Results In Experimental Framework

The presented system valuation and efficiency and the previous scholars are studied in this part. RETINA image database at(www.figshare.com/articles/brain_tumor_dataset/1512427) is used. Some randomly selected RETINA image is depicted in Figure 1.Time in training process and setting the training parameters, the network retrieval efficiency is improved. Back propagation scheme is used to train ANN. the final level of ANN is tuned and keeping all other levels constant with freezing the weights. First level in the ANN consist the textural feature, and upper levels consist the domain spatial features of the biomedical images. The training of the earlier levels can be fast because of the textural features in this level. The upper levels are trained by fine-tuning to learn the RETINA image spatial features. Presented ANN framework learned these features in a self-learning method. The VGG19 is appropriate for feature presentation and detection of special content in biomedical image database.

The target of paper is on retrieval on RETINA images. Findings of paper certify that,VGG19 with weighted features of textural and shape with ANN learning are the best technique in the biomedical datasets retrieval frame work. Retrieval efficiency is achieved utilizing ANN with 90% retrieval compared to 70%using Euclidean metric distance. In addition, good results are obtained by performing the ANN ,to project the feature representations into two dimensional space. So, ANN is affective in memory usage because of dimensionality reduction. An advantage of feature vectors with low-dimension is useful for indexing methods, which enhance the retrieval performance for a large-scale database. The efficiency of the CBMIR relates tosimilarity measurement among the biomedical database and the query. For measuring features similarity, Euclidean and Cosine distances are utilized but they are limited because of the semantic gap [11-12].

The squared Mahalanobis(SM) technique is utilized to specify the optimum measurement parameter, which extends class similarity.SM is used in ANN and the obtained results show that significant results. RETINA image database accidentally divided the into 5sets same as [1-4] with no overlap of the various kinds of brain tumors and RETINA images from the identical patients were notin both testing and training sets at the same time. First set is utilized as the test database, and the others are utilized as the training one. Each RETINA image in the test database (first database) is attend the query

.The mean value of accuracy is the routine parameter for accuracy computation percentage:

This percentage illustrates that the images belong to the defined class. The system efficiency when rating the presented system is illustrated at Table 3.Table 3 depicts, the old methods are less accurate.

The presented system achieve 90% retrieval for all the classes, and other systems[1] & [6] are less. Proposed system has better performance In comparison with [1]& [6]. This system is weighting approach in which High-level feature beside the VGG feature for large data sets are tuned with engineering view. In addition ANN has major role for achieving higher percentage of retrieval rate. Figures 4 depicts the average precision of the retrieval for the different number of RETINA images.

The findings certify that the system is efficient than other systems in large biomedical RETINA image. Tables 2&3 depicts the system performance when using ANN with weighted features are best choice for medical system. It can be a smart assistant for RETINA image medical operators.

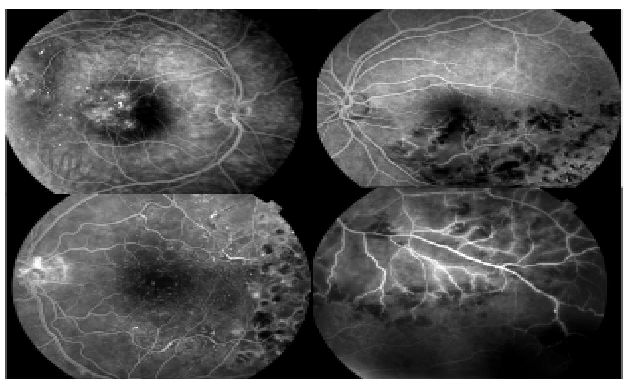

Fig.1. Tumordiffering appearance in class 1& 2

Conclusion

Novel system for the retrieval of RETINA image database is presented based on ANN & combined features with VGG. For each RETINA image, average and standard deviation of the improved R-transform and the modified Hu moments are computed. A weighting features with VGG, generate a robust feature for retrieval of biomedical RETINA image. For image similarity process, an alternative method for training ANN is introduced. It shows the transferability of learning to RETINA images database. The results illustrates that new method has good precious in retrieval and efficiency in appraisement with other proposed CBMIR systems. The presented CBMIR needs RETINA images as a query image to take back the appropriate tumor RETINA images from the biomedical database. The founding of research announce that the presented CBMIR plays an outstanding role on RETINA image database retrieval.

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Table 1. corrected retrieval Number for RETINA images returned from biomedical image dataset in five different tests in three classes.

Class1				Class2				Class3			
ANN+Combined Feature	ANN+RADON		ANN+Shape	ANN+Combined Feature	ANN+RADON		ANN+Shape	ANN+Combined Feature	ANN+RADON		ANN+Shape
10	9		5	10	7		6	10	9		6
10	9		6	10	8		5	9	8		7
10	10		7	10	10		6	9	8		6
10	9		6	10	9		7	10	9		5
10	9		7	9	8		6	10	8		6

Table 2. Average recallpercentage Comparison, thepresentedCBMIR systems for20 images of RETINA imagedataset

	KNN-NN+Shape	ANN+RADON	ANN+Combined Feature
Class1	60%	76%	90%
Class2	65%	71%	95%
Class3	66%	77%	94%

Table 3.correct image Number retrieval for different presented scholars (20 random queries)

	Ref. [1]	Ref. [6]	ANN+Combined Feature
Class1	16	14	**20**
Class2	15	13	**20**
Class3	18	13	**19**

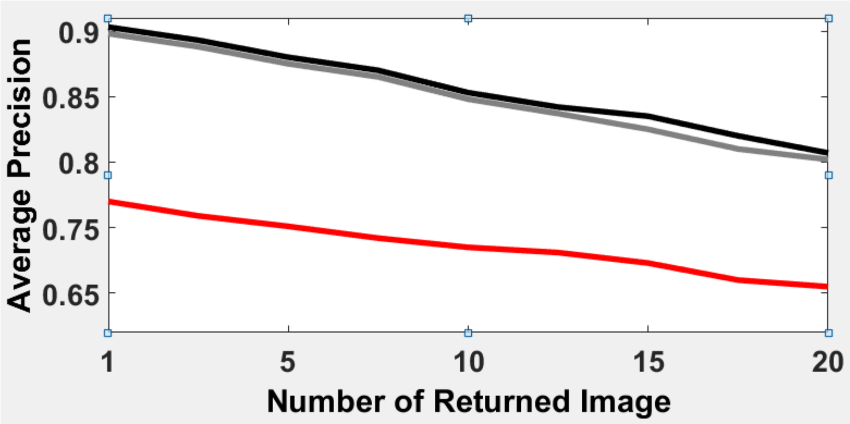

Figure 2.*Average precision of different methods for RETINAI database (black line: proposed method, gray line: ref [1]*

Red line: ref [6])

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