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Robust core-point-ROI based fingerprint identification using a sparse classifier

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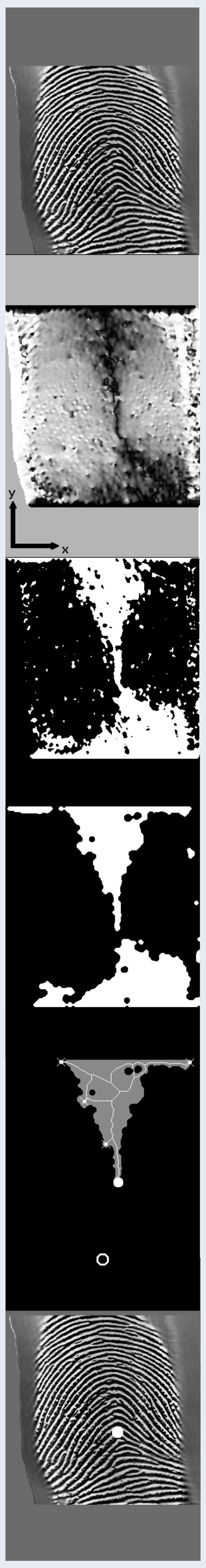
1. Introduction

- **Motivation:**
  - Fingerprints-based identification and verification system are currently becoming ubiquitous.
  - There are many solutions working with high-quality fingerprints and an optimal fingerprint acquisition setup.
  - There is a need for new methods [3] to handle cases where these assumptions do not hold, like for example, poor-quality fingerprints, small overlap area between the query and the enrolled fingerprints, etc.
- **Our research:**
  - We address the problem of automated fingerprints-based person identification from poor-quality fingerprints acquired with sub-optimal acquisition setups.
  - We assume that for each person in the database, several fingerprints of the same finger are available.
  - Our solution includes the following steps:

    Step1: Find the core-point and use it as center for a region of interest (ROI).
    Step2: Compute a set of DCT features from the image patch in the ROI.
    Step3: Classify the feature vector with the help of the sparse classifier.

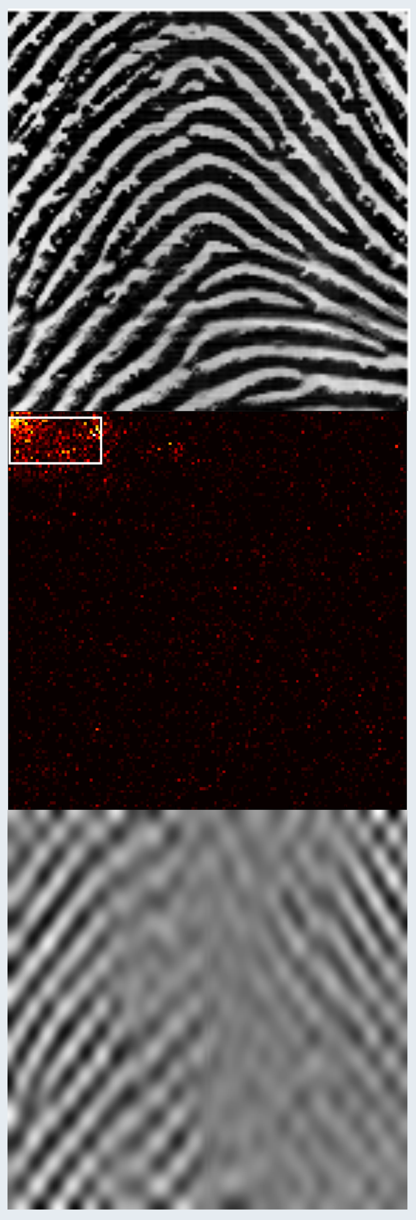
2. Core-point detection



- **The core-point** is the point of minimal ridge flatness when going over the ridge lines from top to bottom.
  - New definition, covering all types of fingerprints.
- Measure **ridge flatness** as $\sin(\alpha)$, with α the angle the X axis makes with the local orientation vector.
  - Compute the orientation vector as the eigenvector corresponding to the minimal eigenvalue of the orientation tensor from the local neighborhood Ω
- **Binarize** the sine image, looking for orientations close to zero.
  - The object region will have minimal width at the position of the core point
- **Break** the object region at its thinnest point.
  - Erode with a disk-like structuring element of diameter d_1 larger than the minimal width of the object region.
  - Dilate with a similar structuring element of diameter $d_2 < d_1$ to improve the precision of the core-point estimate.
- **Select** the upper-central object region.
  - Use as seed-points the pixels in the upper quarter.
  - If several distinct connected regions are found, choose the one closest to the image center.
- **Find the tip** of the upper-central region.
  - Compute the morphological skeleton.
  - Find its termination points.
  - Choose the termination point closest to an empirical reference position.
- Our **core-point estimate** is given by the tip of the upper-central region.

3. The feature vector

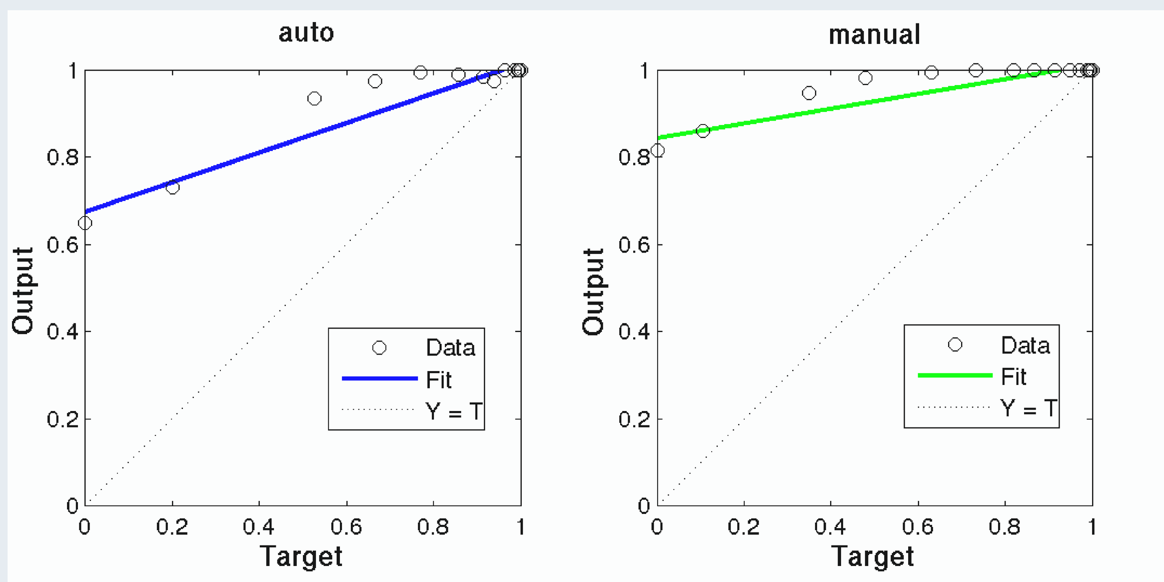
- **Properties:** The feature vector needs to be robust to occlusions, overlays, simple geometrical transforms and contrast variations. It must also contribute to avoiding the curse of dimensionality.



- **Region of interest:** By analyzing just a ROI of the fingerprint, we try to concentrate only on the same most informative part of a fingerprint that is usually always visible.
  - The ROI is 141×141 pixels large and is centered at the core point.
- **Transform features:** We need transform features to be able to obtain a vector representation of the information in the ROI, such as to avoid the curse of dimensionality, and achieve all needed properties.
  - We use DCT features, such that we don't need to recompute the transform each time a new finger is enrolled.
- **Feature selection [2]:** The purpose of feature selection is to get only those coefficients that while providing an accurate-enough representation, generate also a feature vector with the desired properties.
  - Selection is conducted with the help of a small labeled dataset.

4. Sparse classification

- Sparse representations-based classification [5] is similar to nearest-subspace methods [1].
- **Sparse representations:** A query vector $\mathbf{y}$ is represented as $\mathbf{y} = \mathbf{T}\mathbf{x}$.
  - $\mathbf{T} = [\mathbf{T}_1, \ldots, \mathbf{T}_c]$ is the training matrix containing the class-submatrices $\mathbf{T}_i$
  - $\mathbf{x}$ is the sparse vector, ideally having entries $\neq 0$ only for a single class i.
  - We solve the optimization problem: $\hat{\mathbf{x}} = \arg\min \| \mathbf{x} \|_1$ subject to $\mathbf{T}\mathbf{x} = \mathbf{y}$
- **Classification:** We assign the query vector to the class C that best reconstructs it by computing $C(\mathbf{y}) = \arg\min \| \mathbf{y} - \mathbf{T}(1_i(x_j) \odot \hat{\mathbf{x}}) \|_2$
- **Confidence index:** With the help of the sparsity concentration index we obtain a measure of trust in the classification results.
  - A decision is accepted only if: $SCI(\hat{\mathbf{x}}) \geq \tau$
- **Results [4]:** We have investigated how sensitive is our method to the location of the core-point and how accurate it is with respect to various rejection rates.



5. Conclusion and Outlook

- We have described a fingerprint-identification framework designed to work with poor-quality fingerprints.
- The computed feature vector concentrates on information that is imprinted on a grabbed item under most difficult conditions.
- The sparse classifier works despite occlusions or corruptions of large parts of the analyzed fingerprint image as well as with a less-informative feature vector.
- We assume a training set with a small number of examples per class is available, covering most of the variability to be expected in the test sample.

Bibliography

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