Face recognition using Lattice Independent Component Analysis and Extreme Learning Machine

Ion Marqués and Manuel Graña

Computational Intelligence Group, University of the Basque Country

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eman ta zabal zazu

Universidad del País Vasco

Euskal Herriko Unibertsitatea

Outline

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- Classic approach to face recognition: Let's see if I can improve a 99.1% to a 99.2% over a classic database like ORL or Yalefaces. This databases are typically **small, balanced and uniform.**
- Our point of view: Real data bases can be **huge**, with **unbalanced** subject-to-class ratio and contaning photos taken under **diverse** condictions.

Research question

- Lets take some "ugly" databases.

1. Can Lattice Independent Component Analysis (LICA), as a feature extraction method prior to ELM classfication, outperform classic extraction algorithms?
2. Can ELMs outperform state-of-the art classifiers in such experimental environment?

Outline

Classic feature extraction methods

- Principal Component Analysis (PCA)
- Linear Discriminant Analysis (LDA)
- Independent Component Analysis (ICA):
  - Mean-field ICA, ICA Infomax, ICA Molgedey & Schuster.

Lattice Independent Component Analysis

- Generative model where the source matrix is composed of endmembers which define a convex region covering the measured data (Strongly Lattice Independent vectors).

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1. Use an Endmember Induction Algorithm (EIA) to induce from the data a set of Strongly Lattice Independent vectors.
2. Apply least square estimation to project the data.

- The EIA has tolerance parameter α controlling the amount of endmembers detected.

Outline

Classic classifiers

- Random Forest
- Suport Vector Machine (SVM)
- Feed-forward single-layer neural networks:
  - Resilient backpropagation.
  - Scaled conjugate gradient backpropagation.

- We have tried basic ELM and ELM with ridge regression. Basic ELM's output weight calculation is as follows:

$$\boldsymbol{\beta} = (\boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{H})^{-1}\boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{T}$$

- Ridge regression: Optionally, we can add a ridge parameter $1/\lambda$ to the diagonal of $(\boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{H})$, it stabilizes the solution. Thus, the calculation of the output weights $\boldsymbol{\beta}$ is:

$$\boldsymbol{\beta} = \left(\frac{\boldsymbol{I}}{\lambda} + \boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{H}\right)^{-1}\boldsymbol{H}^{\boldsymbol{T}}\boldsymbol{T}, \tag{1}$$

where $\boldsymbol{I}$ is an identity matrix the same size as $\boldsymbol{H}$.

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Face database

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1. We chose frontal and mildly rotated images - with a rotation of 15 ,22.5 and 45 degrees:

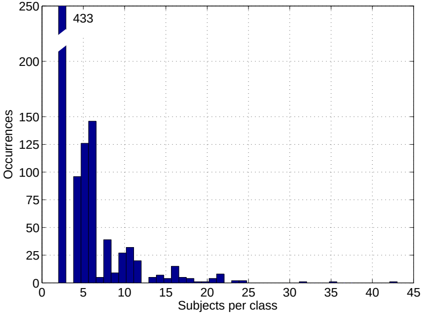
2. We perform face detection: Scilab's SIVP + size discrimination + color test. 99.65% face detection success rate.
3. Scale up/down faces to 100x100 pixels and convert to grayscale using $Gr = 0.85 \cdot R + 0.10 \cdot G + 0.05 \cdot B$ formula.

Face database

- We made 4 subsets:

	DB 1	DB 2	DB 3	DB 4
Number of samples	5169	3249	832	347
Number of classes	994	635	265	79
Mean (samples per class)	4.3924	3.1396	5.2835	5.2002
Standard deviation (samples per class)	5.8560	3.4498	4.9904	4.5012
Median (samples per class)	2	2	4	4
Mode (samples per class)	2	2	2	2

- Highly unbalanced databases, for example DB1:



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Experimental Results using ELM.

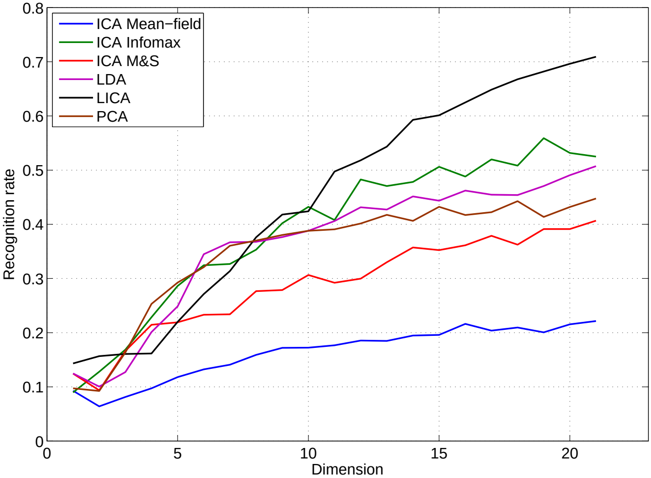

Figure: Recognition rate on DB 4 (347 subjects).

Experimental Results using ELM.

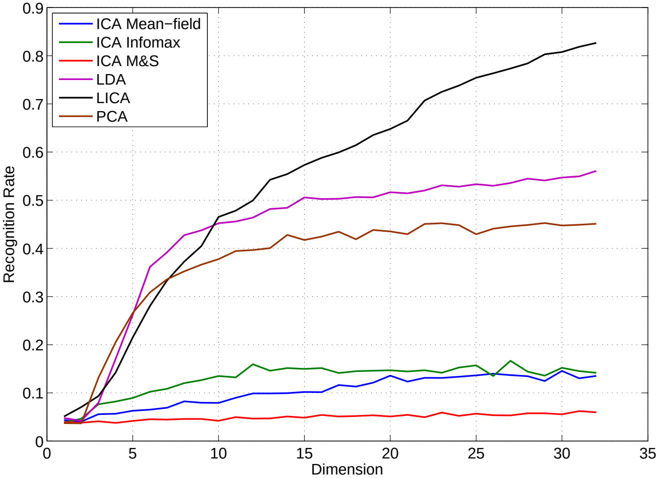

Figure: Recognition rate on DB 3 (832 subjects).

Experimental Results using ELM.

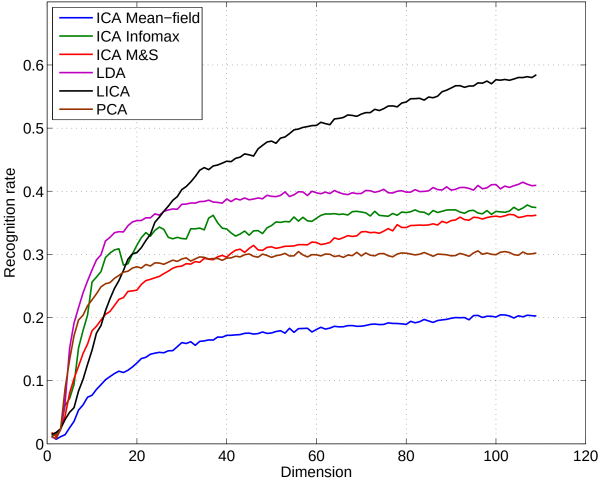

Figure: Recognition rate on DB 2 (3249 subjects).

Experimental Results using ELM.

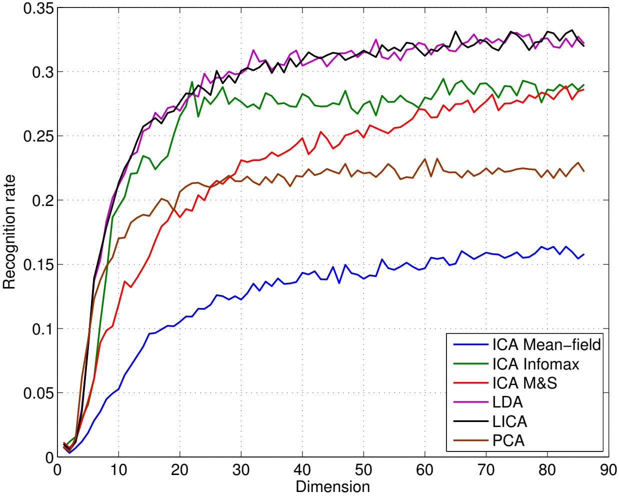

Figure: Recognition rate on DB 1 (5169 subjects).

Experimental Results. Classifier comparison.

	DB 4	DB 3
ELM	0.7093 (0.0385)	**0.8782 (0.0199)**
ELM-FM	**0.9035 (0.0237)**	0.8721 (0.0153)
Random Forest	0.7719 (0.0100)	0.7506 (0.0489)
$\nu - \mathrm{SVM}$	0.8713 (0.0012)	0.8509 (0.0334)
FFNN RPROP	0.8494 (0.0217)	0.7800 (0.0201)
FFNN SCG	0.8692 (0.0198)	0.8166 (0.0244)
	DB 2	**DB 1**
ELM	**0.5834 (0.0126)**	0.4735 (0.0061)
ELM-FM	**0.5834 (0.0143)**	**0.4830 (0.0056)**
Random Forest	0.3457 (0.0135)	0.2431 (0.0126)
$\nu - \mathrm{SVM}$	0.3572 (0.0148)	0.2111 (0.0094)
FFNN RPROP	0.1448 (0.0084)	0.3719 (0.0228)
FFNN SCG	0.1205 (0.0024)	0.2110 (0.0338)

Table: Average testing accuracy (variance) for 4 FERET database subsets on features computed by the LICA feature extraction algorithm.

Outline

Discussion.

- LICA is a better feature extraction algorithm for face recognition when we use big databases with high subject to class ratio variability.

Discussion.

- The joint use of LICA and ELM has retrieved the best recognition results. We can suggest that Lattice-based Endember Induction Algorithms could be best fitted to work with ELMs than other statistical tools (PCA, LDA) or independent component extraction algorithms (ICA Infomax, ICA M&S, Mean-field ICA).

Discussion.

- ELM and ELM-FM are the most robust methods for large databases with high class-variation induced noise. When the database size is increased, ELM show an improvement of 124% and 95% over the results of $\nu - \mathrm{SVM}$ and Random Forest respectively. FFNNs with standard learning algorithms show worse performance than the rest of the classifiers.

Future work.

- The composition of LICA feature extraction and ELM classification show promising results in the domain of face recognition.

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- The composition of LICA feature extraction and ELM classification show promising results in the domain of face recognition.
- We think that it would be interesting to explore further the interplay between Lattice Computing-based feature extraction methods and Extreme Learning Machines.

Thank you for your attention.

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