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Brain Tumor Diagnosis Based on Orthogonal Local Storage Mapping Based on Gabor

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Abstract– The present work introduces a new method for classifying brain tumor features using the extracted features from filtered brain images. Global feature extraction techniques such as Linear Discriminate Analysis (LDA), characteristics of the overall structure of MRI images and local information preserving techniques such as Locality Preserving Projection (OLPP) Local features would maintain the manifold local features of the same images, to exploit the information that can retain the geometry of images to avoid confusion when changes occur. The proposed method is based on the conventional features of the images with some added features for the detection of tumors. To enhance the diagnosis capacity and the hidden features of brain tumor images, firstly Gabor features were determined through the Gabor filter bank of MRI images. These features proved more effective and improved than the original brain images. Then, OLPP was used to extract the conventional features. This included some new features which were different separating information of Gabor features. New images could be classified in terms of the extracted features using a classifier based on the nearest neighbor. The proposed algorithm was used based on a database with 6 other methods. The results showed that the proposed method would show higher detection rates than other detection methods based on the features.

Keywords- Ortogonal Locality Preserving Projections (OLPP), Gabor filters, Tumor Image

I. INTRODUCTION

Image diagnosis generally includes a wide range of applied programs, and in this regard, numerous methods have been developed recently. Many of these methods would encounter the problem of dimension reduction because the dimensions of displaying the image vector (m × n) are too large to allow a timely and appropriate diagnosis. A common method is to solve the problem of dimensionality reduction techniques.(Ding, Zhu, Jia, & Su, 2012) The most popular ways to search the manifold structures are known to be Eigenfeature(Belhumeur, Hespanha, & Kriegman, 1996) Fisherfeature (Keyhanian & Nasersharif, 2014) and Laplacianfeature(Belkin & Niyogi, 2001) Both Eigenfeature and Fisherfeature are methods of linear diagnosis. PCA is a special vector-based method for modeling linear high-dimensional data. PCA tends to reduce the dimension via imaging the n-dimension of the main data to k-dimension (k«n) under a linear subspace using vector calculations and specific values of the covariance matrix.

Eigenfeature ensures the intrinsic geometry of the manifold when data are linear. The dimensions of the LDA method would reduce in a manner in which the mapped data can easily be separated from each other in different classes in the new space. W transmission vectors are extracted to produce the highest rate of dispersion between (S_B) and (Swets) classes(Feng, Hu, & Zhou, 2008) The method can be efficient if the linear structure exists based on Euclidean distance on objective data. Methods, which obtain the underlying structure of the manifolds hidden in the space of image cannot be successful. Recently, in many studies into image processing (Belkin & Niyogi, 2001; Keyhanian & Nasersharif, 2014; Saul & Roweis, 2003) non-linear manifolds are growing and flourishing. Thus, many of the manifold learning algorithms are able to maintain non-linear local structure of data, among which are Isometric feature mapping (Isomap)(Belkin & Niyogi, 2001) Locally Linear Embedding (LLE)(Cai, He, Han, & Zhang, 2006) and LPP (Fan, Qiao, Zhang, & Zhang, 2012) Although LPP includes many prominent features, it has its disadvantages, as well. Firstly, learning without supervision is the nature of this algorithm which can be a failure in separating data structure. Secondly, LP would function based on the performance of the algorithm of Laplacian features, which is a non-orthogonal method (Jin, Ruan, & Wang, 2010)This would lead to an inability to reconstruct the data. For this reason, many algorithms have been proposed with the aim to overcome the disadvantages of LPP, including Orthogonal Laplacian features (Jin et al., 2010)discriminate Locality Preserving Projections (DLPP) (Zheng, Yang, Tan, Jia, & Yang, 2007) and Locality Sensitive Discriminate Analysis (LSDA) (Shen, Bai, & Fairhurst, 2007) OLPP creates the proximity graph which best reflects the geometry of the manifold associated with the class. The image producer is extracted by maintaining the structure of the graph. It can maintain the local characteristics similar to Laplacian, but at the same time requires basic functions that are orthogonal. Orthogonal functions can sustain the foundation of image space structure. In fact, if the mapped vectors derived from OLPP are used for data visualization, the mapped would be the only rotating map not destroying the structure of data. Since OLPP is capable of saving more local information than LPP ,(Shen et al., 2007) OLPP is used here to maintain the conventional features.

The present work is a transplanting approach to combine categories of brain tumor images using a combination of Gabor wavelets and OLPP. Initially, Gabor features were extracted through Gabor filter bank from all MRI images to develop the existing data. Then, OLPP was used to extract the features of Gabor images.

The new series included different separating data on Gabor features. Then, using a classifier based on the nearest neighbor, new input images from educational base were distinguished.

The rest of this article is as follows: In the second part, Gabor features are proposed. OLPP method will be described in Section III. Section 4 will show K of the nearest neighbor algorithm. In the fifth part, the proposed methods will be introduced. The experimental results and discussion will come in Section 6 and conclusion in section VI.

II. ANALYSIS OF GABOR FEATURES

Although there is no standard and precise definition of a two-dimensional Gabor function, despite the fact that various forms of this function have been studied, most of the differences are in various sizes and frequency of the sinusoidal function of the Gaussian function. Based on wavelet theory, a Gabor function which is properly normalized is capable of being used as a mother wavelet to produce a family of non-orthogonal Gabor wavelets (Liu & Wechsler, 2002)

Gabor wavelets are basically suitable for the analysis and display of images aimed at deriving local details and visual features. In the following section, the basic concepts of Gabor wavelets and images of Gabor features will be presented.

A. Gabor wavelets

Gabor filters are considered one of the most popular tools for extracting visual features. They are used as two main factors in diagnosing brain tumors due to their computing and biological communication properties. In general, two-dimensional Gabor filters in a particular spatial domain can be expressed as follows (Seung & Lee, 2000)

Parameters γ and η representing the ratio between the center frequency and size of cover G are set as a fixed amount to ensure that Gabor filters of different sizes and orders could be received.

Typically values of Γ and H η = γ = √2 are regulated. The final parameter as F_Max represents the highest frequency filters that are usually regulated by f_max = 0.25.

When extracting features, a filter bank with multiple filters is created and for the extraction of multi-directional and multi-size features, MRI images are used. This filter bank usually includes Gabor filters of 5 different sizes and eight different directions, i.e. u = 0,1, ..., t-1 and v = 0,1, ..., r-1 when t = 5 and r = 8 (El-Dahshan, Mohsen, Revett, & Salem, 2014; Seung & Lee, 2000)

B. Gabor Features

This section is allocated to a brief description of the features of Gabor whose full details are presented in [16] which is defined in a convolution image (2):

$$G_{u,v}(p,q) = x(p,q) * \psi_{u,v}(p,q) \qquad (2)$$

The asterisk represents convolution operator and G_ (u, v) (x, y) is the corresponding result of Gabor kernel of size *u* and *angle v* called GaborMRI. In order to use all these results at different frequencies and directions, all representations of the images were connected to each other to form image feature vector. G_ (u, v) ^ N (p, q) is a normal vector produced based on Gabor feature vectors, and x ^ N is defined as (3):

$$x^N = (G_{0,0}^N(p,q), G_{0,1}^N(p,q), \dots, G_{4,7}^N(\text{!!! INVALID CITATION!!! })) \qquad (3)$$

III. OLPP

In recent years, many studies have shown that the characteristics of MRI images in a nonlinear subspace are manifold (Saul & Roweis, 2003), However, PCA and LDA can only discover Global Euclidean Structure and are not capable of discovering the underlying structure of MRI images which are located in non-linear manifolds. Thus, manifold structures should be modeled preserving local structures. The main functions extracted based on orthogonal LPP are not mined, which would make reconstruction of the structure difficult. That is why Deng et al (He, Cai, & Han, 2008) created an algorithm called orthogonal LPP (OLPP). OLPP can create mined bases which are able to preserve more local information than LPP. In addition, OLPP emphasizes that separable information, based on related classification, can be very important for categorization. OLPP algorithm is briefly described below.

1. Constructing adjacency graph: If X = [x_1, x_2, ..., x_N] is considered a set of MRI images and G represents a graph with N nodes, in which the i-th node belongs to x_i image, a mane will be set between i and j nodes if x_i and x_j are the nearest neighbor of x_i regardless of k.

2. Choosing weights: If node i and node j are connected to each other, S_ij = e ^ (- (x ‖ 〖〗 _i-x_ (j) ‖ ^ (2) / t)) when t∈R, otherwise, S_ij = 0. G. Weight matrix expresses G graph model of MRI manifold local structure.

C. Calculation of the functions of orthogonal base: Matrix D as a diagonal matrix is the input of S, D_ij = Σ_j▒S_ij, L = D-S, P = XDX ^ T aggregate column.

If a_1, a_2, ..., a_k are orthogonal vectors:

$$A_{k-1} = [a_1, a_2, \dots, a_{k-1}]\,,\ B_{k-1} = A_{k-1}^T P^{-1} A_{k-1} \quad (4)$$

Basic orthogonal vectors {a _1, a_2, ..., a_k} are calculated by formula (5):

- calculating the a_1 of specific vector of matrix P ^ (- 1) XLX ^ T corresponding the smallest specific amount.
- calculating a_k as special vectors through:

M_k = {IP ^ (- 1) A_ (k-1) B_ (k-1) ^ (- 1) 〖A〗 _ (k-1) ^ T} P ^ (- 1) (XLX ^ T) (5) , corresponding the smallest amount of M_k.

A. K of the nearest neighbor

The K of the nearest neighbor method includes a K record of a series of training records that are closest records to the experimental ones, and make decisions about the experimental records based on the priority of category or the related label In other words, this method chooses the category which has the highest records in the selected neighborhood. Thus, the category which is observed more than others among the K of the nearest neighbor will be selected as the category of the new record. Using KNN algorithm requires determining three issues: A) the need to set a series of records b) adding a criterion for similarity measurement C) determining K to act upon. For binary categorization, considering odd values for K can be more appropriate since it can improve the possibility of the victory of one of the two categories over the other.

In this paper, the similarities of the Euclidean distance were used for benchmarking. Thus, a new image would belong to a series closer to it based on the Euclidean distance. If the new image was close to the images containing a tumor, tumor diagnosis would be announced for the new image, otherwise, it would be announced normal.

IV. PROPOSED METHOD

In the first stage of the algorithm, Gabor features based on Gabor filter bank shown in (10) were calculated:

$$G_{u,v}(p,q) = x(p,q) * \psi_{u,v}(p,q) \qquad (10)$$

in which $x \epsilon R^N$ و $G_{u,v} \epsilon R^{N\times 40}$.

Clearly, the mathematical properties of Gabor filters affected the measures of the MRI images and their further details. The response of Gabor filter would offer plenty of benefits. Since these filters are highly resistant to brightness and contrast of images, and extract more local details, using them could be more efficient than using original images.

In the next stage, OLPP space was obtained introducing OLPP to Gabor features. The features of trained Gabor OLPP was mapped in this space to achieve OLPP features based on Gabor. For an input image, the process of feature extraction was performed similar to the process of training images. In the final step, using a classifier based on the nearest neighbor, Gabor features were used to combine the extracted local and general advantages. The method is further elaborated below.

A. Response of OLPP Gabor Filter Bank

The response of Gabor filters was used here as the input of OLPP algorithm to replace original images. This would reduce the sensitivity reaction to rotation and optical differences. Transferring the response of Gabor filter to the new space based on base vectors of OLPP would result in a better categorization of MRI images. To use the response of Gabor filters, values should be collected from both real and imaginary sections as these sections are quite sensitive due to their movement, not capable of being directly used.

If the number of features received from the features of Gabor filter is N, 40 of them can be selected to reach an array of N × 40. Then, the response of Gabor filter and the formation of OLDD space can be used. Finally, an appropriate number of base vectors will be used to extract OLPP features based on Gabor, (11), and (12).

$$G_{u,v} \to z = W_{OLPP}^{T}\, G_{u,v}, \qquad (11)$$

$$W_{OLPP} = \{a_1, a_2, \dots, a_k\} \qquad (12)$$

Where $G_{u,v} \epsilon R^{N\times 40}$ و $z \epsilon R^k (k << N \times 40)$.

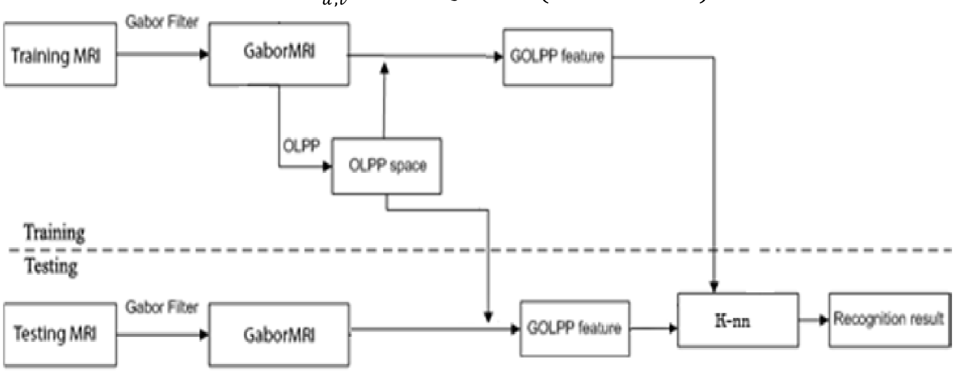

Fig 1.The process of proposed method

B. Integrating Features

As mentioned in section A, OLPP features based on Gabor are different from MRI images extracted directly in terms of the role they play in diagnosing brain tumors. Therefore, it is necessary to take advantage of Gabor filter bank effects on the images. After performing Gabor filtering and feature extraction, the method of nearest categorized neighbor K was used. To extract information from Gabor features, for each trial photo from the input, the K of the nearest neighbor would be calculated based on Euclidean distance in OLPP space, in which the L (x) of an MRI collection was closer to the x and K samples of the neighbors. After the collection of each x was calculated, a new image of MRI was located in a category to which the highest L (x) belonged.

V. THE RESULTS

This section is allocated to the effectiveness of the proposed method in tumor diagnosis. The MRI images were collected from www.med.harvard.edu/aanlib/home.html. In all experiments, there was no pre-processing of MRI images . The original images were manually modified to 32×32 pixels with a gray surface of 256 in each pixel. Each image was then depicted as a 1024 dimensional vector.

In general, the detection process consisted of three stages, here. In the first stage OLPP features based on Gabor extracted from experimental samples were determined. Then, the process of feature extraction of experimental images was carried out similar to the training stage. Finally, the new MRI images were identified through feature integration method. If the images were close to the tumor, the experimental image would be diagnosed as containing the tumor.

The database consisted of 56 images from 38 individuals, with some of them containing tumor and some lacking, i.e.38 with tumor.

To evaluate the efficiency of the proposed method, it was compared to PCA, LDA, LPP, OLPP, and Gabor-based LDA (GLDA) in terms of different features. Two tumor presenting images + two normal images, three tumor presenting images + three normal images, four tumor presenting images + four normal images, five tumor presenting images + five normal images were selected for training and the rest for testing. Table I illustrates the best recognition rates, which clearly shows the superiority of the proposed method over the others, especially with a noticeable distance from GOLDA. When images were selected as 5 + 5 (5Train) for training, the new method could reach its highest recognition rate at almost 100%. Table *1*

Table 1:result of methods

	2Train	3Train	4Train	5Train
PCA	70.4	78.9	84.5	88.1
LDA	79.9	87.0	91.1	93.5
LPP	79.8	87.3	91.1	93.6
OLPP	82.8	90.8	94.4	96.6
GLDA	80.0	88.6	95.4	98.0
GOLPP	**87.2**	**91.8**	**98.8**	**98.5**

VI. CONCLUSION

In this work, a method to preserve Gabor-based traditional features for the experiment and diagnosis of data based MRI images is presented. First, Gabor filters were created to extract all features of the MRI images. Gabor filters responded more strongly to brightness and contrast. They also represented more local details. Therefore, using these images could be much more efficient than when the original images were used. OLPP features based on Gabor using OLPP features were used to preserve the local information of Gabor features. Then, the K category of the nearest neighbor was used for classification. The results showed that the proposed method would be more efficient than the other methods. In this database with 5 training images for each individual, the method would show the highest rate of detection at approximately 98.5%.

REFERENCES

[1] Belhumeur, P. N., Hespanha, J. P., & Kriegman, D. J. (1996). *Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection.* Paper presented at the European Conference on Computer Vision.

[2] Belkin, M., & Niyogi, P. (2001). *Laplacian eigenmaps and spectral techniques for embedding and clustering.* Paper presented at the NIPS.

[3] Cai, D., He, X., Han, J., & Zhang, H.-J. (2006). Orthogonal laplacianfaces for face recognition. *IEEE transactions on image processing, 15*(11), 3608-3614.

[4] Ding, S., Zhu, H., Jia, W., & Su, C. (2012). A survey on feature extraction for pattern recognition. *Artificial Intelligence Review, 37*(3), 169-180.

[5] El-Dahshan, E.-S. A., Mohsen, H. M., Revett, K., & Salem, A.-B. M. (2014). Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm. *Expert systems with Applications, 41*(11), 5526-5545.

[6] Fan, M., Qiao, H., Zhang, B., & Zhang, X. (2012). *Isometric multi-manifold learning for feature extraction.* Paper presented at the Data Mining (ICDM), 2012 IEEE 12th International Conference on.

[7] Feng, G., Hu, D., & Zhou, Z. (2008). A direct locality preserving projections (DLPP) algorithm for image recognition. *Neural Processing Letters, 27*(3), 247-255.

[8] He, X., Cai, D., & Han, J. (2008). Learning a maximum margin subspace for image retrieval. *IEEE Transactions on Knowledge and Data Engineering, 20*(2), 189-201.

[9] Jin, Y., Ruan, Q.-Q., & Wang, Y.-Z. (2010). *3D Face recognition using Tensor orthogonal locality sensitive discriminant analysis.* Paper presented at the Signal Processing (ICSP), 2010 IEEE 10th International Conference on.

[10] Keyhanian, S., & Nasersharif, B. (2014). *Laplacian Eigenmaps modification using adaptive graph for pattern recognition.* Paper presented at the Telecommunications (IST), 2014 7th International Symposium on.

[11] Liu, C., & Wechsler, H. (2002). Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. *IEEE transactions on image processing*, *11*(4), 467-476.

[12] Saul, L. K., & Roweis, S. T. (2003). Think globally, fit locally: unsupervised learning of low dimensional manifolds. *Journal of Machine Learning Research*, *4*(Jun), 119-155.

[13] Seung, H. S., & Lee, D. D. (2000). The manifold ways of perception. *Science*, *290*(5500), 2268-2269.

[14] Shen, L., Bai, L., & Fairhurst, M. (2007). Gabor wavelets and general discriminant analysis for face identification and verification. *Image and Vision Computing*, *25*(5), 553-563.

[15] Swets, J. A. (1988). Measuring the accuracy of diagnostic systems. *Science*, *240*(4857), 1285.

[16] Zheng, Z., Yang, F., Tan, W., Jia, J., & Yang, J. (2007). Gabor feature-based face recognition using supervised locality preserving projection. *Signal Processing*, *87*(10), 2473-2483.

