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Static Signature Matching Using LDA and Artificial Neural Networks

Shaina Kedia

Jan Nayak Ch. Devi Lal Vidyapeeth, Haryana
shainakedia23@gmail.com

Er. Gaurav Monga

Jan Nayak Ch. Devi Lal Vidyapeeth, Haryana
ergauravmonga@gmail.com

Abstract: In recent years, the importance of biometrics in authentication and identification has emerged. Both government and private agencies make use of automated human identification using different biometric traits. Signature based authentication has been used for many years. This paper presents an automated static signature recognition approach. We have used gabor filter for preprocessing of signature images. For matching purpose, artificial neural networks are used, which are trained by the back-propagation learning algorithm. The results show that the given approach yields a good solution to automated signature recognition problem because of its high accuracy (99.5%) and FRR (68%). On the other hand, computational time of the proposed technique is less than the previous approaches.

Keywords: Static Signatures, Gabor filter, Matching, Neural Network.

INTRODUCTION

In the previous decades, biometrics has emerged as a vital facet for human authentication. Many biometric traits are used for the purpose such as fingerprints, ear pattern, iris pattern etc. A handwritten signature is a biometric trait of human beings which is used as a primary means of authentication from many years. Although, the manual signature matching needs analysis by a human, which can be both times to consume and, can be sometimes biased. Because of these demerits, a need for automated signature verification rises. This system does not only advance the signature authentication process but will also give a safe and sound method for authentication of legal documents. The automated signature recognition system must have some important properties such as it should be able to detect forgeries, should neither be very sensitive nor very coarse.

The first automated signature recognition system was developed in 1965 [2]. The signature verification method can be divided into two categories: static and dynamic. The static signature verification is the one which makes use of an optical scanner to acquire handwritten signature written onto the paper. This method is also known as Off-Line signature recognition. While the dynamic signature verification uses signature acquired onto handheld devices to extract information about the signature using dynamic characteristics. This method is also known as On-Line signature recognition. In this paper, an approach for static signature recognition is proposed [1].

Signature Verification System

The goal of designing signature verification system is to detect forgery in signatures, which can be of three types.

1. Random; in which the original signature is unknown.
2. Simple; in which some assumptions are made by knowing the name of the original signer.
3. Skilled; in which original sign are known and a replication of original signal is done.

From these three types, the skilled one is most difficult to find out [3].

Related work

Offline signature recognition system has gained the interest of many researchers. This is a convenient approach and various optimization techniques can be applied to solve the problem.

Sabourin [4] has used the granulometric size distributions to the definition the local shape descriptors in order to differentiate between the quantities of signal activity exciting each retina on the focus of an overlaid grid. After this, he has used k-nearest neighbor, and the classifier based on a threshold in an attempt to detect the random forgeries. A total error rate for both rates were 0.02% and 1.0% respectively. For this task, 800 genuine signatures from 20 writers are used.

Hanmandlu [5], developed a neuro-fuzzy system. He has compared the angle made by the signature pixels which are calculated with respect to reference points. After comparing this, the angle distribution has been clustered using fuzzy c-means algorithm. Finally, for the training of artificial neural networks, backpropagation learning algorithm is used. The proposed system reported False Rejection Rate of 5-16% with changing threshold.

A Kernel Principal Component Self- regression (KPCSR) model for static signature verification problems is given by Zhang [6]. The proposed self-regression model has selected a subset of the principal components from the kernel space for the input variables to precisely exemplify signatures of each person, the system, therefore, offers a good verification and recognition performance. The given model directly work on bitmap images, showing satisfactory performance. A modular scheme with subject-specific KPCSR structure proved to be very efficient, from which each person was assigned an independent KPCSR model for coding the corresponding visual information. The results show that the FRR and FAR of the model are 92% and 5% respectively.

Dipti Verma [7] proposed a signature recognition system based on the center of gravity, hough transform and neural network for static signatures. In the given system, the signatures are preprocessed through binarization, cutting edges and thinning of signature images in order to give an accurate platform for feature extraction. She has measured the center of gravity in two levels by taking into account the center of gravity of all the characters separately instead of considering only one center of gravity for the whole signature. Moreover, she has taken the mean values of all the center of gravity values of various characters present in the signature. Morphological operations are applied on these signature images with Hough transform in finding out the regular shape which aids in the authentication process. The values given by Hough space are used in the feed forward neural network. Back-propagation learning algorithm is used to train the neural network. The efficiency of above more than 95% is achieved after different training stages.

Baskaran [8], has given an Off-Line Signature Verification and Recognition system using SVM (Support Vector Machine). He has used the global, directional and grid features of signatures. SVM has been used by him for classification and verification of the signatures. A classification ratio of 0.95 was obtained by the approach.

A signature verification algorithm based on static and dynamic features of online signature verification system is proposed by Mayank Vatsa [9]. The digital tablet captures in real-time the pressure values, breakpoints, and the time taken to create a signature. One dimensional - log Gabor wavelet and Euler numbers are used for analyzing the textual and topological features of the signature respectively. A multi-classifier decision algorithm combines the results obtained from three feature sets to attain an accuracy of 98.18%.

Proposed method

In the proposed system, image preprocessing is done by using gabor filter. Following this, the linear discriminant analysis is applied to the image. After this, signature matching is done by using artificial neural networks. If the signatures match, then the person is authentic, otherwise, it was a forgery. The figure 1. Shows the workflow diagram for the proposed approach.

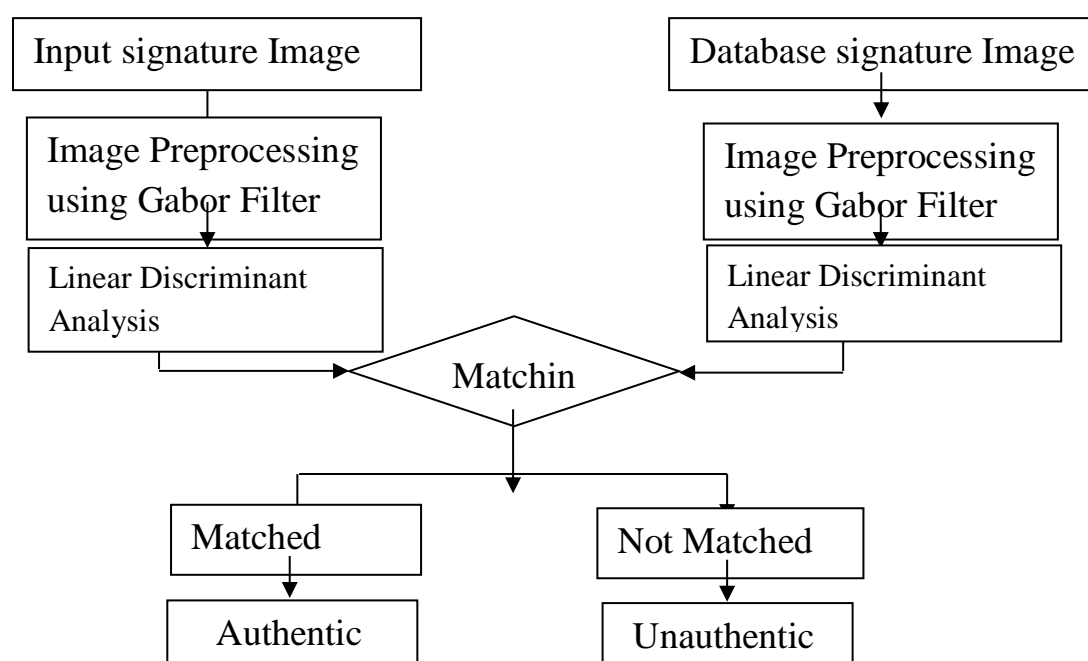


Fig 1. Work Flow Diagram of the proposed method

Results and conclusion: The results show that the given signature recognition technique is a promising solution to the recognition and authentication promising technique as the average accuracy of the proposed method is very high (99.5%). Along with this a False Rejection Rate of up to 73% is achieved. Moreover, the computational time of the method is less than other techniques, which are 0.87s.



Fig2. Preprocessing of signature image

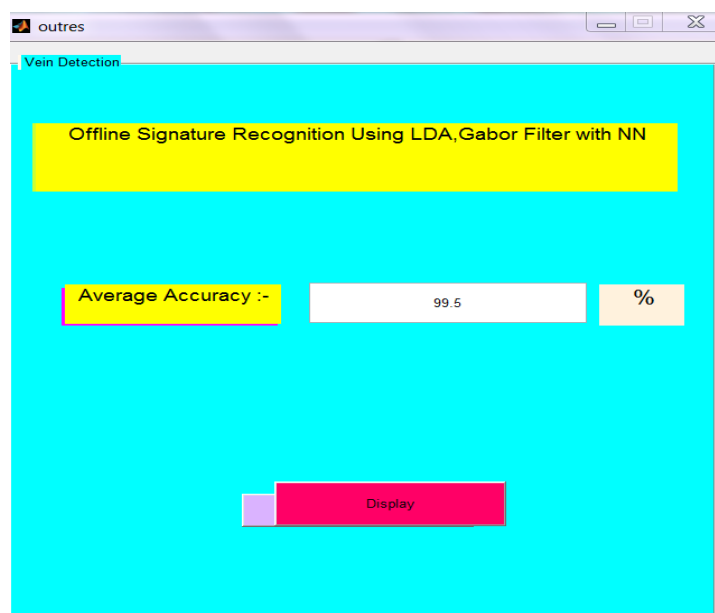


Fig 3. Average accuracy of proposed approach

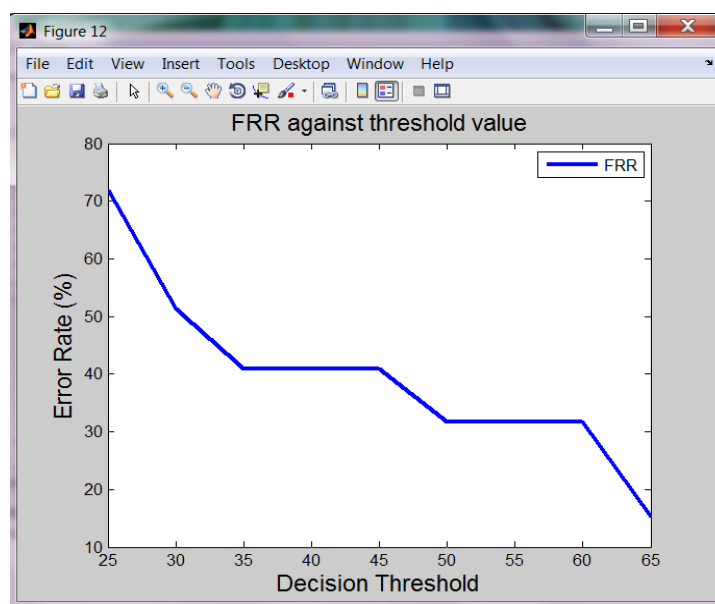
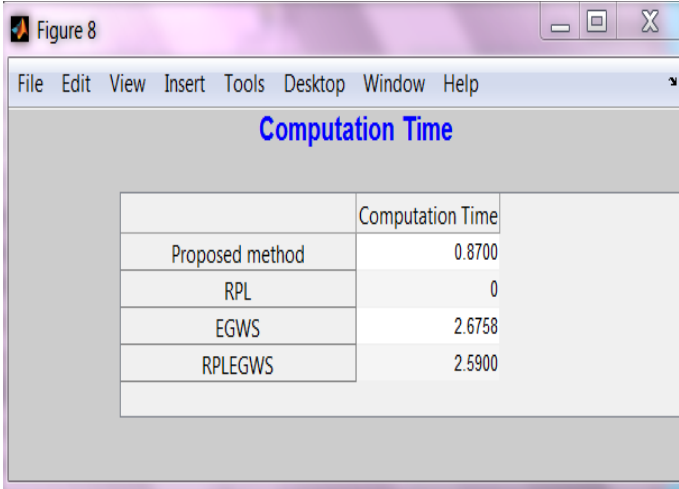


Fig 4. FRR curve for proposed method against variable threshold values



	Computation Time
Proposed method	0.8700
RPL	0
EGWS	2.6758
RPLEGWS	2.5900

Fig 5. Comparison of computational time of various signature recognition methods

REFERENCES

- [1] Komal Pawar, Tanuja Dhope, "Static Signature Verification and Recognition using Neural Network Approach-A Survey", *European Journal of Advances in Engineering and Technology*, 2015, page no. 46-50
- [2] A. J. Mauceri, "Feasibility studies of Personal Identification by Signature Verification", Report number SID6524RADCTR6533, Space and Information System Division, North American Aviation Co., Anaheim, USA, 1965.
- [3] Plamondon and SN Srihari, "Online and Offline Handwriting Recognition: A Comprehensive Survey", *IEEE Tran. on Pattern Analysis and Machine Intelligence*, 2000, 22 (1), page no. 63-84.
- [4] R. Sabourin, G. Genest, F.J. Preteux, "Off-line signature verification local granulometric size distributions", *IEEE Trans. Pattern Anal. Mach. Intell.* 19 (9) (1997), page no. 976-988.
- [5] M. Hanmandlua, Mohd. Hafizuddin, Mohd. Yusofb, V. K. Madasu, "Off-line signature verification and forgery detection using fuzzy modeling" *Pattern Recognition* 38 (2005), page no. 341-356.
- [6] Bai-ling Zhang, "Off-line Signature Recognition and Verification by Kernel Principal Component Self- regression", *Proceedings of the 5th International Conference on Machine Learning and Applications (ICMLA'06)*, 2006, page no. 4 – 6
- [7] Dipti Verma , Sipi Dubey, "STATIC SIGNATURE RECOGNITION SYSTEM FOR USER AUTHENTICATION BASED TWO LEVEL COG , HOUGH TRANSFORM, AND NEURAL NETWORK", *International Journal of Engineering Sciences & Emerging Technologies*, Dec. 2013, Volume 6, Issue 3, page no. 335-343
- [8] S. Audet, P. Bansal, and S. Baskaran , "Off-line signature verification using virtual support vector machines", *ECSE 526 - Artificial Intelligence*, April 7, 2006
- [9] Mayank Vatsa , Richa Singh , Pabitra Mitra, Afzel Noore, "Signature Verification Using Static and Dynamic Features", *Springer-Verlag Berlin Heidelberg* 2004, page no. 350–355