Ranking Eigenfaces Through Adaboost and Perceptron Ensembles

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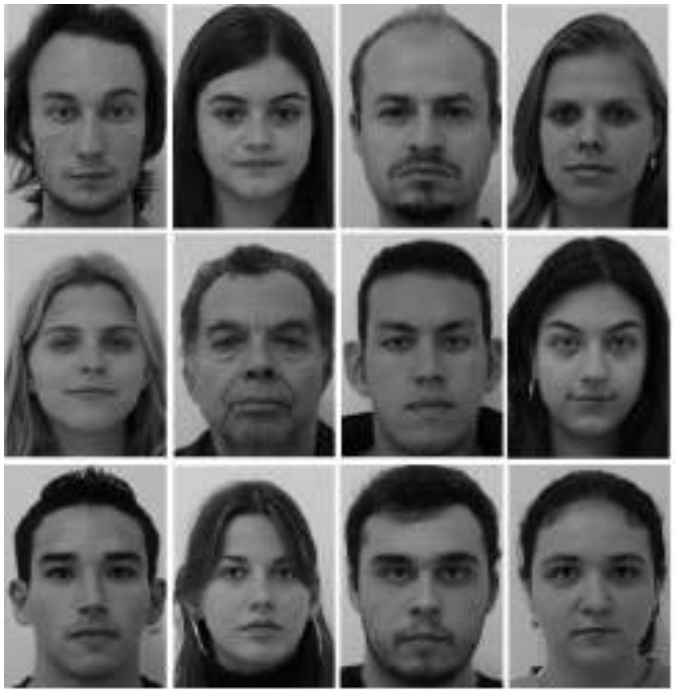
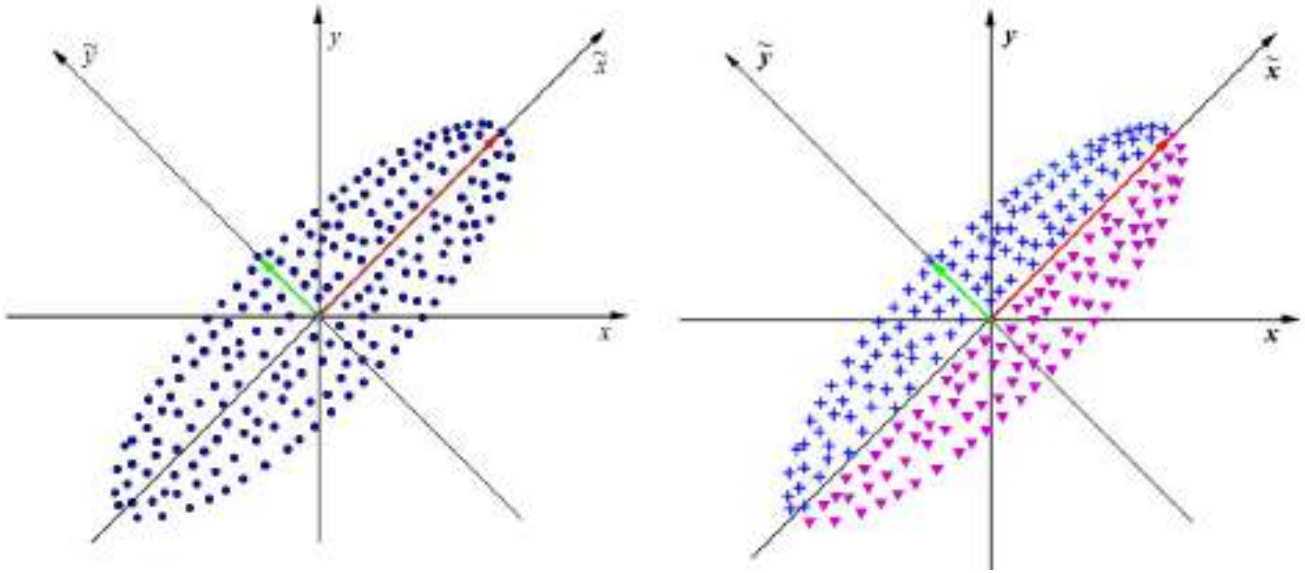
November 6th, 2016

Introduction



- Linear Techniques:PCA



(a) (b)

(a) Scatter plot and PCA directions. (b) The same population but distinguishing patterns plus (+) and triangle (▼).

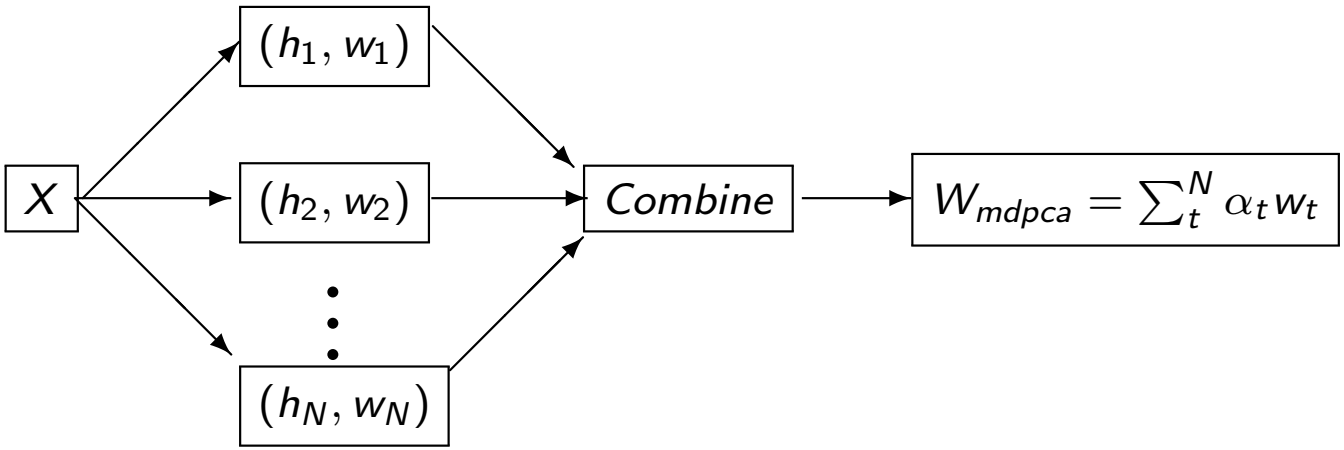
The problem of ranking components obtained by subspace learning techniques is addressed by the discriminant principal components analysis (DPCA) that aims to identify the most discriminant subspaces using weights given by separating hyperplanes [Thomaz and Giraldi, 2010].[1] $\Rightarrow$ Perceptron.

[1] Thomaz, C. E. and Giraldi, G. A. A new ranking method for principal components analysis and its application to face image analysis.Image Vision Comput,2010.

Procedure for DPCA: for Two classes

1: Determine P_{pca}.
2: Form the matrix $\overline{\Theta}$ given by $\overline{\Theta} = (P_{pca})^T \widetilde{\Theta}$, where $\widetilde{\Theta}$ is the centered data matrix $\widetilde{\Theta} = [\widetilde{\mathbf{x}}_1, \widetilde{\mathbf{x}}_2, \cdots, \widetilde{\mathbf{x}}_M]$;.
3: Compute ϕ_{svm}.
4: Sort the discriminant weights such that $|\phi_1| \geq |\phi_2| \geq ... \geq |\phi_{m'}|$.
5: Select the principal components according to the obtained $|\phi_i|$ sequence.

The AdaBoost algorithm belongs to the class of boosting procedures [Zhou, 2012][2] .



SVM ensemble: $y \in \{1, 2, ..., N\}$

[2] Zhi-Hua Zhou.Ensemble Methods: Foundations and Algorithms, 1st edition, 2012.

The Multi-Class DPCA pipeline consists of the following steps:

1. Apply PCA technique for dimensionality reduction in order to eliminate redundancy.
2. Compute a linear perceptron ensemble, based on the "one-against-all" approach.
3. Combine the discriminant weights computed through the separating perceptron hyperplanes using Adaboost as follows [Filisbino et al., 2015][3].
   - $|w_{mdpca}| = |\sum_{t=1}^{N} \alpha_t w_{t,i}|$, where N is number of classes
4. Sort discriminant weights: $|w_{mdpca,1}| \geq |w_{mdpca,2}| \geq \cdots \geq |w_{mdpca,m'}|$
5. Select the principal components according to the obtained $|w_{mdpca,i}|$ sequence.

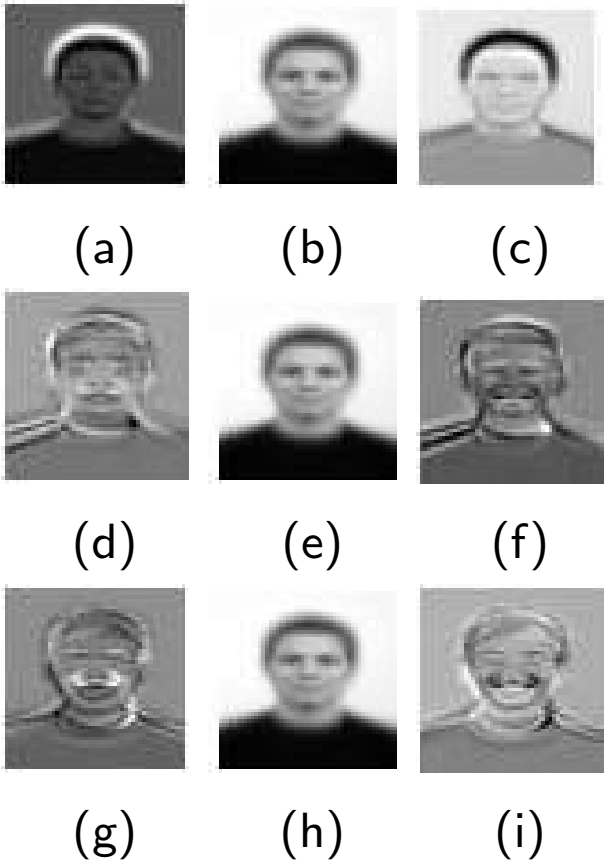
[3] Filisbino, T., Leite, D., Giraldi, G., and Thomaz, C. (2015). Multi-class discriminant analysis based on svm ensembles for ranking principal components. In 36th Ibero-Latin Am. Cong. on Comp. Meth. in Eng. (CILAMCE).

(a) (b) (c) (d) (e)

Images from RaFD database. (a) Sample of neutral class. (b) Image of happiness class. (c) Sample of sad class. (d) Sample of disgust class. (e) Sample of anger class.

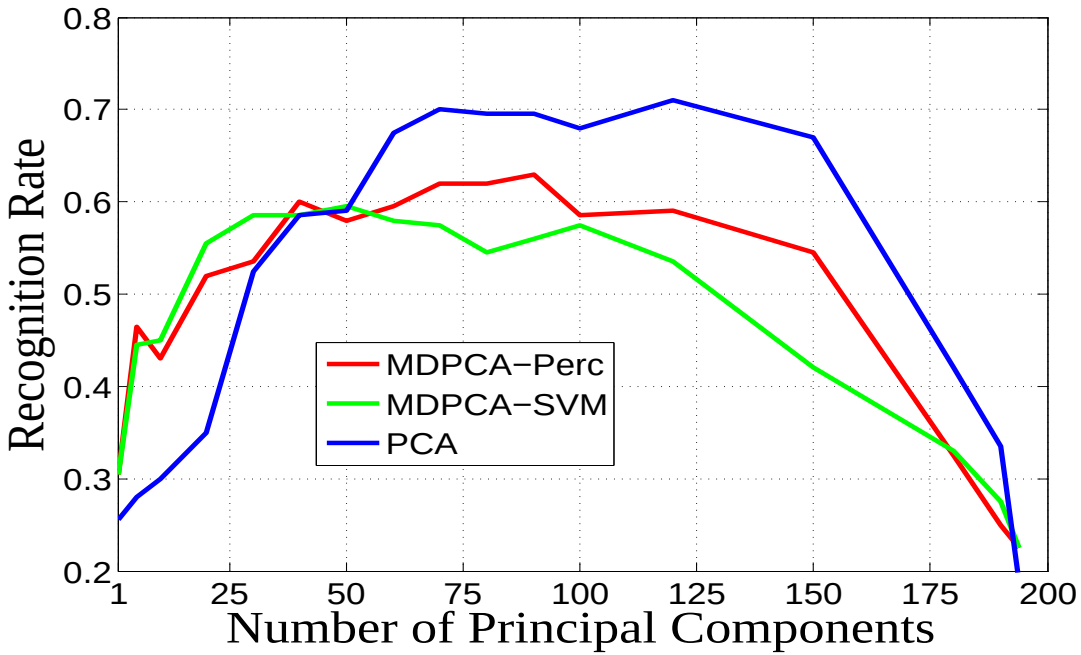
$$I = \widehat{\mathbf{x}} + \beta \cdot \mathbf{p}_i, \tag{1}$$

where $\widehat{\mathbf{x}}$ is the global mean, $\beta \in \{\pm j \cdot \bar{\lambda}^{0.5}, \quad j = 0, \pm 3\}$, and $\bar{\lambda}$ is the average eigenvalue of the total covariance matrix.



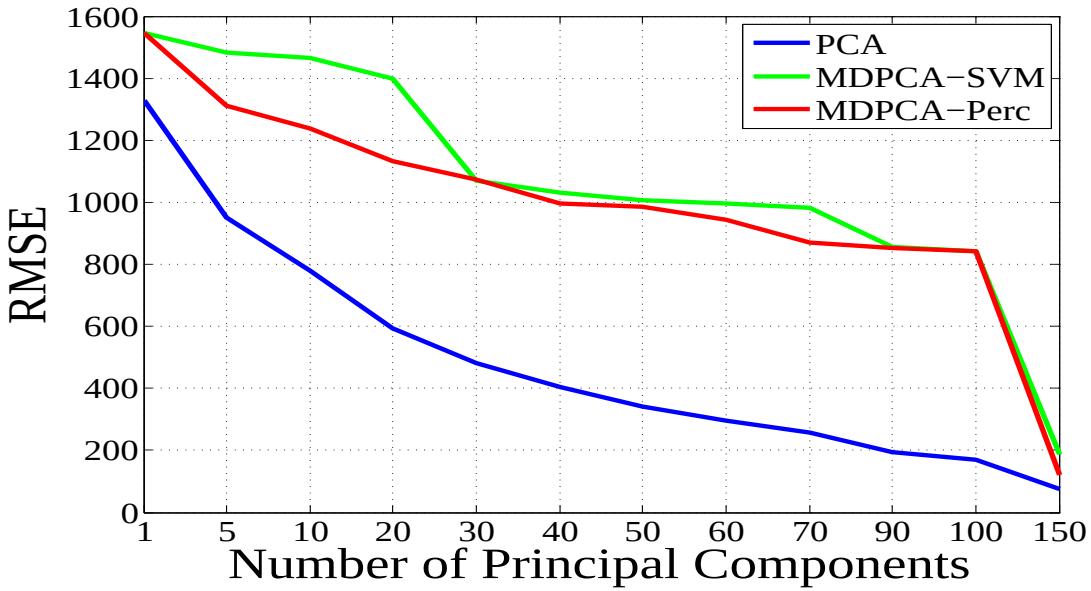
Visualization of the changes described by the principal directions using expression above.(a)-(c) PCA; (d)-(f) MDPCA-Perceptron; (g)-(i) MDPCA-SVM.

$$d_i(\mathbf{x}_r) = \sum_{j=1}^{k} \frac{1}{\lambda_j}(x_{rj} - \widehat{x}_{ij})^2$$

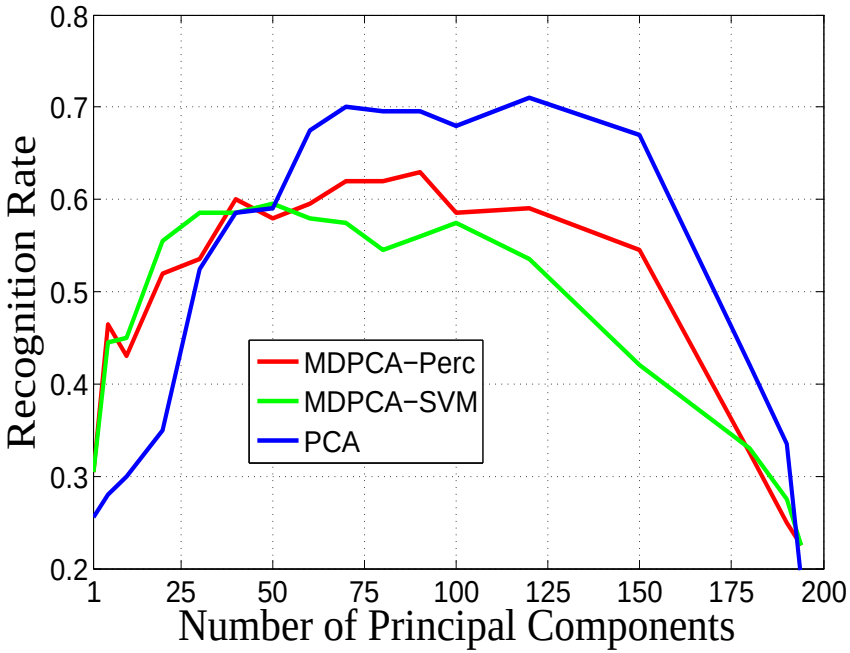


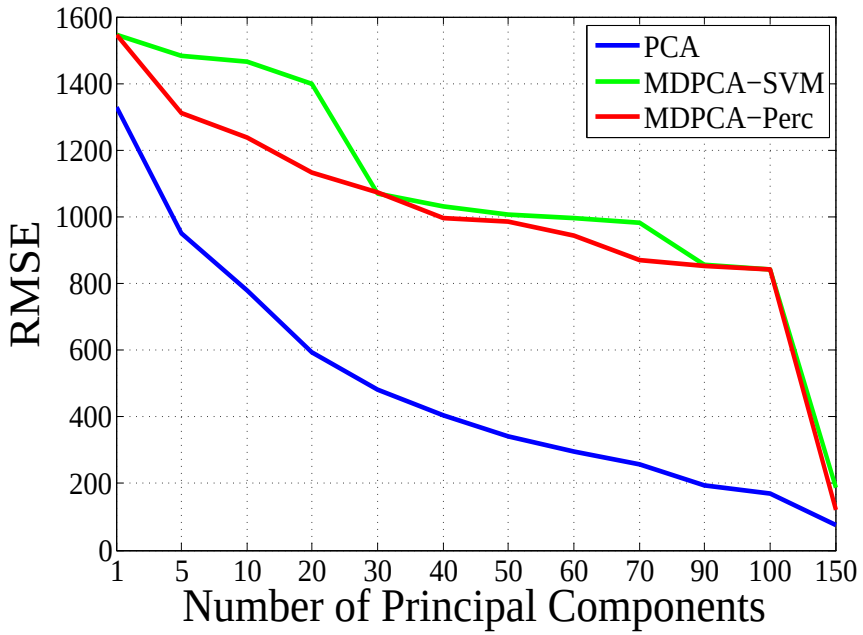
$$RMSE^{I}(k) = \sqrt{\frac{\sum_{i=1}^{N} ||P.I_k^I.P^T x_i - x_i||^2}{N}}, \quad (2)$$

where $I \in \{PCA, MDPCA - Perceptron, MDPCA - SVM\}$, and I_k^I is a truncated identity matrix that keeps the subspace with dimension k that is selected by PCA, MDPCA-Perceptron, and MDPCA-SVM.



In summary,


Recognition Rate
Number of Principal Components
MDPCA−Perc
MDPCA−SVM
PCA
0.8
0.7
0.6
0.5
0.4
0.3
0.2
1
25
50
75
100
125
150
175
200


RMSE
Number of Principal Components
PCA
MDPCA−SVM
MDPCA−Perc
1600
1400
1200
1000
800
600
400
200
0
1
5
10
20
30
40
50
60
70
90
100
150

- This paper proposes an extension of the DPCA technique for multi-class problems, named MDPCA-Perceptron.
- For few components, MDPCA-Perceptron gives competitive recognition rates if compared with the PCA and MDPCA-SVM ones.
- Further work: use Bagging instead of AdaBoost.

Filisbino, T., Leite, D., Giraldi, G., and Thomaz, C. (2015).

Multi-class discriminant analysis based on svm ensembles for ranking principal components.
In *36th Ibero-Latin Am. Cong. on Comp. Meth. in Eng. (CILAMCE)*.

Thomaz, C. E. and Giraldi, G. A. (2010).

A new ranking method for principal components analysis and its application to face image analysis.
Image Vision Comput., 28(6):902–913.

Zhou, Z.-H. (2012).

Ensemble Methods: Foundations and Algorithms.
Chapman & Hall/CRC, 1st edition.

Thanks!

Questions?