Magnetic Resonance Brain Images Individual Recognition with PCA

Yepuganti Karuna, Saritha Saladi, Pramodh Konduru, G Ramachandra Reddy

Abstract: ***Every individual brain is identified as unique by proper consideration of the background for individual difference in the brain functions of the brain morphology. The proposed method is implemented by using structural magnetic resonance imaging brain recognition is performed using segmentation with the Voxel-Based Morphometric (VBM) approach and Feature Extraction(FE) using Principal Component Analysis(PCA). Brain recognition is identified by computing the Euclidean distance among the image pairs, projected into the same subspace. The petite difference in the Euclidean distances is observed between the same subject when scanned twice and it is due to distinct combination of scanners used between test-training image pairs with/without scanner up-gradation. The obtained results of rank identification and receiver operating characteristic curves show that the brain morphology identifies a particular individual with less false acceptance rate.***

Keywords: Brain morphology, Eigen brain, MRI, PCA, Recognition, VBM.

I. INTRODUCTION

Brain morphology is the study of dimension, and structure of the brain. To identify the individual difference, occurs in the functioning of the brain and it is important to know the difference in the individual brain. The information obtained from the brain magnetic resonance imaging is unique and cannot manipulate. In early days, people started to study about brain, there is no proper technology to obtain maximum information from the scanning machines (X-Ray/ CT SCAN). With recent advances in MRI techniques, the study of brain morphometric is extensively used to analyze the shape, size, and structure of the individual brain. The brain goes through structural vicissitudes throughout brain development, growth, and aging related to changes in the functioning. Most of the Neurological and neuropsychiatric disorder occurs when the brain undergoes structural changes. Apart from these reasons brain development also take part due to high-level performance such as cab riders [1], mathematicians [2], musicians [3,4], and bilingual individual [5]. Even training and practicing any special hobby or skill prone to cause changes in brain structures [6]. Here, the structural MRI images are used, during the development of manifesting the brain tissues takes place and it's identified by structural MRI. There exist T1, T2 and proton density MRI images with different properties (contrast and brightness). In recent years, the number of automatic impartial methods has been established and extensively used to observe brain morphology, including volume- deformation-, and surface-based approaches. Among these different automated techniques, voxel- based morphometry (VBM) [7] is widely used for assessing structures of the brain and includes segmentation of tissues into gray matter(GM), white matter(WM) and cerebrospinal fluid(CSF). There exist different algorithms for extracting the features from the brain images and segmenting tumors [8, 9]

In the present study, the analysis is carried out the brain morphology is distant among different individuals and distinguishable information. The 40 subjects of structural MRI datasets were scanned twice (scanning interval=6months) are examined and among them, 12 different subjects are used for evaluation. The normalization is done using unified segmentation with VBM approach [10]; these normalized images were smoothened using the median filter for voxel-by-voxel statistical analysis. Followed by FE based on PCA and Euclidean distance is calculated between image pairs which are subjected to same subspace. This paper outlines the implementation of the proposed methodology in section 2. The results and discussion of the proposed method are described in section 3, and section 4 concludes the paper.

II. METHODS AND MATERIALS

A. Datasets

The datasets used in for investigation include both healthy and unhealthy brains. The 12 different subjects (6 males, 3 females, 3 diseased images) are attained from Open Access Series of Imaging Studies (OASIS). The mean age = 45 ± 9 years, varies =30 – 60 yrs. In this study, both healthy subjects are used to find the similarities and unhealthy subjects the location of the disease by using proposed brain morphology method. T1 weighted scan images are used, where T1 is spin-lattice relaxation and T2 is spin-spin relaxation. In longitudinal relaxation of T1 images, atomic nuclei come to thermal equilibrium in the magnetic field.

B. Unified Segmentation

The normalization is done with unified segmentation [10] and Gaussian mixture model (GMM) to integrate a smooth intensity dissimilarity and non-linear registration with tissue probability maps.

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The two random seed points are selected, two threshold values (0.0555 /0.0255) opted to obtain the false acceptance rate. Normalization is employed to reduce the pixel intensity range to the required range. Unified segmentation is used to obtain the individual tissues of the subject, GM is concentrated in this study.

C. Smoothening

The gray image obtained after normalization is smoothened using the median filter. Smoothening is done to reduce the pixel level of the image and noise present in the GM. The median filter is better than mean filter as unreliable pixel present in surroundings does not affect the median filter values pointedly. Since median values are the actual values of the pixels calculated from the region pixel, shows the better filtered at preserving the sharp edges of the image. Median filter is used for denoising the images, and comparison of various denoising filters [11,12].

D. Voxel-Based Morphometry

In simple, VBM [7] process involves voxel-wise assessment of the confined deliberation of GM inbetween two subjects when mapped to same common space. The procedure is comparatively easy and encompasses the spatial normalizing high-firmness from all the datasets used within the study into the similar stereotactic interim. This is followed by segmentation and smoothing the GM segments using median filter. Rectifications of various assessments are made with the theory of Gaussian random fields. Currently, computational cost of high-resolution deformation fields makes VBM a simple and practical method to addresses small-scale difference within the competences of utmost research components.

E. PCA-based Brain Recognition

MATLAB 15a is the software used for image processing and SPM8 (Statistical parametric mapping) software developed in Institute of Neurology, London. The initially scanned subjects are used as training dataset and second scanned subject (which were scanned after 6$\pm$1 months) are taken as the testing dataset. The ground-truth images are obtained using SPM8 and normalized using unified segmentation [10]. The eigen brain space is generated with PCA for the ‘stabilized training images. The similarities are found using PCA feature extraction to calculate the Euclidean distance between the test and train dataset, projected into the same eigen brain space.

III. PROPOSED METHODOLOGY

A. Image normalization

The acquired steady-state images are spatially normalized and segmented into tissues with a unified segmentation [10]. GM and WM are the major components of the central nervous system. GM is distinguished from WM, in that it contains numerous cell bodies, while WM contains relatively very few bodies cell. CSF is a colorless body fluid which connects in between the brain and spine. WM affects learning, functions and coordinates communication between various brain regions.

B. Principal Component Analysis

The mean image ‘x’ is estimated from all the training data-set and this mean image is deducted from the normalized image. FE in pattern recognition and image processing starts from a primary set of measurable data and builds derived value into informative and non-reluctant data. PCA feature extraction is used to determine eigen-vectors $E_1, E_2, E_3 \ldots . E_{n-1}$, where n is the number of training images. While reducing the dimensions the information that obtained also reduces, to acquire the maximum information the eigen brains with the largest eigen-values are considered. Each (mean subtracted) image is projected into the space and these images are treated as sum of the eigen brains. The weighted vector (feature vector) signifies the spot of the brain in the space and projection.

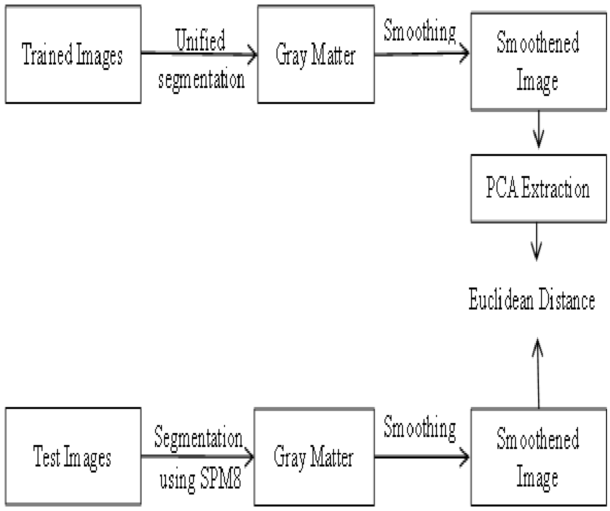

Fig. 1 Block diagram of the proposed method

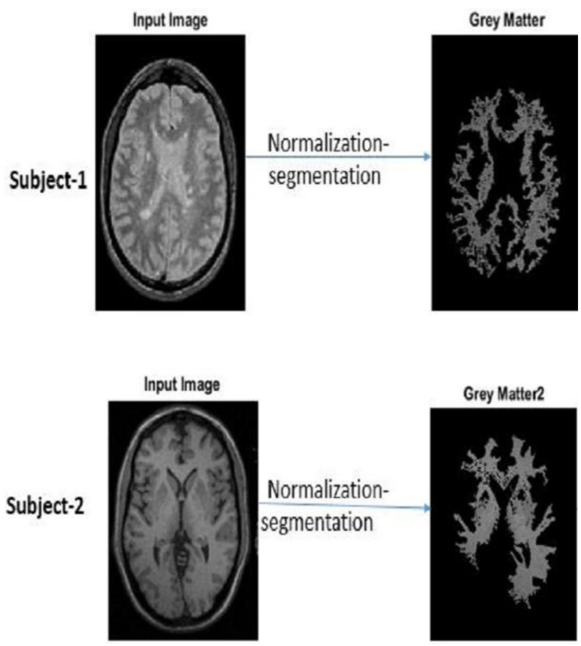

Fig. 2 Two different subjects gray matter obtained after normalization using unified segmentation.

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C. Recognition

The similarities are found between the training dataset and testing dataset, projected to the same eigen brain space. The recognition is measured by calculating the Euclidean distance between two datasets based on the eigenvectors.

IV. RESULTS AND DISCUSSION

A. Eigen Brains

The Fig. 3 shows the mean-image and eigen brains estimated from the training dataset. The mean image is subtracted from the normalized image of the training dataset.

B. Euclidean Distances and Dimensions

The Fig. 4 shows the relationship inbetween the numbers of magnitude (eigen brains) and Euclidean distances inbetween the training and testing datasets. As the number of dimensions (eigen brain) is higher, more accurate information is acquired from the image. Euclidean distance from others is improved, while the distance from one-self is more or less constant. With the trivial number of dimensions (eigen brains) comparatively, poses less information to distinguish the distance from the other is sufficiently elongated when compared with the distance from one-self.

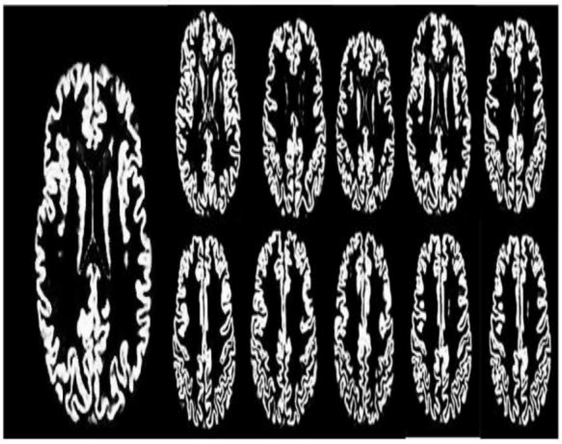

Fig. 3 Mean-image and the eigen brains estimated from the training dataset

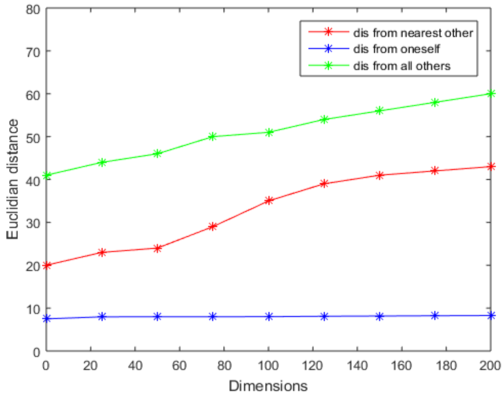

Fig. 4 Euclidean distance inbetween test and training images

C. Identification of Eigen brains

In Fig. 5 the relationship inbetween the eigen brains and rank identification rate. The training images with the least Euclidean distances from test image are the topmost matches. When 32, 64, 96, and 112 dimensions are used for projection, the rank identification rates are 99.5%, 99.95%, 99.5% and 100.0% individually. Fig.6 represents the receiver-operating curve estimated with various number of eigen brains with false acceptance rate of 0.0001 to 0.001% of genuine acceptance rate.

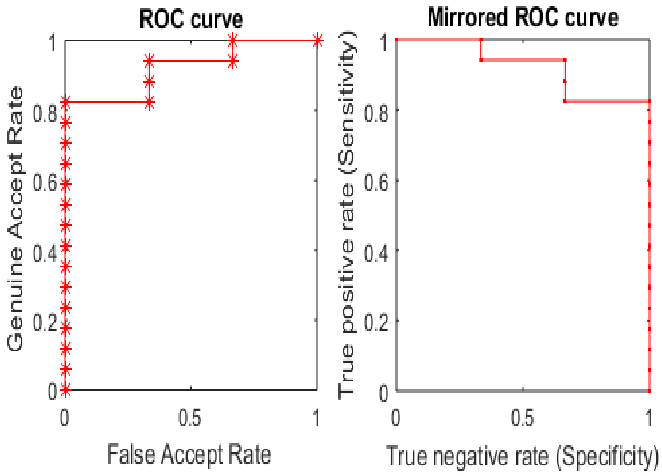

Fig. 5 Rank-identification rate for 32, 64, 96 and 112 Eigen brains

E. Effects of scanner and upgrade

The Fig.7 shows the effect of the different scanning device at 2-time point causes longitudinal change in GM. The GM volume is comparatively steady within the same scanning device, but slightly diverse when it comes with two different scanning devices. Device upgrade has an effect [12] compared to individual scanning devices at the 2-time point. The use of different devices at dissimilar time points suggestively effect longitudinal results.

The result of the proposed method shows that the proper analysis of the difference in the brain morphology is to recognize a particular individual; i.e., brain morphology is personally recognizable evidence. Even with 32 eigen brains the prognosis is possible and its rank identification rate is 99.02%. The rank identification rate is 100% at higher 112 eigen brains used. Every brain endures different enlargement phases based on the skills they develop or the hobbies. Brain morphology also undergoes some changes like development, practicing and aging. Moreover, a multiplicity of neural and neuropsychiatric illnesses causes changes related to the development of brain morphology. Individual difference may occur as a collection of variances in brain structures.

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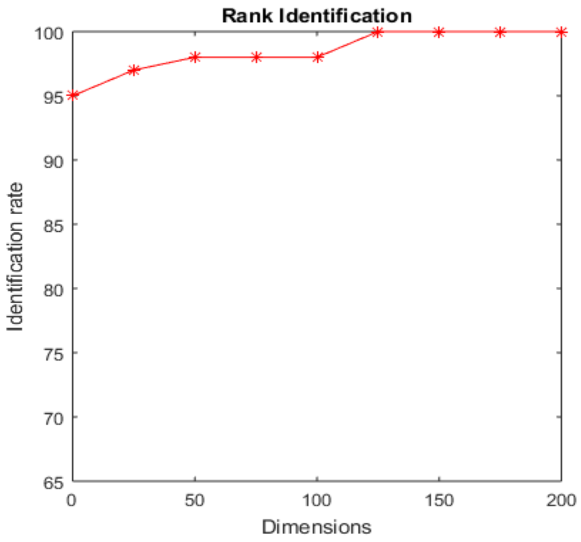

Fig. 6 Receiver operating characteristic curves. At a false accept rate from 0.0001 to 0.01%, the Genuine accept rates graph

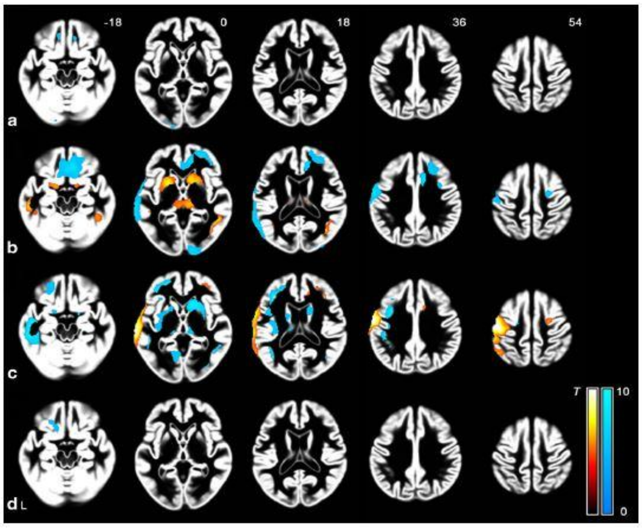

Fig. 7 VBM analysis of longitudinal (1-year) gray matter volume changes

To our knowledge, few previous studies have done their experiment for the point of biometric based on inter individual difference of brain morphology. From the age gap of 40 to 96, the images are clinically showed with mild Alzheimer's disease. Each scan provides 3 to 4 T1 images, provide extremely high contrast to noise, this data is used to measure the differences accompanying the normal age factor and Alzheimer's disease. This is a little complex and long process to study the difference between normal and diseased brain. The normalized images were smoothened to reduce the pixel level of the image and then PCA for feature extraction is performed. Brain morphology is 3D evident and higher in evidences compared with other biometrics like finger-prints, iris-patterns, and face-recognition. The brain recognition befits are more sophisticated compared to other recognitions of biometrics and it will be more accurate and precise. However, the brain images include personal discernible information.

V. CONCLUSION

In the present study, structural MRI subjects are scanned twice at two different times with two different MRI scanning devices with same features. The combinations of scanning devices are used in-between individuals. The both scanning devices are upgraded through the scan interval at the same time. However, there is a slight variation in the Euclidean distance between the combinations of scanning device used or among the training–testing pairs with/without scanning device up-gradation. VBM is used for normalization and it's an erudite technique to optimize the brain recognition possible to overwhelm the effect of using different scanning devices and scanner up-gradation. Brain morphology using VBM based feature extraction using PCA is implemented. The structural MRI data of 12 different subjects are used, scanned twice (6 ± 1 months). The obtained results of rank identification and receiver operator characteristics indicate the by proper analysis of the individual difference. The brain morphology provides personal recognizable data. The use of dissimilar scanning devices and scanner up-gradation has slight effects when equated with inter-subject unpredictability in brain morphology.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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