Parsimonious Coding & Verification of Offline Handwritten Signatures

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http://www.upcv.upatras.gr/

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Signatures

- **Signatures**: A common (behavioral) way to declare our identity or our consent.
  - The outcome of the joint interaction between a person's specific motoric procedure and his/hers taught scripting customs.

- **Taxonomy**:
  - **On-line**
    - Sequence information
    - Considered to be easier
  - **Off-line**
    - No sequence information
    - Digital image – Gray level

- **Applications**: Forensics, Security, e-business, e.t.c.
• **Genuine** = natural execution of signature
  - Regular
  - Unnatural situation = altered behavior by intrinsic (e.g., disease, drugs) or extrinsic (e.g., writing on a wall)

• **Forgery** (only non-specimen w. is trying to copy) & (specimen’s signature is known)
  - Simple => Non-practiced => not much training => one attempt
  - Skilled => Practiced => after practicing, has to be specified

• **Disguise** (intention vs. behavior) by specimen writer.
  - Auto-simulated (intend for the signature to appear to be a forgery)

• **Fictitious signatures** = develop a new signature
  - Formerly called random signatures
Generic SV system

Reference Genuine Samples

Questioned Samples

Signature Verification

Comparing Features

Questioned features

Reference features

Genuine

Not genuine

Disguised

Preprocessing

• Binarization
• Thinning
• Segmentation

Same Preprocessing Steps as in Enrollment

Reference Genuine Samples

Feature Extraction

Enrollment Stage
What we Propose

- Make use of Sparse Representation & Dictionary Learning techniques for creating the “characteristic profile space” of a writer.
  - Employ K-SVD.
  - Create the “atoms” of the writer i.e. the “MODEL”
  - Use a few (e.g. 5) samples to construct his/hers lexicon.
- Use this “lexicon” for any signature which claims that it originates from this specific writer
  - Use OMP to create sparse coefficients
  - Average pooling as feature extractor.
Sketch of Proposed Method
Preprocessing

- Binarization
- Thinning
- Equimass

Segmenting

Original Image
Create patch matrix $X$

$X \in \mathbb{R}^{25 \times N}$

5x5 patch
Modeling a Writer: Dictionary Learning – Sparse Representation

\[ D \times A = X \]

\( D \in \mathbb{R}^{25 \times p} \)
\( A \in \mathbb{R}^{p \times N} \)
\( X \in \mathbb{R}^{25 \times N} \)

- \( p \) atoms
- \( p > 25 \)
- (60)

N-Signature Patches

Sparse Coefficients

N-Signature Patches
Modeling a Writer

Input: #G-REF Genuine signatures

Acquire sample

Yes

1st sample

No

Initialize K-SVD with patches of first signature

D(1st sample)

Update K-SVD

Output: Global Dictionary \( D_{global} \)
Modeling a Writer

\[ X = DA \]

Dictionary Learning Problem  \quad \text{Sparse Coding Problem}

\[
\min_{D,A} \left\{ \|X - DA\|_F^2 \right\} \\
\text{s.t. } \|a_i\|_0 \leq T_0 , \quad i = 1, ..., M
\]

K-SVD for Dictionary Learning

\[ D_{\text{writer}} \]
Operating Parameters

• \( T_0 = 3 \): How many non-zero elements for each \( a_i \)
• Patch size = 25 (5x5)
• Number of Atoms (\( p \)) = 60, \( p > 25 \).
• Number of iterations = 50
• Use of K-SVDbox & OMPBox toolbox
  – by Ron Rubinstein, Computer Science Department Technion -- Israel Institute of Technology
  http://www.cs.technion.ac.il/~ronrubin/software.html
Feature Extraction for Any Signature

Any Sample

Preprocessing
- Binarization
- Thinning
- Segmentation

OMP Sparse Coding

$\mathbf{D}^{\text{writer}}$

OMP Sparse Coding

$\mathbf{D}^{\text{global}}$
Feature Extraction for Any Signature

For Entire Image

1\textsuperscript{st} segment

For each row - atom calculate the average value

4\textsuperscript{th} segment

Overall feature dimensionality is 300
Experimental Procedure - Verification

• Datasets
  – CEDAR: 55 writers, 24 genuine, 24 forgeries
  – MCYT: 75 writers, 15 genuine, 15 forgeries
  – GPDS300, 300 writers, 30 genuine, 24 forgeries

• Training set: for each writer
  – 5 genuine reference samples
  – 1 genuine sample from 10 other writers = 10 RF samples

• Testing set
  – The remaining genuine samples
  – The remaining skilled forgery samples
  – Genuine samples from other writers which did not participate during training
Verification

- **Classifier**
  - SVM with RBF kernel
  - Training set is used for selecting optimal SVM parameters with AUC metric (cross validation).
  - LibSVM library

- **Testing Stage metrics**
  - A function of the score that the SVM outputs.
  - **Test**: Remaining genuine Vs. skilled forgeries
    - FAR, FRR, EER.
    - @ EER threshold calculate random forgery error rate.
    - Per user (writer) EER and global EER
    - Results with hard decisions also: FAR & FRR
## Results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>FRR</th>
<th>FAR$_{\text{random}}$</th>
<th>FAR$_{\text{skilled}}$</th>
<th>EER$_{\text{global_threshold}}$</th>
<th>EER$_{\text{user_threshold}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEDAR</td>
<td>7.32</td>
<td>0.34</td>
<td>6.83</td>
<td>7.58</td>
<td>2.78</td>
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<tr>
<td>MCYT-75</td>
<td>7.32</td>
<td>0.35</td>
<td>10.4</td>
<td>8.43</td>
<td>3.67</td>
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<tr>
<td>GPDS300</td>
<td>6.91</td>
<td>0.33</td>
<td>6.22</td>
<td>7.21</td>
<td>2.70</td>
</tr>
</tbody>
</table>

### Hard Decisions

![Graph showing verification error (EER) versus number of prominent atoms for CEDAR, MCYT, and GPDS300 datasets. The graph indicates a decreasing trend in verification error as the number of prominent atoms increases. The lines for each dataset are labeled: CEDAR, MCYT, and GPDS.]
## Comparisons

<table>
<thead>
<tr>
<th>First Author</th>
<th>Dataset</th>
<th>Method</th>
<th># Genuine Sigs. for training</th>
<th>EER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kumar R.</td>
<td>CEDAR</td>
<td>Signature Morphology</td>
<td>24</td>
<td>11.6</td>
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<tr>
<td>Kumar R.</td>
<td>CEDAR</td>
<td>Surroundness</td>
<td>24</td>
<td>8.33</td>
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<tr>
<td>Kalera</td>
<td>CEDAR</td>
<td>Gradient, Structural and Concavity</td>
<td>16</td>
<td>21.9</td>
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<tr>
<td>Zois</td>
<td>CEDAR</td>
<td>Partially Ordered Sets</td>
<td>5</td>
<td>4.12</td>
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<tr>
<td><strong>Proposed</strong></td>
<td>CEDAR</td>
<td>K-SVD dictionary learning – OMP</td>
<td>5</td>
<td>2.78</td>
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<tr>
<td>Vargas</td>
<td>MCYT75</td>
<td>Local binary patterns (LBP)</td>
<td>5</td>
<td>11.3</td>
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<td>Alonso-Fernandez</td>
<td>MCYT75</td>
<td>Slant and envelope</td>
<td>5</td>
<td>22.4</td>
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<td>Fierrez-Aguilar</td>
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<td>Global and local slant</td>
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<td>11.0</td>
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<td>Wen</td>
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<td>Invariant ring peripheral</td>
<td>5</td>
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<td>Yin Ooi</td>
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<td>Discrete Radon transform</td>
<td>5</td>
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<td>Soleimani</td>
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<td>Deep multitask metric</td>
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<td><strong>Proposed</strong></td>
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<tr>
<td>Hu</td>
<td>GPDS 150</td>
<td>LBP &amp; HOG &amp; GLCM</td>
<td>10</td>
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<tr>
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<td>GPDS 160</td>
<td>Local binary patterns</td>
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<tr>
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<td>LBP &amp; HOG</td>
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<td>GPDS 300</td>
<td>Cosine similarity</td>
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<td>Pirlo</td>
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<td>Optical flow</td>
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<td>4.60</td>
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<td>Parodi</td>
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<td>Deep Convolutional N. N.</td>
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<td>GPDS 300</td>
<td>Deep Convolutional N. N.</td>
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</tr>
<tr>
<td><strong>Proposed</strong></td>
<td>GPDS 300</td>
<td>K-SVD dictionary learning – OMP</td>
<td>5</td>
<td>2.70</td>
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</tbody>
</table>
Conclusions

• Offline Signature Verification Problem
• Using Dictionary Learning and Sparse Representation for building a writer’s model and analyze any other signature which claims the writer’s identity.
• Propose Average pooling as feature extractor
• Testing in three popular datasets provides state of the art results
Many thanks to our... minions...

- Experiments were made with:
- FTS Dual Xeon Server equipped with:
  - 24 threads
  - 100GB RAM
Thank you