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Eigenfaces vs. Fisherfaces:Recognition Using Class Specific Linear Projection

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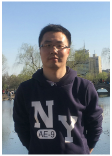
Content

Introduction
Speaker

Jindong Wang [1]

- Ph.D candidate in ICT, CAS, since 2014.09
- Activity recognition, ubiquitous computing, machine learning
- Supervisor: Prof. *Yiqiang Chen*



Liping Jia [2, 3]

The same since 2015.09, but also:

- **Super Brain candidate**
- **Cubic master**

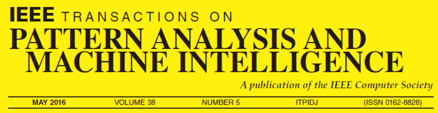
Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection

Peter N. Belhumeur, João P. Hespanha, and David J. Kriegman

- Published in *IEEE TPAMI*, 1997
- Google Scholar citations: 10575
- Recommended by *J. Daugman*, a professor of CVPR at Cambridge [4]

IEEE Transactions on Pattern Analysis and Machine Intelligence

Intro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- Since 1979, published monthly
- Impact Factor: **5.781**(2016.05)
- CCF rank: **A** (Artificial Intelligence)

Scope

- **Computer vision** and image understanding
- Pattern analysis and recognition
- Other related areas in **machine learning**

There are 3 CV related authors:

Peter N. Belhumeur [5, 6]

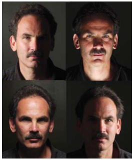
- Ph.D., Harvard, 1993; Professor at Columbia U.
- Google Scholar citations: 26000, h-index:56

João P. Hespanha [7, 8]

- Ph.D, Yale, 1998; Portugal, Professor at UCSB
- Google Scholar citations: 28337, h-index: 63

David J. Kriegman [9, 10]

- Ph.D, Stanford, 1989; Professor at UCSD
- Google Scholar citations: 31435, h-index: 56



Motivation

Many wonderful algorithms in face recognition
But they are **sensitive** to large variation in

- Lighting direction
- Facial expression

Since faces are not truly **Lambertian surfaces**, they have **self-shadows**.

Figure: Same pecrson under different lighting conditions

Basic intro

- Also known as PCA, proposed by *Karl Pearson* in 1901 [11]
- Purpose: **linearly** feature dimensionality reduction
- Assume *X* is a n-dimensional feature vector, after PCA, there will be *Y* with m-dimensional feature vectors, where $m \ll n$, and all new feature vectors **independent**

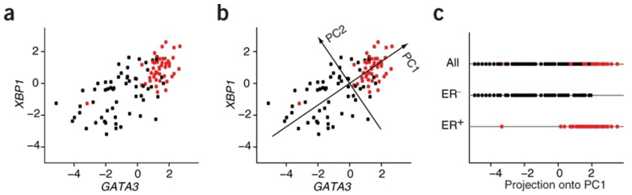


Figure: PCA

PCA Formulation

- Source: N-dimensional vectors X_k, $k = 1, 2, \cdots, N$
- Target: M-dimensional vectors Y_k, $k = 1, 2, \cdots, M, M \ll N$
- Transformation: $Y_k = W^T X_k, k = 1, 2, \cdots, N$, where $W \in \mathbb{R}^{n \times m}$ is a matrix with orthonormal columns.
- Total scatter matrix: $S_T = \sum_{k=1}^{N} (X_k - \mu)(X_k - \mu)^T$
- Objective: $W_{opt} = \arg\max_W |W^T S_T W|$

- Note: The objective is to maximize the **between-class** scatter.
- But does it always yields the **optimal** solution?

- Main idea is **PCA**, proposed by *Sirovich* and *Kirby* in 1987 [13].
- First used in face recognition by *Matthew Turk* and *Alex Pentland* in 1991 [14].

Procedure

- Input: a list of faces as training set
- Output: eigenvectors
- Methods:
  - Calculate the **mean** vector and **covariance** matrix
  - Select the principle components

Figure: Eigenfaces

Basic intro

- Proposed by *Robert Fisher* in 1936 [12]
- Objective: not just maximize the between-class scatter, but with regarding to the **within-class** scatter.

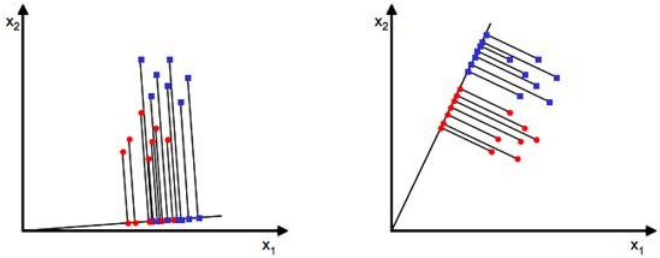


Figure: Fisher Linear Discriminant

Formulation

- Between-class scatter matrix: $S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T$
- With-class scatter matrix:$S_W = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T$
  μ_i: mean image of class X_i
  N_i: # samples in class X_i
- Objective: $W_{opt} = \arg\max_{W} \frac{|W^T S_B W|}{|W^T S_B W|}$
- Solution: $S_B w_i = \lambda_i S_W w_i, i = 1, 2, \cdots, m$, where $\{w_i | i = 1, 2, \cdots, m\}$ is the set of generalized eigenvectors.

Main idea is Fisher Linear Discriminant. The comparison between Eigenfaces and Fisherfaces:

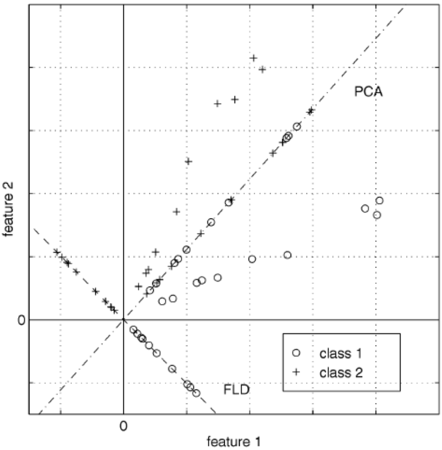


Figure: Eigenfaces vs Fisherfaces

More

- if S_w is single, then
- Objective: $W_{opt}^T = W_{FLD}^T W_{PCA}^T$
  $$W_{PCA} = \arg\max_W |W^T S_T W|$$
  $$W_{FLD} = \arg\max_W \frac{|W^T W_{PCA}^T S_B W_{PCA} W|}{|W^T W_{PCA}^T S_w W_{PCA} W|}$$

3 Experiments

- Variation in Lighting (Harvard dataset)
- Facial Expression, Eye Wear and Lighting (Yale dataset)
- Glasses Recognition

2 Datasets

- Harvard Robotics Laboratory
  330 images of 5 people used (66 each)
- Yale U.
  160 frontal face images of 16 people under 10 lighting conditions

5 Methods

- Eigenfaces (w/o first 3 PCs)
- Fisherfaces
- Correlation
- Linear Subspace

Harvard image dataset:

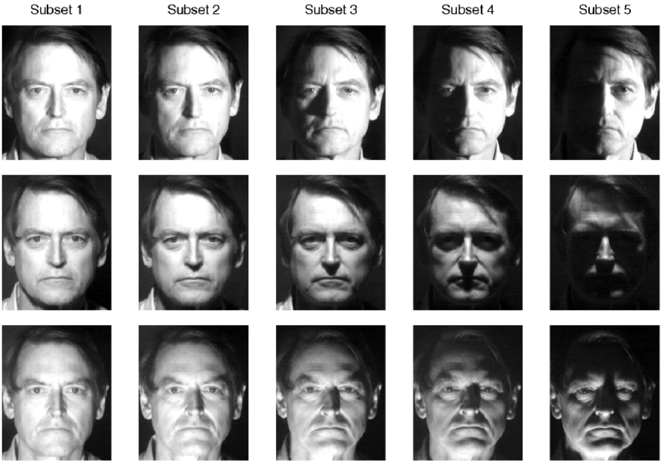


Figure: Harvard database images

Yale image dataset:

Figure: Yale database images

Extrapolation & interpolations experiments:

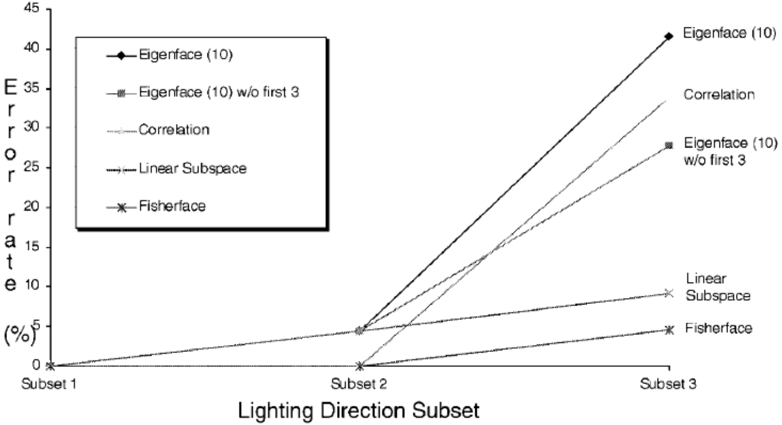


Figure: Extrapolation result on 5 methods

Evaluation
Variation in Lighting

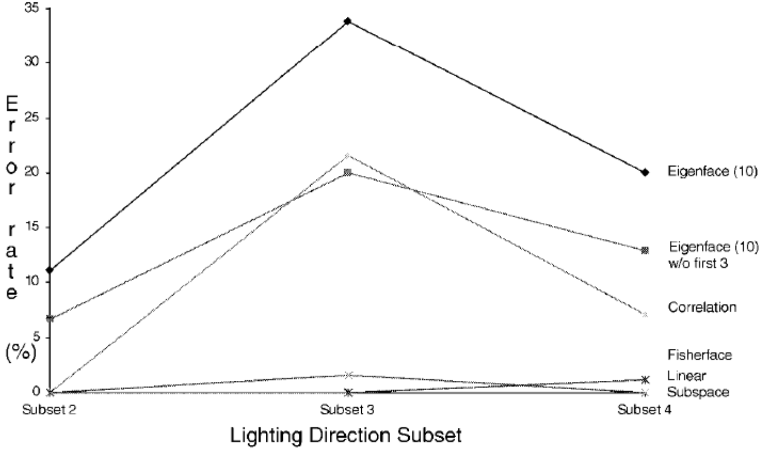


Figure: Interpolation result on 5 methods

Extrapolating from Subset 1				
Method	Reduced Space	Error Rate (%)		
		Subset 1	Subset 2	Subset 3
Eigenface	4 10	0.0 0.0	31.1 4.4	47.7 41.5
Eigenface w/o 1st 3	4 10	0.0 0.0	13.3 4.4	41.5 27.7
Correlation	29	0.0	0.0	33.9
Linear Subspace	15	0.0	4.4	9.2
Fisherface	4	0.0	0.0	4.6

Figure: Extrapolation result on 5 methods

Interpolating between Subsets 1 and 5				
Method	Reduced Space	Error Rate (%)		
		Subset 2	Subset 3	Subset 4
Eigenface	4 10	53.3 11.11	75.4 33.9	52.9 20.0
Eigenface w/o 1st 3	4 10	31.11 6.7	60.0 20.0	29.4 12.9
Correlation	129	0.0	21.54	7.1
Linear Subspace	15	0.0	1.5	0.0
Fisherface	4	0.0	0.0	1.2

Figure: Interpolation result on 5 methods

Variation in Lighting:

Discovery

- All algorithms are perfect when the light is nearly **frontal**
- When **# eigenfaces=|training set|**, Eigenface method = correlation method
- Eigenfaces will be better if **removing** the first 3 principle components
- Although Linear Subspace method is better than Fisherface, it requires more than **3 times** space
- **Fisherface** is better than Eigenface method while requiring less computation time

As # principle component increases:

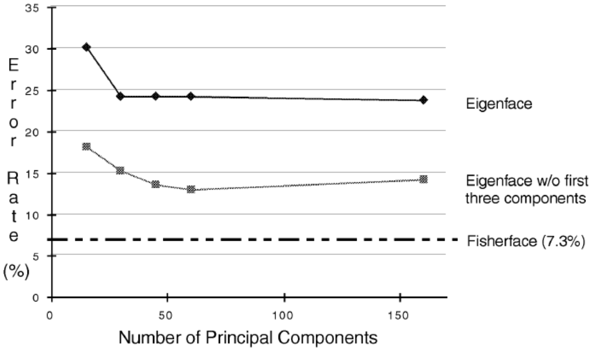


Figure: Eigenfaces vs Fisherfaces as # PC changes

Error rate of different algorithms:

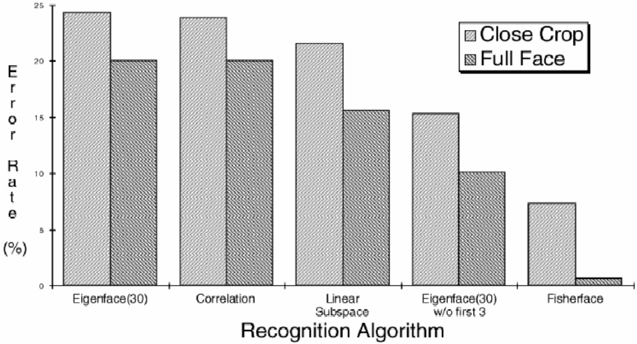


Figure: Error rate of different algorithms

Error rate of different algorithms:

"Leaving-One-Out" of Yale Database			
Method	Reduced Space	Error Rate (%)	
		Close Crop	Full Face
Eigenface	30	24.4	19.4
Eigenface w/o 1st 3	30	15.3	10.8
Correlation	160	23.9	20.0
Linear Subspace	48	21.6	15.6
Fisherface	15	7.3	0.6

Figure: Error rate of different algorithms

Discovery

- **Fisherface** method has better performance
- Linear Subspace methods fails dramatically as different facial expressions make image **nonlinear**
- All algorithms perform well on **full face**

Performance with glasses:

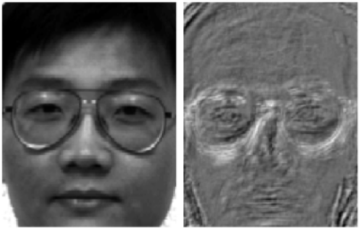


Figure: Left:glasses;right:after Fisherface

Glasses Recognition		
Method	Reduced Space	Error Rate (%)
PCA	10	52.6
Fisherface	1	5.3

Figure: Comparison between PCA and Fisherface

Discovery

- **Fisherface** method wins!

Conclusion

Conclusion

- Lighting variation: **Fisherface** wins, with Linear Subspace second
- Eigenfaces: **removing** the largest 3 PC improves performance
- Fisherface method is the best at handling variation in **lighting** and **expression**

Questions

- Fisherface in **large** databases?
- Performance with **fewer** lighting condition
- **Extreme** lighting condition

References

[1] http://jd92.wang.

[2] http://dwz.cn/3eN8I2.

[3] http://weibo.com/u/1425663374.

[4] http://www.cl.cam.ac.uk/ jgd1000/.

[5] https://scholar.google.com/citations?user=J8YyZugAAAAJ.

[6] http://www.cs.columbia.edu/ belhumeur/.

[7] https://scholar.google.com/citations?user=NAwmHTEAAAAJ.

[8] http://www.ece.ucsb.edu/ hespanha/.

[9] https://scholar.google.com.hk/citations?user=EqetexsAAAAJ.

[10] http://cseweb.ucsd.edu/ kriegman/.

[11] Richard O Duda, Peter E Hart, and David G Stork.
Pattern classification.
John Wiley & Sons, 2012.

[12] R Fisher.
The use of multiple measures in taxonomic problems.
Ann. Eugenics. v7, pages 179–188.

[13] L. Sirovich and M. Kirby.
Low-dimensional procedure for the characterization of human faces.
J. Opt. Soc. Am. A, 4(3):519–524, Mar 1987.

[14] Matthew Turk and Alex Pentland.
Eigenfaces for recognition.
Journal of cognitive neuroscience, 3(1):71–86, 1991.

Q & A

Thank you for your listening!