Off-line Signature Verification Based on Fusion of Grid and Global Features Using Neural Networks

SHASHI KUMAR D R[1], K B RAJA[2], R. K CHHOTARAY[3], SABYASACHI PATTANAIK[4]

[1]Department of CSE, Cambridge Institute of Technology, Bangalore
[2]Department of ECE, University Visvesvaraya College of Engineering, Bangalore University, Bangalore
[3]Department of CSE, Seemanta Engineering College, Mayurbhanj, Orissa
[4]Department of Computer Science, F.M. University, Balasore, Orissa

Abstract:
Signature is widely used and developed area of research for personal verification and authentication. In this paper Off-line Signature Verification Based on Fusion of Grid and Global Features Using Neural Networks (SVFGNN) is presented. The global and grid features are fused to generate set of features for the verification of signature. The test signature is compared with data base signatures based on the set of features and match/non match of signatures is decided with the help of Neural Network. The performance analysis is conducted on random, unskilled and skilled signature forgeries along with genuine signatures. It is observed that FAR and FRR results are improved in the proposed method compared to the existing algorithm.

Keywords: Signature, Neural Network, FAR, FRR, Grid, Global, Feature Extraction.

1. Introduction

Biometrics is the science of automatic recognition of individual depending on their physiological and behavioral attributes. The expansion of networked society and increased use of some personal portable devices like tablet PCs, PDAs, mobile phones and authorization of access to sensitive data, is demanding the most reliable personal identification and authentication systems. Among the different forms of biometric recognition systems such as fingerprint, iris, face, voice, palm etc., signature will be most widely used. The applications like government and legal financial transaction, bank cheques use signature as one of the personal identification system. The financial transactions and shopping using debit cards and credit cards require a bill to be confirmed by handwritten signature. But this leads to increased risk of financial loss due to attempted forgeries. This problem may be resolved by introducing automatic recognition systems which are being successfully used effectively to analyse large quantities of biometric data.

Since olden days handwritten signature has been most widely used and accepted individual attributes for recognition. The design and development of signature recognition system is really big challenge because of the increased dependence of personal identification systems. Signature recognition system is divided into On-line or dynamic and off-line or static recognition. On-line recognition refers to a process where the signer uses a special pen called stylus to create his or her signature, producing the pen locations, speed and pressure, where as off-line recognition deals with signature images acquired by a scanner or a digital camera. In general, off-line signature recognition is a challenging problem, unlike the on-line signature where dynamic aspects of the signing action are captured directly as the handwriting trajectory.

Contribution*:* In this paper, the grid and global features of signature are fused to generate final feature vector of signature. The Neural Network (NN) is used as a classifier for the verification of signatures.

Organization*:* The paper is organized into the following sections. Section 2 is an overview of related work. The SVFGNN model is described in Section 3. Section 4 is the algorithm for SVFGNN system. Performance analysis of the system is presented in Section 5 and Conclusions are contained in Section 6.

2. Related Work

Javed Ahmed Mahar et al.,[1] used feature extraction methods with K-Nearest Neighbor for signature verification. Grid, Global, and Texture Feature Comparison are the three kinds of features used for signature verification. In the grid-based features, a signature image is divided into rectangular regions and ink distribution in each region is evaluated. In the global feature comparison, a number of features extracted globally from the whole signature are compared. The texture-based features comparison is based on the co occurrence matrices of the signature image. The Euclidean distance is used for offline signature verification. Taylan Das and Canan Dulger [2] presented a technique for offline signature verification based on a Neural Network approach trained with Particle Swarm Optimization algorithm. The three types of fingerprint forgeries such as Random, Unskilled and Skilled are considered. A trained Neural Network is treated as a specialist in the category of information.

Ahmad et al., [3] presented an automatic off line signature verification system which uses several statistical techniques. The algorithm involves building reference model for each local feature extracted from a set of signature samples during learning phase. In the verification phase two score analysis and normalization functions were used for fixing the boundary of acceptance and rejection. Li F F [4] proposed the combined use of signatures and utterances of pronounced names to identify or authenticate individuals. Ji Jun- wen et al., [5] presented the method based on feature extraction from every segment segmented from the signature image. Every segment is represented by a set of seven features, which has weighing factors. The appropriate weight of the feature determines whether the signature is skilled forgery or not. Boyko A and Rozorynov G [6] used signature based authentication. The local global features of the signatures were used to train the Neural Network. Classification was done by Multi layer Neural Network trained using back propagation with momentum and bias. Liang Wan et al., [7] described an off-line signature verification system that only requires the genuine signatures of a new user incorporating prior model. At the training stage the system learns the mapping between the parameters of classifiers without simple forgeries and those with simple forgeries. In the application stage, a primary classifier is trained for a new user without his/her simple forgeries. The final classifier is obtained by transforming the primary classifier, via the mapping learnt in the training stage.

Jalal Mahmud and Chowdhury Mofizur Rahman [8] aimed to verify offline signatures using improved feature analysis and artificial neural network. Feature analyzer can reduce the large domain of feature space and extract invariable information. For feature extraction, quad tree representation was incorporated with density analysis, Moment analysis and Structural analysis. For verification from extracted features, multiple feed forward neural networks are used which are trained in the form of ensemble. Bence Kovari et al., [9] described an approach for off-line signature verification using the enhanced method of Off line signature verification based on Feature Matching. The method is able to preserve and take an advantage of semantic information during signature comparison. Feature extraction is characterized by the end points defined by the direction of their corresponding strokes. The matching of signature is performed by Dynamic Time Warping algorithm and Mutual Information algorithm. Banshider Majti et al., [10] used the method of geometric centre for feature extraction of signature. The sub parts of the image are split into vertical splitting and horizontal splitting. Then 24 feature points are extracted for each vertical and horizontal splitting. Euclidean distance is used for classification. Threshold selection is based on average and standard deviation. Cross validation principle is used to select reference signatures. Minf Yeng et al., [11] presented a feature selection method based on Contourlet which is used to capture the structural feature of the signature like directionality and anisotropy information. The Grid is used to get the the contourlet grid gray property, which gives the statistical feature of signature.. Both the feature vectors are given as input to Support Vectors Machine for training and testing.

I.A.Ismail et al., [12] presented a method for Offline recognition and verification of signatures using Principal components analysis. The method consists of image prepossessing, feature extraction. The Principal components analysis is evaluated for the extracted feature. The K nearest-neighbors are used in the recognition process and Neural Network classifier is used in the verification process. Debasish Jena et al., [13] described the scheme based on selecting 60 feature points from the geometric centre of the signature. The parameters like mean and variance are used to classify the feature points. These points are compared with trained feature points for signature verification. Bai Ling Zhang [14] proposed a Kernel Principal Component Self-regression model for off-line signature verification and recognition problems. Developed from the Kernel Principal Component Regression, the self-regression model selects a subset of the principal components from the kernel space for verification and recognition. The model directly works on bitmap images. Each user is assigned an independent Kernel Principal Component Self-regression model for coding the corresponding visual information.

Vu Nguyon et al., [15] proposed an effective method to perform off-line signature verification based on intelligent techniques of Neural Classifiers and Support Vector Machines. Structural features are extracted from the signatures Contour using the Modified Direction Feature and its extended version: the Enhanced Modified Direction Feature. The neural network-based techniques and Support Vector Machines were investigated and compared for the purpose of signature verification. Stephane Armand et al., [16] presented an effective method to perform off-line signature Verification and identification. The signature's contour is first determined from its binary representation. Unique structural features are subsequently extracted from the signature's contour through the use of a combination of the Modified Direction Feature. The other features like Centroid, Trisurface and Length are also extracted. To classify the signatures, the Resilient Back Propogation Neural Network and Radio Basic Function Network are used. Danjun pu and Sargur N Srihari [17] presented a prabobalisitc measure for signature verification using Bayesian learning process. Features such as gradient, structural and concavity were used and the distance between two signatures was computed by the correlation similarity measurement. The distribution of the genuine and forgery signature were taken as Gausian. The Bayesian Learning algorithm was used to learn the prior distributions of the signatures. The probabilities of the query and log likelihood ratio of the query was determined for both genuine and forgery classes. Luana Batista et al., [18] proposed a two stage offline signature verification system based on dissimilarity representation. In the first stage a discrete set of left to right Hidden Markov Models representing both genuine and forged classes of different number of states and different code book sizes were used to measure similarity values which form feature vectors. In the second stage these vectors were used to train a classifier to find the decision between genuine and forgery. Michal Papaj and Ewa Hermanowicz [19] used cross correlation approach and dynamic time wrapping for handwritten signature verification. In the algorithm the signature was treated as a complex trajectory and used on xy co-ordinates. Bhupendra M Chaudhari et al.,[20] proposed signature verification system using Fuzzy Min – Max Neural Network. The input signature image is preprocessed and normalized using Hu's seven moment invariant methods to make them invariant to position, translation, rotation and shear. The normalized image is applied to fuzzy min – max neural network for classification.

Muhammed Reza Pourshahabi et al., [21] presented offline handwritten signature identification and verification using contourlet transform. Noise removal was performed in the preprocessing stages of image enhancement. After size normalization, contourlet transform was applied to compute the contourlet coefficients and feature vector was formed. Classification was performed using the Euclidean distance classifier. Sepideh Afsardoost et al., [22] introduced the offline signature verification system based on geometric centroid features. The data base signatures and test signature were preprocessed for noise removal. The signatures are then subjected vertical, horizontal and diagonal splitting around the geometric centers. Euclidean distance model was used for classification. Sharifah Mumtazah Syed Ahmad et al., [23] presented an automatic off – line signature verification system using different statistical techniques. HMM based modeling was used to build a reference model for each of the local features extracted from signature image. The three layers of statistical techniques were used in the verification. The first stage involves the HMM based log likelihood probability matching score. The second stage maps these scores into soft boundary ranges of acceptance or rejection using z-score analysis. Classification was done by Bayesian inference technique.

3. Proposed Model

The block diagram of Off-line Signature Verification Based on Fusion of Grid and Global Features Using Neural Networks (SVFGNN) discussed in detail and is as shown in the Figure 1. It is divided into three phases viz., Preprocessing Phase, Feature Extraction Phase, and the Verification Phase.

3.1 Test Signature

It is the signature of a person whose authenticity is to be verified.

3.2 *Database*

The signatures are collected using either black or blue ink, on a white A4 sheet of a paper, with four signatures per page. Using the scanner the four signatures are digitized, with 96-dpi resolution in 256 grey levels. A group of 20 persons are used to collect 30 specimens from each persons resulting in 600 signature samples.. The genuine signatures are collected from 10 persons and the forged signatures are collected from the remaining 10 persons.

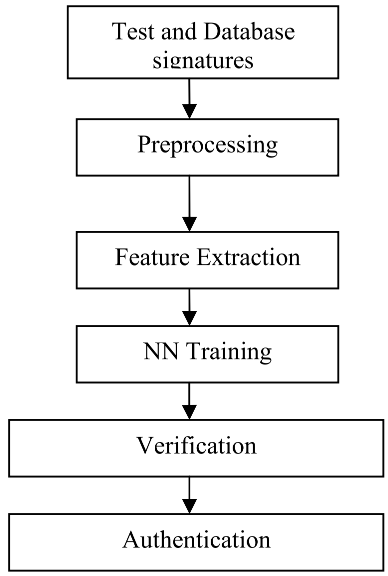

Figure 1: Block Diagram SVFGNN

3.3 Preprocessing

The features of signature are extracted using preprocessing stages such as (i) Noise Reduction (ii) Size Normalization, and (iii) Skelitonization.

3.3.1 Noise reduction

Imperfection in the scanner intensity of light, scratches or dirt on the camera or scanner lens etc., introduces noises in the scanned signature images. A filtering function is used to remove the noises in the image. It is required to eliminate single white pixels on black background and single black pixels on white back ground. In order to eliminate the noise we apply a 3 x 3 mask to the image with a simple decision rule: if the number of the 8-neighbors of a pixel that have the same color with the central pixel is less than two, then reverse the color of the central Pixel. The Gaussian filter is used for the noise removal. Since Gaussian function is symmetric, smoothing is performed equally in all directions, and the edges in an image will not be biased in particular direction. The signature before and after removal of noise are as shown in the Figure 2 and 3 respectively.

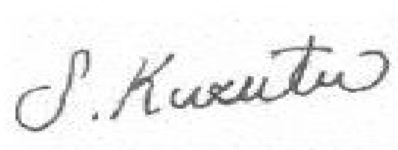

Figure 2. signature before noise reduction.

Figure 3. signature after noise reduction

3.3.2 *Size normalization*

Normally any person while putting his signature uses an arbitrary baseline. The positional information of the signature is normalized by calculating an angle θ about the centroid (x,y) such that rotating the signature by θ brings it back to a uniform baseline. The size normalization in offline signature verification is important because it establishes a common ground for image comparison. Taylor's maximization is used for normalization.

The mean μx of the x –series pixels is calculated by Equation 1.

$$\mu_x = \frac{\sum_t^T x_t}{T} \quad \ldots..(1)$$

Where t varies from t = 1 to t = y .
The function f(θ) is defined as shown in the Equation 2

$$f(\theta) = \sum_t^T (x_t^* - \mu_x)^2 \quad \ldots(2)$$

Where x_t^* indicates a rotated x value. To preserve the centroid, rotation about the coordinate (μ_x, μ_y) is performed using the Equation 3.

$$x_t^* = (x_t - \mu_x)\cos\theta + (y_t - \mu_y)\sin\theta + \mu_x \quad \ldots\ldots(3)$$

The function f (θ) is defined by substituting Equation 3 in Equation 2.

$$f(\theta) = \sum_t^T [(x_t - \mu_x)\cos\theta + (y_t - \mu_y)\sin\theta + \mu_x - \mu_x\ ]^2$$

$$= \sum_t^T a_t^2 \cos^2\theta + 2a_t b_t \cos\theta\sin\theta + b_t^2 \sin^2\theta$$

$$= \cos^2\theta \sum_t^T a_t^2 + 2\cos\theta\sin\theta \sum_t^T a_t b_t + sin^2\theta \sum_t^T b_t^2$$

Where $a_t = x_t - \mu_x$ and $b_t = y_t - \mu_y$

$$P = \sum_t^T (x_t - \mu_x)^2 \qquad R = \sum_t^T (y_t - \mu_y)^2$$

$$Q = \sum_t^T (y_t - \mu_y)(x_t - \mu_x)$$

The derivative of the Equation 4 gives Equation 5

$$\mathrm{f}^1(\theta) = 2\mathrm{Q}\cos^2\theta - 2\mathrm{P}\cos\theta\sin\theta + 2\mathrm{R}\cos\theta\sin\theta - 2\mathrm{Q}\sin^2\theta \quad \ldots.(5)$$

The roots of Equation 5 are given in Equation 6 and 7

$$root\ 1 = \pm\, cos^{-1}\left[\pm \frac{1}{\sqrt{2}} \sqrt{\frac{1+(P-R)}{P^2 + 4Q\ ^2 - 2PR + R^2}}\right] \quad \ldots\ldots..(6)$$

$$root\ 2 = \pm\, cos^{-1}\left[\pm \frac{1}{\sqrt{2}} \sqrt{\frac{1+(R-P)}{P^2 + 4Q\ ^2 - 2PR + R^2}}\right] \quad \ldots\ldots\ (7)$$

Obtaining the smallest value of the roots ie., θ from Equation 6 and 7 results in maximum value of f (θ). Further refinements make the time series to evolve in a consistent direction so that size normalization is perfectly achieved. Figure 4 and 5 shows the signature samples before normalization and after normalization respectively.

Figure 4. Signature before normalization

Figure 5. Signature after the normalization

3.3.3 *Skeletonization*

Reducing image to its single pixel width is called as skeletonization. The generation of a skeleton is realized by applying an iterative process which erodes the object layer by layer until only the object spines, which form the skeleton remains, this iterative process is called thinning. A thinning algorithm contains a set of pixel deleting conditions, which enable it to erode the object iteratively. The skeletonization steps are as follows.

Step 1: mark all the points of the signature that are candidates for removing (black pixels that have at least one black with 8-white neighbor and at least two black with 8-white neighbors).

Step 2: Examine one by one pixel following the contour lines of the signature image, and remove them as their removal will not cause a break in the resulting pattern.

Step 3: If at least one point was deleted then go back to Step 1 and repeat the process once again. Skeletonization makes the extracted features invariant to image characteristics like the qualities of the pen, the paper, the signer, the digitizing method and quality. The Skeletonization process supports the following properties, so that the thinning result can be characterized as a skeleton of the 2D binary object.

- **Geometry preservation** is a major concern of thinning algorithms. For example, an object like *b* should not be converted into an object like *o*. To preserve the geometry of the original image, a thinning algorithm must contain certain geometry preserving conditions.
- **Topology preservation** is the second major concern of thinning algorithms. For example, an object like *o* should not be converted into an object like *c*.
- **Finally,** a skeleton of an object should be, ideally, as thin as possible i.e., one pixel wide and represent the object through its spine or medial axis.

The Figures 6 and 7 shows the signature sample before skelitonization and after skelitonization process respectively.

Figure 6. Signature before skeletonization

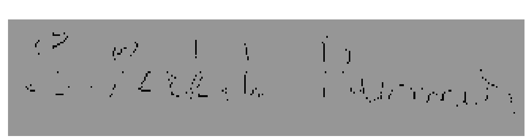

Figure 7. Signature after skeletonization

3.4 The Feature Extraction Phase

The choice of a powerful set of features is crucial in signature verification systems. The features used must be suitable for the application and for the applied classifier. In this system, two groups of features are used such as grid features and global features. For grid information features, the image is segmented into appropriate number of rectangular regions. The global features provide information about specific cases concerning the structure of the signature.

3.4.1 *Grid Feature*

Grid segmentation procedures have been used extensively in the off-line signature verification approach. The skeletonized image is divided into 120 rectangular segments (15x8), and for each segment, the area (the sum of foreground pixels) is calculated. The results are normalized so that the lowest value ie., the rectangle with the smallest number of black pixels would be zero and the highest value i.e., the rectangle with the highest number of black pixels would be one. The resulting 96 values form the grid feature vector.

It is very encouraging to recognize diagonally so that more points may be diagnosed for generating the vector matrix to get results more accurate than the simple grid.

Figure 8. Simple Grid with Image

3.4.2 *Global Feature:*

Some common global features discussed below are implemented in our experiments.

Aspect Ratio: The ratio of signature pure height to signature pure width.

Signature height: It is the height of the signature image, after width normalization.

Image area: It is the number of black pixels in the image. In skeletonized signature images, image area represents a measure of the density of the signature traces.

Pure width: The width of the image with horizontal blank spaces removed.

Pure height: The height of the signature image after vertical blank spaces removed.

3.5 Neural Network (NN) Training:

The standard back propagation neural network classifier for verification is used. Standard back propagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term back propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. Typically, a new input leads to an output similar to the correct output for input vectors used in training which are same as the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.

3.6 Verification process

Multilayer feed forward artificial neural network for verification of off-line digitized signatures is used. The proposed NN consists of 30 input variables which are extracted from signature features, and it is designed to verify one signature at a time. Back propagation algorithm is used for training.

4. Algorithm

Problem Definition: Given a test signature for the verification of authenticity. The objectives are:

(i) The database signatures and test signature are preprocessed to eliminate noise.
(ii) The database signatures are considered and the neural network is trained by the feature of each signature.
(iii) The test signature features are compared with the database signature features using NN.

Assumptions:

(i) The grid size of 15*8 is considered.
(ii) The signature image of type 96-dpi resolution in 256 gray levels.

The algorithm of SVFGNN is explained in the Table 1 for the signature verification using Grid and Global features by training NN.

5. Performance Analysis

The test and the database signatures of 96-dpi resolution in 256 grey levels are considered for the performance analysis. It is observed from the Table 2. that the values of FRR (False Rejection Rate) and FAR (False Acceptance Rate) are improved in the proposed method of combined offline signature verification using neural network compared to existing grid and global feature method. The FAR is improved by a factor 25-30% compared to grid Feature using KNN Classification [1] and 50-60% as compared to Global Feature using KNN Classification method. The FRR is improved by a factor 7-12% in the proposed algorithm compared to grid Feature using KNN Classification and 30-35% as compared to Global Feature using KNN Classification method.

Table 1: Algorithm of SVFGNN

Input: Reference Signatures and Test Signature
Output: Verified Signature
Step 1: Noise Reduction, Normalization and Skelitonization is performed on database signature and test signature.
Step 2: Global Features and Grid Features of database signatures are extracted.
Step 3: Neural Network is trained by features of database signatures.
Step 4: Global Features and Grid Features of test signature are extracted.
Step 5: Compare features of test signature with the features of database signatures using NN.
Step 6: Authentication of test signature.

Table 2: FAR and FRR for different algorithms.

Method	FRR	FAR
Grid Feature using KNN Classification	8.07%	5.91%
Global Feature using KNN Classification	11.26%	9.53%
Proposed SVFGNN algorithm	7.51%	4.16%

6. Conclusion

Signature is a behavioral biometric used to authenticate a person in day to day life. We proposed the algorithm which fuses both the global and grid features to yield better results as compared to individual global features and grid features. The Back Propagation Neural Network is used for verification of offline signatures. It is observed that the values of FRR and FAR are improved in the proposed algorithm compared to the existing algorithm. In future signature may be converted into transform domain for the verification of the performance analysis.

References

[1] Javed Ahmed Mahar, Mumtaz Hussain Mahar, Muammed Khalid Khan. (2006): Comparative Study of Feature Extraction for Off-Line Signature Verification, Second International Conference on Emerging Technologies, pp. 115-120.

[2] Taylan Das, M., L Canan Dulger, L. (2007): Off Line Signature Verification with PS0-NN Algorithm, Twenty Second International Symposium on Computer and Information Sciences, vol 7, issue 9, pp. 1-6.

[3] Ahmad, S. M. S., Shakil, A., Faudzi, M. A., Anwar, R. M., Balbed, M. A. M. (2009): A Hybrid Statistical Modelling, Normalization and Interferencing Technuques of Off-line Signature Verification System, World Congress on Computer Science and Information Engineering, vol 6, pp. 6-11.

[4] Li, F. F. (2010): Sound Based Multimodal Person Identification from Signature and Voice, Fifth IEEE international Conference on Internet Monitoring and Protection, pp. 84-88.

[5] Ji Jum-wen, Chen Chun-bo, Chen xian-su. (2010): Off-line Chinese Signature Verification: Using Weighting Factor on Similarity Computation, Second IEEE International Conference on e-Business and Information System security, pp. 1-4.

[6] Boyko, A., Rozorynov, G. (2010): Signature based Authentication, IEEE International conference on Modern Problems of Radio Engineering, Telecommunications and Compute Science, pp. 300.

[7] Liang Wan, Zhou-chen Lin, Rong-chun Zhao. (2003): Off Line Signature Verification Incorporating the Prior Model, Proceedings of the Second International Conference on Machine Learning and Cybernatics, pp. 1602-1606.

[8] Jalal Mahmud, Chowdhury Mofizur Rahman. (2005): On Analysis of Multi Dimensional Features for Signature Verification, International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce, pp. 735-740.

[9] Bence Kovari, Zsolt Kertesz, Attila Major. (2007): Off Line Signature Verification Based on Feature Matching, Eleventh International Conference on Intelligent Engineering System, pp. 93 – 97.

[10] Banshider Majhi, Santhosh Reddy, Y., Prasanna Babu, D. (2006): Novel Features for Offline Signature Verification, International Journal of Computer Communications and Controls, vol . 1, no. 1, pp. 17 – 24.

[11] Ming Yang, Zhongke Yin, Zhi Zhong, Sheng Shu Wang, Pei Chen Yang Sheng Xu. (2002): A Contourlet Based Method for Handwritten Signature Verification, National Conference on Real-Time Imaging, pp. 227-236.

[12] Ismail, I. A., El danf, T., Ramadan, M. A., Samak, A. H. (2008): Automatic Signature Recognition and Verification using Principal Component Analysis, Fifth International Conference on Computer Graphics, Imaging and Visualization, pp. 356-361.

[13] Debasish Jena, Banshidhar Majhi, Sanjay Kumar Jena. (2008): Improved Offline Signature Verification Scheme Using Feature Point Extraction Method, Journal of Computer Science, vol. 4, issue 2, pp. 111 – 116.

[14] Bai ling Zhang. (2006): Off Line Signature Recognition and Verification by Kernel Principal Component Self Regression, Fifth International Conference on Machine Learning and Application, pp. 28-33.

[15] Vu Nguyen, Michael Blumenstein, Vallipuram Muthukkumarasamy, Graham Leedham. (2007): Off Line Signature Verification using Enhanced Modified Direction Features in conjuction with Neural Classifiers and Support Vector Machine, Ninth International Conference on Document Analysis and Recognition , vol 2, pp.734-738.

[16] Stephane Armand, Michael Blumanstein, Muthukkumarasamy, V. (2006): Off Line Signature Verification based on Modified Direction Feature, Eighteenth International conference on Pattern Recognition, vol 4, pp. 509-512.

[17] Danjun Pu, Sargur Srihari, N. (2010): A Probabolisitic Measure for Signature Verification based ob Bayesian Learning, IEEE International Conference on Pattern Recognition, pp. 1188-91.

[18] Luana Batista, Eric Granger, Robert Sabourin. (2010): Applying Dissimilarity Representation to Off line Signature Verification, IEEE International Conference on Pattern Recognition, pp. 1293 – 1298.

[19] Michal Papaj, Ewa Hermanowicz. (2010): Identity Verification Using Complex Representations of the Handwritten Signatures, Second IEEE International Conference on Information Technology, pp. 79 – 82.

[20] Bhupendra Chaudhari, M., Atul Barhate, A., Anita Bhole, A. (2009): Signature Recognition Using Fuzzy Min – Max Neural Network, IEEE International Conference on Control Automation, Communication and Energy Conservation, pp. 1-7.

[21] Muhammad Reza Pourshahabi, Mohamad Hoseyn Sigari, Pourreza, H. R. (2009): Offline Handwritten Signature Identification and Verification Using Contourlet Transform, *IEEE* International Conference on Soft Computing and Pattern Recognition, pp. 670 – 673.

[22] Sepideh Afsardoost, Siamak Yousefi, Mohammed Ali Khorshidi. (2008): Offline Signature Verification Using Geometric Center Features, IEEE International Conference on Signal Processing, pp. 1491 – 1494.

[23] Sharifah Mumtazah Syed Ahmad, Asma Shakil Masyura Ahmad Faudzi, Anwar, R. M., Muhamad Balbed,M. A. (2008): A Hybrid Stastical Modelling Normalization and Interferencing Techniques of an Offline Signature Verification System, World Congress on Computer Science and Information Engineering, pp. 6 – 11.

Shashikumar D R received BE degree in Electronics & Communication Engineering from Mysore University and ME degree in Electronics from Bangalore University, Bangalore. He is pursuing his Ph.D. in Information and Communication Technology of Fakir Mohan University, Balasore, Orissa under the guidance of Dr. K. B. Raja, Assistant Professor, Department of Electronics and Communication Engineering, University Visvesvaraya College of Engineering, Dr.Sabyasachi Pattanaik Reader & HOD, Department of Information and Communication Technology F M University, Balasore, Orissa R K Chhotaray, Principal, Seemantha Engineering College, Orissa. He is currently working as Professor, Dept. of Computer Science, Cambridge Institute of Technology, and Bangalore. His research interests include Microprocessors, Pattern Recognition, and Biometrics.

K B Raja is an Assistant Professor, Dept. of Electronics and Communication Engineering, University Visvesvaraya college of Engineering, Bangalore University, Bangalore. He obtained his BE and ME in Electronics and Communication Engineering from University Visvesvaraya College of Engineering, Bangalore. He was awarded Ph.D. in Computer Science and Engineering from Bangalore University. He has over 45 research publications in refereed International Journals and Conference Proceedings. His research interests include Image

Processing, Biometrics, VLSI design, Signal Processing and computer networks.

Dr. Sabyasachi Pattnaik has done his B.E in Computer Science, M Tech., from IIT Delhi. He has received his Ph D degree in Computer Science in the year 2003 & now working as Reader in the Department of Information and Communication Technology, in Fakir Mohan University, Vyasavihar, Balasore, and Orissa, India. He has got 20 years of teaching and research experience in the field of neural networks, soft computing techniques. He has got 42 publications in national & international journals and conferences. He has published three books in office automation, object oriented programming using C++ and artificial intelligence. At present he is involved in guiding 8 Ph D scholars in the field of neural networks, cluster analysis, bio-informatics, computer vision & stock market applications. He has received the best paper award & gold medal from Orissa Engineering congress in 1992 and institution of Engineers in 2009.

R K Chhotaray received B.Sc Engineering in Electrical Engineering and M.Sc Engineering in Electrical Engineering with specialization in Control Systems from Banaras Hindu University, and Ph D in Control Systems from Sambalpur University. He was Professor and Head of Department of Computer Science and Engineering, Regional Engineering College, Rourkela, from which he retired in 2003. Currently he is working as Principal of Seemanta Engineering College, Orissa. He has been associated with many Universities of India in the capacity of Chairman and member of various Boards of Studies, syllabus committee, and Regulation committee. He has about hundred publications in International and National journals of repute, and has received Best Technical Paper award in many occasions. His special fields of interest include Control of Infinite dimensional Hereditary Systems, Modeling and Simulation, Theoretical Computer science, signal and Image processing, and optimization.