A Novel Signature Verification and Authentication System Using Image Transformations and Artificial Neural Network

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ABSTRACT: *This paper proposes an Artificial Neural Network based approach for implementing Automatic Signature verification and authentication system. In this era, with the rapid growth of Internet and the necessity of localized verification systems, handwritten signature has become an important biometric feature for the purpose of verification and authentication. The proposed method comprises spatial and frequency domain techniques for transformation. After extracting the Region of Interest Ripplet-II Transformation, Fractal Dimension and Log Polar Transformation are carried out to extract descriptors of the concerned signature to be verified as well as authenticated. In decision making stage Feed Forward Back Propagation Neural Network is used for verification and authentication purpose. This system has been tested with large sample of signatures to show its verification accuracy and the results have been found around 96.15%. Also forgery detection rate has been found 92% which is very encouraging. False Acceptance Rate and False Rejection rate of our system has been determined 5.28% and 2.56% respectively. This approach has been compared with some existing system and it has been observed that this system shows better performance.*

Keywords: Signature Verification, Pattern Matching, Power Law Transformation, Ripplet-II Transformation, Log Polar transformation, Forgery Detection, Statistical Feature Extraction, Feed Forward Back Propagation Neural Network, Offline Signature Verification

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1. Introduction

Signatures are unique identities of an individual and are used extensively throughout the world in various ways such as in banks, official documents and such. Hence, the importance of signatures as a biometric cannot be stressed upon more highly. The verification of signatures has always been an important problem in computation. The ideal algorithm should possess a low False Rejection Rate (FRR). However, perhaps even more important is this signature verification even beyond false rejection is false acceptance. Forgeries accepted by an algorithm can prove utterly disastrous in practice. Hence, a negligible False Acceptance Rate (FAR) is a near given in any algorithm.

Extensive research has been done in the field of signature verification but there is room for further improvement. Hanmandlu et al had used the Takagi-Sugeno Fuzzy modeling technique for offline signature verification. The features proposed are angle features from a box approach [1]. In another technique, Muramatsu et al had proposed using a Monte Carlo based Bayesian scheme for signature verification [2]. The algorithm involves using 2 phases – a learning phase and a testing phase. Semi parametric models are trained during the learning phase using Markov Chain Monte Carlo technique. In the testing phase these samples are used to check the genuineness of the signatures. Also, a technique for signature recognition with curve warping which could handle complex curves has been applied to the field [3].

Armand et al had used the MDF (Modified Direction Feature) and other additional features such as Centroid, Trisurface, Length, Best Fit Features, and Six-Fold Surface as features for verification [4]. The verification is done using 2 neural network classifiers namely the Resilient Back Propagation (RBP) Neural Network and the Radial Basis Function (RBF) neural network. In another approach various morphological features were used to train ANN to verify the authenticity of a signature [5].

Certain techniques have also considered segmentation of the signature from the whole document as well as verification [6]. The use of various classifiers has also played a role in developing techniques for signature verification. Erkmen et al used a CSFNN (Conic Section Function Neural Network) for performing Offline Signature Verification [7]. CSFNN allows the procedure to take the advantage of both MLP and RBF networks at the same time. Exhaustive surveys have also been performed from time to time on signature verification. Impedovo et al. provides a very descriptive survey about the various features, classifiers and approaches for Automatic Signature Verification – both online and offline [8].

Comparative studies with multiple classifiers have also been performed. Emre et al used global, directional and grid features of signatures to perform offline signature verification [9]. The one against all method of the SVM was used for classification and the results were compared to that of ANN back propagation model. Application oriented models have also been suggested. The technique by Ferrer et al takes into consideration the fact that in major studies so far, the signatures are written on a uniform white and non distorting background [10]. One of the primary problems faced by signature verification is low datasets. Sparse datasets have also been a subject of interest in research on signature verification [11].

2. Proposed Method

Figure 1 shows the flow diagram of the proposed method.

3. Implementation

3.1 Sample Image Acquisition

Signatures have been scanned using HP Scanjet G3110 scanner. Scanned signature image in RGB has been taken as input. Figure 2 shows a single scanned signature as a test image.

3.2 Image Enhacement using Power Law Transformation

After getting the sample signature gray scale conversion has been done which is followed by image enhancement technique. Power Law transformation has been used to achieve the enhanced sample signature. It is to be noted that value of Gamma in Power Las Transformation has been taken 1.5. Figure 3 shows the enhanced sample signature.

3.3 Binary Image Conversion & Selection of Region of Interst

After getting the enhanced signature, sample image has been converted into binary image and then region of interest has been extracted in order to get the signature region only. Figure 4 shows the output after the binary conversion and selection of region of interest.

3.4 Application of Ripplet Transformation of Type-II

When image processing, pattern analysis and computer vision are concerned, signals become more important for any transformation or representation purpose. But at current stage there is very limited scope of representation of 2D singularities. In recent trend curvelet and ridgelet showed better performance in comparison with Wavelet transform in resolving 2D singularities. To enhance the performance of 2D singularities significantly Ripplet Transform of Type II has been carried out in the stage of feature extraction during the development of the proposed system.

Ripplet Transformation is efficient in representing texture and edges. Actually after generalization of curvelet transform, ripplet

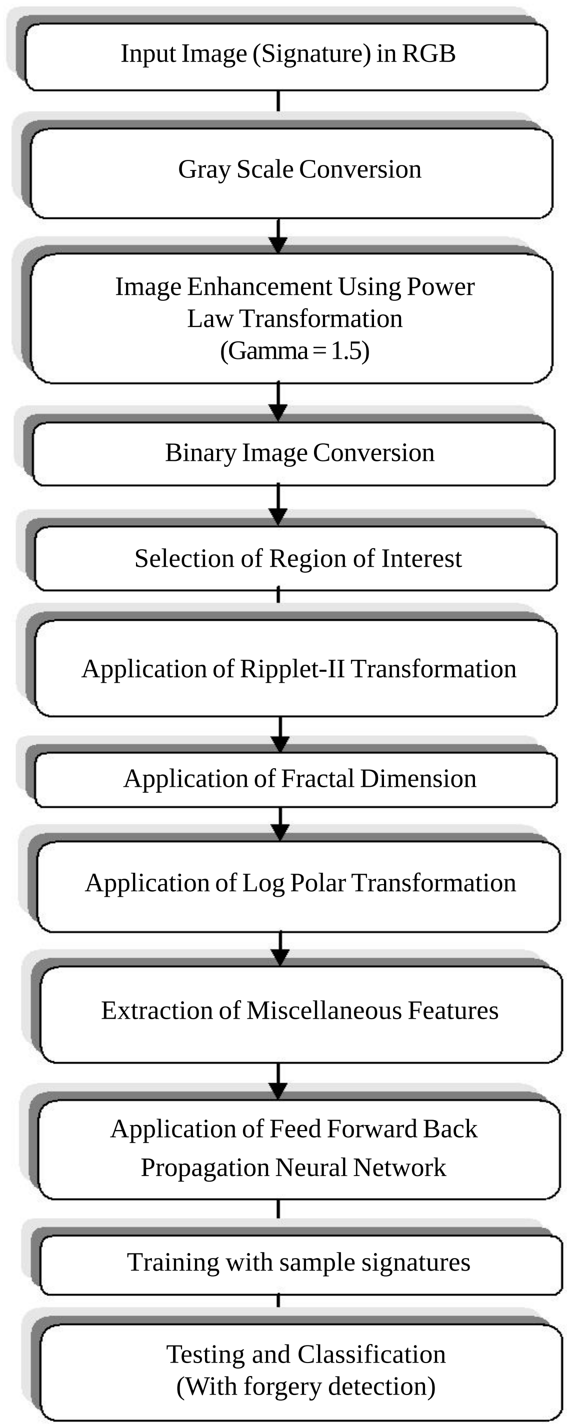


Figure 1. The flow diagram of the proposed method

transform can be achieved. Ripplet transform of type II has been developed in continuous space. In context to image processing, the latent qualities like image de-noising, image restoration and image compression are preserved by ripplet transform.

To express Ripplet-II transform, first ripplet-II function must be defined.

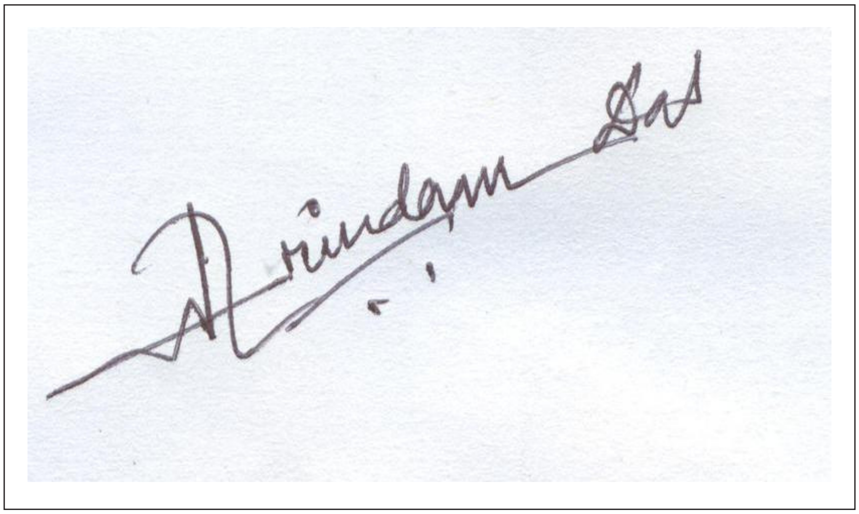


Figure 2. A single scanned signature as a test image

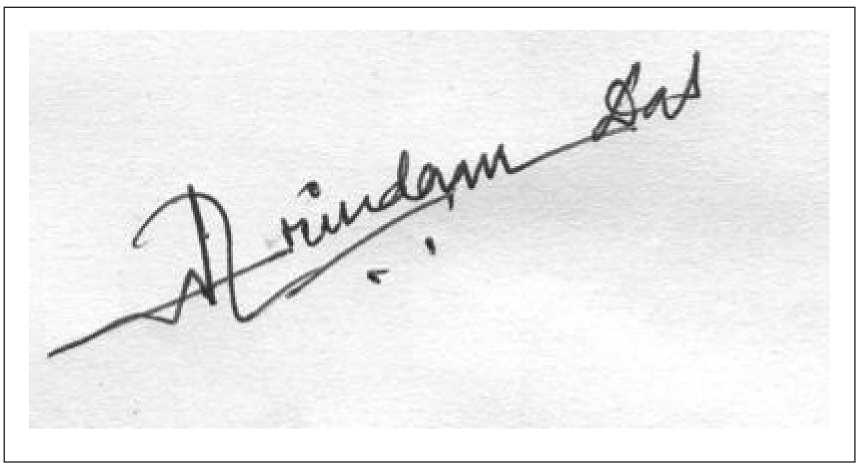


Figure 3. The enhanced sample signature

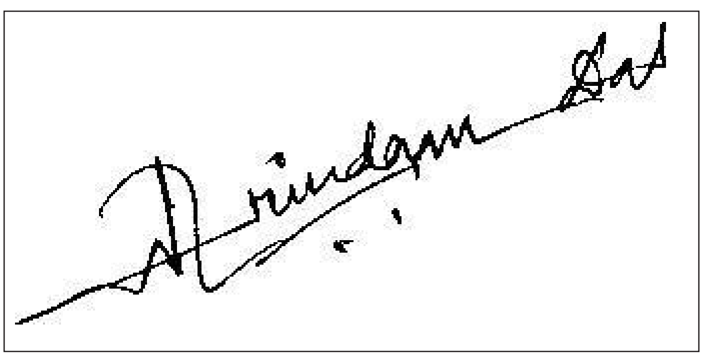


Figure 4. The output after the binary conversion and selection of region of interest

If φ is a univariate wavelet function (which is given and assumed to be smooth) then function $\varphi : \mathrm{R} \rightarrow \mathrm{R}$ and $\int \varphi(t)dt = 0$, then bivariate function would be $\Psi_{x, y, z, \theta} : R^2 \rightarrow R^2$, in the polar coordinate system

$$\Psi_{x, y, z, \theta}(\rho, \phi) = x^{-1/2} \varphi((\rho \cos^d (\theta - \phi) / z) - y) / x$$

Where $x > 0$ signifies scale, $y \in R$ signifies translation, $z \in N$ signifies degree, and $\theta \in [0, 2\Pi)$ signifies orientation. Function $\Psi_{x,y,z,\theta}(\rho, \phi)$ is called ripplet-II function. Here, we have taken $z > 0$ (i.e. positive curves), as positive curves are only considered for their open curve nature. Applying ripplet-II transform standard deviation and mean have been calculated from transformation values.

3.5 Application of Fractal Dimension

Fractal can be addressed as a scale invariant irregular shape of geometric object which comprises of an infinite nesting. In other words, it is a curve or regular figure that's every part has as a whole invariant statistical characteristics. Fractal dimension D is explained below. If the linear size of the boxes is $L = 1/N$. $N_{box}(L)$ be the number of boxes of size L. Then

$$D = \lim_{N \to \infty} \frac{\log_{N_{box}}(1/N)}{\log N} = \lim_{L \to 0} \frac{\log_{N_{box}}(L)}{\log(1/L)}$$

Also we can state that $N_{box}(L)$ obeys Power Law, as above equation can be written as

$$N_{box}(L) \sim 1 / L^D$$

As $L \to 0$. As features we have considered standard deviation and mean of the fractal dimension. Along with a new feature has been introduced in this paper named as Box Property which hold all the box values, though as feature only fourth value has been considered (it is an experimental decision) in this paper. For an example, after applying fractal dimension in Figure 4, the output graph can be shown as Figure 5.

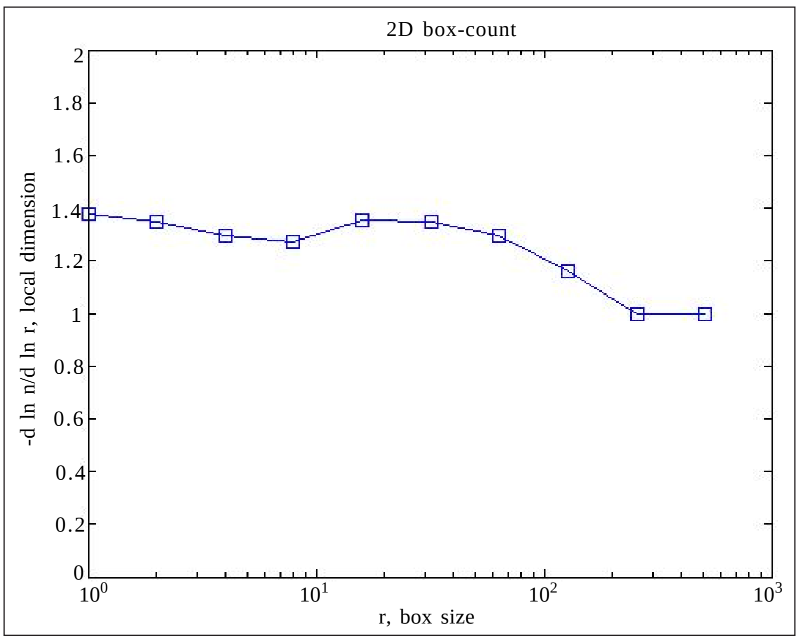


Figure 5. The output graph

3.6 Log Polar Tranformation

Log Polar Mapping has been described as the approximation of a cortical projection of a retinal image [12]. In terms of image processing, it provides a scale and rotational invariant representation of an image. Log-polar transform has been previously used in texture classification systems as an invariant feature [13]. Here we extend its use to signature recognition.

The signature image, after preprocessing, is subject to a log-polar mapping thereby transforming it to a scale and rotational invariant form. The Entropy of the log-polar image is extracted to be used in the feature vector for classification.

The 2 step log polar transformation algorithm described by Arivazhagan et al [13] is followed during the course of this paper. In the first step, the image is transformed into a square image. The polar form of the $N \times N$ image $f(x, y)$ is defined by $\rho(r, \theta)$ where:

$$p(r,\theta) = f\left(\left\lfloor \frac{N}{2} \right\rfloor + \left\lfloor r\cos\left(\frac{2\pi\theta}{S}\right)\right\rfloor, \left\lfloor \frac{N}{2} \right\rfloor - \left\lfloor r\sin\left(\frac{2\pi\theta}{S}\right)\right\rfloor\right)$$

For $\theta = 0,\ldots\ldots, S-1$, and $r = 0, \ldots\ldots, \left\lfloor \frac{N}{2} \right\rfloor - 1$

The polar transformed image is $S \times \left\lfloor \frac{N}{2} \right\rfloor$ in size

The second step involves applying logarithmic functions to all radii values of polar form $p(r,\theta)$. This output, quantized into R bins, gives the log polar image $lp(i, j)$, of size $S \times R$.

$$lp\,(i, j) = p\left(i, \left\lfloor \frac{\log_2(j+2)}{\log_2(R+2)} \right\rfloor \left\lfloor \frac{N}{2} \right\rfloor\right)$$

For $i = 0,\ldots\ldots, S-1$, and $j = 0, \ldots\ldots, R-1$

3.7 Miscellaneous Features

Along with some major transformations including frequency and spatial domain techniques other features have also been taken into consideration in order to verification and authentication purpose.

3.7.1 Height Width Ratio

As our input sample signatures are constant in dimension and resolution as scanner definition has been fixed, so height width ratio can be considered as one of the invariant feature.

$$Ratio = \frac{Height\ of\ region\ of\ interest}{Width\ of\ region\ of\ interest}$$

3.7.2 Scale Invariant Area

Area occupied by the signature can be deliberated as one of the important feature. Most importantly this feature can be considered as scale and translation invariant feature.

$$Ratio = \frac{Number\ of\ white\ pixels\ in\ the\ region\ of\ interest}{Number\ of\ black\ pixels\ in\ the\ region\ of\ interest}$$

3.7.3 Calculation of centroid

As our input specification is constant this is mentioned earlier.

So, coordinate of the centroid of region of interest of the concerned signature can be determined to make another invariant feature.

After getting all features, from large samples of signature some of them have been furnished in table 1.

Where A=Height Width ratio, B=Signature Area, C=Mean from Ripplet-II Transformation, D=Standard Deviation from Ripplet-II Transformation, E and F=X and Y coordinate of centroid of the signature, G and H= Mean and Standard Deviation of Fractal Dimension of the signature, I=Box Property of the signature from Fractal Dimension, J=Entropy from Log Polar Transformation.

3.8 Application of Feed Forward Neural Network

Our prior knowledge says that artificial neural network has been designed to achieve the performance of the human brain neuron system which consists of multilayered approach. These several layers are input layer, output layer and hidden layer respectively. Though all layers may contain multiple neurons which is user defined and those are considered as the source of information in the process of compilation. Figure 6 shows the internal architecture of artificial neural network.

In this proposed system 30 neurons have been considered in the hidden layer of artificial neural network. It is to be noted that whole classification process depends on the number of neurons which contribute to enhance the classification process in specific manner.

Sample Signature	*A*	*B*	*C*
Ronik Basak	25.766871	6.290735	18.429135
Pragna Lobani Sardar.	21.551724	8.430894	29.520246
Kumari Rajlaxmi	32.684825	16.85607	91.960061
Priti Dwibedi	27.54491	8.300242	24.368556
Abhishek Sengupta	19.113573	10.47880	57.225423

Sample Signature	*A*	*B*	*C*
Parthick Saha	14.671815	7.648506	15.911802
Riyanka Mondal.	23.236515	8.564848	37.64166
Pulak Ghosh	21.463415	7.104223	20.877802
Subhasis Kundu	18.076923	9.804598	25.283236
Anindya Mahanty	26.744186	10.59739	57.768389

D	*E*	*F*	*G*	*H*
31.56794	82.380904	20.803623	139.5455	60.656456
46.014211	116.353713	25.534812	153.3067	49.418791
110.59990	129.210756	42.796899	150.0765	54.362255
39.64403	84.816657	23.322345	139.5455	60.656456
75.662678	181.29135	35.899424	153.8697	55.65406
28.694388	130.744256	19.381778	127.3264	57.47117
55.669748	121.418453	29.102193	155.2310	51.349957
35.112892	103	22.32389	145.7080	45.709368
40.737775	130.943548	23.277843	132.5871	63.202165
77.219267	129.441261	35.664966	144.2863	49.961749

I	*J*
126	16.303906
203	20.192383
363	12.366995
126	24.834043
414	18.431444
165	22.359476
217	17.574989
156	21.155649
198	21.424595
297	15.645933

Table 1. Samples of Signatures

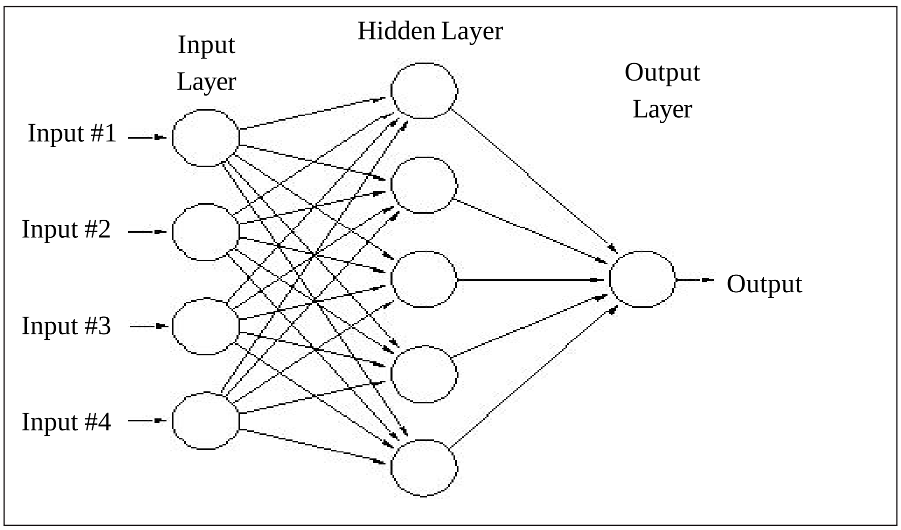


Figure 6. The internal architecture of artificial neural network

<table>
<tr><th rowspan="2">SL No.</th><th colspan="4">Feature details</th></tr>
<tr><th>Techniques</th><th colspan="3">Features</th></tr>
<tr><td>1</td><td>Ripplet - II transformation</td><td>Standard Deviation of Ripplet feature</td><td colspan="2">Mean of Ripplet feature</td></tr>
<tr><td>2</td><td>Fractal Dimension</td><td>Standard Deviation of Fractal Dimension</td><td>Mean of Fractal Dimension</td><td>Box Property</td></tr>
<tr><td>3</td><td>Log Polar Transformation</td><td colspan="3">Entropy of Log Polar Transformation</td></tr>
<tr><td>4</td><td>Miscellaneous</td><td>Height Width Ratio</td><td>Signature Area Calculation</td><td>Centriod</td></tr>
</table>

Table 2. Classification of Features

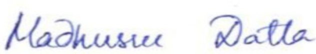
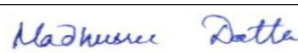
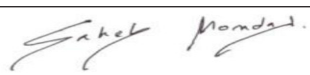
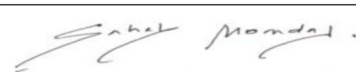
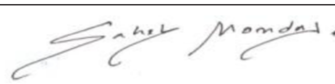
Sample Signature	Test Signature (Threshold value to be original signature > 75%)	Result from classifier
		99.66%
		99.1%
		99.84%
		79.92%
		89.19%
		93.57%
		101%
		89.19%
		92.8%
		154.6%
		81.62%
		122.4 %
		109 %

Table 3. Testing Results

In this proposed system 30 neurons have been considered in the hidden layer of artificial neural network. It is to be noted that whole classification process depends on the number of neurons which contribute to enhance the classification process in specific manner.

Feed Forward Back Propagation Neural Network needs three stage processes to accomplish the classification.

3.8.1 Training of Neural Network

Training data that means the features to be extracted has already been discussed above in order to verify and authenticate the sample signature. All the features have been furnished below.

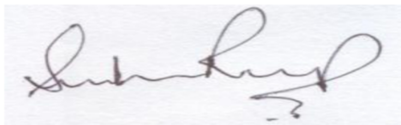
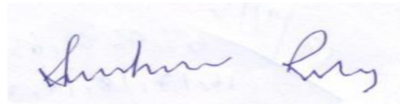
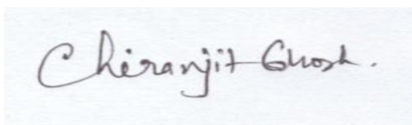
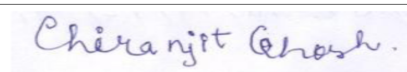
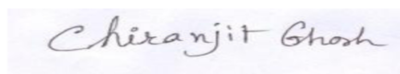
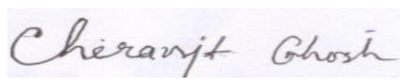
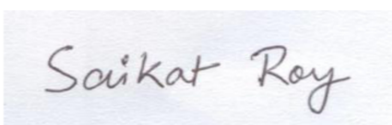
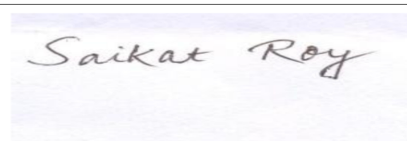
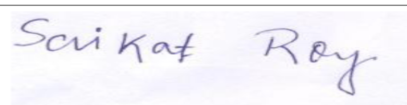
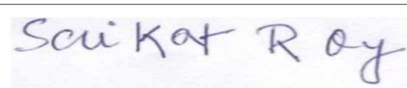
Original Signature	Forged Signature (Threshold value to be original signature > 75%)	Result from classifier
		-61.80% (forgery detected)
		-88.39% (forgery detected)
		-83.14% (forgery detected)
		-11.76% (forgery detected)
		-45.43% (forgery detected)
		-58.05% (forgery detected)
		-25.76% (forgery detected)
		-15.12% (forgery detected)
		-12.82% (forgery detected)
		-12.7% (forgery detected)

Table 4. Forgery detection

Number of Test Images		Number of Correct Output	Number of InCorrect Output	Performance (%)
Verification	78	75	3	96.15
Forgery Detection	50	46	4	92

Table 5. Performance Evolution of NN

3.8.2 Testing of Neural Network

For the testing purpose a large set of signature samples were collected and this proposed method has been applied on thesample set. In the testing phase all feature values have been passed through feed forward back propagation neural network. To verify a signature we have taken threshold value of greater than 75%. That means prior to the knowledge from training set input pattern must be matched greater than 75% with the training set. It is to be noted that in case of forgery detection same algorithm has been applied.

Number of the methods	False Acceptance Rate (%)	False Rejection Rate (%)
C. Santos et al [17]	15.67	10.33
K. Huang and Y Han [15]	11.8	11.1
E.A.Fadhel and P. Bhattacharyya [16]	5.5	6.2
P. S Deng et al [14]	10.98	5.6
Proposed Approach	5.28	2.56

Table 6. Comparison study

For the testing purpose a large set of signature samples were collected and this proposed method has been applied on the sample set. In the testing phase all feature values have been passed through feed forward back propagation neural network. To verify a signature we have taken threshold value of greater than 75%. That means prior to the knowledge from training set input pattern must be matched greater than 75% with the training set. It is to be noted that in case of forgery detection same algorithm has been applied.

3.8.3 Results of Testing

After training, testing phase was taken place. Detailed testing results have been furnished in Table 3.

Forgery detection has been furnished in table 4.

3.8.4 Performance Evolution of NN

The performance of the proposed system has been given in Table 5.

A comparison study has been shown in Table 6 in order to prove that our system shows better performance than some existing methods.

4. Comparison Study

During comparison study we found that Graphometric feature was taken and Euclidean Distance with Multilayered Perceptron approach was followed [17]. Also Geometric based and Neural Network based approach was found [15]. Global (wavelet based) statistical and grid based feature showed good performance with neural network approach [16]. Wavelet transformation with DTW approach was even better to mention [14].

5. Results

Result of this novel approach towards offline handwritten signature verification shows an encouraging performance accuracy which has been found around 96.15%. Here, in the proposed approach authentication has also been taken in to consideration and the performance accuracy has been found around 92%.

6. Conclusion

The proposed method to automatic verify and authenticate handwritten signature using multiple image transformations like power law transformation, ripplet-II transformation, fractal dimension and log polar transformation proves to be an effective and efficient approach. Also our system shows better performance than the systems already exist. With addition this is to be noted that our system in language independent, it can verify and authenticate any pattern given at the time of training and testing. As a future work, this system can be made online with some extra features and better performance rate.

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