# Identification of Degraded Fingerprints using PCA and ICA-Based Features

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**M. Mehrubeoglu and L. McLauchlan, "Identification of degraded fingerprints using PCA and ICA-based features,"** ***Proc. of SPIE Volume 6696: Applications of Digital Image Processing XXX, pp. 66961D-1 – 66961D-10 (10 pages), Sept. 2007.***

# Presentation Outline

- Introduction
  - Biometrics
- Motivation
- Background
  - PCA,ICA, Neural Networks
- Presented Work
  - Fingerprint Identification
  - Image Preconditioning
  - PCA and ICA Feature Extraction
  - Fingerprint Classification
- Fingerprint Recognition Experimental Results
- Findings & Discussion
- Summary and Conclusions
- Future Directions

# Introduction

- **Biometrics – "Life Measures"**
  - **Security, Verification, and Identification**
  - **Characteristics Needed**

    Acceptability
    Universality
    Immutability
    Collectability

  - **Commonly used**

    Iris
    Retina
    Gait
    Signature
    Voice
    Face
    Fingerprint

# Introduction (cont.)

- **Fingerprint Identification**
  - Previous techniques

    Correlation, minutiae, or ridge features

  - Common features used include
    1. Delta and loop points
    2. Ridge terminations and bifurcations
    3. Sweat pores

# Motivation

- **Fingerprint recognition of degraded images**
  - Recognition highly dependent on image quality due to any number of factors such as
    sweat, humidity, rotation or orientation, noise or smudge, incomplete prints, etc.
  - Identification of degraded fingerprint images can be challenging
  - Need to be able to handle these non-ideal cases

# Background

- PCA (Principal Component Analysis)
  - Finds set of orthogonal components
  - Larger eigenvalues and associated components are kept
  - Reduces data required to represent set

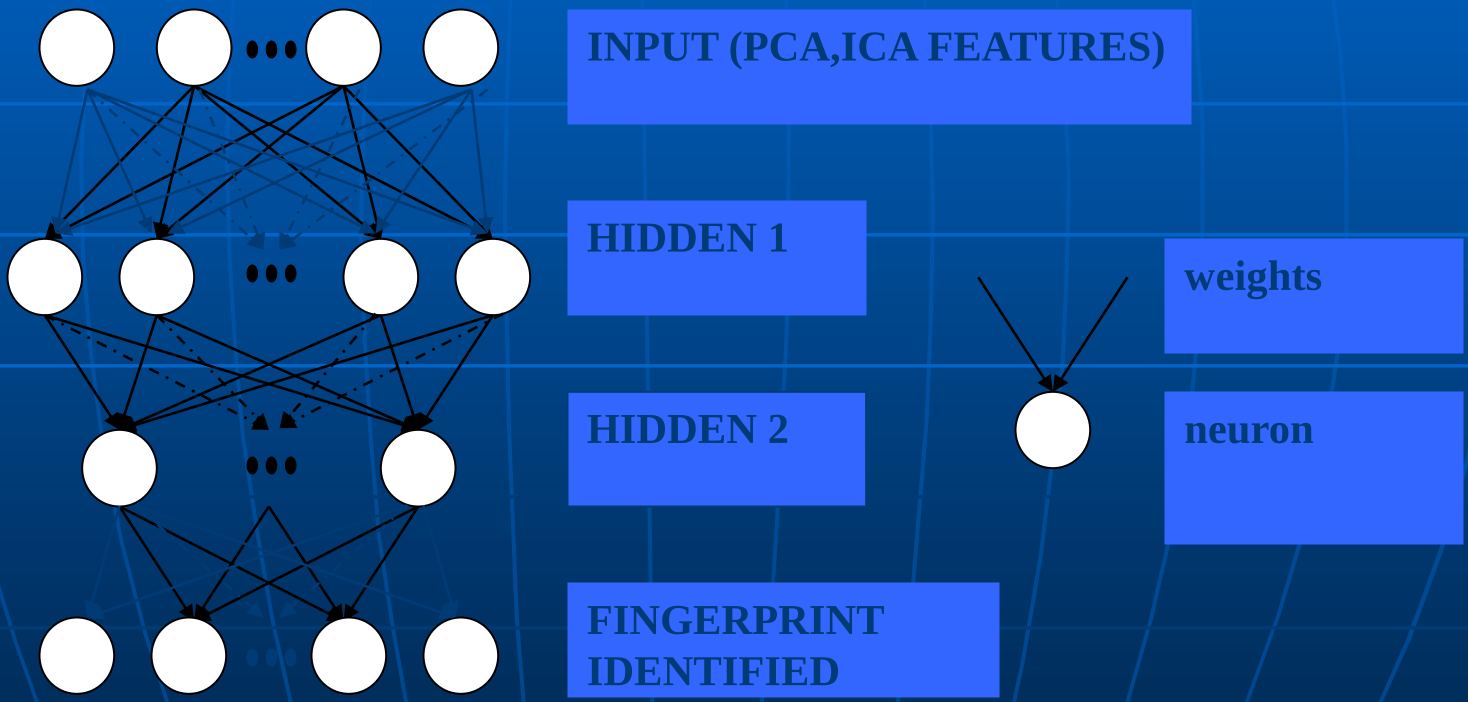
# Background (cont.)

- ICA (Independent Component Analysis)
  - Blind source separation (BSS)
  - Finds set of independent components
  - Source signals $\boldsymbol{S}$ estimated using demixing matrix $\boldsymbol{W}$ and output signals $\boldsymbol{X}$

$$\boldsymbol{S} = \boldsymbol{W}\boldsymbol{X}$$

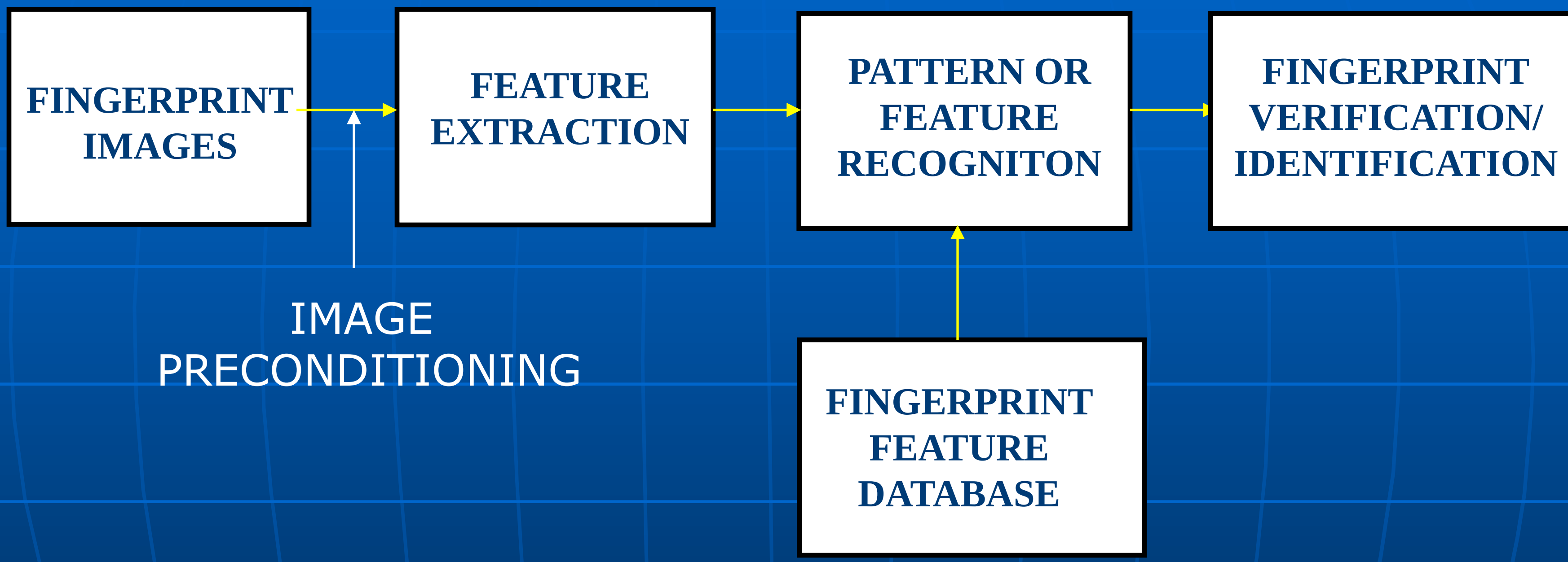
# Background (cont.)

- Neural Networks: Example



# Presented Work

## Fingerprint Recognition



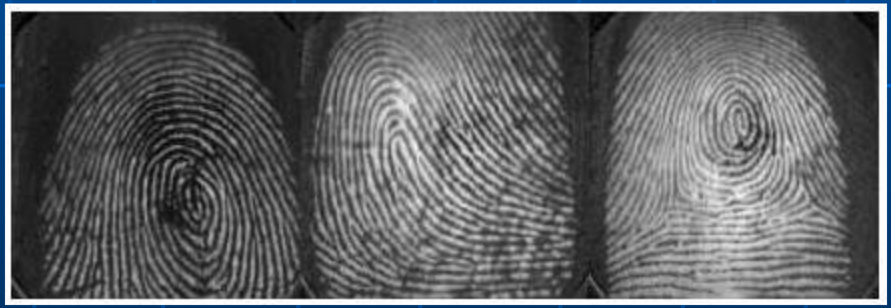

**Basic Fingerprint Recognition**

# Image Preconditioning

- Sample Original Images (im)

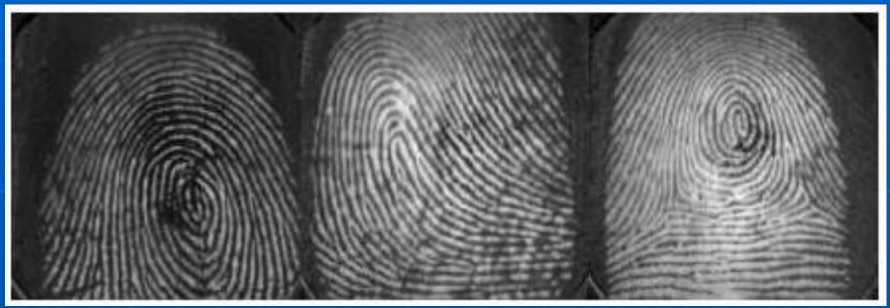
**8-bit gray-level**

- Original Images Inverted (im = 255-im);



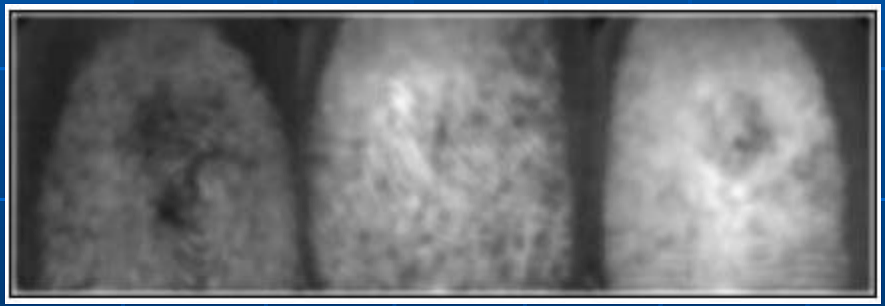
# Image Preconditioning:
## Degrading Fingerprints

- Original inverted images



- Mean-filtering for smudge effect

  **5x5 window applied twice**



- Random noise added

  **Multiplicative noise: image multiplied by random numbers [0,1]**

# Feature Extraction: PCA

- PCA:
  - Principal components were computed for each image in the training set (the database) and test set (degraded images)
  - Then, principal component variances (the eigenvalues of the covariance matrix of input image) were used as features; the features were scaled [0, 1]
  - Top 5 and 10 features, respectively, were used as input to the classifier

  - MATLAB functions were utilized for PCA

# Feature Extraction: ICA

- ICA:
  - Independent components were computed for each image in the training set (the database) and test set (degraded images)
  - First 10 independent components were computed for each image
  - The average of the independent component vectors was used as the input features to the classifier (10x1 vector for each image); the features were scaled [0, 1].

# Fingerprint Identification - Classification
## The Neural Network

- Backpropagation Network
  1 Input Layer
  1 Hidden Layers -150 Neurons
  1 Output Layer
- Adaptive Learning Rate 0.8 with Momentum
- Max Epochs 500
- Training Error Goal 0.0001
- 500-3000 Feature Vectors – Training Set
- Trained Using Supervised Learning
  - PCA/ICA Features as Input
  - Fingerprint Identification as Output

# Table 1: PCA Peak Signal to Noise Ratio (SNR)

| Fingerprint Image # | Image LPF PASS 1 Feature Vector | Image LPF PASS 2 Feature Vector |
|---|---|---|
| 1 | 25.6103 | 23.3510 |
| 2 | 25.6798 | 24.3233 |
| 3 | 23.4427 | 22.0885 |
| 4 | 25.5568 | 24.0305 |
| 5 | 26.7869 | 25.1693 |
| 6 | 28.6486 | 26.7159 |
| 7 | 26.6328 | 24.9653 |
| 8 | 29.0466 | 26.9904 |
| 9 | 27.3831 | 25.8665 |
| 10 | 26.9443 | 25.5395 |
| Mean of Images 1-50 | 26.1012 | 24.6235 |

# Table 2: PCA Fingerprint Recognition Rates Using FVC2000, 50 Images, 10 Coefficients 500 Epochs for Training

| Test Run | Ideal Fingerprint Feature Vector | Image LPF PASS 1 Feature Vector | Image LPF PASS 2 Feature Vector | Feature Vector Gaussian LPF, m=0.01, var=0.0001 | Feature Vector Salt and Pepper, d=0.05 |
|---|---|---|---|---|---|
| 1 | 59.2 | 6.9 | 7.0 | 36.7 | 37.5 |
| 2 | 65.2 | 6.8 | 6.3 | 33.9 | 43.2 |
| 3 | 73.7 | 8.5 | 8.1 | 36.8 | 47.8 |
| | | | | | |
| Average | 66.0 | 7.4 | 7.13 | 35.8 | 42.8 |

# Table 3: PCA Fingerprint Recognition Rates Using FVC2000, 50 Images, 5 Coefficients 500 Epochs for Training

| Test Run | Ideal Fingerprint Feature Vector | Image LPF PASS 1 Feature Vector | Image LPF PASS 2 Feature Vector | Feature Vector Gaussian LPF, m=0.01, var=0.0001 | Feature Vector Salt and Pepper, d=0.05 |
|---|---|---|---|---|---|
| 1 | 82.3 | 10.8 | 7.2 | 54.2 | 65.1 |
| 2 | 79.2 | 6.4 | 6.7 | 55.9 | 64.2 |
| 3 | 84.8 | 6.5 | 4.8 | 59.3 | 66.5 |
| | | | | | |
| Average | 82.1 | 7.9 | 6.23 | 56.5 | 65.3 |

# Table 4: PCA Fingerprint Recognition Rates Using FVC2000, 30 Images, 10 Coefficients 500 Epochs for Training

| Test Run | Ideal Fingerprint Image | Image LPF PASS 1 Feature Vector | Image LPF PASS 2 Feature Vector | Feature Vector Gaussian LPF, m=0.01, var=0.0001 | Feature Vector Salt and Pepper, d=0.05 |
|---|---|---|---|---|---|
| 1 | 90.6 | 6.0 | 10.0 | 54.6 | 59.0 |
| 2 | 90.1 | 11.5 | 10.2 | 56.8 | 57.9 |
| 3 | 91.6 | 7.1 | 9.5 | 58.2 | 62.6 |
| | | | | | |
| Average | 90.8 | 8.2 | 9.9 | 56.5 | 59.8 |

# Table 5: PCA Fingerprint Recognition Rates Using FVC2000, 30 Images, 5 Coefficients 500 Epochs for Training

| Test Run | Ideal Fingerprint Image | Image LPF PASS 1 Feature Vector | Image LPF PASS 2 Feature Vector | Feature Vector Gaussian LPF, m=0.01, var=0.0001 | Feature Vector Salt and Pepper, d=0.05 |
|---|---|---|---|---|---|
| 1 | 100.0 | 10.2 | 11.7 | 74.7 | 78.8 |
| 2 | 97.1 | 14.4 | 9.5 | 74.2 | 77.3 |
| 3 | 89.5 | 10.5 | 11.1 | 66.2 | 71.5 |
| | | | | | |
| Average | 95.5 | 11.7 | 10.8 | 71.7 | 75.2 |

# Table 6: PCA Fingerprint Recognition Rates Using FVC2000, 20 Images, 10 Coefficients 500 Epochs for Training

| Test Run | Ideal Fingerprint Image | Image LPF PASS 1 Feature Vector | Image LPF PASS 2 Feature Vector | Feature Vector Gaussian LPF, m=0.01, var=0.0001 | Feature Vector Salt and Pepper, d=0.05 |
|---|---|---|---|---|---|
| 1 | 91.9 | 14.1 | 14.1 | 62.2 | 61.7 |
| 2 | 96.1 | 13.5 | 13.5 | 67.2 | 67.2 |
| 3 | 100.0 | 13.9 | 15.5 | 71.2 | 69.3 |
| | | | | | |
| Average | 96.0 | 13.8 | 14.4 | 66.9 | 66.1 |

# Table 7: PCA Fingerprint Recognition Rates Using FVC2000, 20 Images, 5 Coefficients 500 Epochs for Training

| Test Run | Ideal Fingerprint Image | Image LPF PASS 1 Feature Vector | Image LPF PASS 2 Feature Vector | Feature Vector Gaussian LPF, m=0.01, var=0.0001 | Feature Vector Salt and Pepper, d=0.05 |
|---|---|---|---|---|---|
| 1 | 100.0 | 16.6 | 14.6 | 78.5 | 81.9 |
| 2 | 100.0 | 13.8 | 15.3 | 81.6 | 82.8 |
| 3 | 100.0 | 15.0 | 14.9 | 80.0 | 82.6 |
| | | | | | |
| Average | 100.0 | 15.1 | 14.9 | 80.0 | 82.2 |

# Table 8: ICA Fingerprint Recognition Rates Using FVC2000, 20 Images, 10 Coefficients 500 Epochs for Training

| Test Run | Ideal Fingerprint Image | Image LPF PASS 2 Feature Vector | Feature Vector Gaussian LPF, m=0.01, var=0.0001 | Feature Vector Salt and Pepper, d=0.05 |
|---|---|---|---|---|
| 1 | 100.0 | 0.1 | 23.7 | 60.6 |
| 2 | 100.0 | 4.9 | 22.8 | 62.2 |
| 3 | 100.0 | 8.3 | 24.2 | 62.2 |
| | | | | |
| Average | 100.0 | 4.43 | 23.6 | 61.7 |

# Table 9: ICA Fingerprint Recognition Rates Using FVC2000, 20 Images, 5 Coefficients 500 Epochs for Training

| Test Run | Ideal Fingerprint Image | Image LPF PASS 2 Feature Vector | Feature Vector Gaussian LPF, m=0.01, var=0.000 1 | Feature Vector Salt and Pepper, d=0.05 |
|---|---|---|---|---|
| 1 | 100.0 | 8.7 | 16.8 | 79.4 |
| 2 | 100.0 | 4.1 | 18.8 | 79.1 |
| 3 | 100.0 | 0.1 | 17.0 | 76.8 |
| | | | | |
| Average | 100.0 | 4.3 | 17.5 | 78.4 |

# Findings & Discussion

- PCA- and ICA-based features can be used to represent degraded images in ways that traditional spatial geometric analysis techniques may be inadequate.
- PCA- and ICA-based features used individually still face challenges in fully discriminating severely degraded images.
- The underlying mapping between image features in degraded images and their PCA- and ICA-based feature representation needs further investigation

# Summary and Conclusions

- PCA- and ICA- based features have been extracted from degraded fingerprint images and used as input to a neural network classifier.
- The preliminary results show that PCA- and ICA-based features could offer additional information in degraded images that might otherwise be undetectable using spatial analysis techniques.
- A combination of features is expected to enhance recognition rates in degraded images, and is the subject of future work.

# Future Directions

- Use PCA/ICA in conjunction with minutiae or correlation fingerprint identification
  - First pass - Classify fingerprint images by type
    - whorls, tented arches, loop, etc
  - Second pass – Identify specific fingerprint from smaller set
- Find optimal length of feature vector
- Neural network size and characteristics
- Combine PCA/ICA instead of using as separate features, to increase recognition