Fingerprint Image Enhancement Using Unsupervised Hierarchical Feature Learning

Presented in partial fulfilment of the requirements of MS by Research

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Outline

Background

Learning Local Orientation Fields

Hierarchical Learning of Fingerprint Features

Epilogue
Part 1

Background

Biometrics
Fingerprint Recognition
Scope of the Thesis
Biometrics

- Biometric traits: anatomical and/or behavioural
- Identify/verify individuals
- *Employing biometric traits for automatic recognition/verification of individuals*
- Face, fingerprint, iris, hand geometry, signature, voice, etc.
Fingerprints

▶ Impression left by a finger
▶ Caused by presence of skin patterns and moisture/dirt/oil
▶ Have been used for over a century
▶ Uniqueness is assumed
Part 1: Background

Fingerprint Recognition

Patterns and Minutiae

- A fingerprint is a pattern of ridges and valleys
- Points of interest include ridge-endings and ridge-bifurcations
- Ridges might form loops and deltas (singularities)

![Fingerprint Image Enhancement Using Unsupervised Hierarchical Feature Learning](image)
Patterns and Minutiae

Most commonly found ridge patterns in fingerprints:

- Ridge ending
- Ridge bifurcation
- Lake
- Independent ridge
- Island
- Spur
- Crossover

![Diagram showing fingerprint patterns](image-url)
Part 1: Background

Intrinsic Images

- **Intrinsic properties**: orientation field, frequency and region mask.
- **Orientation**: ridge direction at a point
- **Frequency**: number of ridges per pixel, \( \perp \) to orientation
- **Region mask**: places where a fingerprint is present

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Original Region

Mask

Frequency

Image

Orientation

Field

Original

Orientation

Field

Frequency

Image

Region

Mask
Part 1: Background

Fingerprint Recognition

Fingerprint Enhancement

- Improve ridges and valleys
- Make them easily distinguishable
- Remove creases, cuts, and improve too wet/too dry regions.

Figure: from left to right: Fingerprints of decreasing quality
Fingerprint Enhancement

- *Low-pass filtering along the orientation* and *band-pass filtering to the orientation*

*Figure:* *left:* the original image; *centre:* the enhanced image; *right:* the binarised image
Fingerprint Enhancement Using Contextual Filters

Using Gabor filters [Hong et al. (1998)]: Two-dimensional gaussian, multiplied by a cosine along one dimension:

\[ G(x, y : f, \theta, \phi, \sigma_1, \sigma_2) = \exp \left( -\frac{x'^2}{2\sigma_1^2} - \frac{y'^2}{2\sigma_2^2} \right) \cos \left( 2\pi x' f + \phi \right) \]

where \( x' = x \cos \theta + y \sin \theta \), and \( y' = -x \sin \theta + y \cos \theta \)
Fingerprint Enhancement in Frequency Domain

**STFT analysis**: Ridge pattern in a small region is like a 2-dimensional sine wave (Chikkerur *et al.* 2006)

![Figure: left: A patch from a fingerprint; and right: its power spectrum](image)

- Compute and apply appropriate filters
Scope of the Thesis

- Fingerprint image enhancement
- Unsupervised feature learning
- Feature learning on fingerprint images
- Enhancement of fingerprints using learnt features
- Estimation of intrinsic images of fingerprints
Part 2: Learning Local Orientation Fields

Learning Local Orientation Fields

Idea
RBM and Continuous RBM
Gabor-based Enhancement
The Model
Using the Trained Model
Results
Idea

- Consideration of neighbourhood of a point in enhancement
- A limited number of ridge patterns
- Learn patterns from prints, and use the learning to estimate noisy regions
- Using feature learning, we can “correct” damaged patterns
- Unsupervised feature learning to learn and correct patterns
**Idea**

- RBMs can reconstruct patterns based on learning
- Demonstrated on MNIST:

![Figure: An RBM trained on images of handwritten 2s reconstructs a 4 to look like a 2.](image)
Restricted Boltzmann Machine (RBM)

- Smolensky (1986)
- Became popular after introduction of fast learning algorithms (Hinton)
- 2-layered networks that learn a non-linear subspace
Restricted Boltzmann Machine (RBM)

- Can be thought of as dimensionality reduction models
- Each unit in the hidden layer learns a feature
- Unsupervised learning

Features learnt from a dataset of handwritten digits:
Restricted Boltzmann Machine (RBM)

- Infer hidden units from visible, and vice versa. $V \leftrightarrow H$
- $H = \sigma(W \cdot V + C); \quad V = \sigma(W' \cdot H + B)$
- Weight updates at each iteration of training
- $\Delta W_{i,j} \propto \langle v_i h_j \rangle^0 - \langle v_i h_j \rangle^\infty$
Continuous Restricted Boltzmann Machine (CRBM)

- RBMs are classically only binary-valued
- Continuous RBMs can take inputs in \([0, 1]\)
- Chen and Murray (2003)
Gabor-based Enhancement

- Hong et al. (1998)
- Enhancement using oriented Gabor filters
  1. Segmentation
  2. **Compute orientation field using gradient-based method**
  3. Estimate frequency image
  4. Prepare bank of Gabor filters
  5. Apply appropriate filters from the bank
Gabor-based Enhancement

- Significant neighbourhood not considered
- Irregularities, if noise is present

Figure: left: original image; centre: bad orientation estimate; right: better estimate (Rama Reddy, 2011)
The Model

- Need: A framework to learn local orientation fields
- We will use continuous RBMs to learn
- Training data is clean, noise-free orientation fields
The Model

- Break down each training orientation field $\theta$ into $(s(\theta), c(\theta))$
- Orientation fields might have sharp transitions
  - Sharp transitions are removed in the decomposed images
  - Learning and reconstructions are made easier
The Model

The model, illustrated with a diagram:
The Model

$s(x)$ and $c(x)$ are:

![Graph showing $s(x)$ and $c(x)$](image-url)
Training the Model

- Train both CRBMs with the respective training data
- Training patches are resized to $10 \times 10$ from $60 \times 60$
- Each resized image is flattened into a vector
- Learnt weights for c-CRBM and s-CRBM:
Using the Trained Model

- Split and feed test orientation fields extracted by gradient-based method to CRBMs
- Use the reconstructions and combine them
- Compute appropriate Gabor filters and apply them
Qualitative Results

Some examples of enhancements using Continuous RBMs:

- Patches from greyscale images
- Gradient-only enhancement
- After correction using CRBMs
Quantitative Results

Receiver Operating Characteristics on FVC 2002 Db3 a:

![Graph showing ROC curves for different methods: Gradient only, STFT analysis, and CRBMs.]
Quantitative Results

Spurious and missing minutiae analysis (FVC 2002 Db3-a):

<table>
<thead>
<tr>
<th>Method</th>
<th>Gradient-only</th>
<th>STFT</th>
<th>CRBM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground Truth</td>
<td>19032</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Detected</td>
<td>53389</td>
<td>48936</td>
<td>41674</td>
</tr>
<tr>
<td>Spurious</td>
<td>38415</td>
<td>33096</td>
<td>26324</td>
</tr>
<tr>
<td>Missing</td>
<td>4058</td>
<td>3165</td>
<td>3592</td>
</tr>
<tr>
<td>EER</td>
<td>24.34</td>
<td>21.99</td>
<td>22.65</td>
</tr>
</tbody>
</table>
Part 3: Hierarchical Learning of Fingerprint Features

Hierarchical Learning of Fingerprint Features

Idea
Convolutional DBNs
Feature Extraction
Hierarchical Probabilistic Inference and Enhancement
Estimating Intrinsic Images
Results
Idea

- Feature extraction directly from greyscale images
- Hierarchical learning
- Reconstruction/inference using learnt features
- Estimating orientation field, frequency image and mask
Part 3: Hierarchical Learning of Fingerprint Features

Idea

Need

- Unsupervised feature learning from greyscale images
- A hierarchical model
- A scalable model
- A generative model
- A way to combine top-down and bottom-up signals
Convolutional Deep Belief Networks

- Conv DBNs fit the requirements
- Lee et al. (2009)
- Hierarchical, scalable and generative
- Hierarchical probabilistic inference
Convolutional Deep Belief Networks

A two-layered network:

Layer 1:
- Convolutions and Sampling
- Hidden Units
- Weights
- Features or Weights
- Visible Units

Layer 2:
- Pooling
- Hidden Units
- Weights
- Pooled Units
- Training Images

Training Image
Visible Units
Features or Weights
Training Image
Part 3: Hierarchical Learning of Fingerprint Features

Convolutional Deep Belief Networks

Layers learn edges, object parts, and objects:

Layer 1
Layer 2
Layer 3

Lee et al. (2009)
Convolutional Deep Belief Networks

- $H_k \leftarrow f(V \ast \tilde{W}_k + b_k)$; $f$ is a non-linearity
- Proabilistic max-pooling to generate pooling units
- $V \leftarrow \sum_k H_k \ast W_k$
- $\Delta W_k \propto \frac{1}{N_H^2} \left( \langle H_k \ast V \rangle^0 - \langle H_k \ast V \rangle^1 \right)$
Part 3: Hierarchical Learning of Fingerprint Features

Probabilistic Max Pooling

- Downsample images while preserving features

Bottom-up inference:

\[
P(h_i = 1) = \frac{\exp(l_i)}{1 + \sum_j \exp(l_j)}
\]

\[
P(p_B = 1) = \frac{\sum_j \exp(l_j)}{1 + \sum_j \exp(l_j)}
\]
Probabilistic Max Pooling

Combines top-down and bottom-up signals (signals from two layers)!

\[
P(h_i = 1) = \frac{\exp(T + l_i)}{1 + \sum_j \exp(T + l_j)}
\]

\[
P(p_B = 1) = \frac{\sum_j \exp(T + l_j)}{1 + \sum_j \exp(T + l_j)}
\]

where \( T \) is the top-down signal.
Model Parameters

We used the following model in this work:

- 2-layered network
- 60 features in each layer
- 200 epochs of training for each layer
- L2 and sparsity regularisation
- 15 training images from different datasets
Part 3: Hierarchical Learning of Fingerprint Features

Training

- Training is done similar to deep belief nets, Hinton et al. (2006)
- Greedy layer-wise
- Lower layer’s weights frozen once trained
- Pooling units serve as training data for next layer
Hierarchical Probabilistic Inference

- Reconstructing an image from its representation
- $\text{Hidden}(\ell)$ conditioned on $\text{Visible}(\ell) + (\text{signal from } \ell + 1)$
- ‘Odd’ numbered layers grouped together, and so are ‘even’ numbered ones
Enhancing Fingerprints

- Use HPI to reconstruct an image
- 20 iterations
- Hidden units in both layers are affected at each iteration
- Final activations of L1’s hidden units used in reconstruction

Reconstruction, $V' = \sum_k W_{1,k}^{1,k} * H_1^k$, where $H_1^k$ denotes the $k$-th set of hidden units of Layer 1 after 20 iterations
Part 3: Hierarchical Learning of Fingerprint Features

Hierarchical Probabilistic Inference and Enhancement

Learnt Features

- Layer 1: oriented ridges
- Layer 2: Local ridge structures
What Happens During Enhancement (Reconstruction)

- Layer 1 detects learnt features in the input image
- Layer 1 alone is unable to interpret some regions
- These are estimated by Layer 2 using surrounding, interpreted regions (combining top-down and bottom-up signals)

Input (greyscale) image → Reconstructions

0 5 10 20

Binarisation
Estimating Intrinsic Images

- Orientation field, region mask, and frequency image estimated by the network

\[ D = \frac{1}{2} \arctan \frac{\sum_k \sin(2d_k) \left( W_{1,k} \ast H_1^k \right)}{\sum_k \cos(2d_k) \left( W_{1,k} \ast H_1^k \right)} \]

followed by smoothing

- \( F = \left( \sum_k f_k \left( W_{1,k} \ast H_1^k \right) \right) \ast V' \) followed by smoothing

- \( f_k \) and \( d_k \) computed for each \( W_{1,k} \) from its Fourier transform

- \([M]_{x,y} = ([V']_{x,y} \neq 0)\)
Part 3: Hierarchical Learning of Fingerprint Features

Results

Qualitative Results

Enhancements using CDBN:

Original  Gabor  STFT  CDBN-1  CDBN-20

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Fingerprint Image Enhancement Using Unsupervised Hierarchical Feature Learning
Part 3: Hierarchical Learning of Fingerprint Features

Quantitative Results

Receiver Operating Characteristics:

![ROC Curves for FVC 2000 Db1_a and FVC 2000 Db2_a](#)
## Results

### Quantitative Results

Equal-error rates on several datasets:

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Gabor</th>
<th>STFT</th>
<th>CDBN-20</th>
<th>CDBN-10</th>
<th>CDBN-5</th>
<th>CDBN-1</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000 Db1_b</td>
<td>9.46</td>
<td>6.67</td>
<td>5.82</td>
<td>6.55</td>
<td>11.65</td>
<td>13.11</td>
</tr>
<tr>
<td>2000 Db2_a</td>
<td>7.71</td>
<td>7.98</td>
<td>8.52</td>
<td>9.14</td>
<td>10.24</td>
<td>10.66</td>
</tr>
<tr>
<td>2000 Db2_b</td>
<td>14.00</td>
<td>9.24</td>
<td>10.44</td>
<td>17.32</td>
<td>16.29</td>
<td>19.65</td>
</tr>
<tr>
<td>2002 Db3_a</td>
<td>24.34</td>
<td>21.99</td>
<td>23.95</td>
<td>25.00</td>
<td>25.45</td>
<td>24.48</td>
</tr>
</tbody>
</table>
With different number of features

- Two networks: 20 features in L1, 30 in L2; 40 in L1, 60 in L2
With different number of features

FVC 2000 Db1_a

1 - FNMR

FMR

CDBN-20 20x30
CDBN-20 40x60
CDBN-20 60x60
With different number of features

- Networks with few weights aren’t able to reconstruct completely
- Some features might not be learnt

Original 60x60 20x30 40x60 60x60
Intrinsic Images

Estimated intrinsic images:

Original  Enhanced  Binarised  Orientation Field  Frequency Image  Region Mask
Part 4: Epilogue

Part 4

Epilogue

Conclusion
Future Work
Related Publications
Conclusion

- Feature learning applied to fingerprints
- Feature extraction using neural nets
- Orientation field learning and reconstruction
- Hierarchical learning boosts enhancements
- Same model computes intrinsic images
Future Work

- Addings more layers
- Synthetic fingerprint generation
- Segmentation
- Minutiae detection
- Classification
Related Publications

1. **Learning Fingerprint Orientation Fields Using Continuous Restricted Boltzmann Machines**
   Mihir Sahasrabudhe and Anoop M. Namboodiri.
   *2nd Asian Conference on Pattern Recognition, 2013.*

2. **Fingerprint Enhancement Using Unsupervised Hierarchical Feature Learning** (Oral)
   Mihir Sahasrabudhe and Anoop M. Namboodiri.
   *9th Indian Conference on Vision, Graphics and Image Processing, 2014.* (to appear)
Thank you!