

Handwritten Signature Verification Technique based on Extract Features

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ABSTRACT

In this paper, we describe a new method to identify the handwriting signature. There are many methods for signature verification, but most of them require segmentation or connected component analysis. A robust Verification technique for identifying and verifying human-signature images is presented. The Verification process utilizes the determinant value that produces the features for the handwritten signature. Image's determinants values are computed, by divided image into blocks then find centric point to calculate distance. The least square criterion is then utilized to determine the similarity between the existed (in Database file) signatures with a new signature's images. A threshold value is designed to differentiate between existed and non-existed stored signature's images.

Keywords

Signature, Determinant value, Euclidean Distance

1. NTRODUCTION

Signature has been a distinguishing feature for person identification through ages. Signatures for long have been used for automatic clearing of cheques in the banking industry. Despite an increasing number of electronic alternatives to paper cheques, fraud perpetrated at financial institutions in the United States has become a national epidemic. Since commercial banks pay little attention to verifying signatures on cheques—mainly due to the number of cheques that are processed daily—a system capable of screening casual forgeries will prove beneficial. Most forged cheques contain forgeries of this type. We in our project have tried developing a robust system that automatically authenticates documents based on the owner's handwritten signature.

Biometrics can be categorized as behavioral and physiological. Handwritten signature belongs to behavioral biometric. In most of the places the verification is done manually either by a person who is familiar to the signature or by matching it against a few signature templates handwritten signature verification can be classified into offline signature recognition system and online signature recognition system. Between the two, online signature recognition systems are more reliable because of its higher efficiency in terms of accuracy and time than offline. However, offline signature recognition systems cannot be ignored, since its applicability and ease of use

are more in comparison to online signature recognition systems in many parts of the world [1] .

There are many approaches discussed earlier. Our approach contain five major phases for verifying a signature .These are Data gathering, Preprocessing, Training, and Testing. Data gathering is nothing but collecting sample signature of each person. Preprocessing is required for making signature image compatible with the requirement of our approach. Feature extraction is a phase in which we extract various features from signature like its projection, local point density, spatial frequency distribution etc. Training is a phase in which we will find determinant value between the features of signature then we find the distance and least square error from determinant correlation values and save them in database. Testing is done to test the input image is correct

2. PRIOR WORK

For authentication and authorization in legal matter humans are recognized by their Signature. Every human being has their own writing style and hence their signature is used in the financial domain for identity verification. So it is necessary to develop a technique which is efficient in verifying the Handwritten Signature is correct or forge. In another paper presents a technique of Handwritten Signature Verification based on Correlation between Handwritten Signature images using feature extracted from it. In that paper we have proposed a method to extract features from scanned image of signatures store it in database. We correlate features of all sample signatures for each person. Then find a mean value from the correlation value of one person signature then compute deviation from it which is used for verification [1].

The fact that the signature is widely used as a means of personal verification emphasizes the need for an automatic verification system. Verification can be performed either Offline or Online based on the application. Online systems use dynamic information of a signature captured at the time the signature is made. Offline systems work on the scanned image of a signature. We have worked on the Offline Verification of signatures using a set of shape based geometric features. The features that are used are Baseline Slant Angle, Aspect Ratio, Normalized Area, Center of Gravity, number of edge points, number of cross points, and the Slope of the line joining the Centers of Gravity of two halves of a signature image. Before extracting the features, preprocessing of a scanned image is

necessary to isolate the signature part and to remove any spurious noise present. The system is initially trained using a database of signatures obtained from those individuals whose signatures have to be authenticated by the system. For each subject a mean signature is obtained integrating the above features derived from a set of his/her genuine sample signatures. This mean signature acts as the template for verification against a claimed test signature. Euclidian distance in the feature space between the claimed signature and the template serves as a measure of similarity between the two. If this distance is less than a pre-defined threshold (corresponding to minimum acceptable degree of similarity), the test signature is verified to be that of the claimed subject else detected as a forgery. The details of preprocessing as well as the features depicted above are described in the report along with the implementation details and simulation results [2].

3. Methodology

3.1 Gathering Information

Basically in this method we collect the 6 scanned images of signature of different person. These images are stored in a database which we are going to use in training of our software, but not for actual matching. In our proposed work we have to use an interface with scanner for getting an image and storing it in desired database. The size of each image (n×n) and each image can represent as array thus illustrated in *Eq.1*

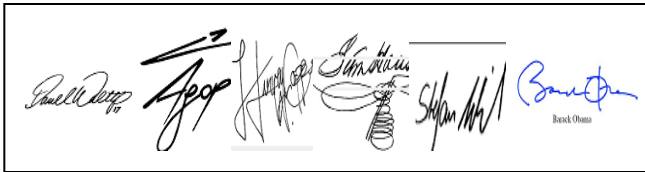


Fig1. Training set of handwritten signature

3.2 Determinant value

The term determinant of a square matrix A, denoted $\det(A)$ or $|A|$, refers to both the collection of the elements of the square matrix, enclosed in vertical lines, and the value of image represented by that array. Thus,

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \dots \dots \dots (1)$$

Only square matrices have determinants. The scalar value of the determinant of a 2×2 matrix is the product of the elements on the major diagonal minus the product of the elements on the minor diagonal. Thus,

$$\det(A) = |A| = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = a_{11}a_{22} - a_{12}a_{21} \dots \dots \dots (2)$$

The scalar value of the determinant of a 3×3 matrix is composed of the sum of six triple products which can be obtained from the augmented determinant [5].

The 3×3 determinant is augmented by repeating the first two columns of the determinant on the right-hand side of the determinant. Three triple products are formed, starting with the elements of the first row multiplied by the two remaining elements on the downward-sloping diagonals. Three more triple products are formed, starting with the elements of the third row multiplied by the two remaining elements on the right-upward sloping diagonals. The value of the determinant is the sum of the first three triple products minus the sum of the last three triple products. Thus [5],

$$\det(A) = |A| = \begin{bmatrix} a_{11} & a_{22} & a_{33} & a_{12} & a_{23} & a_{31} & a_{13} & a_{21} & a_{32} & a_{12} & a_{23} & a_{31} & a_{13} & a_{21} & a_{32} & a_{12} & a_{23} & a_{31} \end{bmatrix} \dots \dots \dots (3)$$

Each image subdivided into blocks. The size of each block is 2×2 . Then find the determinant for each block, which is illustrated in *Eq.2*

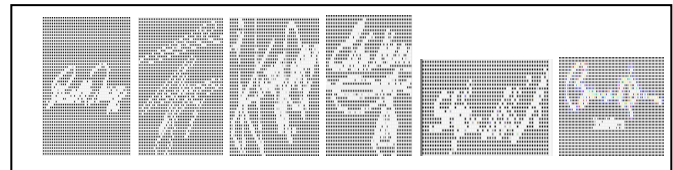


Fig2. Determinant value size block (2×2)

Each image subdivided into blocks. The size of each block is 3×3 . Then find the determinant for each block, which is illustrated in *Eq.3*

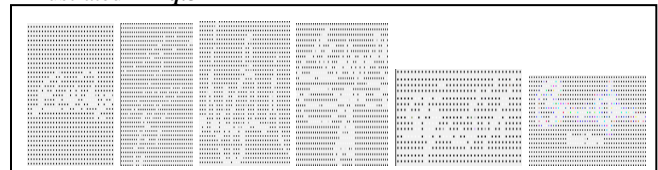


Fig3. Determinant value block size (3×3)

3.3 Determine Centric Point and Distance

The next stage in our approach is determining the centric point. The information we have up to now is the boundary of the signature as sequential coordinates in the image. Now, we show that using this boundary pixels and the centric point of the boundary image, the centric point of the signature boundary image is calculated by the equations (4, 5, 6). Here $f(i, j)$ is our signature image function and X Centroid Y Centroid is the coordinates of the centric point.

$$m_{pq} = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} i^p j^q f(i, j) \dots \dots \dots (4)$$

$$X_{Centroid} = \frac{m_{10}}{m_{00}} \dots\dots\dots (5)$$

$$Y_{Centroid} = \frac{m_{01}}{m_{00}} \dots\dots\dots (6)$$

We calculate the Euclidean distance between each pixel (x, y) on the boundary and the centric point as **Eq.(7) shown in Table-1.**

$$D(x, y) = \sqrt{(x - x_{centriod})^2 + (y - y_{centriod})^2}$$

..... (7)

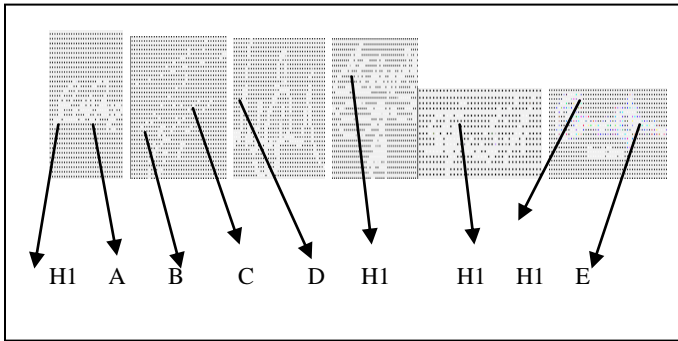


Fig 4. centric point of images

Using these key points, we find points A, B, C, D, E that are the initial and end points of the holes between edge in the boundary image. A sample of the way we find these points is shown in Fig-5. we find H1 and then calculate Euclidean distance of pixels on the boundary

Table1.The Euclidean Distance of handwritten signature

No	ED sign1	ED sign2	ED sign3	ED sign4	ED sign5	ED sign6
1	12.3	22.31	32.32	42.33	52.34	62.35
2	12	10.5	9	7.5	6	4.5
3	21	5.2	10.6	26.4	42.2	58
4	3.3	10.2	17.1	24	30.9	37.8
5	11.5	10	8.5	7	5.5	4
6	16	8.9	1.8	5.3	12.4	19.5
7	12.9	10	7.1	4.2	1.3	1.6
8	12	14.2	16.4	18.6	20.8	23

As it is obvious, the similarity between the verify hand and the trained set can be represented by the minimum distance test (i.e. utilizing the Mean-Square-Error “MSE” criterion), given by:

$$Min\{MSE_K\} = Min\left\{\sum_{i=1}^M (V_{K,i} - V_{M+1,i})^2\right\},$$

for $K = 1, 2, \dots, M$ (8)

4. Experiments and Results

We used the database for signature recognition experiments. Here we have experimented with nearly 100 images with variations of 60 persons. The global texture energy features were used to guide the dynamic selection for a small set of similar candidates from the database at coarse level for further processing. An interesting point based image matching was performed on the selected similar patterns at fine levels for the final confirmation. The experiment results show the effectiveness of the proposed method. A preview image of the Database of signature is as shown in Fig-(6,7,8,9). The experimental observations of the experiments performed on datasets are shown in Table-2 and Table-3 , Table-4 and Table-5 as follows: Suppose you have trained set of hand image°, as illustrated in **Fig5.**

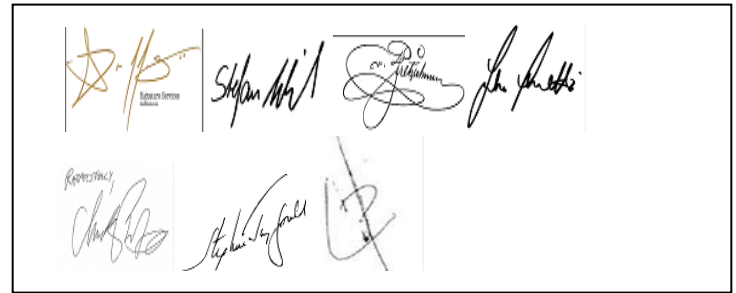


Fig5. training set of handwritten signature

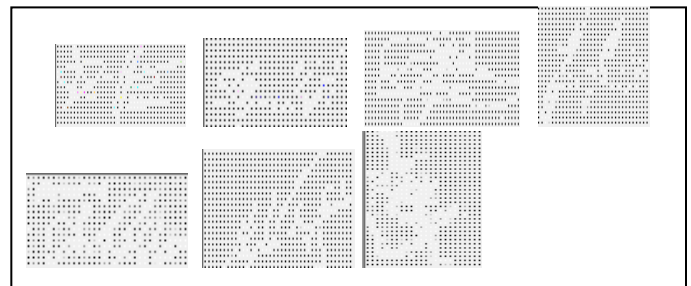


Fig6. Determinant value signature image block size (3×3)

Let us now examine a different scene for an existed signature, as illustrated in **Fig7.**below;

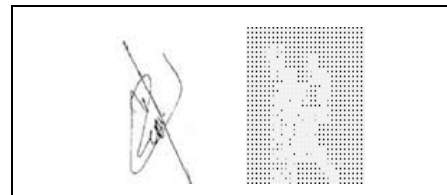


Fig7. Verified image in different scene

No	ED sign1	ED sign2	ED sign3	ED sign4	ED sign5	ED sign6	ED sign7	ED sign8
1	10.32	2.31	-5.7	13.71	21.72	29.73	37.74	36.04
2	1.9	10.51	19.12	27.73	36.34	44.95	53.56	50.5
3	2.22	9.5	16.78	24.06	31.34	38.62	45.9	45.9
4	12.23	22.1	31.97	41.84	51.71	61.58	71.45	60.45
5	9.43	15.12	20.81	26.5	32.19	37.88	43.57	43.49
6	16.11	8.4	0.69	7.02	14.73	22.44	30.15	32.15
7	13.8	7.3	0.8	5.7	12.2	18.7	25.2	20.2
8	14.77	4.3	6.17	16.64	27.11	37.58	48.05	40.55

Table-2.The Euclidean Distance of handwritten signature

The Min{MSE} between trained set and the verifying signature image is, obvious, between sign7 and sign8; i.e. Min{MSEK}=MSE7, as listed below:

Table-3.The Minimum Mean Square Error

N0	MSE1	MSE2	MSE3	MSE4	MSE5	MSE6	MSE7
1	25.72	33.73	41.74	22.33	14.32	6.31	1.7
2	48.6	39.99	31.38	22.77	14.16	5.55	3.06
3	43.68	36.4	29.12	21.84	14.56	7.28	0
4	48.22	38.35	28.48	18.61	8.74	1.13	11
5	34.06	28.37	22.68	16.99	11.3	5.61	0.08
6	16.04	23.75	31.46	25.13	17.42	9.71	2
7	6.4	12.9	19.4	14.5	8	1.5	5
8	25.78	36.25	34.38	23.91	13.44	2.97	7.5

Let us now examine another different scene for an existed signature, as illustrated in **Fig-8** below:

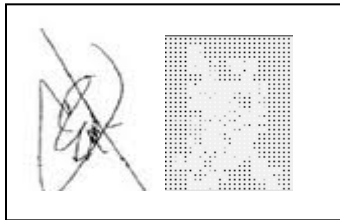


Fig8. Verified image in different scene

No	ED sign1	ED sign2	ED sign3	ED sign4	ED sign5	ED sign6	ED sign7	ED sign8
1	10.32	2.31	-5.7	13.71	21.72	29.73	37.74	31.14
2	1.9	10.51	19.12	27.73	36.34	44.95	53.56	53.5
3	2.22	9.5	16.78	24.06	31.34	38.62	45.9	47.9
4	12.23	22.1	31.97	41.84	51.71	61.58	71.45	70.4
5	9.43	15.12	20.81	26.5	32.19	37.88	43.57	41.4
6	16.11	8.4	0.69	7.02	14.73	22.44	30.15	30.55
7	13.8	7.3	0.8	5.7	12.2	18.7	25.2	20.31
8	14.77	4.3	6.17	16.64	27.11	37.58	48.05	49.2

Table4.The Euclidean Distance of handwritten signature

The Min{MSE} between trained set and the verifying signature image is, obvious, between sign7 and sign8; i.e.

Min{MSEK}=MSE7, as listed below:

Table-5.The Minimum Mean Square Error

N0	MSE1	MSE2	MSE3	MSE4	MSE5	MSE6	MSE7
1	20.82	28.83	36.84	17.43	9.42	1.41	6.6
2	51.6	42.99	34.38	25.77	17.16	8.55	0.06
3	45.68	38.4	31.12	23.84	16.56	9.28	2
4	58.17	48.3	38.43	28.56	18.69	8.82	1.05
5	31.97	26.28	20.59	14.9	9.21	3.52	2.17
6	14.44	22.15	29.86	23.53	15.82	8.11	0.4
7	6.51	13.01	19.51	14.61	8.11	1.61	4.89
8	34.43	44.9	43.03	32.56	22.09	11.62	1.15

5. CONCLUSION

In this paper we discussed method for verifying handwritten signature. Here we have used extract features which are based on Determinant value. The method proposed in this paper has the following important advantages: small database storage. , any texture classification and analysis technique can be applied in our method. We have proposed different phases through which we are able to identify the forgery in handwritten signature.

6. RESOURCE

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