Personal Authentication Using Signature Recognition

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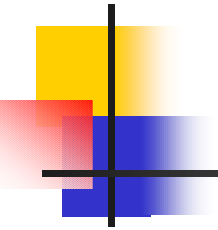


Main Topics

- Definition
- Approaches
- Forgery Types
- Capturing devices
- Off-line methods
- On-line methods
- Providers of Signature Verification Solutions

To’s and Fro’s

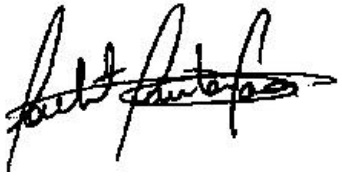
- Advantages
  - Highly accepted
  - Low cost of capturing devices
- Disadvantage
  - High error rates

Definition

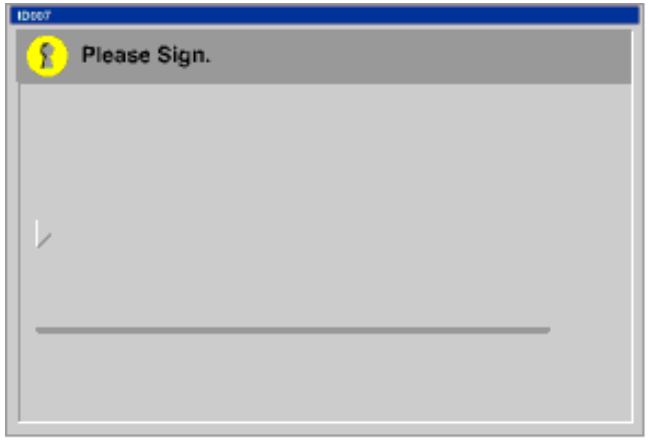
- The name of a person written with his or her own hand
- The act of signing one’s name

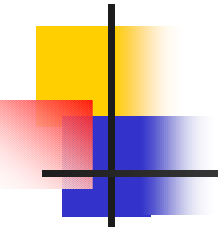
Approaches to Signature Verification

- Off-line signature verification



- On-line signature verification



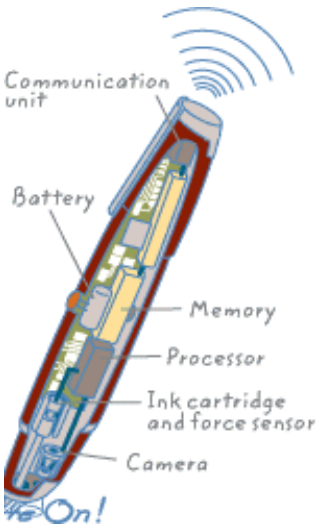


Forgery

- Random forgery
- Simple forgery
- Skilled forgery

Capturing Devices

- Interlink electronics ePad solutions
- Wacom Tablets
- Anoto
- others

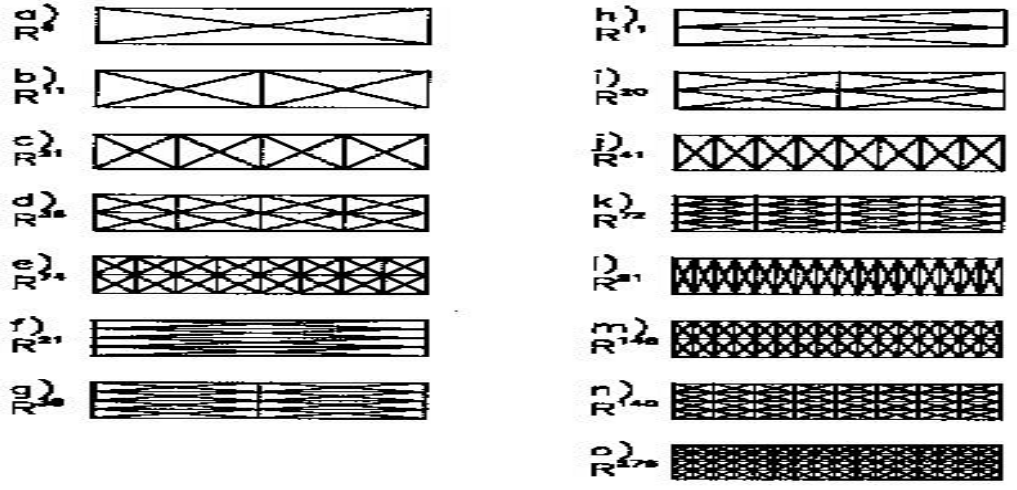


Off-line Methods

- 2D transforms
- Histograms of directional data
- Curvature
- Horizontal and vertical projections of the writing trace of the signature
- Structural approaches
- Local measurements made on the writing trace of the signature
- The position of feature points located on the skeleton of the signature
- etc

Off-line Methods: Extended Shadow Code

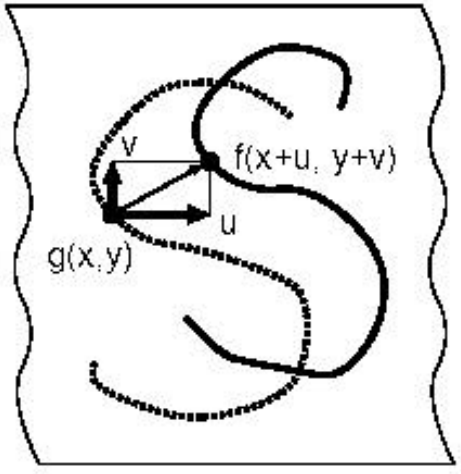
- The most accurate at the moment (mean total error of approximately 1%)
- Used as a shape factor
- Superposition of a bar mask over the binary image of a signature



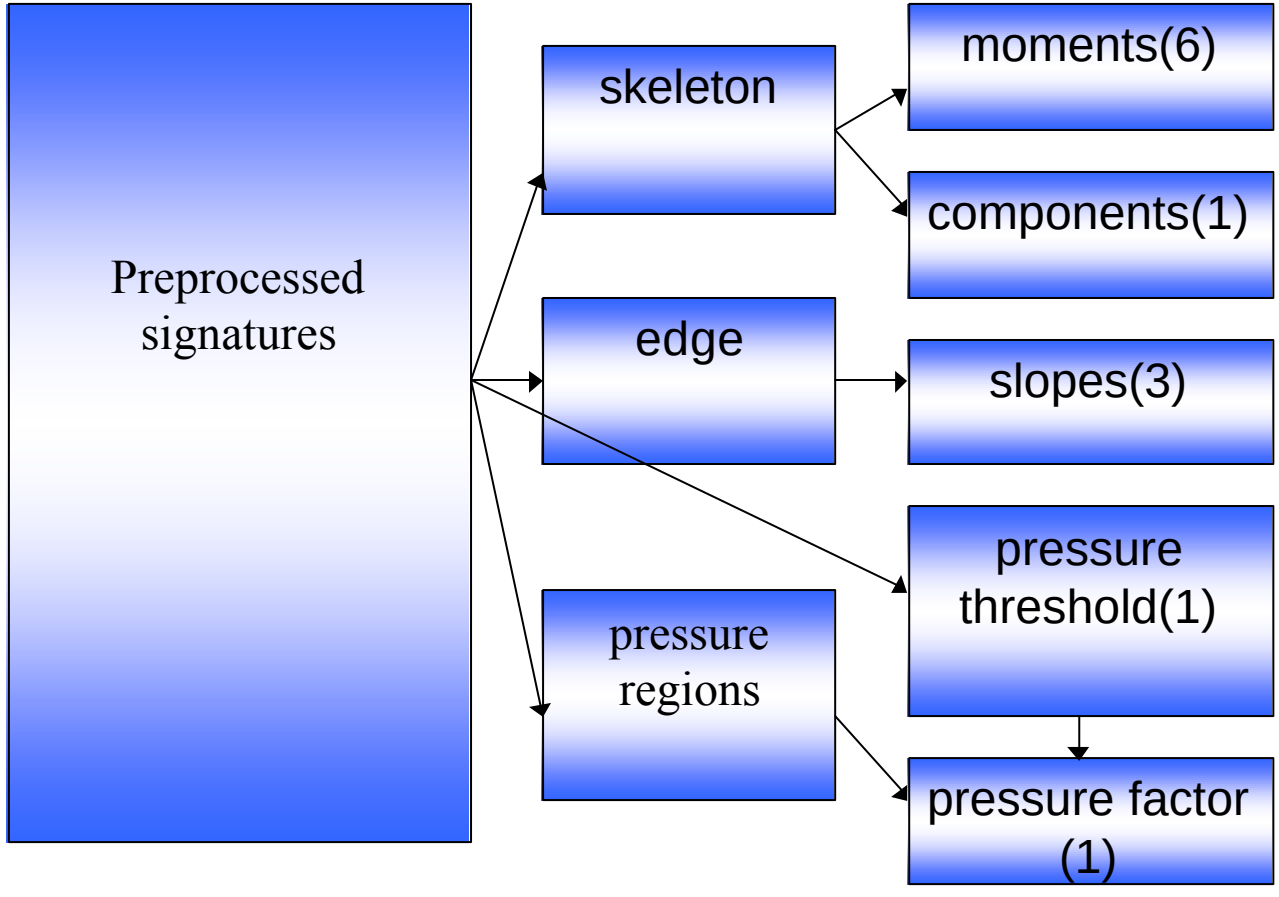
Off-line Methods: Displacement Function

- The method consists in minimization of a function, defined as a weighted sum of a squared Euclidean distance between two signatures and a penalty term of the smoothness of the displacement function.

Average error rate 25%



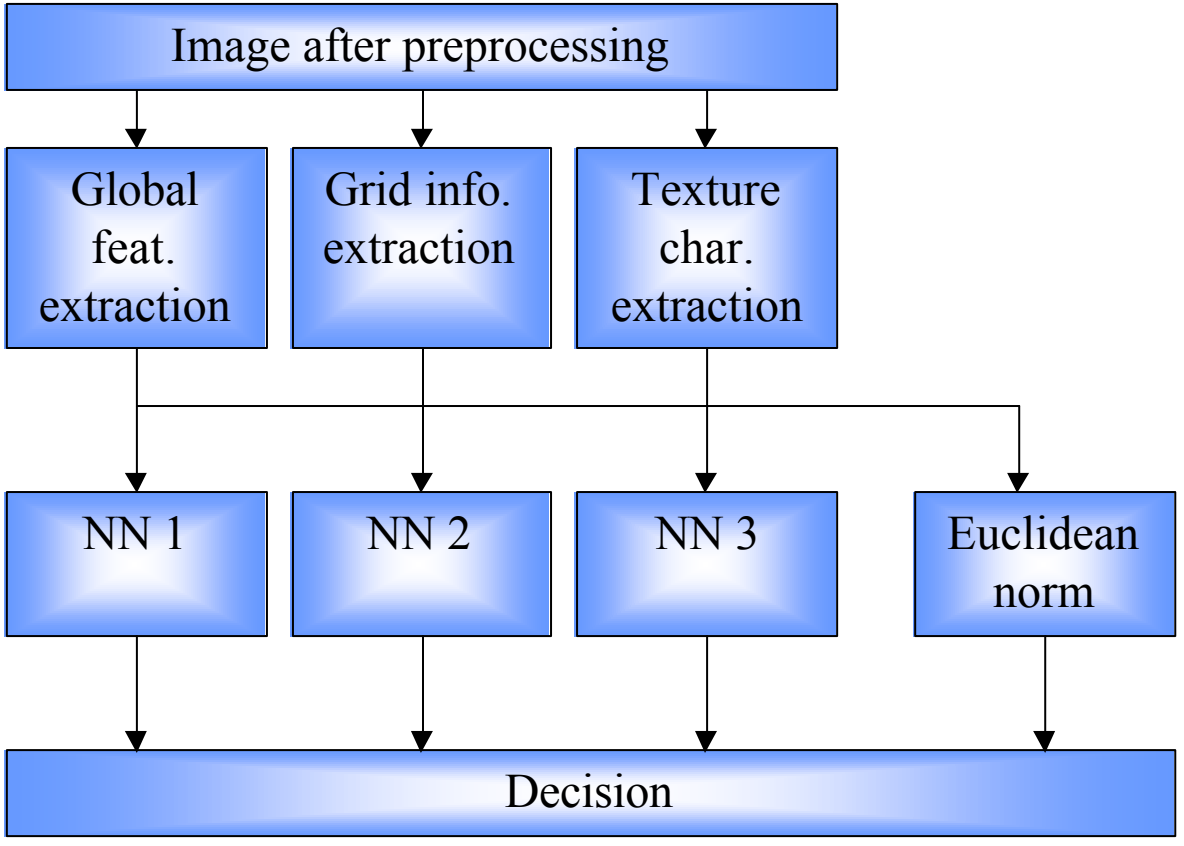
Off-line Methods: Autoassociator Neural Network



Off-line Methods: Multiple Neural Networks (1)

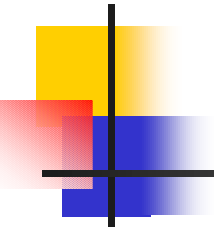
- Signature height
- Image area
- Pure width
- Pure height
- Baseline shift
- Vertical center of mass
- Horizontal center of mass
- Maximum vertical projection
- Maximum horizontal projection
- Vertical projection peaks.
- Horizontal projection peaks
- Global slant angle
- Local slant angle
- Number of edge points
- Number of cross points
- Number of closed loops

Off-line Methods: Multiple Neural Networks (2)



On-line Signature Verification

- Data acquisition
- Feature extraction
- Feature selection
- Decision-making
- Performance evaluation



On-line Signature Verification

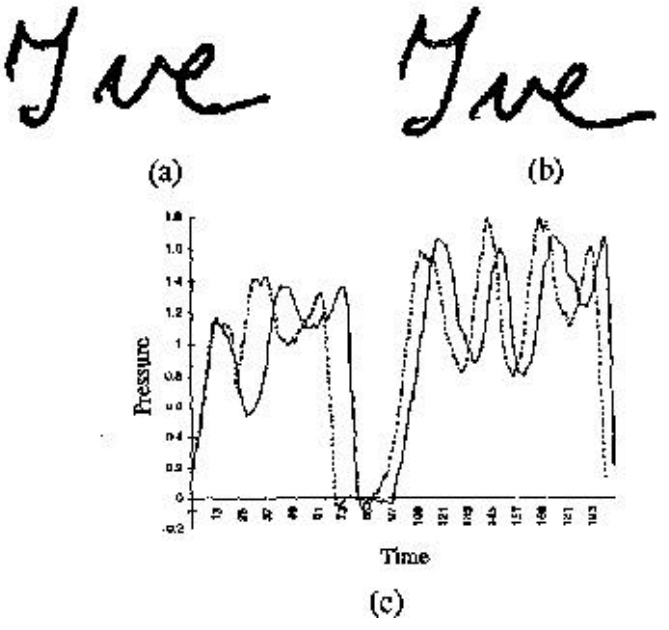
- probabilistic classifiers
- time warping or dynamic warping
- neural networks
- HMM
- signal correlation
- hierarchical approach
- Euclidean and other distances

On-line Signature Verification: Probabilistic classifiers

- Determines the degree of importance of certain features based on probability distribution of the genuine signature set features and general probability distribution of the whole set of signature features

On-line Signature Verification: Time warping and dynamic matching (1)

- The goal of the DTW algorithm is to find the most optimal time alignment between the reference signature and the signature in question.



On-line Signature Verification: Time warping and dynamic matching (2)

- Having two signature patterns R (Reference) and T (Test). The warping path (time-alignment) p can be defined as:

$$p = c(0), c(1), c(2) \ldots, c(K) \quad (1)$$

$$p_k = c(k) = (i(k), j(k)) \quad (2)$$

where i and j refer to i^{th}/j^{th} sample of R/T.

On-line Signature Verification: Time warping and dynamic matching (2)

- Assume:

$$d(p_k) = d((i(k), j(k))) = \left\| R_i - T_i \right\| \tag{3}$$

$$D(p) = \frac{\sum_{k=1}^{K} w(k) d(p_k)}{\sum_{k=1}^{K} w(k)} \tag{4}$$

Then the algorithm attempts to find the path p, so that is minimizes the value of D(p), thus showing the best time-alignment between the T and R.

On-line Signature Verification: Neural Networks (1)

- Features: number of pen lifts, percent of pen contact length between lifts, total pen contact length, average pen stroke angle, pen speed against time with pen lift information removed etc.
- A three layer artificial neural network, trained using supervised learning with back propagation.
- FRR reduces to 7% and FAR to 6%

On-line Signature Verification: Neural Networks (2)

- In this case linear predictor cepstrum coefficients (LPC) are selected to be the features of the signatures.
- A number of single output multilayer perceptrons (each for each word in the signature) are created for each user.
- The performance of the system shows that an equal error rate of as low as 4% has been obtained in the experiments.

On-line Signature Verification: Hidden Markov Models (1)

- Incorporate dynamic normalized directional angle function of the distance along the signature trajectory and model this information by HMMs. A Baum-Welch algorithm has been used for training and classification.. The system produced a 1.75% FRR and 4.44% FAR.

On-line Signature Verification: Hidden Markov Models (2)

- Another experiment performed using the same technique yielded an equal error rate of approximately 1.2%. What is computed in this case is a log-likelihood of the HMM for a given signature sample. The decision is made on the basis of a predefined threshold.

Providers of Signature Verification Solutions

1. Communication Intelligence Corporation
2. Cyber-SIGN Japan Inc.
3. DATAVISION corporation
4. WonderNet
5. SOFTPRO
6. Security Biometrics, Inc.
7. Valyd, Inc.
8. Hesy

Conclusions

- According to the requirements set by Association for Payment Clearing Services (APACS) the FRR should be equal 0.001% and FAR 5%. However, none of the commercially available systems meet the requirements nowadays.
- Signature is a de facto mean of confirming the identity of the person, and therefore will provide a far less disruptive migration to an advanced technology than any other biometric can.

Questions and Comments

Thank you for your attention!