Indian Journal of Science and Technology, *Vol 9(31), DOI: 10.17485/ijst/2016/v9i31/71863, August 2016*

ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

A Novel Bank Check Signature Verification Model using Concentric Circle Masking Features and its Performance Analysis over Various Neural Network Training Functions

D. Ashok Kumar and S. Dhandapani*

Department of Computer Science and Applications, Government Arts College Tiruchirapalli - 620 022, Tamil Nadu, India; drashoktrichy22@gmail.com, sdpudt@rediffmail.com

Abstract

Background: Handwritten signature is a person's unique identity. Signature verification is an economical biometric method with online and offline schemes. This paper deals with the offline verification of signatures found in bank checks. **Method:** Extracting feature is the most vital part of a signature verification process. An efficient feature extraction method, Concentric Circles Masking Method, is used to extract robust, scale invariant and rotation invariant features. The extracted feature values are normalized and fed to a feedforward backpropagation neural network for classification of the signatures into genuine or forged ones. The feature's performance is measured with various training functions of the neural network. The system modeled is tested with the well-known CEDAR database. **Findings:** Experimental Analysis shows that the features extracted by this method prove to be efficient. The scanned signature is covered by concentric circles and the pixel distribution ratio in each circle is calculated and used for verification purpose. Since a circle is used, the extracted features are scale and rotation invariant which makes the feature robust. The neural network's training, validation and testing ratio are varied and the performance of various training functions is studied. It is inferred that conjugate gradient backpropagation with Fletcher-Reeves updates (traincgf) training function has the maximum average accuracy of 97.89% for the CCMM features.

Keywords: Feature Extraction, Signature Verification, Training Functions Comparison

1. Introduction

Authentication of a person can be something the user knows, something the user has or something the user is[1]. Signature is widely accepted and used for personnel verification means. Signature is used to authorize legal and official transactions. The bank cheque signature fraud cases are increasing[2] as the technology and communications advances. The signature placed on a bank check should be verified for its genuineness. So an offline signature verification system is the need of the hour. Many research works are in progress and gaining momentum.

The advantage of signature is that it cannot be stolen as in the case of passwords and PIN numbers. Signature verification scheme can be largely classified as online or offline as shown in Figure 1. Online signature verification scheme uses electronic digitizing tablets and stylus. Online methods can measure the dynamic features of the signature like pen pressure, angle, number of pen lifts and time taken. In offline mode, the verifier will be presented with the scanned copy of the signature. The rest of the paper is organized as follows. Section 2 deals with signature verification system. Section 3 deals with neural network which classifies the signature. Section 4 briefs the literature review. Section 5 deals with performance measures. Section 6 deals with experimental results and analysis. Finally conclusion is drawn in Section 7.

**Author for correspondence*

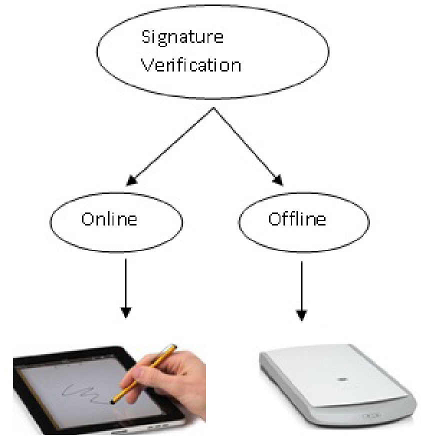

Figure 1. Types of signature verification.

2. Signature Verification System

Signature verification is easy but the problem occurs when the signature has to be immediately verified like credit card payments and bank checks. Since signature is a behavioral biometric, inter-class and intra-class variations does exist. When the signature on the check is wrong or suspected, forgery creeps in. Signature forgeries can be named into random, simple and skilled forgeries. In random forgeries the forger puts the signature without knowing the name and signature copy or shape. In simple forgery, the forger or the imposter knows only the name. In skilled forgery, the forger has both, the name and the signature copy in hand and after several trials forges the signature. To be fine, the signature samples could be taken at different intervals. But in the real time scenario, the sample specimen signatures are collected all at once. This can be relaxed for taking intra-personal signature variations. If all the specimen signatures are collected at once, the signature signed first can have more weight when fed to the neural network. Because of this complex nature of the handwritten signature, offline signature verification is still a challenge[3]. Man is the good machine god has ever created. Man creates the signature verification system and whatever the machine verifies, he should intervene for some critical decisive purposes. There are several common stages in signature verification process.

2.1 Signature Acquisition

Signature acquisition is the process in which the signature from the bank check is digitized or scanned using a scanner or photographed with a camera of high resolution. A digital 2d image of the signature is the input to the signature verification system.

2.2 Preprocessing

There may be noises in the scanned image. It may be due to the mutilation of the check or dust from the acquiring device. Sometimes by mistake, rubber stamp seal may overwrite the signature. To improve the verification accuracy, to enhance the signature image and clear the unwanted noise in the scanned image, preprocessing is done.

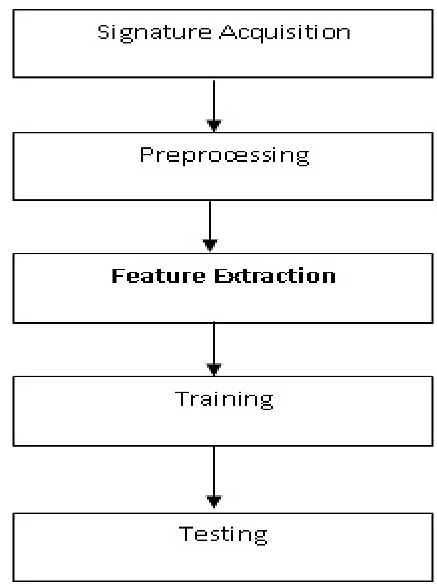

Figure 2. Signature verification system.

2.3 Feature Extraction

Feature extraction is the main part of a signature verification system as shown in Figure 2. It extracts the unique characteristics of the signature. Features help to represent the image information more meaningful for classification. Features are mainly of two types - Global features and Local features. Global features consider the image has a whole and gives description like height and width. Local features examine the image in small segmented areas and give maximum information. The signer may put his signature straight or sometimes in an inclined manner. Sometimes he may place his signature small or large in size than the specimen signature available for testing. Orientation and scaling are the two major factors of high concern in offline signature verification. The signer may place his sign at any angle and the sign may be large or small because of the behavioral biometric feature of the signature. The concentric Circle Masking Method (CCM) will extract features that may avoid the above problems.

2.3.1 Feature Extraction Methodology

The scanned preprocessed signature is covered by concentric circles with the centroid of the signature as the center for all the concentric circles. The number of black pixels inside each circle from the center is calculated and tabulated. The signature's pixel distribution ratio in the concentric circles is found and the distribution ratio is fed as input to the first layer of the neural network designed for verification. Both the genuine and forged signature sample's feature value is used for verification. The neural network designed will classify the signature as genuine or forged. Complex types of signatures which the neural network identifies need human intervention.

Feature Extraction Algorithm using CCMM:

Step 1: Start the process.

Step 2: Scan the signature and preprocess it for removal of noise.

Step 3: Find the centroid of the signature image.

Step 4: Draw concentric circles on the signature keeping the centroid of the signature image as center for all circles.

Step 5: Continue until all the signature portions are covered.

Step 6: Find the number of black pixels in each circle.

Step 7: Stop the Process

Table 1 shows the sample pixel distribution values. As the counting of pixels starts from the center, the number increases as we go outwards.

Table 1. Sample number of pixels in concentric circles for four signatures

	Sign. 1	Sign. 2	Sign. 3	Sign. 4
Circle 1	131	104	140	130
Circle 2	149	115	166	145
Circle 3	169	126	188	157
Circle 4	185	147	205	172
Circle 5	204	171	223	184
Circle 6	216	200	241	199
Circle 7	234	228	258	213
Circle 8	246	250	273	230
Circle 9	257	280	288	248
Circle10	273	324	303	263
Circle 11	284	381	318	278
Circle 12	300	433	334	292
Circle 13	314	475	347	305
Circle 14	329	511	364	319

In Table 1, Signature 1 is the first signature on which the concentric circles are drawn. The first circle which is represented by Circle 1 has 131 black pixels. Second circle has 149 black pixels. Circles are drawn until the entire signature is covered.

2.4 Training and Testing

The training signatures used for the study are taken from Center of Excellence for Document Analysis and Recognition (CEDAR) database. Three different sets of signatures are used for the study. Each set of signature contains 24 genuine and 24 forged signatures. A feedforward backpropagation neural network is designed for the study. The number of neurons for three sets are varied. The ratio of the training, validation and testing parameters are also varied for three sets of signature (80:10:10, 70:15:15). The neural network performance is measured using the MSE (Mean Squared Error). MSE is the difference between the actual output and the desired output. The MSE is made minimum during the training process.

3. Neural Network

Machine learning methods train themselves with the existing data and predicts the output[4]. A neural network is a representation of human brain artificially to simulate the learning process. Neural network is a problem solving technique by building a software which works almost like our brain. Artificial Neural Networks (ANNs) are a complex connection of interconnected neurons mimicking human brain. All neurons are interconnected. The main components of a neural network are weights, bias, neurons, activation function and training function. ANN has provided excellent solutions for very complex problems in forecasting, task scheduling, data mining and optimized resource allocation problems. Any neural network modeled has the ability to learn. ANNs can easily extract the properties of the input dataset because of their unique learning capability[5]. ANN is a Mathematical model designed to train, visualize and validate neural network models[6]. It is a complex *adaptive* system, which can change its internal structure according to the problem for maximizing the accuracy of the result. They learn from the input data and deliver the corresponding target output data, so they are widely used for pattern classification. It is achieved through the adjusting of *weights*. Each connection has a *weight*, a number that controls the signal between the two neurons. If the network generates a desired or good output there is no need to adjust the weights. If the output is not the expected value or bad, then the system adapts, altering the weights in order to improve subsequent results. Biases are values that are added to the weighted sums at each node during the feed-forward phase. They can also be called as threshold value. MSE (Mean Squared Error) index and number of epochs used for training are inversely proportional to each other[7].

Activation function performs mathematical operations on the neural network's output value. The activation function selection depends on the type of the problem chosen. Neural networks mostly pass the output values of their layers through the activation function. The activation function or sometime transfer function scales the output of the neural network into required or proper ranges[8]. It is very complicated to identify which neural network training algorithm will be the better for a given problem[9]. It is based on many factors like the number of training dataset, complexity of the problem chosen, the value of weights and biases of the network, the target and actual error and whether the network designed is applied for pattern recognition problem or function approximation. Two of the most frequently used activation functions are sigmoid and hyperbolic tangent[10].

Figure 3 shows the block diagram of the neural network. 'x' is the input and weight is 'w'. The weighted sum (xw) and bias b is fed to the activation function which produces the neuron output.

The extracted CCM features are fed to the designed neural network for performance evaluation. Fourteen training functions are used for the purpose. BFGS quasi-Newton backpropagation (Trainbfg) is a neural network training function which updates its weight and bias according to the BFGS quasi-Newton method. Bayesian regulation backpropagation (Trainbr) is a network train-

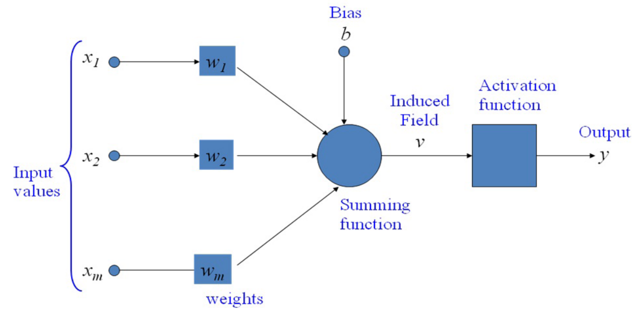

Figure 3. Neural network.

ing function which updates the values of weight and bias according to Levenberg-Marquardt optimization. Conjugate gradient backpropagation with Powell-Beale restarts (Traincgb) is a neural network training function that updates its weight and bias values according to the conjugate gradient backpropagation with Powell-Beale restarts. Conjugate gradient backpropagation with Fletcher-Reeves updates (Traincgf) is a network training function which updates its weights and biases according to conjugate gradient backpropagation with Fletcher-Reeves updates. Conjugate gradient backpropagation with Polak-Ribiere updates (Traincgp) is a neural network training function which updates its weights and biases according to conjugate gradient backpropagation with Polak-Ribiere updates. Gradient descent backpropagation (Traingd) is a neural network training function which updates its weights and biases according to gradient descent. Gradient descent with momentum backpropagation (Traingdm) is a neural network training function which updates its weights and biases according to gradient descent with momentum. Gradient descent with adaptive learning rate backpropagation (Traingda) is a neural network training function which updates its weights and biases according to gradient descent with adaptive learning rate. Gradient descent with momentum and adaptive learning rate backpropagation (Traingdx) is a neural network training function which updates its weight and bias values according to gradient descent momentum and an adaptive learning rate. Levenberg-Marquardt backpropagation (Trainlm) is a neural network training function that updates its weights and biases according to Levenberg-Marquardt optimization. Trainlm is often the fastest backpropagation algorithm and is the most preferred supervised training algorithm, but it requires more memory space when compared to other algorithms. Trainlm performance is relatively poor on pattern recognition problems[10]. One-step secant backpropagation

(Trainoss) is a neural network training function which updates its weights and biases according to the one-step secant method. Random order incremental training with learning functions (Trainr) trains a network with weight and bias learning rules with incremental updates after each presentation of an input. Inputs are presented in random order. Resilient backpropagation (Trainrp) is a network training function which updates weight and bias values according to the resilient backpropagation algorithm (Rprop). Scaled conjugate gradient backpropagation (Trainscg) is a network training function that updates weight and bias values according to the scaled conjugate gradient method.

4. Literature Review

In[11] worked on face image classification using different neural network training functions and the results show that trainlm had the lowest MSE values and minimum number of iterations. Indra, Devi and Viajayalakshmi carried out a study on training algorithms for Control Charts Pattern identification and the best function is found out for type 1 and type 2 errors. In[7] worked on cancer classification. ANN has higher classification rate and only the training time is its disadvantage. Once trained, ANN shows reliable results. In[12] proposed a new feature extraction method and these features considerably reduced FAR and FRR.

Table 2. Accuracy for different features using neural network as classifier

Feature Type	Accuracy %
Polar domain features[13]	71.00
GLCM features[14]	92.08
Gradient, Structural and Concavity features[15]	78.00
Smoothness Index Based Approach[16]	79.00

Table 2 shows the various feature types extracted by researchers. The accuracy rate is depending on the features extracted. Features extraction may be based on shape or regional property. It depends upon the application it is used.

5. Performance Measures

Signature verification system can classify the test signature as genuine or forged. The system has various performance measures like True Positive (TP), TN (True Negative), FP (False Positive), FN (False Negative), FAR (False Acceptance Ratio),

Table 3. Performance measures

FAR	FN / (TN + FN)
FRR	FP / (TP + FP)
Sensitivity	TP / (TP + FN)
Specificity	TN / (TN + FP)
Accuracy	(TP + TN) / (TP +TN + FP +FN)

FRR (False Rejection Ratio), ERR (Equal Error Rate), Sensitivity, Specificity and Accuracy. Table 3 shows the performance measures. TP is the actual positives. It conveys the correct signature as correct ones. TN is the actual negatives. It conveys the forged signatures as forged or false. FP is the incorrect positives. It conveys the correct signature as false ones. FN is the incorrect negatives. It conveys the forged signature as genuine ones. Sensitivity measures the proportion of actual positives whereas the specificity measures the proportion of actual negatives. Accuracy can be calculated by means of TP, TN, FP, FN and also by the sensitivity and specificity analysis.

6. Experimental Results and Analysis

Table 4. Experimental results of signature set I

Number of Neurons: **10** Parameters: **80:10:10**			
Training Function	**perfmse**	**MSE**	**accuracy**
trainbfg	0.0011	1.08E-03	100
trainbr	0.8748	8.75E-01	72.92
traincgb	2.6707	2.67E+00	50
traincgf	0.1125	1.13E-01	97.92
traincgp	0.1451	1.45E-01	97.92
traingd	0.0418	4.18E-02	100
traingdm	2.5406	2.54E+00	50
traingda	0.1233	1.23E-01	97.92
traingdx	1.0099	1.01E+00	64.58
trainlm	0.0066	6.57E-03	97.92
trainoss	0.0926	9.26E-02	100
trainr	0.0016	1.58E-03	100
trainrp	0.0754	7.54E-02	100
trainscg	0.0025	2.55E-03	100

Table 4 shows the mean square value and accuracy for the first signature set. The number of neurons are 10 and the training, validation and testing ratio of input data are 80:10:10. Table shows that when the mean square error is low, the accuracy is high. The network is trained so that the MSE is low. Functions traincgb and traingdm has the lowest accuracy rate for 10 neurons in 80:10:10 ratio.

Table 5. Experimental results of signature set II

Number of Neurons: **10** Parameters: **70:15:15**			
Training Function	perfmse	MSE	Accuracy
trainbfg	0.2504	2.50E-01	89.36
Trainbr	9.20E-08	9.20E-08	97.87
Traincgb	0.0381	3.81E-02	95.74
Traincgf	0.0683	6.83E-02	97.87
Traincgp	0.0865	8.65E-02	95.74
Traingd	0.0017	1.69E-03	97.87
Traingdm	1.4648	1.46E+00	59.57
Traingda	0.4574	4.57E-01	80.85
Traingdx	0.2152	2.15E-01	97.87
Trainlm	7.26E-04	7.27E-04	95.74
Trainoss	0.3547	3.55E-01	89.36
Trainr	5.12E-04	5.12E-04	97.87
Trainrp	0.0267	2.67E-02	95.74
Trainscg	0.0454	4.54E-02	97.87

Table 5 shows the mean square value and accuracy for the second signature set. The number of neurons are 10 and the training, validation and testing ratio of input data are 70:15:15. When the ratio is changed, the accuracy for traincgb increases to 95.74 and there is no favorable effect in traingdm.

Table 6 shows the mean square value and accuracy for the third signature set. The number of neurons are 5 and the training, validation and testing ratio of input data are 70:15:15. When the neurons are reduced from 10 to 5, there is an adverse effect on accuracy for trainbfg, traingd, traingda and trainoss.

Table 6. Experimental results of signature set III

Number of Neurons: **5** Parameters: 7**0:15:15**			
Training Function	perfmse	MSE	accuracy
Trainbfg	4.0719	4.07E+00	48.93617
Trainbr	2.9E-10	2.96E-10	97.87234
Traincgb	0.0059	5.89E-03	97.87234
Traincgf	0.061	6.10E-02	97.87234
Traincgp	0.0011	1.14E-03	97.87234
Traingd	1.2132	1.21E+00	57.44681
traingdm	0.6532	6.53E-01	78.72340
traingda	4.3479	4.35E+00	48.93617
traingdx	0.5816	5.82E-01	80.85106
trainlm	0.6275	6.27E-01	80.85106
trainoss	1.423	1.42E+00	51.06383
trainr	0.0033	3.32E-03	95.74468
trainrp	0.0406	4.06E-02	97.87234
trainscg	0.0897	8.97E-02	95.74468

Figure 4 shows accuracy in percentage for three different signature set for 14 training functions. The accuracy for traincgf remains same when the parameters are changed. Traingdm projects lower performance for the CCM features and traincgf projects maximum performance and accuracy. [17]Has proposed that backpropagation is considered as a universal classifier.

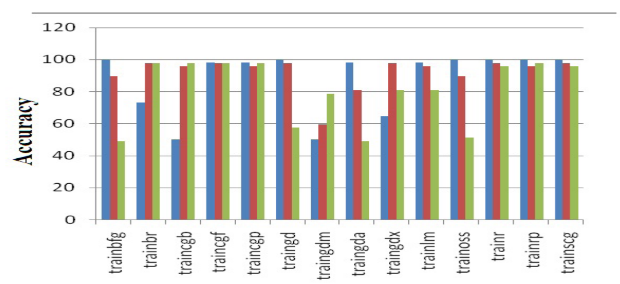

Figure 4. Chart showing accuracy in percentage for 14 functions for 3 sets of signature.

7. Conclusion

An efficient offline signature verification system is needed for verification of signatures in legal documents and bank checks. Since, only static images of the signatures are available, features extracted may not be efficient like online signature features. They also can project low accuracy rates. So to overcome, concentric circle masking method is modeled to extract efficient and robust features. These features are rotation and scale invariant, which is a requirement for signature verification. Experimental results show that these features are efficient. The features are tested using various neural network training functions and of those traincgf function shows the maximum average accuracy of 97.89 %.

8. Acknowledgement

The authors thank all the researchers for their research inputs which helped us a lot to design this model. They also extend their thanks to all who have helped and supported in bringing out this article.

9. References

1. Saini BS, Kaur N, Bhatia KS. Keystroke dynamics for mobile phones: A survey. Indian Journal of Science and Technology. 2016 Feb; 9(6). DOI: 10.17485/ijst/2016/v9i6/82084.
2. Al-Omari YM, Abdullah SNHS, Omar K. State-of-the-art in offline signature verification system. International Conference on Pattern Analysis and Intelligent Robotics (ICPAIR); Putrajaya. 2011 Jun 28-29. p. 59–64.
3. Jarad M, Al-Najdawi N, Tedmori S. Offline handwritten signature verification system using a supervised neural network approach. 6th International Conference on CSIT; Aman. 2014. p. 189–95.
4. Parikh MC, Maradia KG. Comparative analysis of motion base image segmentation using machine learning techniques. Indian Journal of Science and Technology. 2016 Mar; 9(9). DOI: 10.17485/ijst/2016/v9i9/86605
5. Manjunatha R, Narayana PB, Reddy KH, Reddy KVK. Radial basis function neural networks in prediction and modeling of diesel engine emissions operated for biodiesel blends under varying operating conditions. Indian Journal of Science and Technology. 2012 Mar; 5(3):2307–12.
6. Moustafa AA. Performance evaluation of Artificial Neural Networks for spatial data analysis. Contemporary Engineering Sciences. 2011; 4:149–63.
7. Hari Kumar R, Vasanthi NS, Balasubramani M. Performance analysis of Artificial Neural Networks and statistical methods in classification of oral and breast cancer stages. IJSCE. 2012 Jul; 2(3):263–9. ISSN: 2231-2307.
8. Suttisinthong N, Seewirote B, Ngaopitakkul A, Pothisarn. Selection of proper activation functions in backpropagation neural network algorithm for single-circuit transmission line. Proceedings of the International Multi Conference of Engineers and Computer Scientists IMECS; Hong Kong. 2014 Mar 12–14. p. 1–5.
9. Sharma B, Venugopalan K. Comparison of neural network training functions for hematoma classification in Brain CT Images. IOSR-JCE. 2014 Jan; 16(1):31–5. e-ISSN: 2278-0661, p-ISSN: 2278-8727.
10. Indra Kiran NVN, Pramiladevi Devi M, VijayaLakshmi G. Training multilayered perceptrons for pattern recognition: A comparative study of five training algorithms. Proceedings of the International Multi Conference of Engineers and Computer Scientist 2011 IMECS; Hong Kong. 2011 Mar 16-18. p. 1–5.
11. Anusree K, Binu GS. Analysis of training functions in a biometric system. International Journal on Recent and Innovation Trends in Computing and Communication. 2011; 2(1):150–4. ISSN: 2321-8169,
12. Samuel D, Samuel I. Novel feature extraction technique for offline signature verification system. International Journal of Engineering Science and Technology. 2010; 2(7):31–7.
13. Pushpalatha KN, Gautham AK, Shashikumar R, Shivakumar KB, Das R. Offline signature verification with random and skilled forgery detection using polar domain features and multi stage classification regression model. International Journal of Advanced Science and Technology. 2013; 59:27–40.
14. Kumar AD, Dhandapani S. A bank check signature verification system using ffbp neural network architecture and feature extraction based on GLCM. IJETTCS. 2014 Jun; 3(3):46–52.
15. Kalera MK, Srihari S, Aihua Xu A. Offline signature verification and identification using distance statistics. International Journal of Pattern Recognition and Artificial Intelligence. 2004 Nov; 18(7):1339–60.
16. Fang B, Wang YY. A smoothness index based approach for offline signature verification. Proceedings of the Fifth International Conference on Document Analysis and Recognition, ICDAR '99; Bangalore. 1999 Sept 20-22. p. 785–7. DOI: 10.1109/ICDAR.1999.791905.
17. Joy CU. Comparing the performance of backpropagation algorithm and genetic algorithms in pattern recognition problems. International Journal of Computer Information Systems. 2011 May; 2(5):7–52.