A Fuzzy Hybrid Framework for Offline Signature Verification

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Abstract. Signatures are widely used means of personal verification. This paper presents a fuzzy hybrid framework based person-dependent off-line signature verification using fuzzy inference rules in image contrast enhancement, fuzzy rough reduction for feature selection and Simplified fuzzy ARTMAP for verification. Three sets of experimental studies are conducted on CEDAR benchmark dataset and the results reported are comparable to other techniques in terms of classification accuracy and time.

Keywords: Off-line signature verification, Simplified fuzzy ARTMAP, fuzzy inference rules, contrast intensification, fuzzy rough sets, feature selection.

1 Introduction

Signature is a widely used biometric for authentication of an individual or a document. A signature verification system aims to verify the identity of an individual based on the analysis of the signature. Signatures of some people vary substantially: even successive impressions of their signature are significantly different due to shape and relative position of the characteristic features. Hence, developing a robust signature verification system is a very challenging task. Signature verification is either on-line or off-line. Off-line verification lacks any form of dynamic information and has to rely on the features that are extracted from the static signature image and hence much more difficult to verify. Forgeries are random, simple or skilled. A skilled forgery is a close imitation of the original signature produced by a forger who has seen and practiced writing the genuine signature.

The complexity of signature verification lies in the variability of signing. The uncertainties related to the complexity of patterns and the lack of complete information about a signature motivated to develop a system for writer-dependent off-line signature verification for skilled forgeries. In this paper, the features of the signatures, the gray level intensities based on a gradient direction histogram are extracted and verified using Simplified fuzzy ARTMAP. As contrast intensification plays a major role in enhancing image quality, contrast intensification

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is done using fuzzy inference rules. As more features may introduce more measurement noise and reduce accuracy, relevant features are selected using fuzzy rough rules. All the algorithms are performed on the commonly used CEDAR [6] benchmark dataset and results reported.

The paper is organized is as follows. Section 2 discusses the related work. Section 3 discusses the proposed method. Section 4 elaborates on image enhancement, feature selection and verification. Section 5 reports on the experiments conducted and the results obtained. Finally, Section 6 concludes the work.

2 Related Work

Signature verification system is an active area of research. The Centre of Excellence for Document Analysis & Recognition (CEDAR) signature data set [6] is a commonly used data set for off-line signature verification. Schemes that used the CEDAR data set are referred here.

Kalera et al.[6] proposed an approach based on quasi-multi resolution technique using Gradient, Structural & Concavity (GSC) features for feature extraction and obtained 78% accuracy. Srihari et al.[14] developed a distance statistics method and acquired 78.1% accuracy. Chen et al.[1] proposed Zernike moments based features and distance similarity measure to get 83.6% accuracy. Chen et al.[2] presented a method based on graph matching, thin-plate spline mapping and word shape descriptors to get an accuracy of 90%. Larkins et al [10] introduced adaptive feature thresholding (AFT) combined with spatial pyramids [11] and equimass sampling grids [3] for feature extraction using gradient direction and achieved 90% accuracy. Kumar et al.[8] proposed a set of morphological features for extraction and multi-layer perceptron (MLP) and support vector machine (SVM) for classification and obtained an accuracy of 88.4%. Kumar et al.[9] proposed a set of features based on Surroundedness property of a signature image and based on MLP and SVM obtained an accuracy of 91.67%.

3 Proposed Fuzzy Hybrid Framework for Signature Verification

In Signature Verification, direct methods to generate features from image pixels or some form of transforms have been proposed in feature extraction and machine learning technique / similarity measure based approach for verification.

In this paper, we use grey level intensity and gradient direction histogram combined with spatial pyramids [11] and equimass sampling grids [3] for feature extraction as in [10]. We propose the following methodology:1) In preprocessing fuzzy rules based contrast enhancement is applied to increase the gray level intensity of the signature 2) gradient direction histogram combined with one level of equimass is used for feature extraction 3) Fuzzy Rough approach is applied for feature selection and 4) Simplified fuzzy ARTMAP is used for verification.

The feature extraction used in this paper depends on the gray level intensity of the signature image. A gray scale image possesses some ambiguity within the pixels due to the possible multi-valued levels of grayness. Contrast enhancement improves the overall visibility of the image gray levels by transforming the dark pixels to appear darker and the light pixels to appear lighter. The advantage of the fuzzy methods compared to conventional image enhancement algorithm is their stability under nearly uncertain conditions on the one hand and the simple adjustment to reach a desired effect in the resulting image on the other hand; The fuzzy rules based approach is a powerful and universal method for many tasks in image processing [15]. Hassanien et al [4] have done a comparative study of 5 fuzzy based image enhancement algorithms on digital mammogram images and showed that fuzzy histogram hyperbolization method and fuzzy rule based system (FRBS) are comparatively better. Hence this paper uses FRBS for image enhancement with contrast intensification.

Feature Selection addresses the problem of selecting those input features that are most predictive of a given outcome. More features may introduce more measurement noise and, hence reduce accuracy. Hence an efficient and effective reduction is necessary. The success of rough set theory is due to finding a minimal representation of data without requiring additional information like thresholds. Rough Sets and Fuzzy sets can both tolerate inconsistency and uncertainty. Fuzzy sets are concerned with vagueness and rough sets are concerned with indiscernibility. Fuzzy-rough feature selection (FRFS), that employs fuzzy-rough sets to provide a means by which discrete or real-valued noisy data can be effectively reduced without the need for user-supplied information [5]. Rough set based approach provides a filter-based tool by which knowledge may be extracted from a domain in a concise way by using the granularity structure of the data. A reduced feature set is obtained by applying fuzzy Rough Reduct algorithm [5] to the set of features extracted from the signature image.

Traditional Neural Network algorithms like Radial Basis Function (RBF), MLP with BackPropagation have limitation on generalization. Fuzzy ARTMAP (FAM) neural network achieves a synthesis of fuzzy logic and adaptive resonance theory(ART). Kasuba's [7] Simplified FAM (SFAM) is a vast simplification over FAM. The fast learning capability of SFAM is thus utilized in classifying the signatures. The features extracted are given as inputs to a SFAM to determine if a signature is genuine or forged. False Acceptance Rate (FAR), a type II error that expresses the percentage of forgeries accepted as genuine and False Rejection Rate (FRR), a type I error that expresses the percentage of genuine rejected as forgery are used to compute the accuracy.

4 Verification of Signatures

The raw signature image undergoes preprocessing to reduce noise, feature extraction, feature subset selection and verification phases.

Preprocessing of Signatures: Preprocessing is a required step to modify the signature image to improve the representation of the extracted features. Each signature is binarized followed by Weiner noise reduction. Fig. 1.a represents the original image of a sample signature.

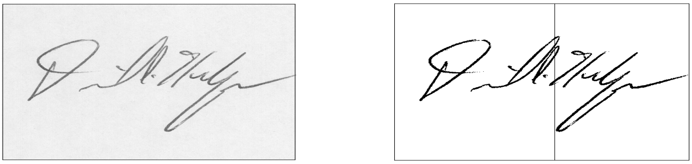

Fig. 1. Signature image : a. original b. one level of equimass

Feature Extraction: A feature vector is created for each signature based solely on the gradient direction of each pixel from across a signature. This direction θ of a pixel at (x,y) is found by $\theta = \tan^{-1}(\frac{G_x}{G_y})$ where G_x is the Sobel kernel for horizontal change and G_y for vertical change. The resulting direction value ranging between 0 to 2π radians, is split into 18 non-overlapping segments allowing a gradient direction histogram to be created from the count of each direction. Equimass is an adaptive grid based on the number of black pixels or Mass M of a signature, where the grid lines are found at the equimass divisions of the horizontal and vertical mass histogram. An effective approach as in [10] by combining the spatial pyramids [11] and the equimass sampling grids [3] were used. The features extracted as above are normalized. As each box (Fig.1.b) contains 18 segments, the signature image provides a first level of 36 features by equimass. Alg. 1 states the procedure for feature extraction and its time complexity would

Algorithm 1. Feature Extraction

1: **for** each image in a set **do**
2: Get the original image, apply Weiner filter to reduce noise
3: Apply fuzzification operator to the image
4: Apply constrast Intensification to the Fuzzified image
5: Apply defuzzification operator to the Intensified image
6: Divide the image into one level of equimass (2 boxes)
7: Get gradient direction histogram for the 18 segments (20deg) in each box
8: Normalize the data
9: **end for**

be O(n*w*h)where n would be the number of signatures per signer and w*h would be the size of the signature image. Steps 3, 4 & 5 are executed when fuzzy rule based contrast intensification is done.

Verification: Verification of Signatures is done by utilizing a SFAM [7]. SFAM contains two layers, the input and the output. The input to the network flows through the complement coder to the input layer. Weights from each of the output category nodes flow down to the input layer. The category layer holds the number of classes that the network has to learn. Vigilance parameter and match tracking mechanism are employed for network training. During training, the input data (36 features) are presented to the SFAM network together with their respective categories (genuine/forgery : 1/-1). During testing, the test input is presented to the network. All the output nodes compute the activation functions with respect to the input. The winner is the node with the highest activation function and the input is classified to the category to which the winning output node belongs to. The training and testing phases of SFAM were adapted from [13]. The algorithms are applied for all 55 sets and the overall accuracy is computed. The time complexity for training algorithm would be O(n*e), where n is the number of training signatures and e is the number of epochs. The complexity for testing would be O(n), n being the number of test signatures.

Fuzzy Rule Based Contrast Intensification: The signature image is subjected to contrast intensification of gray levels using fuzzy inference rules as in [4]. A very simple inference system is formulated. The methodology is to first fuzzify the gray level, contrast intensify the fuzzy gray level and defuzzify the fuzzy value back to gray level values. Triangular membership functions are used for dark, gray and light fuzzy sets employed in the rules:
If pixel is dark then black
If pixel is gray then gray
If pixel is light then white
The fuzzy gray level is intensified by applying the INT operator [12] and is defuzzified back by inverse transformation. The complexity would be O(n*r*c) where n is the number of signatures and rxc is the size of the image.

Fuzzy Rough Feature Selection: The signature image based on gradient direction histogram and one level of equimass produce 36 features per signature. These features are fed into the fuzzy rough reduct algorithm [5] to select relevant features. The algorithm starts off with an empty set and adds in turn, one at a time, those attributes that result in the greatest increase in the rough set dependency metric, until this produces its maximum possible value for the dataset. The algorithm terminates when the addition of any remaining attribute does not increase the dependency. For n attributes, O(n*(n+1)/2) evaluations may be performed for the worst case data set. As the features are specific to a signer, we have a feature subset for each signer. A superset was created from these subsets which had 80% of features in common. The feature subset that got selected is {1, 2, 3, 4, 5, 14, 16, 17, 18, 19, 20, 21, 22, 23, 32, 33, 34, 36}. This set of 18 features, is a 50% reduction from our original feature set which consisted of features from 1 to 36.

5 Results and Discussion

The CEDAR signature dataset [6], a popular benchmark dataset used for off-line signature verification, consists of 55 signature sets, with each set being composed by one writer. Each set consists of 24 genuine and 24 skilled forgery signatures in a space measuring 2 x 2 inches, scanned at 300 dpi in 8-bit gray scale. In total, the dataset contains 1,320 genuine signatures and 1,320 forgeries. The experiment process was carried out on each signature set, where 14 each from genuine and forgery randomly chosen signatures were used as training set and the remaining 10 each in genuine and forgery were used for testing. The training set keeps varying for each trial and 10 such trials were conducted in order to average the effect of possible outliers in the training set and also to obtain a reliable estimate of the accuracy. The evaluation was carried out on all the 55 sets. Table 1 compares the error rates and the accuracy against the existing methods, of which [8] and [9] are person independent. FRR keeps decreasing from FRBS contrast intensification to FRFS in the proposed methods implying that forgeries are being identified more accurately by contrast enhancement and feature selection. The vigilance parameter was 0.99 in SFAM. Table 2 lists the results when the training set is varied. All the experiments described above have been written in MATLAB running on Intel Core 2 Quad CPU @ 2.66 GHz PC with 2GB of RAM. Contrast intensification of Gray levels combined with spatial

Table 1. Results When Training set size is 16 (CEDAR data)

Method	Acc %	FRR	FAR
Existing			
Gradient Structural & Concavity [6]	78.50	22.45	19.50
Zernike Moments [1]	83.60	16.60	16.30
Graph Matching [2]	92.10	7.70	8.20
Adaptive Feature Thresholding [10]	90.44	1.86	10.96
Signature Morphology [8]	88.41	11.59	11.59
Surroundedness [9]	91.67	8.33	8.33
Proposed			
Only SFAM	88.95	6.27	15.83
FRBS Contrast + SFAM	92.85	1.71	12.60
FRBS + FRFS + SFAM	93.99	2.83	9.19

Table 2. Results for varying Training set size

Set Size	Acc %	FRR	FAR
10	92.79	3.30	11.13
11	92.97	3.85	10.21
12	93.47	3.57	9.48
13	93.65	3.45	9.25
14	93.99	2.83	9.19
15	94.13	2.69	9.04

pyramids [11] and equimass sampling grids [3] in feature extraction, and fuzzy rough sets in feature selection have helped to boost the classification accuracy.

6 Conclusion

Differentiating skilled forgeries from genuine is a very difficult task. In this paper, an offline signature verification system based on a fuzzy hybrid framework was proposed. The algorithms were tested on the benchmark CEDAR data set. The method used SFAM for verification and obtained an accuracy of 88.95%. FRBS based contrast Intensification and enhancement improves the accuracy to 92.85% and FRFS further enhances the accuracy to 93.99%. With the system being related to skilled forgeries, it can be concluded that the fuzzy based framework augurs well in uncertain and ambiguous situations in terms of accuracy and time. Less number of features makes the system less computationally intense and this factor is more suitable for real-time systems.

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