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Introducing Fuzziness on Snake Models for Off-line Signature Verification: A Comparative Study

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Outline

- Introduction
- Overview of snakes
- Signature adjustment with fuzzy snakes
- Fuzzy signature verification system
- Experimental results
- Conclusions and future work

Introduction

- Human signatures provide secure means for authentication and authorization in legal and banking documents.
- Signatures are one of most common behavioral biometric patterns due to their easy acquisition and to be one of the less intrusive biometric modalities.
- *Signature verification* problem is concerned to determine if a particular signature is genuine or it is a forgery.
- Practical problems involving off-line signature verification can be classified in two main categories: (a) those related to the extraction of the signature from the document and (b) those related to the verification task itself.

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Introduction

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- Many off-line signature verification methods follow an standard Image Analysis approach: signature pre-processing, segmentation, feature extraction and classification.
- Most used signature features are: centers of gravity (COGs), baselines, number of holes, signature skeleton, bounding box, signature contour, major and minor signature axis, area-to-perimeter ratio, density of points in the different signature regions, slant angle, number of signature strokes, crossing points, ...
- Off-line signature verification techniques: HMM-based approaches, fuzzy logic, neural networks, neuro-fuzzy approaches, genetic algorithms, elastic graph matching techniques, optimal displacements functions, ...

Introduction

- We compare different hybrid snake-based approaches (crisp+NN, crisp+TS, fuzzy+NN and fuzzy+TS) for this verification problem using the corresponding FAR and FRR biometric errors.
- This verification task can be decomposed in two main stages:

  1) *Adjustment stage*: a snake model, obtained from a reference signature, is adjusted over the test signature image to be verified using a crisp or a fuzzy approach.

  2) *Classification or verification stage*: several measures extracted from the similarity between the test signature with the snake model are the inputs to a multilayer perceptron (MLP-NN) or to a first-order Takagi-Sugeno (TS).

  Both classifiers are trained using three discriminative features (coincidence, distance and energy), which measure the degree of similarity between the two signatures being compared.

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Overview of snakes

- Snakes are based on the movement of a closed or open parametric curve on an image to which it iteratively tries to adjust.
- Mainly applied to the contour-based segmentation of images. Other Computer Vision snake applications are related to object tracking and shape recognition.
- An associated energy functional, with internal and external constraint terms, is attached to the snake: *internal energy* is related to restrictions of elasticity and flexibility imposed to the parametric curve, and *external* (or *image*) *energy* is caused by the influence of image features (i.e. intensities of pixels, edges or corners) which guide the snake movements.
- The aim is to minimize the snake energy functional. In this way, the problem of finding the contour of objects is reduced to an energy minimization problem.

Overview of snakes

- A parametric representation is generally used to describe the snake position on a two-dimensional image:

$$E_{snake} = \int_0^1 E(v(s))ds = \int_0^1 \left[E_{\text{int}}(v(s)) + E_{image}(v(s)) + E_{cons}(v(s))\right]ds$$

- Kass et al snake formulation has some drawbacks: initialization of the parametric curve in the image, appropriate selection of snake parameters, existence of local minima in the snake energy minimization function, ...
- Several authors have proposed different improved hybrid algorithms which combine the traditional snakes with soft-computing techniques.

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Signature adjustment with fuzzy snakes

- The first stage of the signature verification task is building a signature model for each writer using only one signature.
- This signature is needed to create a snake which is adjusted over the test image to be verified.
- The adjustment process has three steps:

1) For each "class signature", construct a polygonal line or snake *P*, defined by a variable number of equal-spaced control points.

2) Place *P* over the image of the signature to verify such that the centres-of-gravity of both figures are made coincident.

3) Use Amini et al. dynamic-programming snakes algorithm to adjust *P* as best as possible to the signature image using an appropriate internal and image energy formulation.

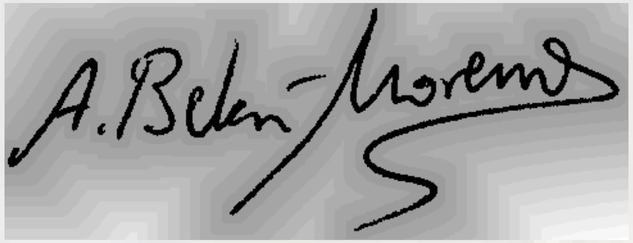
Heuristic crisp energy definition (I)

- Based on the original snake formulation by Kass et al. A new energy definition E'snake was adopted by considering two aspects.
- First, to solve the snake locality problem, we use a potential map for the image energy term E'image associated to the test image.
- Second, to avoid an excessive deformation of the snake, a new internal energy term E'shape is proposed to maintain the snake shape.

$$E'_{snake} = E'_{image} + E'_{shape}$$

Heuristic crisp energy definition (II)

- Cohen and Cohen proposed the use of a potential map defined as the Euclidean distance in pixels $m_{image}(x,y)$ from each signature image point to the closest point belonging to a signature stroke.



- The energy term E'_{image} attached to each snake control point v_i is:

$$E'_{image}(v_i) = m_{image}(v_{i-1}) + m_{image}(v_i) + m_{image}(v_{i+1})$$

- The term E'_{shape} is defined as:

$$E'_{shape} = E'_{angle} + E'_{prop}$$

Alternative fuzzy snake energy (I)

- Difficulty of adjusting the involved snake parameters in the previous formulation.
- A new simplified fuzzy snake energy expression is introduced.
- The output fuzzy snake energy for each snake control point v_i is computed using IF/THEN fuzzy rules that consider three input variables (angle, proportions and distance).
- Each one of these variables is fuzzified and described by the corresponding fuzzy sets represented by linguistic labels.

Alternative fuzzy snake energy (II)

- The fuzzy snake is represented by two-rule fuzzy inference system (FIS):

  Rule 1: IF angle changes much
  OR proportions change much
  OR distance is large THEN energy is high
  Rule 2: IF angle changes few
  AND proportions change few
  AND distance is small THEN energy is low

- Finally, the corresponding crisp energy value is obtained by applying a centre-of-gravity (COG) defuzzification method.
- This fuzzy formulation makes possible to achieve a limitation for the energy values in a natural way.

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Similarity measures: coincidence (f_c), distance (f_d) and energy (f_e)

- An adjustment measure of the snake model over the signature image is computed.
- The factor f_c uses the potential map $m_{image}(x,y,\alpha)$ to assign a value to each snake point (not only to the control points):

$$f_c = 1 - \frac{1}{N}\sum_{i=0}^{N} c(p(i)) \qquad where : c(p(i)) = \frac{m_{\text{image}}(p(i))}{k_{fc}/g}$$

- The factor f_d also uses the potential map map $m_{image}(x,y,\alpha)$, which permits to compute the distance of the signature pixels with respect to the snake position:

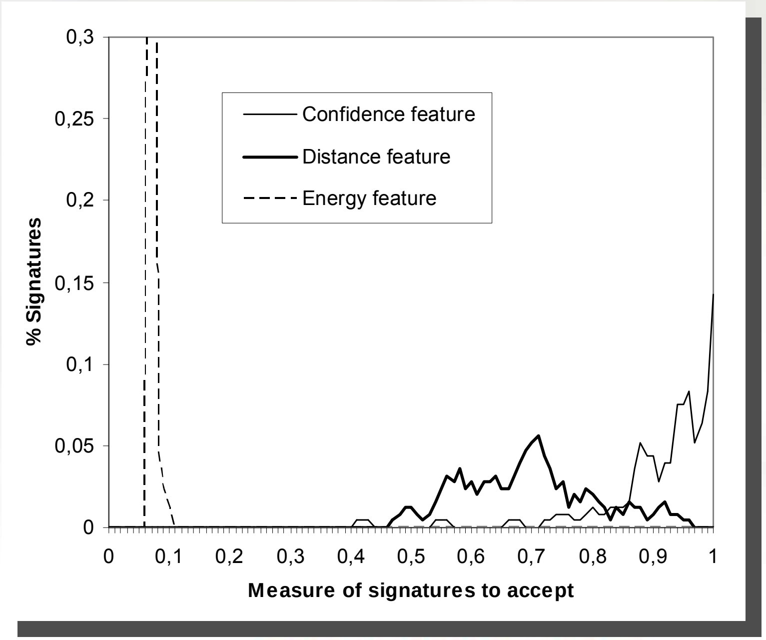
$$f_d = \sum_{i=0}^{M} d(r(i)) \qquad where : d(p(i)) = \begin{cases} 1 & \text{if } \ m_{image}(r(i)) < g \\ 0 & \text{if } \ m_{image}(r(i)) \geq g \end{cases}$$

- In the fuzzy approach, the snake energy is limited to values between 0 and 100 and it is introduced as a third similarity measure f_e.

Fuzzy signature verification system

MLP-NN signature verification system

- We used a 2-layer perceptron as signature classifier.
- This neural network (NN) has three input neurons corresponding to the values of the three computed similarity measures.
- The number of neurons in the hidden layer was experimentally set to 10 units and the output layer had only one neuron.
- For training this NN, the neural simulator JNNS was used: http://www-ra.informatik.uni-tuebingen.de/software/JavaNNS/welcome_e.html



First-order Takagi-Sugeno (TS) signature verification system (I)

- To establish the degree of genuineness of a given test signature, a fuzzy approach is proposed.
- A system with tolerance to imprecision can be designed to achieve a more robust, tractable and low-cost solution.
- In our application, we use a fuzzy modelling of the extracted features: coincidence f_c, distance f_d and energy f_e factors.
- For the purpose of signature verification, we introduced a first-order Takagi-Sugeno (TS) model.
- The three distributions f_c, f_d and f_e, obtained using the training signatures, define three respective fuzzy sets A_c, A_d and A_e.
- The IF-THEN fuzzy rules in the first-order TS model are:

$$\text{Rule}_k : \text{IF } x_k \text{ is } A_k \text{ THEN } y_k = c_k + d_k\, x_k \qquad \forall k=1, 2, 3$$

First-order Takagi-Sugeno (TS) signature verification system (II)

- Each fuzzy set A_k can be represented by the following Gaussian membership function which includes the parameter x_k :

$$\mu_k(x_k) = e^{-\frac{(x_k - a_k)^2}{b_k}}, where: k = 1,2,3$$

- The output of the fuzzy system is a crisp value obtained after the defuzzification, as follows:

$$o = \sum_{i=1}^{2} \mu_i y_i$$

- This value *o* defines the final resulting similarity between a test signature and a reference signature to which it is compared.
- If the value is less than an experimental threshold, then the test signature is considered genuine, otherwise it is a forgery

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Signature database

- Due to the private nature of the signatures, there is a lack of standard databases referenced in the literature.
- We created our own signature database that can be obtained from: http://gavab.escet.urjc.es.
- This database contains the signatures of 56 individuals with 6 samples per writer.
- These patterns were acquired in different periods of time and also using different types of pens.
- Signatures were scanned as binary images with a spatial resolution of 300 dpi and stored as BMP files.

Experimental results

MLP-NN training stage

- Trained during 5000 iterations using a standard backpropagation algorithm and a learning rate equal to 0.01.
- The training error converges in about 1000 iterations.

First order TS training stage:

- The fuzzy TS model was trained until the error was smaller than a value of 0.01 using a gradient descent algorithm.
- A total of 28 from 56 individuals of the database were used for training purposes and the other 28 individuals were used for testing the models.
- For each person *i*, we have 6 genuine signatures (one is used to build the snake and the other five to train the system).
- For each person all the signatures from the 27 remaining individuals are used to define the set of patterns to be rejected by the snake (class) *i*.
- For the 28 training individuals, a set of $28\times5=140$ train signatures as patterns to accept, and a set of $28\times27\times6=4536$ test signatures as patterns to reject is obtained.

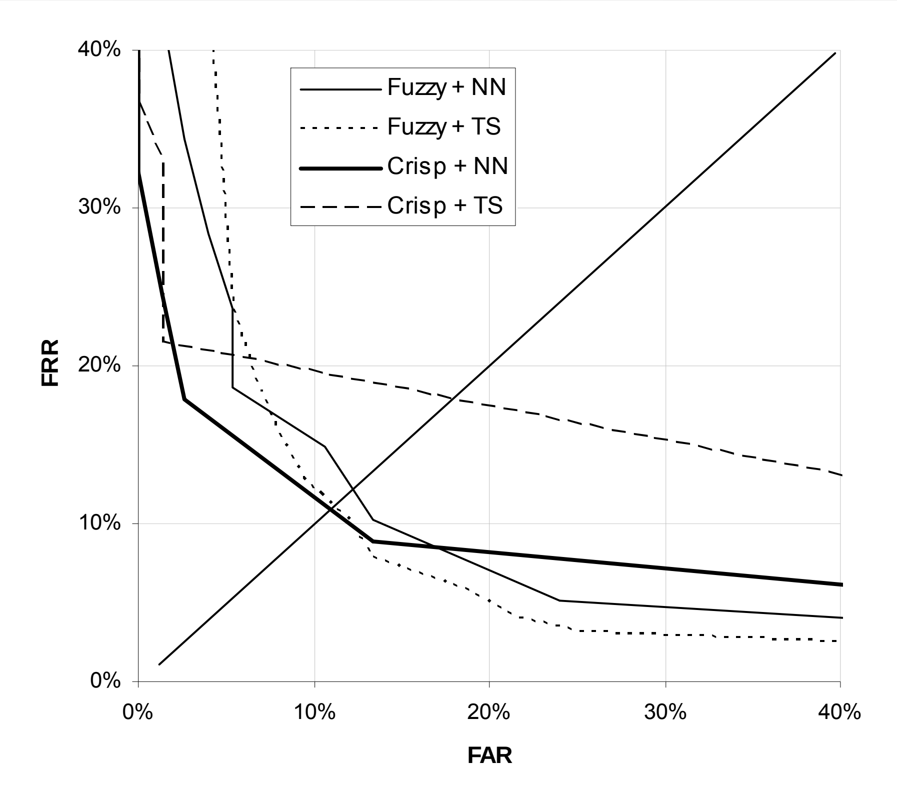
Test stage

- Each test signature is compared with the corresponding snake, using the explained verification methods, yielding a real value between 0 and 1.
- This value defines the similarity degree with the corresponding model signature.
- Finally, these results were compared with different threshold values to decide whether to accept or to reject a test signature.

ROC curves (I)

- ROC curves display the trade-off between False Acceptance Rates (FAR) and False Rejection Rates (FRR) values for different thresholds.
- The Receiver Operating Characteristic (ROC) curves for the four hybrid snake algorithms are presented.
- We implemented and tested four hybrid snake models:
  - (a) crisp + NN
  - (b) crisp + TS
  - (c) fuzzy + NN
  - (d) fuzzy + TS

ROC curves (II)



Comparative ROC curves for the four proposed hybrid snake models

Experimental results

ROC curves (III)

- We have also visually checked how both (heuristic crisp and fuzzy) energy snake models adjust the test signatures.
- Experiments have shown a more accurate adjustment when using the fuzzy definition of the snake energy.
- This is due to the fuzzy energy definition does not require any parameters and, at the same time, is more intuitive and easy to understand than its equivalent crisp definition.
- None of the tested approaches clearly outperforms the other ones.
- If our specific application domain is signature verification in bank check processing (where only checks with an amount over certain threshold are manually verified), high FRR values produce trouble to customers and higher processing costs.
- For this scenario, the best considered solution is the "Fuzzy +TS" approach since this solution presents the lowest FRR value versus an acceptable FAR value (about 20%-30%).

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Conclusions

- This paper presented an experimental study to evaluate the introduction of a fuzzy approach in snakes formulation for the automatic off-line signature verification problem.
- Four different hybrid snake algorithms were tested (crisp+NN, crisp+TS, fuzzy+NN, and fuzzy+TS, respectively).
- Experimental results showed that, in general, none of the considered hybrid snake algorithms clearly outperformed the other algorithms when they were applied to the off-line signature verification problem.
- However, a fuzzy formulation of snake parameters with a first-order TS classifier (fuzzy+TS) can be considered as the most suitable one in bank check processing environments.

Future work

- We are working in several directions to improve the complete signature verification system.
- In particular, two components are needed to have a complete automatic off-line signature verification system:
  - (a) a method to automatically define the snake using one training signature image, and
  - (b) an algorithm for segmenting the signature in a generic noisy document.