PCA VERSUS LDA IN IMPLEMENTING OF NEURAL CLASSIFIERS FOR FACE RECOGNITION

Marian Dorin PÎRLOAGĂ*, Ciprian RĂCUCIU, Emil CRETU**, Marius ROGOBETE***

*Military Technical Academy, Bucharest, Romania, **University Titu Maiorescu, Bucharest, Romania,

Abstract: *This paper propose to better determine people's face recognition methods using images. Using the selection of features principal component analysis and linear discriminant analysis I conducted experiments by implementing two methods called Self Organizing Map classification (SOM and CSOM 1). I tried to get the best recognition rates for different color components, followed by selection of features concatenation. Applications training consisted of images from a database of its own. Analysis was performed by changing a number of 80 to 360 neurons trained with a pitch of 40 to obtain a recognition rate of 100%. Finally I concluded for the best versions of selections for features that the two methods give proposing future research.*

Keywords*: principal component analysis, linear discriminant analysis, Self Organizing Map, number of neurons, the recognition rate.*

1. METHODS OF EXTRACTION AND SELECTION OF FEATURES FROM IMAGES

Extraction and selection characteristics for faces of people in an image are two important stages on the success and performance of the recognition and face detection (fig. 1).

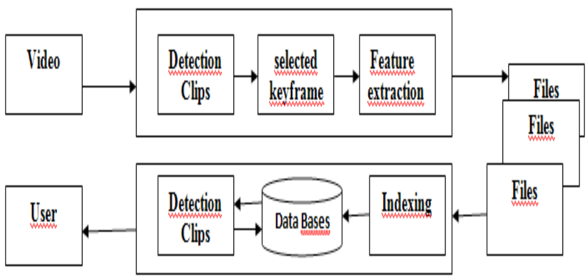

Fig. 1. Extraction and selection of features in an image

A correct implementation of the recognition regions obtained from image segmentation process requires input video representation in a stable form of data analyzed by eliminating redundant information and retaining information for face recognition.

The process of obtaining such a representation of the region of interest is known as the step of description / retrieval features.

Description is directly related to the chosen data structure for representation, against which there is a strong dependence on the developed application.

The possibilities for description of a region is diversified depending on the methods implemented for selection of features:

• characterization of the region contour shape (contour descriptors);
• characterize the region based on its interior (descriptors regional or time);
• topological description of the region of interest (textures);
• morphological description of the region of interest (morphological descriptors).

Choosing a proper description is essential for the success of the shape recognition process. Also, a fundamental principle which oversees construction shape descriptors is their invariance principle to various types of linear or nonlinear transformations applied form of interest. The desired invariance of the set of descriptors used at the starting point, scaling, translation, rotation and reflection.

Practical experience shows that the most important aspect for the recognition of forms is the selection characteristics / properties or descriptors used.

Selection is a process characteristic features data compression and can be equated with a linear or nonlinear transformation of the initial space of n-dimensional observations assumed in a space with fewer dimensions.

The transformation performed conservation information and enables the development of algorithms in real time with efficient algorithms in terms of computation time and memory resources required only small spaces.

If a single class of forms, selection of characteristics is considered optimal if the dimensionality reduction achieved with the original information preservation majority.

If there are several classes of shapes, selection efficiency characteristics is given in particular the possibility of separability of classes, which depends mostly on the distribution of classes and selected classifier.

As a reference in this work we have demonstrated in various [1-7], the performance of classifiers, and as a measure of the effectiveness of selected features can be considered the possibility of their error.

Note that most transformations used to select characteristics are linear but non-linear transformations can be used even if they are difficult to implement

They can provide a higher efficiency expressing the dependence of the real forms observed raw data extracted and selected characteristics of those forms.

2. METHODS FOR THE SELECTION OF CHARACTERISTICS

Size space features large extent influence the efficiency and performance of classification algorithms. Thus, a number of classification algorithms effective in small spaces become impractical in larger spaces.

Therefore we sought to implement changes to prioritize the importance of characteristics and allow transformed space thus reducing its size by removing the least significant data, while retaining the essential information for classification.

In this paper we experienced select those features that contain the greatest amount of information on that form.

We presented the results of selection methods that provide an application characteristics in the area of military interest through proven performance on recognition rate.

2.1. Principal components analysis (PCA). Principal components analysis (PCA Principal Component Analysis) is a standard method of data analysis that enables the detection of the most prominent trends in a set of data.

PCA reduces the number of variables that the size of a data set.

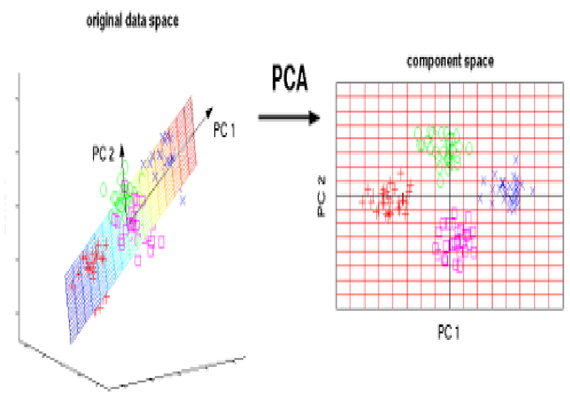

Fig. 2. Version for representation using PCA projection

The picture shows a network in a two-dimensional subspace. PCA is used to view the data by reducing the dimensionality of the data.

The three variables are reduced to a smaller number, two new variables called principal components (PC). Using PCA, we can identify two-dimensional plane which best describes the varied data.

Space using PCA rotating selection of original data that the axes of the new terms have the largest variation of data in a certain direction. Axes and new variables are called principal components are ordered and variation.

The first component, PC 1 is the direction with the largest variance of the data. PC Division 2 is the largest variance that remained after the first orthogonal component. The representation allows to obtain the required number of components that covers a space and the desired amount of variance.

Let X be a space ^{n} cloud data. The main components of this set are the directions along which ^{n} elongation is the most significant cloud. Knowing these directions can serve both purposes of classification and to determine the most important characteristics of point cloud analysis.

Most transformations used to select characteristics are linear, nonlinear transformations while having a higher complexity, are more difficult to implement, but may have a higher efficiency, better expressing the dependence of the forms observed raw data observed characteristics selected these forms [11].

Karhunen-Loeve transform is a linear method for selecting features. Let X be an n-dimensional random vector. Looking for an orthogonal transformation enabling optimal representation of the vector X with respect to the minimum mean square error criterion. Projecting cloud directions given by its main components, the immediate effect is a compression of the information contained in that crowd.

According to reference [8], identifying the main components of cloud data analysis reduces to determining the values of vectors and eigenvalues of the matrix analyzed crowd dispersal.

Linear nature of the standard PCA method, performed by linear projection data analyzed components or main directions suppose but a number of major shortcomings in the processing of input data. Thus, they developed a series of nonlinear generalizations of the classical variant, an example being Kernel PCA algorithm presented in reference [9].

2.2. Linear discriminant analysis (LDA). Linear discriminant analysis (Linear Discriminant Analysis, LDA), as the main component analysis is a statistical method for selecting the characteristics.

Unlike PCA, in which case projection for the purposes of seeking to maximize total covariance matrix, here is seeking a projection in terms of maximizing the covariance matrix of the covariance matrix interclase and minimizing the accumulated inside other classes.

LDA tries to find the best projection direction vectors belonging to different classes drive are best separated.

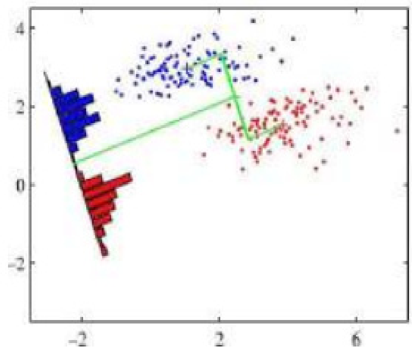

Fig. 3. Variant of projection for representation using LDA

Presentation of the algorithm and the applications that have been described in [10]. There were also tested for applications of LDA transform two-dimensional vector and pixel classification of soil and vegetation images using LDA transformed.

3. EXPERIMENTAL RESULTS

Through various experiments we tried validating theoretical interest arising from the comparative study of methods for selecting features using PCA and LDA methods for classification as SOM and CSOM1 80-400 neurons in neural networks trained with a step 40.

The database contains 556 personal photos of 46 subjects who were asked to stimulate different physiognomic states, against a pale and normal lighting. It was shown in [6].

The main criterion for validating the importance of selection methods analyzed is the performances in the subsequent classification / recognition and entry forms as classifier we used a trained neural network.

Experiments to determine the most effective method of selection.

The experiment consisted in selecting 4 of the 46 subjects of the database in 7 test images / 7 training images.

The 7 images drive and 7 test images were chosen at random, and are analyzed in terms of the form RGB color spaces, C1, C1C2 and C1C2C3.

The original images were reduced in size by using the Paint for 90/120 pixels.

Fig. 4. Images of individual photographing subjects in the database used for testing / training

Considering the fact that a large percentage of an image in the database is the background, I applied a face detection algorithm discovered by prof. Neagoe presented in reference [9], implemented in Matlab.

Methods for selecting features that we used PCA and LDA are and classifiers that I used CSOM and SOM. They are presented in the paper [9,11,13,14].

Concurrent Self Organizing Maps CSOM method was discovered by Neagoe and Ropot and presented in [13].

For the selection of features with PCA we retained 100 features for each color, and then the resulting concatenated vectors of the three colors 100 features 3x = 300 features being used in classification.

LDA for the selection of characteristics we used the same conditions as in [9].

We imposed the following parameters CSOM networks and SOM: stop condition after 400 epochs of training; neighborhood radius decreases by 1 at every age; for the first 200 periods, and for the next 200 era.

The results obtained using images resulting from the scan, which have been reduced in size 90/120 interpolated pixels.

Table 1. Results using the database 7i / 7t, the recognition rate for PCA method C1C2C3 components [%] feature selection process followed by concatenation

Method	Features selection	Number of neurons									
		40	80	120	160	200	240	280	320	360	400
SOM	PCA	23.55	37.42	43.22	55.16	58.19	64.70	**67.99**	63.90	**67.99**	62.22
	LDA	78.34	93.56	89.14	88.25	91.37	98.23	**100**	**100**	**100**	**100**
CSOM 1	PCA	46.22	29.32	47.16	46.12	6302	61.38	72.88	71.15	72.99	**74.93**
	LDA	**100**	67.52	69.91	75.23	87.38	89.29	96.62	97.44	99.34	97.39

Table 2. Results using the database 7i / 7t, the recognition rate for PCA method C1C2 components [%] feature selection process followed by concatenation

Method	Features selection	Number of neurons									
		40	80	120	160	200	240	280	320	360	400
SOM	PCA	26.06	36.58	43.35	51.62	61.40	61.02	**67.7**	62.90	61.02	62.15
	LDA	79.44	98.24	94.85	96.36	96.36	98.61	**100**	**98.61**	**100**	**100**
CSOM 1	PCA	45.23	33.58	45.98	46.36	57.64	60.64	64.40	66.66	70.79	**71.55**
	LDA	**100**	91.10	92.22	89.05	95.23	94.10	97.86	97.4	98.24	98.24

Table 3. Results using the database 7i / 7 t, the recognition rate for PCA method for component C1 [%] feature selection process followed by concatenation

Method	Features selection	Number of neurons									
		40	80	120	160	200	240	280	320	360	400
SOM	PCA	27.33	37.43	46.68	49.51	58.76	63.72	64.16	**69.70**	60.44	59.98
	LDA	65.48	95.22	99.01	**100**	99.61	100	**100**	**100**	**100**	**100**
CSOM 1	PCA	3947	33.73	43.12	46.99	57.58	59.66	66.42	67.45	**70.13**	69.15
	LDA	**100**	97.66	97.32	97.99	**98.40**	99.26	**100**	**100**	**100**	**100**

Table 4. Results using the database 7i / 7 t, the recognition rate for RGB component PCA method [%], using the classifier CSOM

Method	Features selection	Number of neurons									
		40	80	120	160	200	240	280	320	360	400
CSOM 1	PCA	46.73	35.86	48.32	48.19	60.33	63.36	64.95	67.45	**71.54**	**71.54**
	LDA	78.53	70.23	57.58	67.95	75.19	75.50	78.40	79.37	80.56	**82.86**

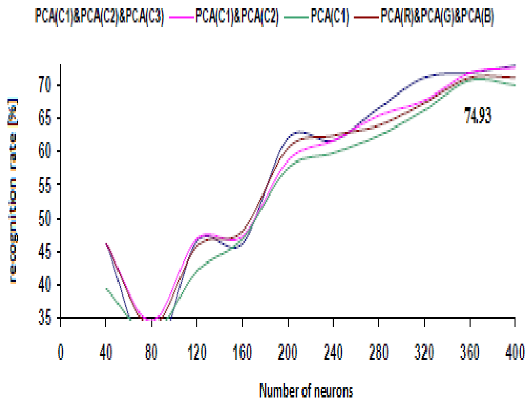

Fig. 5. Graphical representation database 7i / 7t, the recognition rate using PCA, CSOM 1 and fusion of features

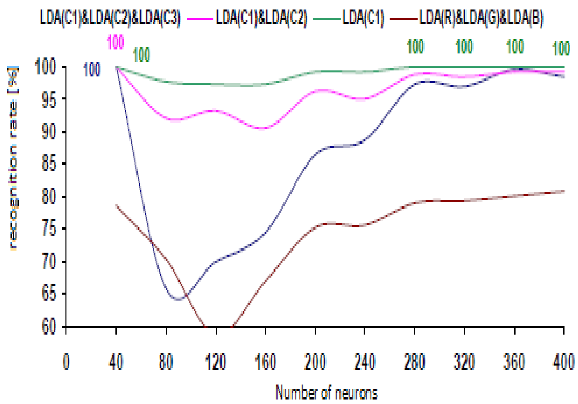

Fig. 6. Graphical representation database 7i / 7t, the recognition rate using LDA, CSOM1 1 and fusion of features

The final experiment conducted training entire database with 46 individual photos surprised in normal subjects and testing their recognition in one of the screen shoot made of crowds Agomer sites and contains 3 subjects in the first database.

The same conditions were used as in the previous experiment to give the following results:

Table 6. Results using the database 46i / 1t, the recognition rate for RGB component PCA method [%], using the classifier CSOM 1

Method	Features selection	Number of neurons									
		40	80	120	160	200	240	280	320	360	400
CSOM 1	PCA	48.43	37.36	50.22	50.23	62.45	65.34	66.56	69.43	**73.14**	**73.14**
	LDA	80.52	72.21	59.60	69.80	77.10	77.52	80.43	81.40	82.59	**84.88**

Table 7. Results from the database 46 and / 1t, the recognition rate for PCA method C1C2C3 components [%] feature selection process followed by concatenation

Method	Features selection	Number of neurons									
		40	80	120	160	200	240	280	320	360	400
SOM	PCA	25.43	39.44	45.45	57.56	60.75	66.71	**69.90**	65.32	**69.90**	64.12
	LDA	80.30	95.50	91.16	90.67	93.98	99.09	**100**	**100**	**100**	**100**
CSOM 1	PCA	48.54	31.85	49.16	48.87	65.00	63.48	74.56	73.54	74.99	**76.93**
	LDA	**100**	69.85	71.90	77.32	89.87	91.09	98.54	99.45	**100**	**100**

4. CONCLUSIONS

The final results, involving the entire database showed that the best solution is to implement color components C1C2C3 [%] selection process followed by concatenation of features offered by the SOM method of classification and feature selection using LDA.

If CSOM1 using the same selection method features a 100% recognition rate results from the training of 360 neurons. Regarding the recognition rate for RGB component PCA method [%], using classifier Csömöri 1 all features using LDA selection proved with the best rate of 84.88% recognition for 400 neurons involved. In this case the selection of features using PCA smaller achieve results that a recognition rate of only 73.14% from 360 neurons involved. Looking processing time this is tens of minutes in both cases.

Future opportunities for the development of research is emerging in the real-time image processing. Therefore I will follow different implementations other than Matlab, which carries a large number of computing that require processing time and high computing power.

We will continue to implement the application using Python modules offered by Accord.Net The framework provided by OpenCV. Experiments show actual processing time of about 400 ms. using this method, compared to tens of minutes offered by The experimental using Matlab.

Relevant is that the military applications of detection and / or individuals face recognition that local Trackbacks detection, suspicious persons or prohibited in various sports events, the data recorded at the border of the fugitives, etc., are needed both to obtain a 100% recognition rate and the processing of a real-time / signaling themselves- all in order not to lose the operating time.

Aknowledgement:
This paper has been financially supported within the project entitled "Horizon 2020 - Doctoral and Postdoctoral Studies: Promoting the National Interest through Excellence, Competitiveness and Responsibility in the Field of Romanian Fundamental and Applied Economic Research", contract number POSDRU/159/1.5/S/140106. This project is co-financed by European Social Fund through Sectoral Operational Programme for Human Resources Development 2007-2013. Investing in people!"

BIBLIOGRAPHY

1. Pîrloagă, M.D., Mihăilescu, M.I. *Considerations on implementation of biometrics technologies in military surveillance system.* Megabyte Article code: MGBT-2011-2-CS-MDP-350, ISSN:1841-7361, nr. 12/2011.
2. Pîrloagă, M.D., Mihăilescu, M.I.. *Comparative Study on Optoelectronic Tracking Models which can be used in Biometrics.* ISI Web of Science. index of conference 18965,ISBN 978-1-4673-2573-8, IEEE catalog number CFP1241J-PRT,pag.107-111.
3. Pîrloagă, M.D., Mihăilescu, M.I. *Optimisation strategies for data collections used in evaluating dynamic signature authentication system.* Revista ISI Web of Science.index of conference 18965,ISBN 978-1-4673-2573-8,IEEE catalog number CFP1241J-PRT,pag.343-349.
4. Pîrloagă, M.D., Mihăilescu, M.I.. *Contribution to the modelling of a communication channel by RB*. DAAAM International Scientific Book 2011. Vol. 10 EBSCO bibliographic database ISSN 1726-9687, ISBN 978-3-901509-84-1, Editor: B. Katalinic, Publisher DAAAM International Vienna, Vienna.
5. Pîrloagă, M.D., Mihăilescu, M.I. *A new framework for biometric face recognition using visual cryptography*" - DAAAM International Scientific Book 2011. Vol. 10 EBSCO bibliographic database ISSN 1726-9687, ISBN 978-3-901509-84-1, Editor: B. Katalinic, hard cover, Publisher DAAAM International Vienna.
6. Pîrloagă, M.D., Apostol C.G., Rogobete, M.. *Optimizing image classification using a neural network*". The 23th International Scientific Conference NAV-MAR–EDU 2013. Naval Academy, Constanta.
7. Pîrloagă, M.D.. *Implementing a real-time recognition of the person using scanning chaotic.* The Strategies XXI Conference The complex and dynamic nature of the security environment.Carol I Defense University, Centre for Defence and Security Strategic studies 21-22 nov. 2013.
8. Pîrloagă, M.D., Răcuciu, C., Cretu, E..*Optimization of biometric technologies for military applications using face recognition*. Proc of Carol I. Defence University, 2014.
9. Domany, E.. *Models of neural networks*, Adisson-Wesley Publishing Co., 1995
10. Bishop, C.. *Neural Networks for Pattern Recognition*, Oxford Press London, 1995.
11. Neagoe, V.E., Mugioiu, A.C.. *A fully neural approach to color facial image recognition. Proc. of the World Automation Congress. 2008 (WAC2008), International Symposium on Soft Computing in Industry.*
12. Yambor W.S., A*nalysis of PCA-Based and Fisher Discriminant-Based Image Recognition Algorithm.* Technical Report CS-00-103,Computer Science Department. Colorado State University, July 2000.
12. http://www.cis.hut.fi/projects/somtoolbox/ Available: ianuary 2015.
13. Neagoe, V.E., Ropot, A.. *Concurrent Self-Organizing Maps for Pattern Classification.* Proc. of First IEEE International Conference on Cognitive Informatics. ICCI 2002, 19-20 August 2002, Calgary, Alberta, Canada, ISBN 0-7695-1726-9, pp. 304-312.
14. Kohonen, T.. *Self-Organization and Associative Memory.* ISBN: 978-3-540-51387-2, 1989.
15. Andrienko, N.,Andrienko, S., Bremm,T., Schreck, T., Landesberger , V., Bak ,P., Keim, D.. *Space-in-Time and Time-in-Space Self-Organizing Maps for Exploring Spatiotemporal Pattern.* The Eurographics Association and Blackwell Publishing Ltd., Issue Computer Graphics Forum,Volume 29, Issue 3, pages 913–922, June 2010.