CONTENT BASED IMAGE RETRIEVAL SYSTEM FOR MEDICAL IMAGES (INFARCT) USING PCA

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Abstract

The main goal of content based image retrieval is to efficiently retrieve images that are visually similar to a query image. This paper proposes a methodology for CBIR of Infarct (Brain). The maximum accuracy in classification of Infarct was 85% achieved by PCA. Our experimental result shows that the proposed technique outperforms the other existing Histogram Bin Technique and Combination of PCA & Histogram Bin with better accuracy.

Keywords: PCA, Histogram Bin, Eigenvector, Eigenvalue, Covariance matrix.

I. INTRODUCTION

Growth of Medical image databases is enormous in the past few years. Imaging studies, such as magnetic resonance (MR) and computed tomography (CT) result in a large volume of data. A large number of existing image databases are indexed by text annotations that routinely contain only patient demographic details such as age, gender, date of study, modality. Manual methods to retrieve required image from the database with more comprehensive text annotation is tedious and time consuming (1). In contrast, Content Based Image Retrieval (CBIR) systems allow users to query based on the image content (i.e. image-derived features) rather than the related text annotation. The main idea is to represent each image as a feature vector (important features of the image) and to measure the similarity between images based on their corresponding feature vectors according to some metric. Finding the correct features of the image and the similarity calculation are important steps in the construction of any CBIR system. The Fig. 1. represents the overview of the CBIR system.

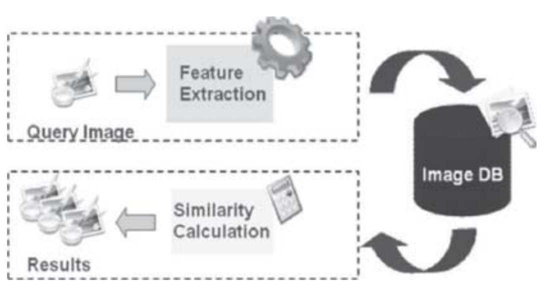


Fig. 1. Overview of CBIR System

A CBIR system for brain lesions has been proposed earlier based on the analysis of histogram features derived from brains (2) (3). We propose a CBIR system for Infarct that can classify a CT image as normal, abnormal or infarct. We are considering only cerebral sequence of Brain CT images. The algorithm is based on data reduction technique principal component analysis (PCA).The PCA technique is mainly used for Face Recognition. We tried to use this technique for the retrieval of Infarct image. If the given image is Infarct it will show all the possible treatment details of different patient from the database.

This paper is organized into 5 sections. Section 2 discusses how to form the EigenImage. Section 3 presents the recognition of the query image. Results will be discussed in section 4 and conclusion in section 5.

II. FORMATION OF EIGENIMAGE

The PCA is mainly used for dimensionality reduction. It includes following steps.

- Formation of Covariance Matrix.
- Construction of Eigenvalue and Eigenvectors for the covariance matrix.
- Formation of Feature vector and the calculation of Euclidean distance.

The Database is trained by set of CT images with similar features. Each CT image is represented by MxN Matrix. All 2D images of the training database are converted into 1D column vectors which are combined together to form 2D matrix 'T'(Training Database Matrix).The fig 2 and fig 3 represents the Normal and

Infarct images respectively.

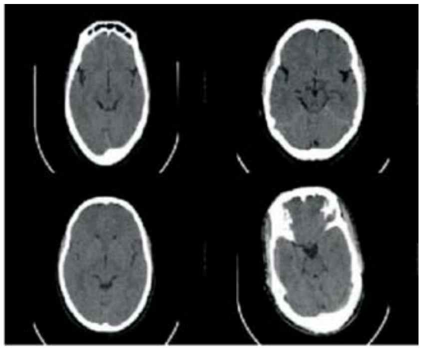


Fig. 2. Samples of Normal Brain Images

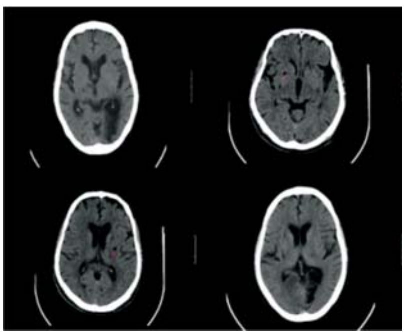


Fig. 3. Samples of Infarct Images

Suppose all P images in the training database have the same size MxN then the length of 1D column vectors is MN and the dimension of 'T' will be MNxP.

The average image (MI) from the matrix 'T' is calculated using

$$MI = \frac{\sum T_j}{P} \quad (1)$$

where T_j represents the j^{th} row of the T matrix.

The deviation of each image from mean image is calculated. All the centered image vectors (mean deviated image vector) are merged to form a matrix 'A'.

The covariance matrix is calculated from A. We know from linear algebra theory that for a matrix of dimension (KxL), the maximum number of non-zero eigenvalues that the matrix can have is min (K-1, L-1)(4).Since the number of training images (P) is usually less than the number of pixels (MxN), the most non-zero eigenvalues that can be found are equal to (P-1). So we can calculate eigenvalues of ATxA (a PxP matrix) instead of AxAT (a (MxN) x (MxN) matrix). It is clear that the dimensions of AxAT is much larger that ATxA which decreases dimensionality (5).

$$L = A^T X A \quad (2)$$

where L is the surrogate of covariance matrix (C=AxAT). Hence, C and L have same Eigenvalues.

Eigenvalues and Eigenvectors [5]can be calculated from the covariance Matrix 'L'. The Eigenvalues of 'L' are the Diagonal elements of matrix D and V represents the Eigenvectors of the corresponding Eigenvalues. The Eigenvalues are sorted and those < 1 are eliminated. The Eigenvectors corresponding to the remaining Eigenvalues are combined to form L_eig_vec matrix.

EigenImage (EI) is calculated by multiplying the centered image vector and the eigenvector of the matrix L.

III. RECOGNITION

Here the comparison between the query image and the images present in the Training Database is done by projecting the images into image space and measuring the Euclidean distance between the images. All centered images are projected into image space by multiplying with Eigenimage (6). Projected Image vector of each image in the training database will be its corresponding feature vector.

$$EI = A X L\_EIG\_VEC \quad (3)$$

where F represents the Feature Vector of the Training Database Images. The calculation of the Feature vector of the query image is done as follows. The Centered Test Image (D) is calculated using

$$F = EI^T X A \quad (4)$$

$$D = II = MI \quad (5)$$

where II represents input image matrix. The Test Image Feature Vector (TIF) can be calculated by

$$TIF = EI^T X D \quad (6)$$

The Euclidean distance [7] between the training images and the query image is calculated. The image in the training database with the minimum Euclidean distance is retrieved. If the retrieved image is normal then the query image is also normal. If the retrieved image is a case of infarct, then the query image is also infarct.

IV. RESULT

A total of 16 patients' CT images were used as the training dataset. Out of this 8 patients' CT were Normal and 8 patients' CT were Abnormal (Infarct). There are a total of 112 images of which 56 images are Normal and 56 images are Infarct. In these 56 images, the first 6 images of the cerebrum sequence of each patient are taken. A new set of 6 patients' CT images are taken as input images (test case) and the performance analysis for the different algorithms based on their accuracy is shown in the fig . 4.

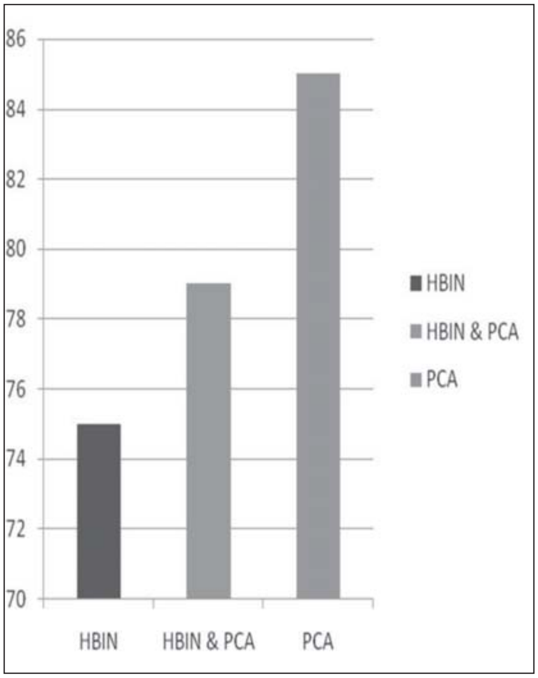


Fig. 4. Bar Chart for PCA and Histogram Bin

The resulting image for the given query image under various test cases is shown in the Table 1. Where case I represent Normal images, case II represent Infarct images with high defect and case III represents Infarct with fewer defects. The accuracy rate for various cases for both algorithms PCA and Histogram Bin are represented in the Table 2.

Table 1. Resulting Image for Various Algorithms

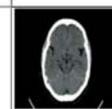
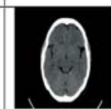
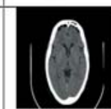
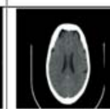
Test Cases	Query Image	Resulting Image		
		PCA	PCA & Histogram Bin	Histogram Bin
Case I				
Case II				
Case III				

Table 2. Comparison of accuracy rates

Cases	Images	Accuracy rate		Histogram Bin
		PCA	PCA and Histogram Bin	
I	Normal, Infarct(highly affected)	100%	75%	72%
II	Normal, Abnormal (other than infarct) , Infarct(medium and highly affected)	85%	79%	75%
III	Infarct(less affected)	82%	72%	70%

V. CONCLUSION

This algorithm is proposed to be a part of a CBIR system that can assess a new MR imaging study of the brain for anomaly. In the current implementation we considered only the feature vector obtained from PCA .In the further we will involve the other non-linear classifiers such as kernel PCA , SVM that have revealed much guarantee in classification. Future work will also involve expanding the training sets for both Normal and Infarct CT images, applying texture and shape feature filters for higher classification accuracy of Infarct and we will try to implement the current CBIR system for other medical images such as for identifying stone in the kidney, identifying Tumors in the Brain and etc.,

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REFERENCES

[1] Sinha, U, Kangarloo H, 2002, "Principal Component Analysis for Content-based Image Retrieval", Radiographics, 22(5):1272-1289.

[2] James Hafner, Harpreet S.Sawhney, Will Equits, Myron Flickner and Wayne Niblack,1995, "Efficient Color Histogram Indexing for Quadratic Form Distance Functions",IEEE Trans.on Pattern Analysis and Machine Intelligence, Vol. 17, No. 7.

[3] J. R. Smith and S.-F. Chang, 1995, " Automated image retrieval using color and texture", Technical Report CU/CTR 408- 95-14, Columbia University.

[4] T. Kohonen, 1972, "Correlation Matrix Memories", IEEE Transactions on Computers,Vol.C-21, 4.

[5] M. A. Turk and A. P. Pentland, 1991, "Recognition in face space, Int. Soc. for Optical Engineering Bellingham, WA, USA.

[6] Korn, Granino A, Korn, Theresa M, 2000, "Mathematical Handbook for Scientists and Engineers: Definitions, Theorems, and Formulas for Reference and Review", 1152 p., Dover Publications, 2 Revised edition, ISBN 0-486-41147-8.

[7] Wendy S. Yambor, M.S, 2000, "Analysis of PCA-Based and Fisher Discriminant-Based Image Recognition Algorithms", Thesis, (Technical Report CS-00-103, Computer Science).

[8] Meyer, Carl D, 2000, "Matrix analysis and applied linear algebra, Society for Industrial and Applied Mathematics (SIAM)", Philadelphia, ISBN 978-0-89871-454-8.