Automatic Off-Line Signature Verification

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Abstract: **A method for off-line signature verification based on Neural Network Classification is proposed. The method uses geometric and pseudodynamic features of the signatures. The main steps during system performance are described. Innovation of the method proposed – Optimal combining of both, Signature Attributes and the Neural Network Parameters. The optimization is a result of the Statistical Feature Analysis and Neural Network Learning. Innovation of the educational method: Students can modify the parameters of the steps. They can optimize the result of the recognition.**

Keywords: **Feature Extraction and Analysis, BP Neural Network, Automatic Signature Verification.**

I. INTRODUCTION

A reliable automatic person identification is critical in a wide variety of forensic, civilian and commercial applications. Biometrics, which refers to identification of people on their physiological (face, iris pattern and fingerprint) and behavioral (speech and handwriting) characteristics. Handwritten signature verification is behavioral biometrics verification and it is either on-line or off-line. In an on-line system, signature traces are acquitted in real time, during the signing process [1,2,3]. In an off-line system, signature images are acquired after the complete signatures have been written [1,4,5,7]. The two types signature verifications use static calligraphic information (geometric properties) and dynamic or pseudodynamic features.

Signature recognition could be presented as classification in two classes: true and false [1]. Let suppose that C_i is a cluster of all true signatures of the person "i" and C_j is a cluster of all false signatures, which do not belong to this person. Respectively, σ_i is the intrapersonal dispersion in C_i – cluster and σ_{ij} is the interpersonal dispersion in C_j – cluster.

A method and a program system for handwritten signature recognition are proposed in this article. The system is aimed at getting students practical knowledge and skills about the Image Processing and the Pattern Recognition and to support some science studies. The proposal is to realize the aim by means of an Automatic Handwritten Signature Verification System (AHSVS).

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The AHSVS is based on a Neural Network with Back Error Propagation (BPNN).

This system is based on a static method with the followed steps: signature images data base creation; preprocessing; feature recognition selection and description; feature analysis; the rules or functions for classification; learning of the recognition system; recognition (classification).

II. SIGNATURE IMAGES DATABASE CREATION

The genuine signatures of 180 students (3800 total) are put into the database. The signatures are made during a period of 7 days, three times daily and they reflect the intrapersonal variation of emotions. These signatures are scanned, one page at a time (one page contains 21 signatures per every person), at resolution of 300dpi, 8-bit gray-scale. There are 3800 false (imitation) signatures – 21 imitation signatures for every person, in the database.

III. PREPROCESSING OF SIGNATURE IMAGES

The aim of preprocessing is to make the features recognition extraction easily. The process of preprocessing contains the following steps [9,10,11]: background reduction by equalization (in line); filtering with smoothing matrix; bright segmentation with a chosen threshold of image histogram [6,7]; binarization of the image; signature marking and all small objects erasing.

IV. FEATURES FOR CLASSIFICATION – CHOICE

Effective feature choice and extraction are important in all signature recognition tasks. A very important problem is the correctly reduction of the dispersion σi, also. The sets of reference and test signature images need to be carefully aligned before the feature extraction. They are examined for σ i, but are not examined for σ_{ij}. There are 17 features in this system (geometrical, topological, brightness and contour features). It is possible to add new features during the work. All features must be normalized after their extraction. The features are the following:

1. Area of signature A_0;

2. The relative bright range of signature $B = B_{min}/(B_{max}-B_{min})$;

3. Shape coefficient $C_s = L_s/H_s$, were L_s and H_s are the dimension of signature;

4. The number of connected components - P_s;

5. The holes number in signature - Q_s;

6. The number of contour pixels in five defined directions: NW (north/west), NE (north/east), NS (north/south), SW and SE. These features are normalized to the number of contour pixels;

7. The threshold θ_P of segmentation inside strong pressure domains. The threshold θ_P is defined in the gray level histogram of the signature (Fig.1). It is fixed at the level 0,7 of the maximal level – 0,7Max (to the left of Max);

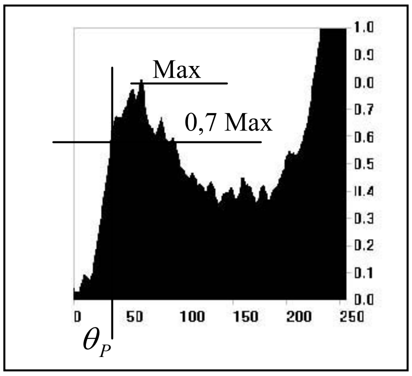

Fig.1

8. The number of pixels whose brightness is less than θ_P. These pixels form the strong pressure domains.

9. The pressure factor PF [6]:

$$PF = \frac{A_{PF}}{A_o} = \frac{A_{PF}}{A_I - A_B} \times 100 \qquad (1)$$

A_{pf} is the area of strong pressure domains; A_j - the area of the whole picture; A_B - the area of background.

Fig.2 a, b

Fig.2 c, d

Fig.2 a,b shows true and false signatures. Fig.2 c,d shows strong pressure domains for the same signatures.

Fig. 2.c is the result at PF=2,515 and Fig. 2d - at PF=16,244;

10. The position of a vertical line having max number of crossings with the signature (Fig.3). This feature is normalized to H_s;

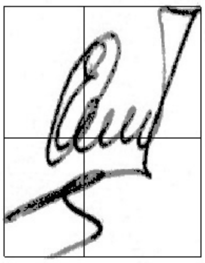

Fig.3

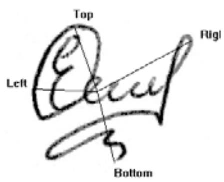

Fig.4

11. The position of a horizontal line having max number of crossings with the signature (Fig.3). This feature is normalized to L_s;

12. Signature's center of gravity (X_C, Y_C). The values of Xc,Yc are defined in relation to the bottom left angle of the rectangle wrapping the signature - Fig. 4:

$$X_C = \frac{1}{A_0} \sum_{i=1}^{N} X_i \qquad (2)$$

$$Y_C = \frac{1}{A_0} \sum_{i=1}^{N} Y_i \qquad (3)$$

13. The angularity of the signature, which is described, with the stretches of the motion in the horizontal and the vertical directions:

$$\cos\theta_{LCR} = \frac{(y_L - y_C)^2 + (x_L - x_C)^2 + (y_C - y_R)^2 + (x_C - x_R)^2 - (y_L - y_R)^2 - (x_L - x_R)^2}{2\sqrt{\left((y_L - y_C)^2 + (x_L - x_C)^2\right)\left((y_C - y_R)^2 + (x_C - x_R)^2\right)}}$$

$$\cos\theta_{BCT} = \frac{(y_T - y_C)^2 + (x_T - x_C)^2 + (y_C - y_B)^2 + (x_C - x_B)^2 - (y_B - y_T)^2 - (x_B - x_T)^2}{2\sqrt{\left((y_C - y_B)^2 + (x_C - x_B)^2\right)\left((y_T - y_C)^2 + (x_T - x_C)^2\right)}}$$

where $\cos\theta_{LCR}$ and $\cos\theta_{BCT}$ are obtain from the angles: a) the angle LCR is formed between the points left- X_L,Y_L, X_C,Y_C and right-X_R,Y_R, and b) the angle BCT is formed between the points bottom- X_B,Y_B, X_C,Y_C and top X_T,Y_T - Fig. 4.

14. The number of skeleton pixels F_{core} of a signature [3], defined in (6) and (7) -Fig. 5:

$P \in F_{core}$, on the condition

$$\sum_{k=0}^{7} (g_p \le g_k) \ge 6 , \qquad (6)$$

$$\text{where } (g_p \le g_k) = \begin{cases} 1, if\ (g_p \le g_k) \\ 0 \end{cases} \qquad (7)$$

This feature is normalized to Ao;

Fig.5

Fig.6

15. The number of contour pixels (Fig. 6) [3]:

$$\theta_{outline} = g_{\min} + 0.75\left(g_{\max} - g_{\min}\right) \quad (8)$$

16. The total number of pixels for coarse distribution of ink (Fig. 7. a).

17. The total number of pixels for fine distribution of ink (Fig. 7. b).

Fig.7 a

Fig. 7 b

V. STATISTICAL METHOD FOR FEATURES ESTIMATION

When the training vectors are formed, it necessary to check their features – how effective they are during the process of recognition [9,10]. The efficiency of every feature could be examined by calculating of the mathematical expectation, dispersion and regression for one training set (Fig.8). The Neural Network efficiency **E** is described by:

$$\mathrm{E} = \left(\left(\varepsilon_1 P[\omega_1]\right) + \left(\varepsilon_2 P[\omega_2]\right)\right), \qquad (9)$$

where ε_1 is the error of false rejection (error of type I); ε_2 - the error of false acceptation (error of type II); $P[\omega_1]$ - the probability for error of type I; $P[\omega_2]$ - the probability for error of type II.

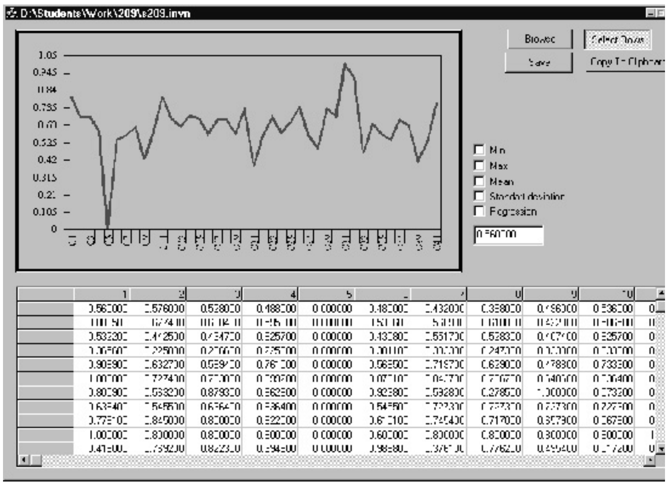

Fig.8

VI. SIGNATURE RECOGNITION WITH NEURAL NETWORK

It was chosen to use a Back Propagation Neural Network as a signature classifier. It has two steps of working: learning and recognition. The learning-rate parameter η is chosen constant, but it is possible to make changes during the time of learning as it is shown:

$$\eta(t+1) = \eta(t) + \Delta\eta(t)$$

$$\Delta\eta(t) = \begin{cases} +a, if\, \Delta E < 0(t-1; t-s); \\ -b.\eta, if\, \Delta E > 0; \\ 0, if\, \Delta E = 0, \end{cases} \qquad (10)$$

where **a** and **b** are predefined constants; ΔE - a variation of the average squared error. The designation 0 (t-1, t-s) indicates that ΔE must be less than zero during several consecutive steps – the latest s-steps. The speed of learning depends on the momentum **α** of the weight variation. The weight variation is described by the expression:

$$\Delta w_{ij}(t) = -\eta \frac{\partial E}{\partial w_{ij}} + \alpha \Delta w_{ij}(t-1). \qquad (11)$$

The time of learning depends of all mentioned parameters. It could vary in wide ranges.

Fig.9 shows the Neural Network initialization.

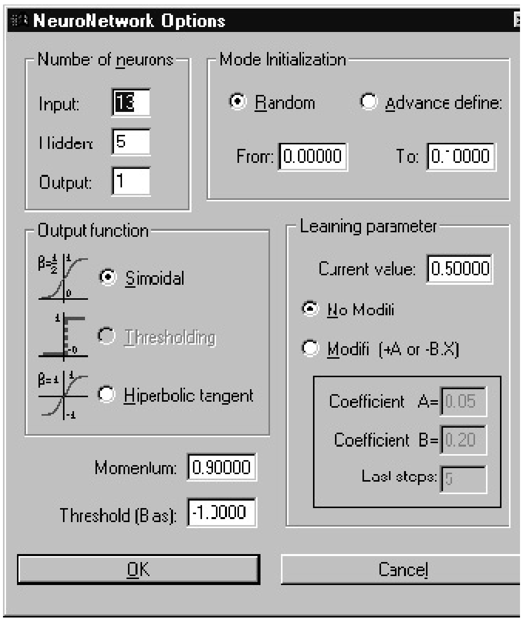

Fig. 9

VII. EXPERIMENTAL RESULTS FOR EDUCATION

An Automatic Handwritten Signature Verification System should be able to discriminate between genuine signature and forgeries. There are four kind's of forgeries: random, freehand, simulated and photocopies. The random and the freehand forgeries represent almost 95% of the cases in practice.

200 pictures of signatures have been studied up to now during the practical work of students. The features "rotation and scaling" of invariant parameters are analyzed. 63 true signatures are chosen, their parameters are: intrapersonal dispersion σ_I less then 15%, and regression angle of 10°. 63 forgeries are chosen. The initial set of the Neural Network is realized as described: input vector dimension–13; number of training vectors–63; number of output neurons–2; number of neurons in the hidden layer–23; type of weight values in initialization - random in the range of 0 to 0.5; learning-rate parameter η – 0,5; activation function – sigmoid; momentum **α** – 0,9. The experimental results show that the signature classifiers constructed with the proposed method is effective in random and freehand forgeries recognnition. The error of Type I for genines is 10%. The error of Type II for forgeries is 12%.

VIII. CONCLUSION

The neural network with their multi-layer structure and BP algorithm for learning give good results (90% recognition). The precision of this recognition system (used for education) can be increased by using the students and with the increasing of database containing more signatures.

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