CLASSIFICATION OF 3-D MRI IMAGES BASED ON SPATIAL DEFORMATIONS IN THE SCHIZOPHRENIA RESEARCH

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Abstract

Automatic classification of schizophrenia patients and healthy controls based on their 3-D MRI deformation images is introduced here. The image data are reduced by 2DPCA to avoid high computational expenses. Consecutively, reduced data are classified into the two groups according to the centroid method or the average linkage method. The results show that the algorithm gives better results while using the average linkage method than the centroid method. The main advantage of the algorithm lies in its low memory and time requirements.

1 Introduction

In the schizophrenia research, large 3-D magnetic resonance imaging (MRI) brain data are acquired. Recently, principal component analysis (PCA) is a widely used technique for reducing large image data sets [1]. Huge image data lead to large covariance matrices which are difficult to evaluate. In [2], two-dimensional principal component analysis (2DPCA) was developed to overcome these problems in 2-D face recognition. Here, the concept of [2] is followed and further modified to solve classification of 3-D MRI brain data sets.

2 Methods

An algorithm for automatic classification of schizophrenia patients and healthy controls based on their 3-D MR brain images is proposed here. Unlike in [2], 3-D deformation images are used here instead of 2-D intensity images. The deformations are results of high-dimensional nonlinear registration of MR images with a digital brain atlas [3]. The deformation images clearly show how the brain anatomy of a diagnosed subject differs from normal template anatomy in the terms of local volume expansions and contractions.

According to [2], 2-D image is supposed to be the input into the 2DPCA algorithm unlike the common usage of PCA that demands transformation of images into 1-D vectors. Here, 3-D deformation images (184 x 224 x 184 voxels) are preprocessed before 2DPCA. Transversal slices are lined up to create a 2-D matrix with the size of 184 x 41216 pixels.

The first step of 2DPCA is to create an image covariance matrix **G**:

$$\mathbf{G} = \frac{1}{M}\sum_{j=1}^{M}\left(\mathbf{A}_j - \overline{\mathbf{A}}\right)^T\left(\mathbf{A}_j - \overline{\mathbf{A}}\right), \tag{1}$$

where M is an overall number of deformation images, $\mathbf{A}_j$ is a jth image and $\bar{\mathbf{A}}$ is an average image of all images. Eigenvectors and eigenvalues of the covariance matrix **G** (184 x 184 pixels) are computed afterwards. Set of projection axes, $\mathbf{X}_1,...,\mathbf{X}_d$ is selected which are eigenvectors of **G** corresponding to the first d largest eigenvalues. Principal components $\mathbf{Y}_k$ of a sample image **A** are derived by:

$$\mathbf{Y}_k = \mathbf{A}\mathbf{X}_k, k = 1,2,..., d \tag{2}$$

The principal components are lined up to form matrix $\mathbf{B}=[\mathbf{Y}_1,...,\mathbf{Y}_d]$ with the size of 41216 x d pixels. The matrix is called the feature image [2,4] of the sample image **A**. In [2], the feature image of an acquired face image is compared with all feature images in a database using the nearest neighbor classification rule. Here, the feature image is classed as the patient image or the healthy control one according to the centroid method or the average linkage method.

The centroid method includes computing distances of a new feature image from centroids of both the feature image groups (patients and healthy controls). The shorter one indicates classification of the new feature image into a group. In the average linkage method, the shorter one of the average distances of the new feature image from all patient feature images and from all healthy control ones indicates classification of the new image into a group.

All described steps of the classification algorithm are visualized in Fig. 1. A new deformation image is classified into the group of schizophrenia patients or healthy controls according to distances in a vector space, in which images are represented as points. The vector space is high dimensional due to the large size of the images and classification algorithms are too computationally expensive. The images can be reduced by 2DPCA to avoid such expenses.

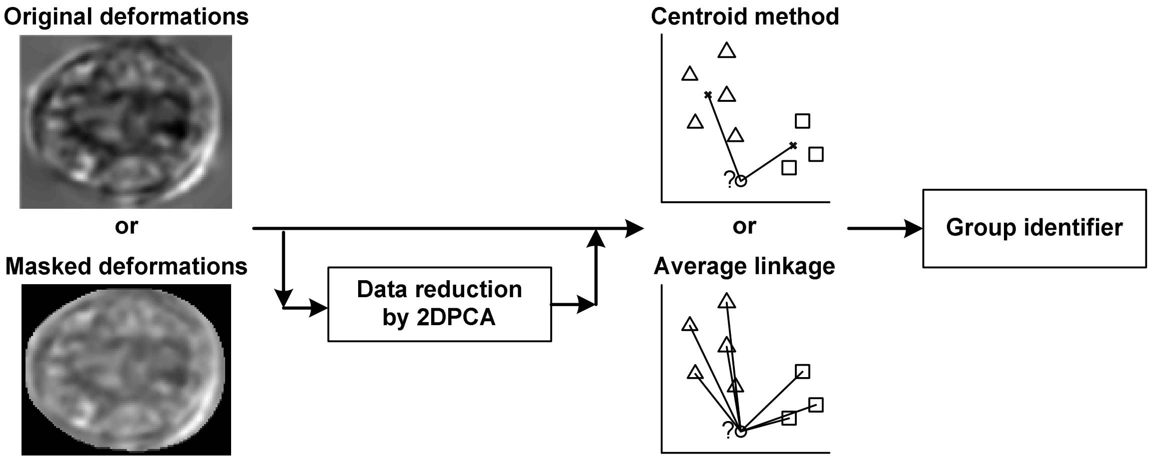

Figure 1: Block scheme of classification steps. The input images are original deformation data or masked deformation data. The input images are reduced by 2DPCA or they are classified directly without any data reduction. Images are classed using the centroid method or the average linkage method. As the output of classification an identifier of patients or healthy controls is obtained.

3 Experiment and results

The classification algorithm was tested in an experiment with 3-D MRI data sets of 19 schizophrenia patients and 124 healthy controls in MATLAB. An efficiency and time requirements of classification are compared with the cross-validation technique while using various clustering methods and original or reduced input deformation data. The classification algorithm was also tested when masked deformation data were used. The deformation data were masked with a binary head mask to remove extracranial image voxels.

There are no considerable differences between classification efficiencies when using original and reduced MRI data (Tab. 1). However, there is a substantial decrease in time requirements when data reduced by 2DPCA are used. The algorithm gives better results while using the average linkage method than the centroid method. There is also evident that classification of masked deformations is slightly more efficient than classification of original deformations.

Table 1: EFFICIENCY AND TIME REQUIREMENTS (IN SECONDS) OF CLASSIFICATION WHILE USING VARIOUS INPUT DATA AND CLUSTERING METHODS

Data	Reduction	Centroid method		Average linkage method	
		Efficiency	Time requirements	Efficiency	Time requirements
Original deformations	No	79.7%	619.0	81.8%	8721.8
	Yes	79.7%	58.0	81.8%	209.4
Masked deformations	No	80.4%	649.1	83.2%	9354.5
	Yes	80.4%	58.4	82.5%	210.7

Efficiency of classification is visualized in Fig. 2 for better illustration.

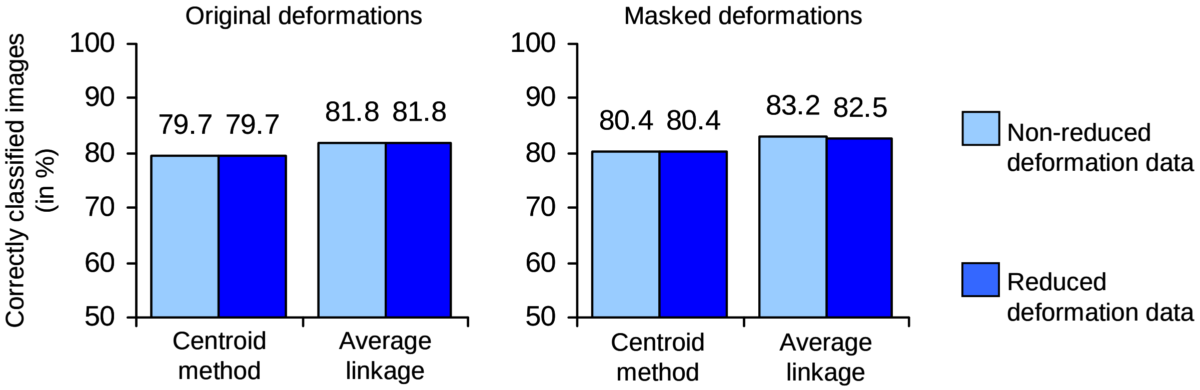

Figure 2: The bar graph of classification efficiency. The efficiency is compared while using various input images (original deformation images or masked deformation images), clustering methods (the centroid method or the average linkage method) and reduced or non-reduced data.

4 Conclusions

An algorithm for automatic classification of schizophrenia patients based on their 3-D MRI deformation data is introduced here. The algorithm is built up from 2DPCA for data reduction and from the average linkage method which provides better results than the centroid method. The preliminary results showed that the data reduction step enables classification of 3-D data sets with low memory and time requirements.

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