Data Reduction In Classification Of 3-D Brain Images In The Schizophrenia Research

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Abstract. Multidimensional image data are usually reduced during preprocessing to lower high computational requirements and to cope with the well-known small sample size problem in the huge data analysis. Two reduction methods based on principal component analysis (PCA) are compared and further modified here to be used in classification of 3-D MRI brain images of first-episode schizophrenia patients and healthy controls. The first reduction method is the two-dimensional principal component analysis (2DPCA) and the second one is the PCA based on covariance matrix of persons (pPCA). The classification efficiency of data reduced by 2DPCA and pPCA are compared while using various input image data and two classification methods – the centroid method and the average linkage method.

1 Introduction

Recently huge image data sets and the small sample size problem have been discussed in many fields of image analysis such as face recognition [1], processing of magnetic resonance imaging (MRI) data [2] or functional MRI data [3]. Image data have been reduced with selecting interesting parts of images [4] or choosing the most significant voxels from voxel-based or deformation-based morphometry [5]. However, neither focusing on regions of interest in images nor picking out voxels on the basis of results of univariate tests enable to use information from all voxels in images. Therefore principal component analysis (PCA) became a widely used technique for reducing large image data sets because it allows more complex reduction of all voxels simultaneously. PCA is based on computation of a covariance matrix of data and its eigenvectors and eigenvalues [6]. However, the 3-D MRI images are so huge that they lead to large covariance matrices which are difficult to evaluate. In [7], two-dimensional principal component analysis (2DPCA) was developed to overcome these problems in 2-D face recognition. In [8] and [9], PCA based on covariance matrix of persons (pPCA) was used in analyses of fMRI data of schizophrenia patients and MRI brain images of preterm infants respectively. Here, the concepts of data reduction from [7], [8] and [9] are compared and further modified to be used as a preprocessing step in classification of patients with schizophrenia and healthy controls based on their 3-D MRI brain images.

2 Methods

Unlike in [7], [8] and [9], 3-D deformations and gray matter density images are used in the proposed classification procedure instead of intensity images. The deformations are results of high-dimensional nonlinear registration of MR images with a template anatomy from a digital brain atlas [10]. The deformations which are represented by displacement fields or their Jacobians clearly show how the brain anatomy of a diagnosed subject differs from a normal template anatomy in the terms of local volume expansions and contractions. The gray matter (GM) density images are by-products of a segmentation step in voxel-based morphometry [11]. The GM density images are appropriate for the classification of schizophrenia patients because a lot of anatomical areas where patients with schizophrenia differ from healthy people lie in GM [12].

A new deformation or GM density 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 high spatial dimension of the images. Therefore classification algorithms are often very computationally expensive. The images can be reduced by 2DPCA or pPCA to avoid such expenses.

According to [7], 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 deformations or 3-D GM density images are transformed into 2-D images before computation of an image covariance matrix **G** which is computed by:

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

where $\mathbf{A}_j$ is the 2-D image, $\bar{\mathbf{A}}$ is their average and M their overall number. Eigenvectors of the covariance matrix **G** which correspond to the first d largest eigenvalues are selected afterwards. The reduced data are acquired by multiplying the original deformations or the GM density images with the selected eigenvectors.

In [8] and [9], images are reduced with the use of all eigenvectors $\mathbf{V}_j$ with non-zero eigenvalues. It allows to preserve all data variance and thus maintain the whole information important for classification contrary to the commonly used PCA which leads to decrease of the sample variance. Eigenvectors $\mathbf{V}_j$ are computed according to linear algebra rules (the proof is given in appendix in [8]) from eigenvectors of a covariance matrix of persons by:

$$\mathbf{V}_j = \frac{\mathbf{Z}^T\mathbf{\Phi}_j}{\sqrt{\lambda_j}}, \tag{2}$$

where $\mathbf{Z}^T$ is a matrix where rows are original images transformed into 1-D vectors, $\boldsymbol{\Phi}_j$ and λ_j are j^{th} eigenvector and j^{th} eigenvalue of a covariance matrix of persons respectively.

In [7], a reduced face image is compared with all reduced face images in a database using the nearest neighbor classification rule. In [8], fMRI images are assigned to a group of patients with schizophrenia or to a group of healthy controls using the projection pursuit algorithm. In [9], brain images of preterm infants and term controls are classified with the use of the maximum uncertainty linear discriminant analysis. Here, the reduced deformations or the GM density images are classified as the schizophrenia patient images or the healthy control ones according to the average linkage method or the centroid method.

In the average linkage method, the shorter one of the average distances of the new reduced image from all reduced patient images and from all reduced healthy control ones indicates classification of the new image into the group. In the centroid method, distances of a new reduced image from centroids of both the image groups (patients and healthy controls) are computed. The image is then classified into the group represented by the closer centroid.

A simple method for visualization of the centroid method is proposed here (Fig. 1). The two centroids are symbolized by stars and the reduced image of schizophrenia patients or healthy controls is symbolized by a dot. The two centroids and the image constitute a triangle with sides a, b, c, where a is the Euclidean distance between the classified image and the centroid of patients, b is the Euclidean distance between the classified image and the centroid of healthy controls and c is the Euclidean distance between both centroids. The centroid of controls is placed into the point [0,0] and the centroid of patients into the point [c,0]. Y-coordinate of the classified image can be computed as a height v_c of the triangle and x-coordinate as c_b which is a part of the side c. v_c and c_b can be derived from Euclidean theorems about a height and catheti in a right triangle by their generalization for all types of triangles:

$$c_b = \frac{b^2 + c^2 - a^2}{2c}, \tag{3}$$

$$v_c = \sqrt{b^2 - c_b^2}, \tag{4}$$

Fig. 2 shows a visualization of the deformations with the use of the proposed visualization method. Images which are closer the centroid of controls, thus they lie to the left of the classification boundary, will be classified as healthy control images. Images closer the centroid of patients, it means images to the right of the boundary, will be classified as patient images.

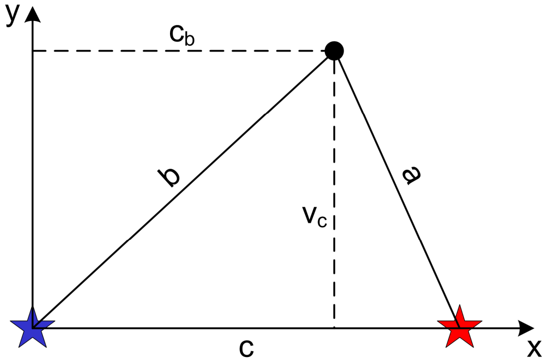

Fig 1. Visualization of the centroid method with the use of triangles. The blue star represents the centroid of healthy controls, the red star stands for the centroid of patients and the black dot represents the image which is classified. *a* is the Euclidean distance between the classified image and the centroid of patients, *b* is the Euclidean distance between the classified image and the centroid of healthy controls and *c* is the Euclidean distance between both centroids. v_c is the y-coordinate of the classified image and c_b is the x-coordinate of the classified image.

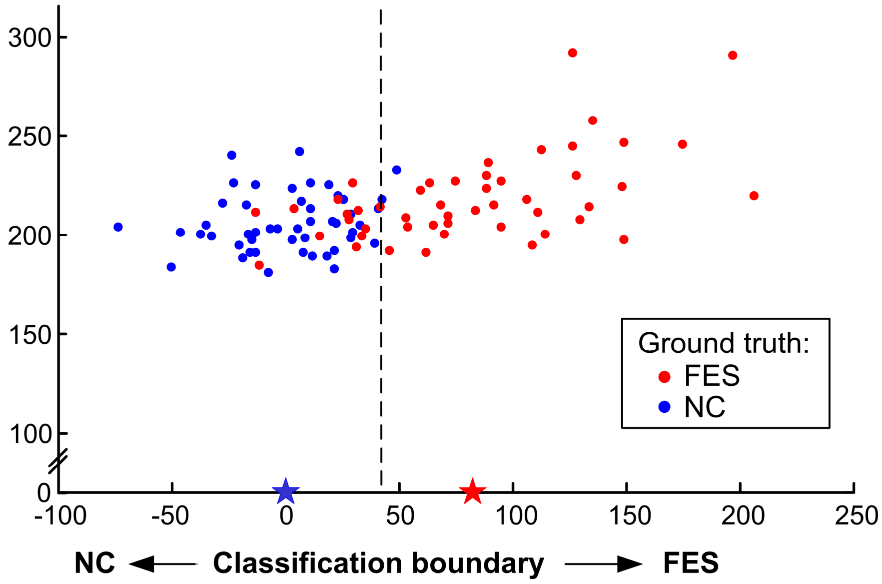

Fig 2. Visualization of the deformation data using the centroid method. The blue star represents the centroid of healthy controls and the red star represents the centroid of patients. Blue dots stand for healthy control (NC) images and red dots stand for images of first-episode schizophrenia patients (FES). Images left from the classification boundary will be classified as NC and images right from the boundary as FES. Nondimensional factors are on the axes.

3 Experiment and results

The classification of images reduced by 2DPCA or pPCA was tested in an experiment with 3-D MRI data of 49 first-episode schizophrenia patients and 49 sex- and age-matched healthy controls. Efficiencies and computational requirements of the classification procedure with various input data and various classification methods are compared using leave-one-out cross validation.

Tab. 1 summarizes the efficiency of classification based on various reduction and classification methods. The classification efficiency is compared for the deformation data, the GM density images and also for the original MRI intensity data. The best results, it means the highest accuracy (80.6%) and sensitivity (71.4%), were achieved in the classification of the deformations using the centroid method. The second best sensitivity was obtained in the classification based on the GM density images and the worst sensitivity in the case of the original MRI intensity images. The table also shows that the centroid method is more appropriate for the classification than the average linkage method because of the low sensitivity of the average linkage classification method for all image data. When the classification efficiency of data without reduction and data reduced by pPCA or 2DPCA is compared, the table proves that in the case of pPCA, selection of all eigenvectors with non-zero eigenvalues causes no loss of information important for the classification. Thus, the classification efficiency of images reduced by pPCA is same as the classification efficiency of data without any reduction. On the other hand, reduction using 2DPCA, which decreases the data variance, leads to the different classification efficiency than the classification of data without any reduction. In the case of the classification of first-episode schizophrenia patients and healthy controls, decrease in the data variance caused by 2DPCA results in the same or better efficiency in comparison to the classification of non-reduced data. However, in the case of our other experiments with data of patients with chronic schizophrenia and healthy controls, data reduction by 2DPCA led to a lower classification efficiency.

Image data	Classification method	Reduction	Accuracy (in %)	Sensitivity (in %)	Specificity (in %)
Deformations	Centroid	No	80.6	71.4	89.8
Deformations	Centroid	pPCA	80.6	71.4	89.8
Deformations	Centroid	2DPCA	80.6	71.4	89.8
Deformations	Average linkage	No	67.3	34.7	100.0
Deformations	Average linkage	pPCA	67.3	34.7	100.0
Deformations	Average linkage	2DPCA	67.3	34.7	100.0
GM density imgs	Centroid	No	64.3	63.3	65.3
GM density imgs	Centroid	pPCA	64.3	63.3	65.3
GM density imgs	Centroid	2DPCA	65.3	63.3	67.3
GM density imgs	Average linkage	No	69.4	49.0	89.8
GM density imgs	Average linkage	pPCA	69.4	49.0	89.8
GM density imgs	Average linkage	2DPCA	69.4	49.0	89.8
Intensity imgs	Centroid	No	61.2	59.2	63.3
Intensity imgs	Centroid	pPCA	61.2	59.2	63.3
Intensity imgs	Centroid	2DPCA	61.2	59.2	63.3
Intensity imgs	Average linkage	No	54.1	18.4	89.8
Intensity imgs	Average linkage	pPCA	54.1	18.4	89.8
Intensity imgs	Average linkage	2DPCA	57.1	24.5	89.8

Tab 1. Efficiency of classification using various input image data, classification and reduction methods.

Tab. 2 shows a comparison of the two reduction methods according to memory requirements of the 3-D deformation data classification. It is evident that the pPCA-based classification is less computationally intensive than the 2DPCA-based classification. The memory requirements of the classification based on the GM density images and the original MRI data are similar to the computational demands of the classification based on the deformations.

Deformation data	Memory requirements (in kB)
Original data	753 897
Data reduced by 2DPCA	54 150
Data reduced by pPCA	38

Tab 2. Memory requirements of classification based on the original and reduced 3-D deformation data.

4 Conclusions

The classification of 3-D MRI data reduced by two modifications of PCA is described here. 2DPCA leads to lower memory requirements than the classification of data without any reduction. However, 2DPCA-based reduction decreases original data variability and therefore causes a certain change of information important for the classification. The second modification of PCA is pPCA, which is based on the covariance matrix of persons. pPCA gives the same classification efficiency as in the case of data with no reduction and also enables computations with the lowest memory requirements. Therefore, pPCA is more appropriate for data reduction than 2DPCA in the case that no loss of original information in data is needed for subsequent data analysis.

The comparison of classification efficiencies on the basis of various input data and classification methods shows that the highest accuracy (80.6%) and sensitivity (71.4%) was achieved in the classification procedure based on the deformation data and the centroid method. The centroid classification method outperforms the average linkage classification method in sensitivity for all image data. Among the image modalities, the deformations are the most appropriate for the classification. The second best efficiency was achieved in the GM density image classification and the worst efficiency in the original MRI intensity data classification.

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