

## Multimedia Appendix 1: PCA

The PCA computation process with mathematical formulas is explained as follows:

An orthonormal basis vector is generated by the PCA. This vector makes it possible to maximize the dispersion of all projected samples. After the preprocessing steps, the  $n$  remaining voxels for each subject are rearranged into a vector form. Let  $X = (x_{ij})_{n \times m}$  be the sample set of these vectors, where  $n$  is the number of samples (patients),  $m$  is the number of features and  $x_{ij}$  represents the  $j^{\text{th}}$  feature value of the  $i^{\text{th}}$  sample, where  $i = 1, 2, \dots, n$  and  $j = 1, 2, \dots, m$ . In this research, some gray-scale features are selected as characteristics of the sample. The chosen gray-scale features are: mean, variance, skewness, kurtosis, energy and entropy. The specific steps of PCA are as follows:

1) Standardize the original data by subtracting all samples from the corresponding feature's mean value.

$$\bar{x}_j = \frac{1}{n} \sum_{i=1}^n x_{ij} \quad (1.1)$$

2) Calculate the covariance matrix  $P = (r_{jk})_{m \times m}$ , where  $r_{jk}$  represents the correlation between the  $j^{\text{th}}$  and  $k^{\text{th}}$  feature.

$$P = \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mm} \end{bmatrix} \quad (1.2)$$

3) Compute the eigenvalue  $\lambda_i$  and the eigenvector  $e_i$  of the covariance matrix  $P$ :

$$\lambda_i e_i = P e_i \quad (1.3)$$

4) Record the resulting eigenvalues in the order of large to small:  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_k$ . Calculate the contribution rate of each principal component.

$$\frac{\lambda_g}{\sum_{g=1}^k \lambda_g} \quad (1.4)$$

The higher the contribution rate, the stronger the information about the original variables contained in the principal component.

5) Transform the original sample matrix  $X$  into a new matrix  $Y = (Y_{ij})_{n \times m_1}$ , where  $i = 1, 2, \dots, n$  and  $j = 1, 2, \dots, m_1$ .

$$Y = X \times [e_1, e_2, \dots, e_{m_1}] \quad (1.5)$$

where  $[e_1, e_2, \dots, e_{m_1}]$  represents a new feature space composed of  $m_1$  feature vectors.  $m_1$  are the principal components extracted by PCA.

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