Identification Systems
Lecture 12

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2021-06-01

Motivation and history

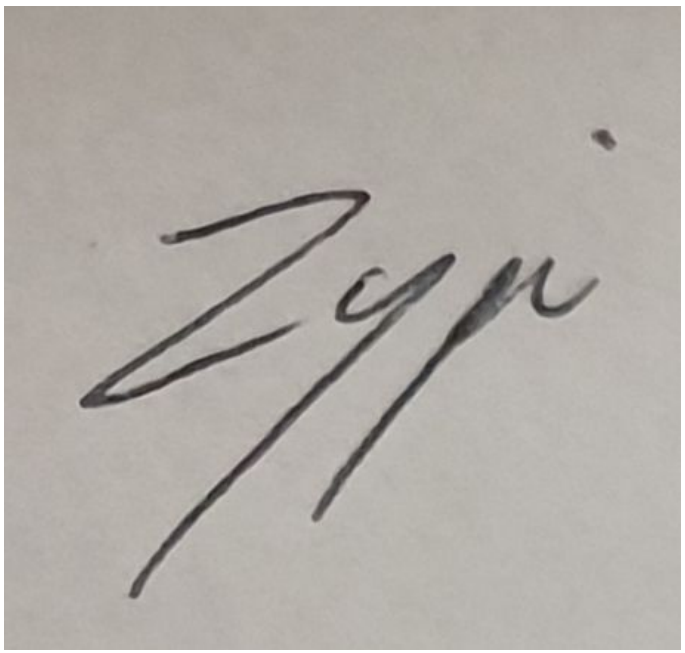
- signature has been used as a 'proof' of authorship since ancient times
- graphology – analyzing person's character based on handwritting dating from late XVI century, has been shown to be a pseudoscience, yet allowed to classify repeating shape-patterns between samples from different subjects
- graphoanalysis – started in early XX century, studies the characteristic features of a handwritten text to asses the authorship (American Society for Testing and Materials released several standards including E2290-07a: Examination of Handwritten Items)
- worldwide literacy rate is estimated at 78.5% and constantly is increased
- utilizing touch screens and piezoelectric surfaces enhances the possibilities of identification procedure

On-line and Off-line

- *Off-line signature* is a ready mark (not necessarily a full name nor limited to the name) on a surface equivalent to set of points on a background – the timing of a signature, order of the strokes and any other information is not recorded.
- *On-line signature* is a signature verified during the process of signing (or later with full information) – the information includes an 'offline signature' as well as timings on the whole mark and individual strokes, may include pressure at each point, pen position $(x(t), y(t), \alpha(t), \theta(t))$ and orientation at each point and information on the writing hand and its position and pressure on the surface

Random Forgery vs skilled forgery

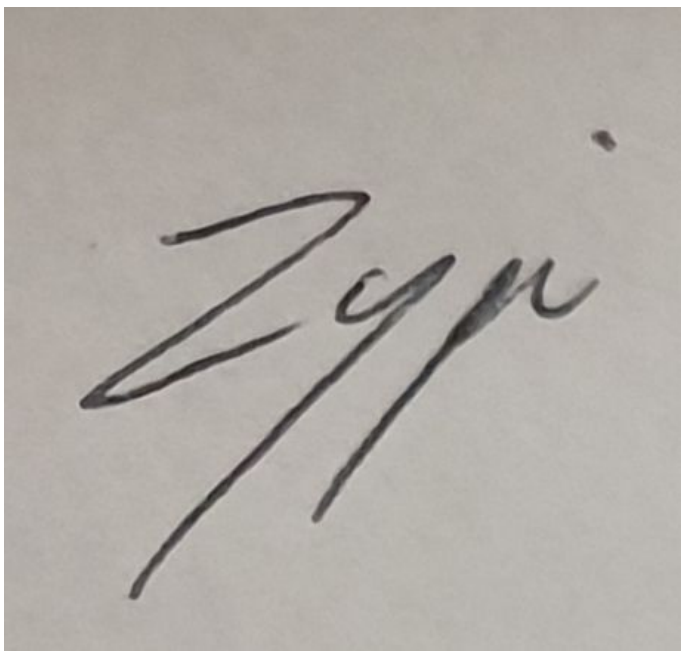
- We can grade the degree of a forgery based on the knowledge of the attacker, further biometric verification procedure is evaluated using standard metrics (e.g. FAR and FRR).
- a random forgery – the attacker knows nothing about the victims signature, so a random signature is passed as a genuine

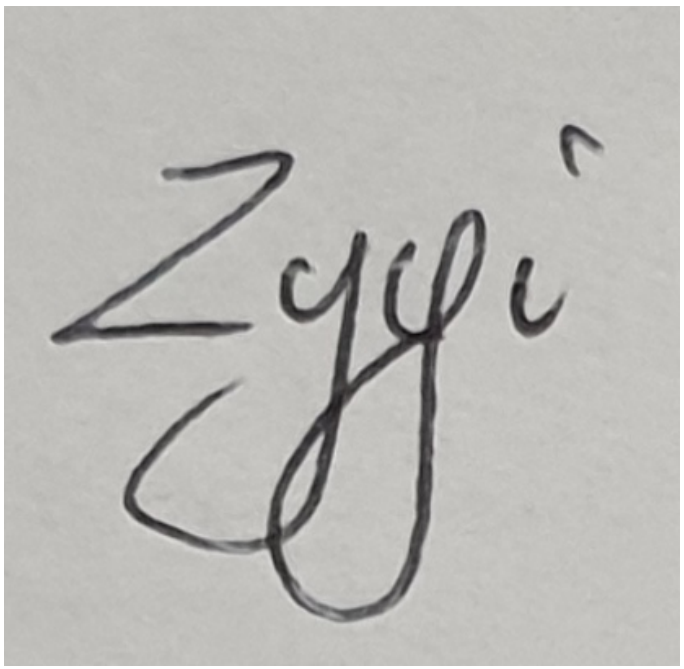




Random Forgery vs skilled forgery

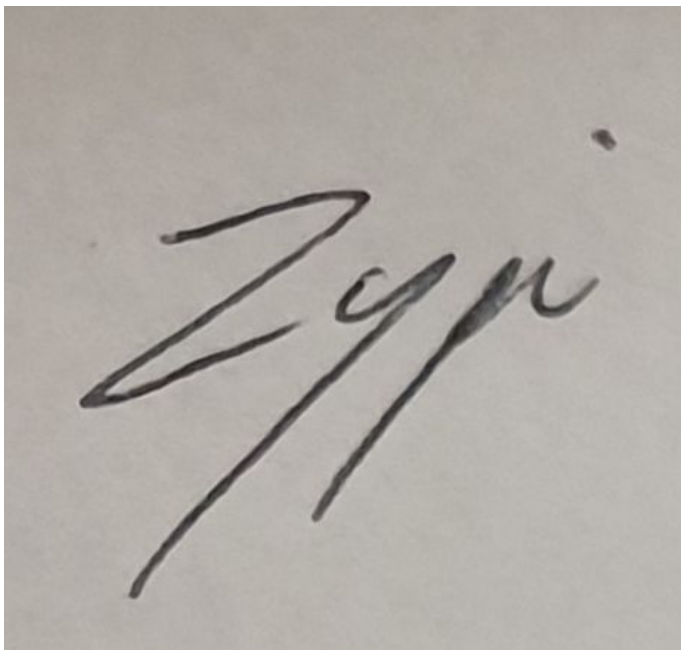
- an informed forgery – the attacker knows the name of the victim and selected details if the signature (does it consists full name or only last name etc.)

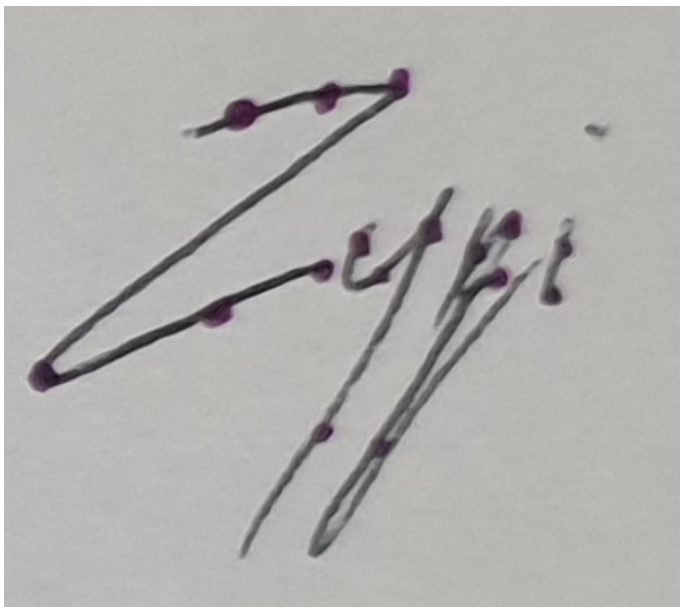




Random Forgery vs skilled forgery

- a skilled forgery – the attacker has access to genuine signatures or their extensive parts (in terms of on-line signatures the adversary observes the process of signing and receives the full log), multiple training trials (non verified), carbon copies and artificial dots and helper lines are allowed





Off-line sample acquistion

- Collecting using a stylus and a touchscreen
- Scanning of the signature
- Photo of the signature

Main issues:

- resolution and dot density
- image compression
- local contrast
- aliasing and anti-aliasing techniques

On-line sample acquistion

- General purpose touchscreens with a timer
- Tablets with a dedicated stylus measuring the position of the tip and the end of the pen with internal clock and microprocessor
- Biometric tablets

Main parameters:

- resolution
- sampling rate (clock resolution)
- pressure level resolution
- the range of the sensor of pen position
- size (of the device and signature area)
- data protection
- open SDK

On-line sample acquistion



Evolis Sig200



Motion Touch



Wacom STU 540

Selected features

Off-line signatures:

- height and length (or ratio) of the signature
- center of mass
- area and direction of the signature
- thickness of the signature
- number of lines, length of the longest lines, number of line intersections
- number of loops
- number of background segments intersected
- texture and gradient analysis
- Haar-like features
- spectral analysis (Gabor, cosine, . . .)

Selected features

On-line signatures:

- offline features
- quantization and localization of point in n-dimensional space
- movement of the tip and the pen in time
- pressure analysis

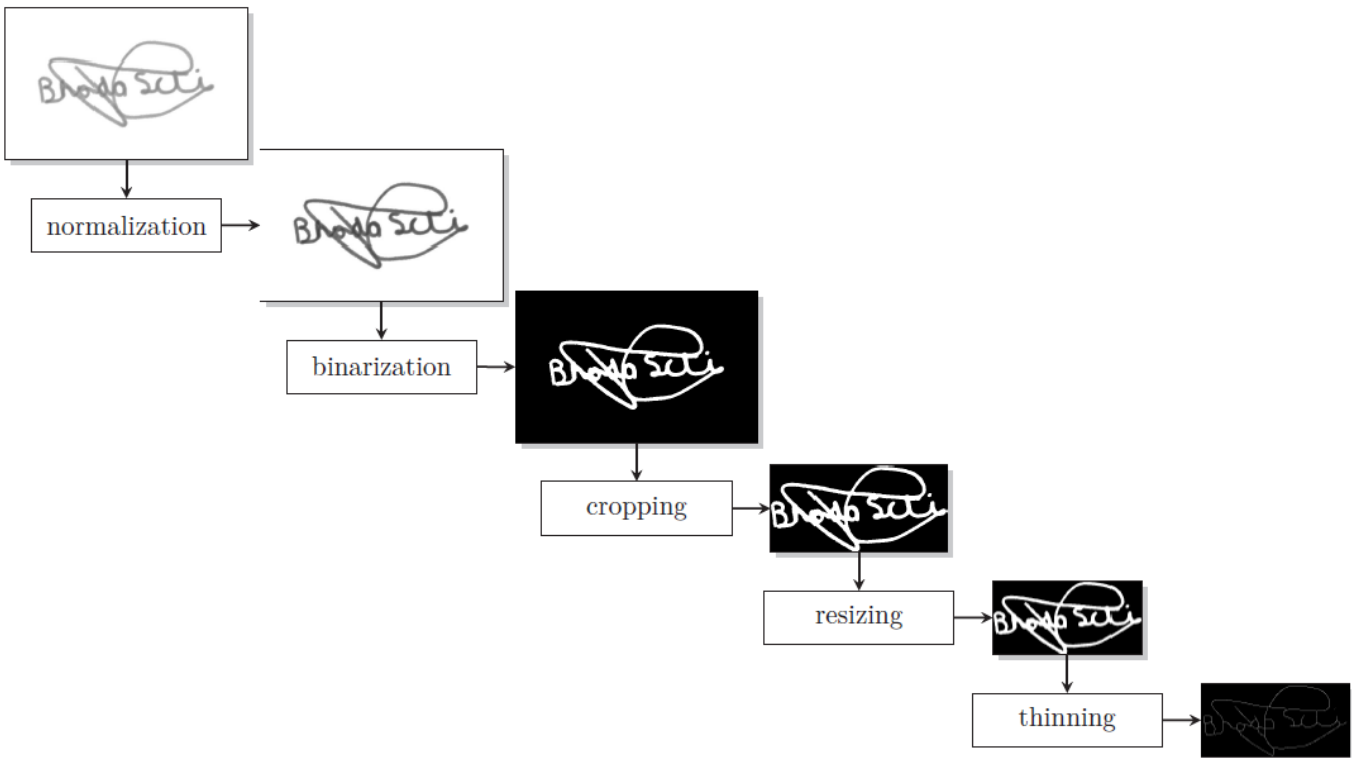
Preprocessing

Selected preprocessing steps:

- lighting adjustment
- denoising and sharpening
- signature extraction (via bounding box)
- realignment according to the longest orthogonal lines through the signature
- color rebalancing
- binarization of the image
- skeletonization, thinning or line correction
- segmentation (static vs overlapping, uniform vs heterogeneous)
- resampling (uniform vs heterogeneous)

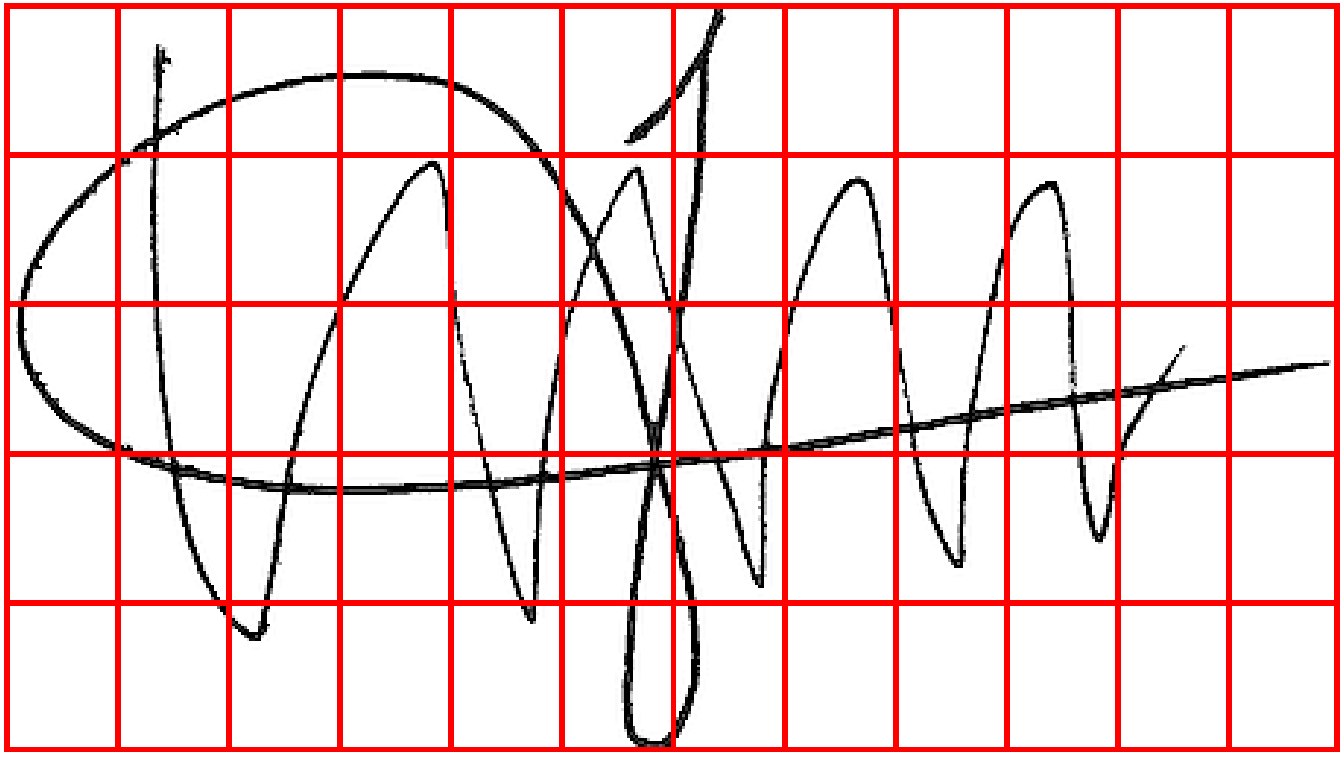
Preprocessing

Example of sample preprocessing:



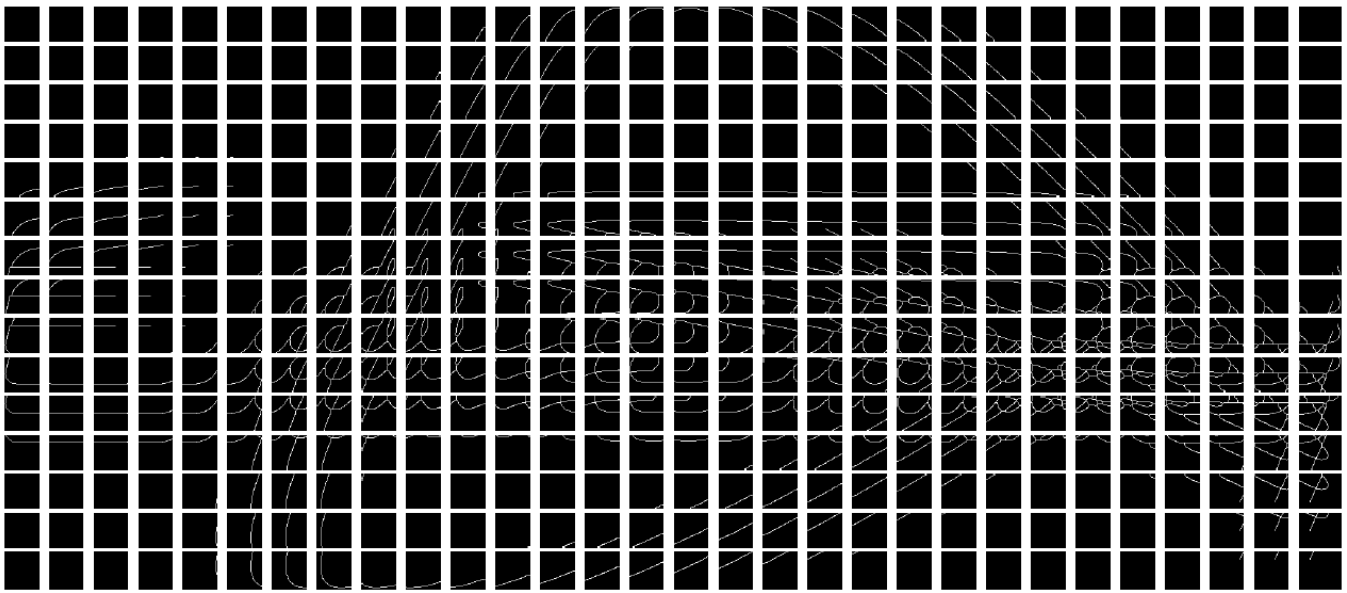
Preprocessing

Example of uniform segmentation:



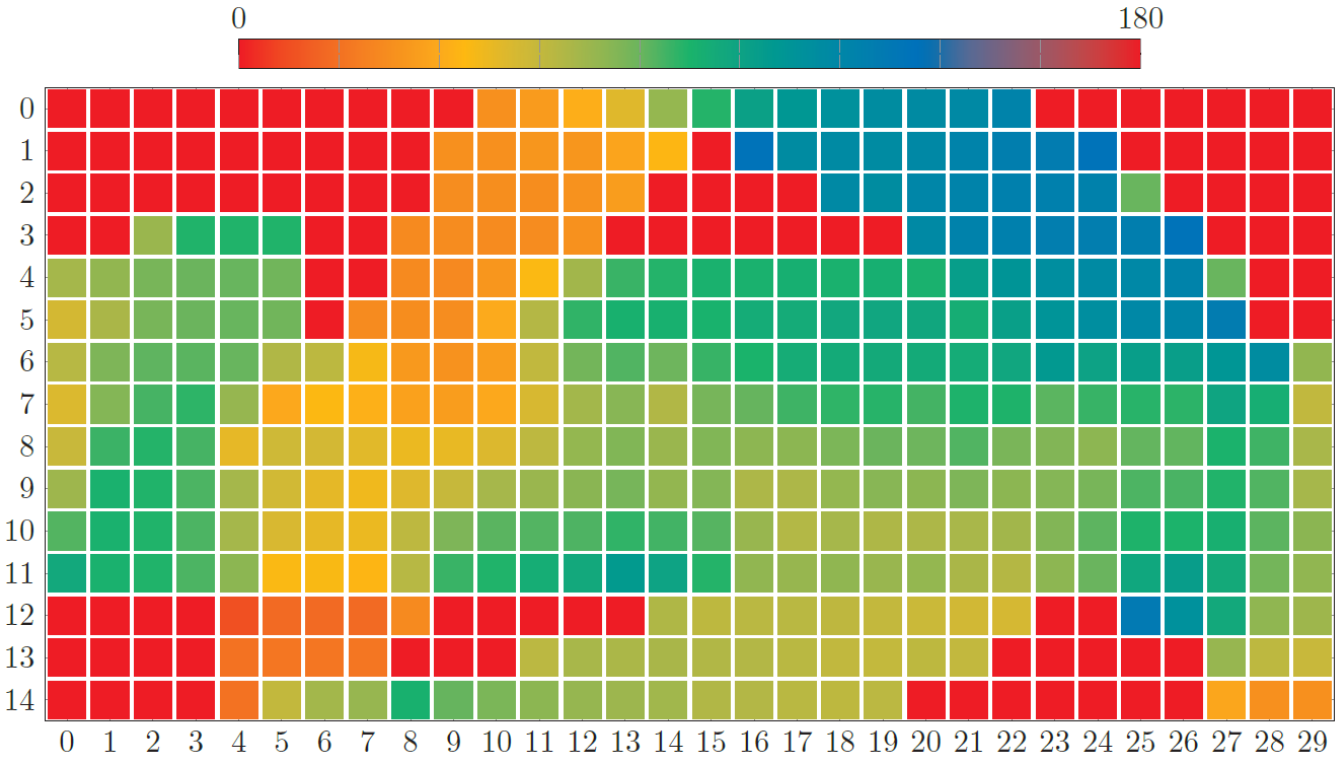
Preprocessing

Example of grid segmentation with overlapping moving window:



Preprocessing

Mean HOG angles in the overlapping grid:



Preprocessing

Example of heterogeneous segmentation:



General approaches

- correlating visible marks with additional properties (pace of the mark, pen pressure, pen movement)
- selecting features with the highest Fisher's ratio in the database and classification (k-NN, SVM, Fully Connected or Convolutional Network)
- utilizing additional properties is required for skilled-forgery prevention (which allows training with carbon copies and helper dots)
- confidence intervals for the samples utilizing mean and the standard deviation
- matching space- or frequency-domain series using linear matching or DTW

Curvlet Transform

B.Hadjadj et al.: *An Efficient Open System for Offline Handwritten Signature Identification based on Curvelet Transform and One-Class Principal Component Analysis*

- The paper considers identification instead of verification.
- Two sets of features generated using curvelet transform.
- Systems combined using fuzzy integrals.
- Verification on CEDAR database achieves almost 98% IR.

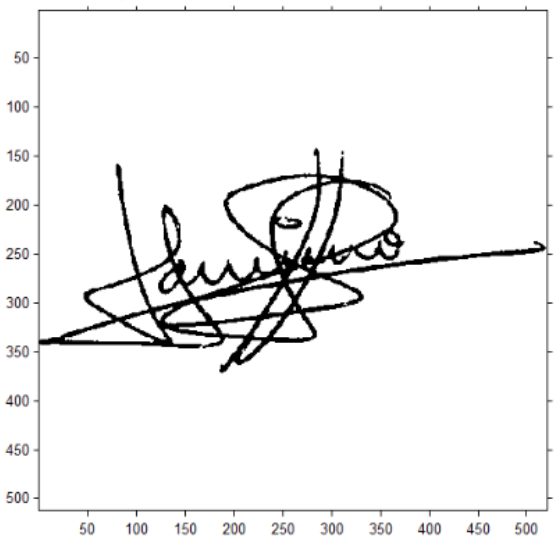
Curvlet Transform

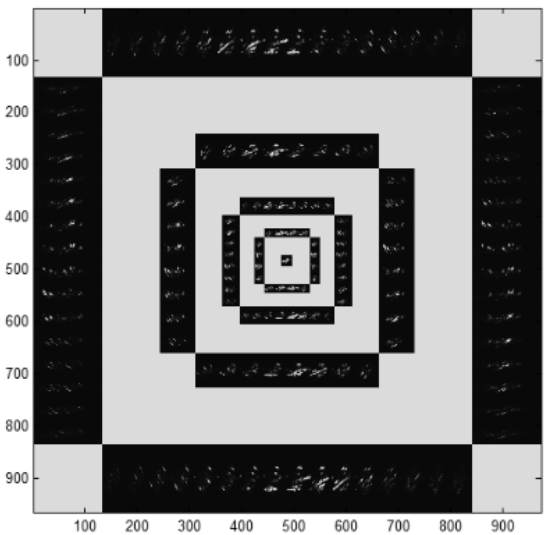
Curvelet coefficients:

- We apply FFT to the image and get frequency samples $\hat{f}[n_1, n_2]$
- We apply discrete localizing window $\hat{U}_{j,k}[n_1, n_2]\hat{f}[n_1, n_2]$
- We wrap the product around the origin, limiting the range of the frequencies n_1, n_2 and obtain $\hat{f}_{j,k}[n_1, n_2]$.
- We perform the inverse FFT for each curvelet $\hat{f}_{j,k}[n_1, n_2]$ to obtain discrete curvelet coefficients $C(j, k, l)$, where j, k, l are scale, orientation and spatial location parameters (t_1, t_2), respectively.

Curvlet Transform

CT example:



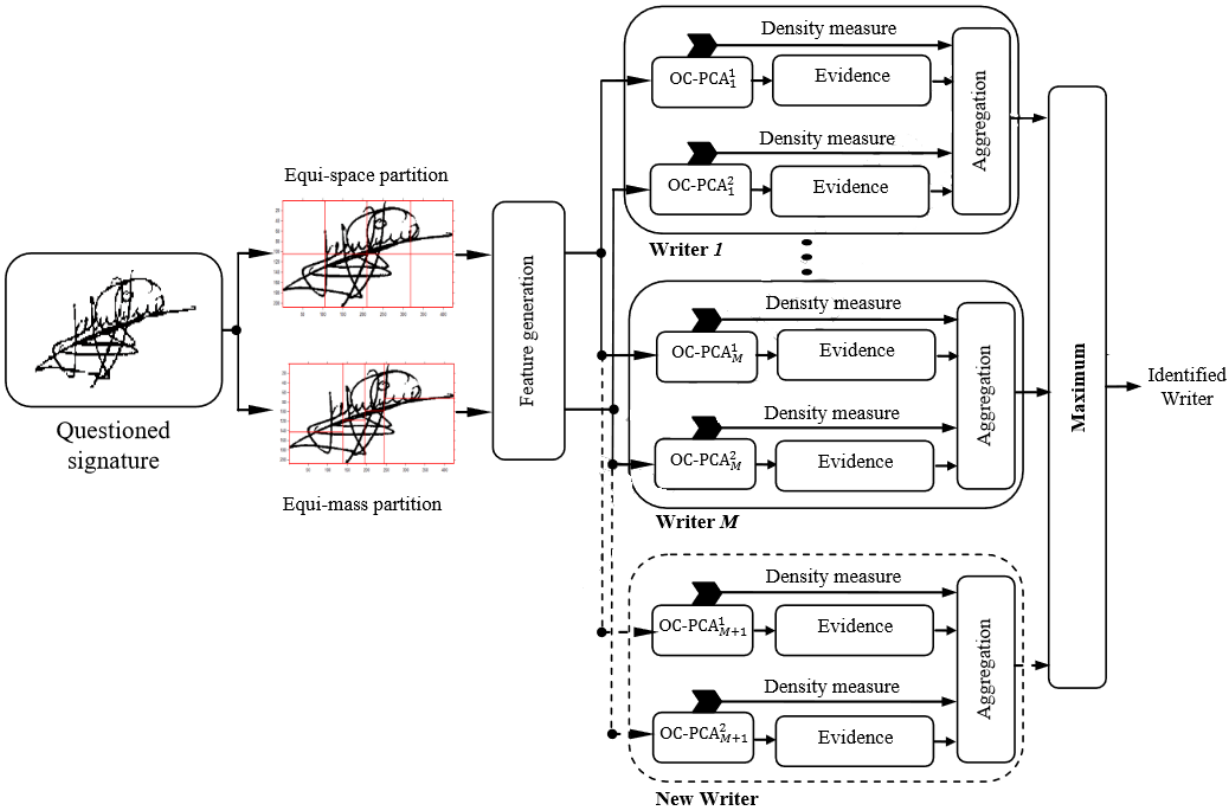


Curvlet Transform

Identification method:

- Binarization of the signature is performed.
- Signature is divided into several cells via equi-space or equi-mass grid.
- Normalization of each grid cell to $N \times N$ size is performed by filling the background.
- CT wrapping is performed to each cell.
- Energy $E(j,k) = \sum_{t_1} \sum_{t_2} |C(j,k,(t_1,t_2))|$ for each scale and orientation.
- Energies from sub-images are concatenated, obtaining feature vector.
- Classification is performed using One Class PCA.
- Both models are combined using Fuzzy Integral.

Curvlet Transform



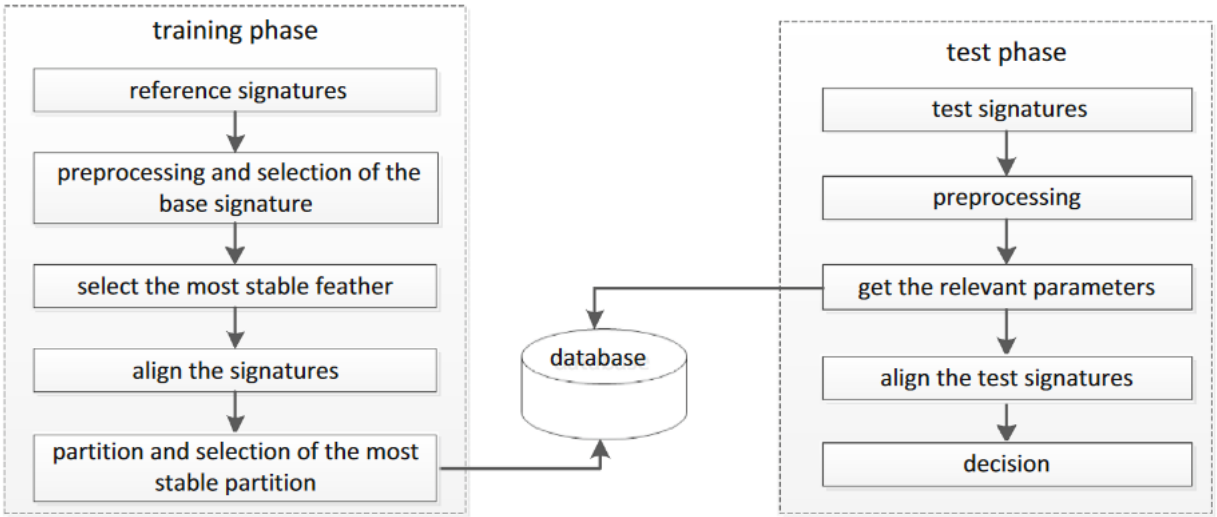
Writer-dependent features

L. Yang et al.: *Online handwritten signature verification based on the most stable feature and partition*

- Writer dependent feature and partitions are used during the enrollement.
- Signature trajectories are decomposed depending upon pressure, velocity direction, value and angle.
- Verification is made on the most stable partition.
- The authors achieve 5% FAR and 4% FRR on SVC2004 database.

Writer-dependent features

The idea:



Writer-dependent features

The method:

- On-line samples are collected.
- Positional and scale normalization of the samples.
- Removing spatial and velocity information corresponding to low pressure time. The pressure threshold is calculated as $t_j^i = \frac{1}{M}\sum_{m=1}^{M} z_j^i(m) - 3\sqrt{\frac{1}{M}\sum_{m=1}^{M}(z_j^i(m) - \sum_{m=1}^{M} z_j^i(m))^2}$, where $z_j^i(m)$ is pressure of the mth sample point of jth signature of user i and M denotes the number of sample points for a pair (i, j).
- For each user a *base signature* is used, as the one with the smallest distance to all the user signatures.
- All other signatures of the user are realigned to the base signature using DTW.
- The most stable feature is selected, by calculating all the dynamic features (pressure, velocity, acceleration, pen angle and azimuth, ...) in order and selecting the one where distance between each sample and the base signature of the user has the smallest variance.

Writer-dependent features

The method cont.:

- The signatures are partitioned according to velocity direction angle, velocity and pressure of the signature.
- The most stable partition is selected.
- In order to verify a user parameters for the user are obtained from the database (trajectories of base signature, sample index set for each partition, templates from the reference signatures, most stable feature, most stable partition and the confidence interval).
- The verified signature is realigned w.r.t base signature and the most stable feature is calculated.
- If the distance of the verified signature is within the confidence interval, the identity is confirmed.

Further reading

- A. Kholmatov, B. Yanikoglu, Identity authentication using improved online signature verification method
- G.H. Rosa et al., Person Identification Using Handwriting Dynamics and Convolutional Neural Networks
- J. Putz-Leszczyńska, SIGNATURE VERIFICATION: A COMPREHENSIVE STUDY OF THE HIDDEN SIGNATURE METHOD
- R. Sanchez-Reillo et al., Improving Presentation Attack Detection in Dynamic Handwritten Signature Biometrics
- S. Wang, Sh. Jia, Signature handwriting identification based on generative adversarial networks
- L.G. Hafemann et al., Learning features for offline handwritten signature verification using deep convolutional neural networks
- V.L.F. Souza et al., A white-box analysis on the writer-independent dichotomy transformation applied to offline handwritten signature verification