Experiments on Lattice Independent Component Analysis for Face Recognition

Ion Marqués Manuel Graña

Computational Intelligence Group, Universidad del Pais Vasco

IWINAC'11

Outline

Lattice Independent Component Analysis

Experimental Results

Linear Mixing Model (LMM).

Linear Mixing Model (LMM) basic equation:

$$\mathbf{y} = \sum_{i=1}^{M} a_i \mathbf{s}_i + \mathbf{w} \longrightarrow \mathbf{Y} = \mathbf{S}\mathbf{A} + \mathbf{w}$$

- $\mathbf{y}$ is the d-dimension measured vector.
- $\mathbf{S}$ is the $d \times M$ matrix whose columns are the d-dimension endmembers $\mathbf{s}_i, i = 1, .., M,$.
- $\mathbf{a}$ is the M-dimension abundance vector.
- $\mathbf{w}$ is the d-dimension additive observation noise vector.

Lattice Independent Component Analysis (LICA).

1. Use an **Endmember Induction Algorithm (EIA)** to induce from the data a set of Strongly Lattice Independent vectors.
2. Apply the Full Constrained Least Squares estimation to obtain the **abundance matrix** according to the conditions for LMM.

Definition

Strong Lattice Independence

- Abundance coefficient non-negative - negative contribution is physically impossible.
- Fully additive: $\sum_{i=1}^{M} a_i = 1$. Consequently, $a_i \leq 1, i = 1, .., M$.
- *In other words:* The convex polytope defined by the endmembers covers *all* the data points.

Advantages of LICA.

- We are **not imposing statistical assumptions** to find the sources.
- The algorithm is **one-pass** and **very fast** because it only uses lattice operators and addition.
- It is **unsupervised** and **incremental**.
- It can be tuned to detect the number of endmembers by adjusting a noise-filtering related parameter.

Fact

When $M \ll d$ the computation of the abundance coefficients can be interpreted as a ***dimension reduction transformation****, or a* ***feature extraction process****.*

LICA for Face Recognition: Setting.

How we apply LICA for the face recognition problem?:

$$\mathbf{y} = \sum_{i=1}^{M} a_i \mathbf{s}_i + \mathbf{w} \longrightarrow \mathbf{Y} = \mathbf{SA} + \mathbf{w}$$

- Measured vector matrix $\mathbf{Y} \longrightarrow$ Face images in the form of column vectors $Y = \{\mathbf{y}_j; j = 1, \ldots, N\} \in \mathbb{R}^{n \times N}$
- Induced SLI vectors (endmembers) $\mathbf{S} \longrightarrow$ Face images which define the convex polytope covering the data.
- Abundance matrix $\mathbf{A} \longrightarrow$ Obtained by $\mathbf{A} = \mathbf{S}^{\dagger}\mathbf{Y}^{T}$, where $\dagger$ is the pseudo-inverse.

LICA for Face Recognition: Algorithm

1. Build training face image matrix X_{TR} and testing matrix X_{TE}.
2. Data preprocessing, two options: Perform PCA over X or not. We obtain T.
3. Obtain k endmembers $E = \{\mathbf{e}_j; j = 1, \ldots, k\}$ using an EIA over T. Number k depends on α value.
4. Unmix X_{TR} and X_{TE} by doing $Y_{TR} = E^{\#} X_{TR}^T$ and $Y_{TE} = E^{\#} X_{TE}^T$.
5. Nearest Neighbour (1-NN) classification.

Induced Endmembers example.

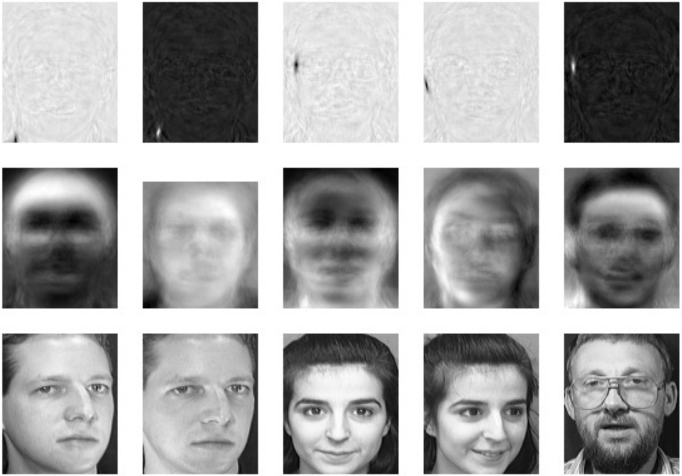

Figure: An instance of the first 5 eigenfaces (PCA), independent components (ICA) and endmembers (LICA)

Research questions.

- In the pattern recognition domain, can we effectively see Endmember Induction Algorithms and Lattice Independent Component Analysis as feature extraction and dimension reduction techniques?
- Is LICA a valid dimension reduction and feature extraction algorithm for the face recognition problem?

Used databases.

We have used two well known databases:

	ORL database	Yalefaces
Number of subjects	40	15
Images per subject	10	11
Total images	400	165
Angle	Frontal*	Frontal
Variations	*small head pose and sight changes	Illumination, expression, glasses

Results (I).

Method	prep. data	ORL		Yalefaces original		Yalefaces normalized	
		Acc.	Dim.	Acc.	Dim.	Acc.	Dim.
PCA	-	0.94	25	0.70	25	0.70	27
ICA	PCA	0.86	30	0.76	26	0.80	27
LICA	PCA	0.87	24	0.73	10	0.76	30
LICA	-	0.91	15			0.78	30

Table: Face recognition results.

Results (II).

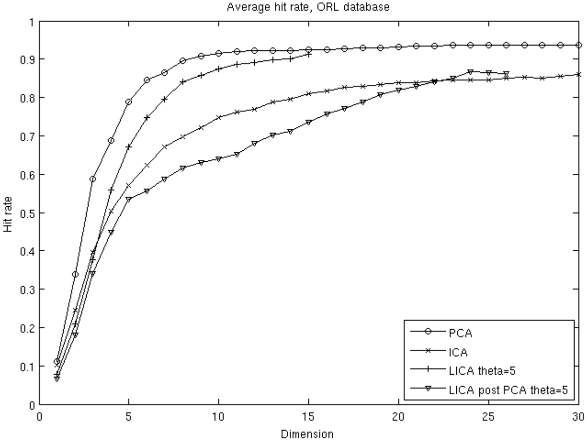

Figure: Plots of accuracy versus dimension on the ORL database

Results (III).

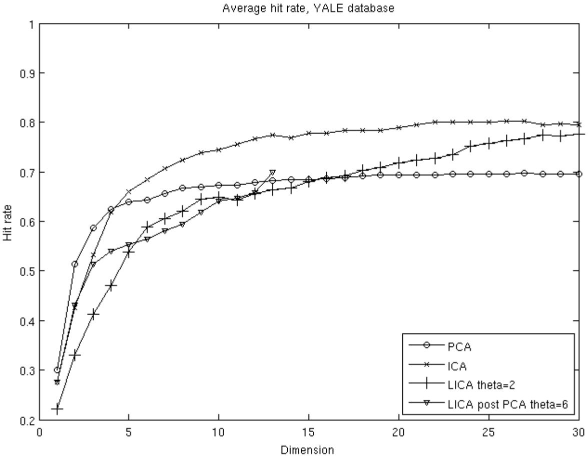

Figure: Plots of accuracy versus dimension on the Yalefaces database

Results (IV).

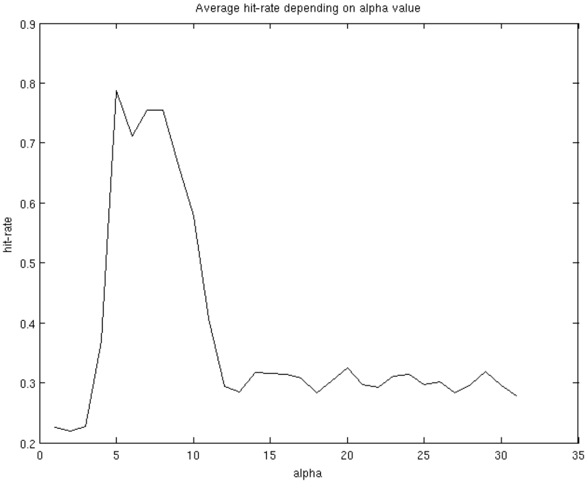

Figure: Accuracy of LICA on the Yalefaces database for different α values.

Results (V).

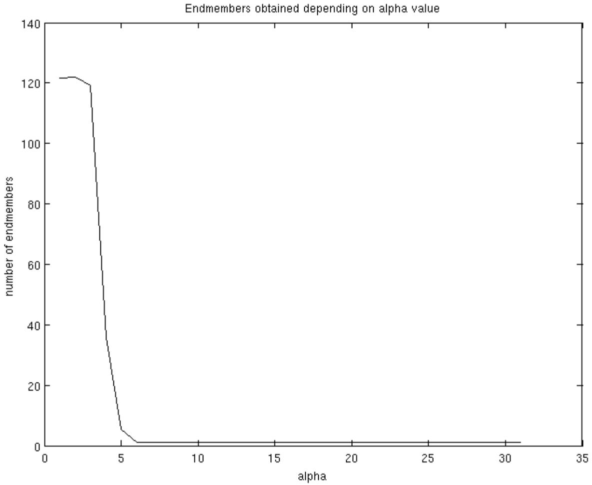

Figure: Number of endmembers retrieved by LICA depending on α.

Conclusions.

- LICA features **perform comparable** to both linear feature extraction algorithms (ICA and PCA).
- This results open a **new computational approach to pattern recognition**, specially biometric identification problems.
- Issues popped:
  - Uncertainty about the amount of endmembers found and therefore the high variance of recognition rates.

Future work.

- Confirm obtained results performing this same experiment over more complex and/or unbalanced databases like FERET. [Done with good results, article pending approval]
- Combine the non-linear algorithm LICA with other well known statistical tools like PCA, LDA, and other state-of-the art face recognition approaches.
- Work on Lattice Theory mathematical foundations in order to apply energy function-like methods to Lattice Computing implementations that may allow more robust endmember induction.
- Test LICA's capabilities of dealing with face recognition well known problems: Illumination, pose, occlusion, etcetera.

Other recent applications of LICA.

- Functional Magnetic Resonance (fMRI) imaging:
  - Graña, M.; Manhaes-Savio, A.; Garcia-Sebastián, M. & Fernandez, E., *A Lattice Computing approach for On-line fMRI analysis,* **Image and Vision Computing**, 2010, 28, 1155-1161
  - Graña, M.; Chyzhyk, D.; Garcia-Sebastián, M. & Hernández, C., *Lattice independent component analysis for functional magnetic resonance imaging*, **Information Sciences**, 2011, 181, 1910 - 1928
- Mobile Robot Localization:
  - Villaverde, I.; Fernandez-Gauna, B. & Zulueta, *Lattice Independent Component Analysis for Mobile Robot Localization,* **Hybrid Artificial Intelligence Systems, pt 2,** E. Corchado, E.; Romay, M. & Savio, A. (ed.), Springer-Verlag, 2010, 6077, 335-342

More on Lattice Methods and it's applications

- Hyperspectral image unmixing:
  - Ritter, G. X. & Urcid, G., *A lattice matrix method for hyperspectral image unmixing,* **Information Sciences**, 2010, 181, 1787-1803
  - Graña, M.; Villaverde, I.; Maldonado, J. & Hernandez, C. *Two Lattice Computing approaches for the unsupervised segmentation of Hyperspectral Images,* **Neurocomputing**, 2009, 72(10-12), 2111-2120
- Lattice Computing and Endmember Induction Algorithms (EIAs) reviews:
  - Graña, M. *A brief review of lattice computing,* **Fuzzy Systems**, FUZZ-IEEE 2008, (IEEE World Congress on Computational Intelligence), 2008, 1777 -1781
  - Veganzones MA, Grana M, *Endmember extraction methods: A short review,* KES 2008, **Knowledge-Based Intelligent Information and Engineering Systems, pt 3**, (International Conference on Knowledge-Based Intelligent Information and Engineering Systems), 2008, 400-407

Experiments on Lattice Independent Component Analysis for Face Recognition

Ion Marqués   Manuel Graña

Computational Intelligence Group, Universidad del Pais Vasco

IWINAC'11