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Offline Signature Verification based on Edge Histogram using Support Vector Machine

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ABSTRACT: Investigation on verification of offline signature has explored a huge sort of techniques on more than one signature datasets, which can be amassed beneath managed conditions. However, these records will not necessarily reflect the characteristics of the signatures in some useful use cases. In this work, introduced a novel feature representation technique called edge histogram and 4 directional histograms for offline signature verification system. For classification of signature support vector machine (SVM) technique employed. Edge is a curve or point where the intensity of an image changes rapidly. Edges represent the boundary of object of an image. Edge detection is a process of detecting edges of an image. Several algorithms are available to detect edges effectively from an image. Canny, Roberts, Prewitt and Sobel are several popular available edge detectors.

KEYWORDS: Signature, Recognition, SVM, Forgery, Genuine

1. Introduction

Signatures are behavioral biometric traits of a person, used to authenticate a person. In all the legal transaction and documentations signature is required to authenticate its legality. In such cases there may be chances to forge the signature by someone to get the benefits. Therefore in order to check the genuineness of the signature, signature authentication system is required. There are several algorithms are proposed by different authors but still there are challenges to address the skilled forgery and intra class variation.

Traditional cashier examinations, bank loans, credit cards and various legal documents has become a staple of modern work. Unavoidable the side effect of signing is that it can be used to make a document look like it is genuine. As a result, there is a growing need for research on efficient automation solutions for recognizing and validating signatures. The signature verification system aims to automatically distinguish whether the biometric sample is actually from the requested individual. That is, it is used to determine whether a query signature is fake or real. Fake is usually classified. It can be divided into three types: simple, random, and clever (or simulated) fake. The counterfeiter has no information about the user or his signature when they counterfeit randomly. Instead, the counterfeiter uses his own sign. In this instance, the fake carries something else that means more than the user's actual signature. It has a completely different shape overall. It's just a fake, and the fake knows only the user's name, not the signature. In this case, especially if it is fake, it indicates that it resembles a real signature. An individual who signs with their entire name or a portion of it. In the subject Counterfeiters, counterfeiters have access to the user's name. Sign and frequently practice spoofing a user's signature. This leads to a more similar fake. It is difficult to recognize because it is an actual signature.

2. Related Work and Motivation

In [1, 2], the authors proposed a new convolutional neural network model called Large-Scale Signature Network (LS2Net), which is aimed to address the problem of small number of signature sets to train the model from large dataset. Authors introduce Class Center based Classification (C3) to classify embedded features. C3 uses class centers which are achieved by averaging in-class properties. Under these class centers, 1-nearest neighbor classifier is derived as classification task. Authors also addressed Large-Scale recognition problem, the influence of Leaky ReLU on the performance of network is examined. Along with the addition of the C3 (Class Center for Classification) algorithm, the default network is defined as C3+BN+LS2Net called as LS2Net_v2. In [3] author has presented fusion of two methods one is Curvelet Transform (CT) and another is One-Class Principal Component Analysis (OC PCA) for Open Handwritten Signature Identification System. In [4,5,6] author has presented back propagation method of Neural Networks. If the output obtained at output layer having higher error rate then it can be propagate back to the previous layers to minimize the error by adjusting the weights of the nodes of the hidden layers, where the data processes again and gives the result at output layer. This process repeats until the desired output obtained with minimum error rate. In [7]-[9], authors has presented a Back Propagation Artificial Neural Network Matching Technique for offline signature verification. The suggested model consists pre-processing phase, codebook generation phase and matching phase. In [10], authors propose a method that uses the information from DTW cost matrix and warping paths alignments. The decision is made by the conjunction of warping path score and DTW score. In signature verification, solid signatures may be damaged up into 3 one-of-a-kind classes. In [11, 12], authors used Extreme point and stroke point for recognition. In addition, some works make a fusion of DTW with other methods. In [13], author has presented fuse the Fast Fourier Transform with DTW and the fusion system lowers the error rate by up to about 25%. In [14], authors explained how to extract a set of features for comparing DTWs based on dissimilarities between test signatures and template databases. In addition, the closest submission and majority vote will be proposed for classification. In [15] - [17], author has presented model-based approach is a generation classifier like the Hidden Markov Model (HMM). In [18, 19, 20] author has presented a neural network (NN) based signature recognition. In [21, 22] author has presented support vector machine (SVM) based offline signature recognition system. In [23] author explained the use one of the discriminating classifiers. There are also some hybrid methods that combine the various methods described above. In [24, 25], author has presented a multi-level cascade framework and multi-level decision level score fusion or a multi-expert system for signature verification has been reported in the literature. In [26, 27], author has explained several RNN-based validation methods have recently been proposed. In [28], authors propose a new descriptor called the Length Normalized Path Signature (LNPS) for feature representation, which is then fed to the GRU (Gated Recurrent Unit) network. We trained the network with the BP algorithm using triplet loss and center loss. In [29], author has explained how to extracts 23 hand-crafted time function features and uses bidirectional LSTM (long short-term memory) and a Siamese architecture GRU network to learn dissimilarity metrics from signature pairs. In [30], author has presented the distance-based and model-based approaches are the two main methods. In [31], author has explained design context and functionality and a two-step strategy for accurate online signature verification. In particular, in the first stage, shape context features are extracted from the input and the classification is based on distance metrics. In [32], author has presented the optimum feature subspace is selected according to the contribution rate. In addition, to solve the problem of large-scale DTW computation, we proposed a simple and effective modified dynamic time warping (DTW) with signature curve constraints. In [33] author has presented the DCT technique to get a compact representation of your online signature using a fixed number of coefficients. This simplifies the fitting procedure and provides an effective alternative for working with time series of varying lengths.

There are both writer-independent and writer-dependent signature verification methods in the literature. However, in the actual signature verification settings, the user Registration is very common. For this the writer-dependent method is not applicable. In Writer-independent methods, the themes for training and testing are different, so personal characteristics are not possible. It will be used. Writer-independent methods try to learn efficient representation of signatures in order to distinguish them from each other. As a person, creating a universally discriminatory expression of a signature is a challenge, not a specialty. I found an extraction method to solve this problem.

To improve the accuracy and efficiency of matching, use the edge histogram function and SVM to compare the test signature with the registered reference signature based on the extracted features. A classifier based on the symbolic representation of interval values is proposed to determine if the test signature is genuine.

The contributions of this paper are as follows:

- A fast and accurate edge histogram-based SVM method is proposed based on the fact of the imbalanced probability of occurrence of clever and random signature forgery.
- Edge histogram feature Extractor was developed to describe the global shape features of signatures for fast classification of random counterfeiting, along with basic pre-processing that applies to all records.
- SVM applied to fulfil comparison task and interval valued based representation classifier is proposed for

final decision making to achieve state of the art verification performance

- The rest of the work consists of: Section 2 reviews related work. The presented method is described in Section 3. Experiment setup and the corresponding result is Section 4. Finally, complete the work in Section 5.

3. Proposed Method

We are going to use novel approach for signature verification using Support Vector Machine classifier. Figure 1 shows the flowchart of proposed offline signature verification system. This system will use static as well as dynamic features for verification. The static functions include momentary functions and 4 direction distribution, while the dynamic functions include gray distribution and stroke width distribution.

Finally, the signature is categorized by support vector machines.

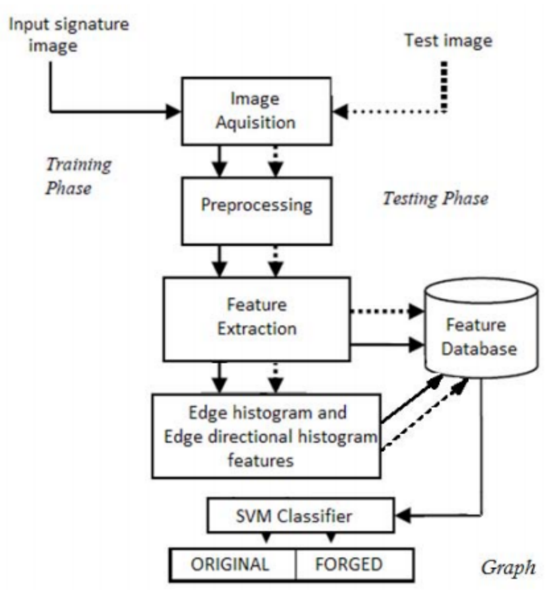

Figure 1: Proposed Offline Signature Verification Flowchart

3.1. Signature Enrolment

In the first phase, to find the parameters which characterize the variance of the signatures which are used as a reference, we use a set of signatures for reference. The extracted parameters along with the set of reference signatures are stored in the system database with unique user identification.

3.2. Preprocessing

Preprocessing stage can be divided further in five parts:

3.2.1. Noise Reduction

It's the process of removing noise from the image. It can be done by using median filters. The widely used noise type is salt and pepper noise. The noise present in the image is certainly degrades the image and it is difficult to select the exact features. To obtain usable information, noise must be removed.

3.2.2. Image Binarization

The acquired image sample may be in different colour model like RGB, gray scale or binary. The advantage of converting to binary scale is, processing will become easy because the intensity of the image will be in 0 and 1 range. There are several algorithms are available to convert, we employed Otsu's method.

3.2.3. Data Area Cropping

Image cropping is the processes where the image data area is extracted from the background area. Usually offline signature samples are acquired using a paper sheet; signatures are not spread across whole paper but on some portion of the paper. The data sample is the region of interest, so extracting only data area from the background and processing it, will helps in getting better accuracy.

3.2.4. Width Normalization

As we know signature samples are collected from different contributors, so obviously there will be more variations in the sample signatures, during pre-processing stage its necessary to normalize the data samples not only scaling but also its width. Width is one of the local features and varies from sample to sample. Normalized width will helps to get better accuracy.

3.2.5. Image Thinning

It's the process of keeping one pixel width information and removing redundant pixels. The collected samples are written on a paper, which having different pen width. Thinning operation makes uniform pixel width and also reducing pixel width will minimize the processing time.

3.3. Feature Extraction and Training the model

The study adopted HOG as a feature Extraction technology for recognition and authentication Signature image. Theoretically, the HOG descriptor method is important Occurrence of localized gradient orientation an image or part of a region of interest (ROI). Divide the image into smaller contiguous zones Calculate the histogram of (cell) and each area Gradation direction or edge direction Use pixels in cells, then gradients Receive orientation. Then discretise each Put the cells in a square bin, then the pixels in each cell gives a weighted gradient to the corresponding gradient.

3.4. Signature Verification

Let`s have an perception in SVM. Signatures are usually represented with the aid of using sparse vectors beneath the vector area model. When schooling classifiers on huge collections of signature, each the time and reminiscence necessities related with those vectors can be prohibitive. This requires using a characteristic choice approach now no longer most effective to lessen the quantity of capabilities however additionally to boom the sparsity of vectors. We advise a characteristic choice approach primarily based totally on linear Support Vector Machines (SVMs). Linear SVM is used on a subset of schooling facts to teach a linear classifier that is characterised with the aid of using the ordinary to the hyper aircraft dividing fantastic and bad instances.

Components of the everyday with better absolute values have a bigger effect on statistics classification. Instead of predefining the quantity of maximum scoring capabilities to be protected in a classifier we practice characteristic choice that targets at a predefined common sparsity stage throughout files and classifiers for a given schooling set. After the characteristic set is determined, the version is educated on the entire schooling statistics set represented in the decided on characteristic set. The check signature is then, primarily based totally on its price for the parameters from the characteristic set, is mapped and categorized as “GENUINE” or “FORGED”.

4. Experimentation

The following figure is the snapshot of Graphical User Interface for Offline Signature Verification developed using GUID tool available in MATLAB. Experiments are conducted on benchmark datasets namely CEDAR (Center for Document Analysis and Recognition) and GPDS Synthetic Signature database. The know-how repository includes the TSE capabilities extracted from each signature pattern of the records set such as each proper and professional forge signature samples. With every dataset, the signature samples are categorized into two groups: the education pattern set and the trying out pattern set with various wide variety of samples. We have achieved 4 units of experiments. With Set-1, the first 10 proper and primary ten professional fakes are selected as education samples and compared with the ultimate samples of the respective datasets. With Set-2, the first 15 samples of proper and primary 15 samples of professional fakes are considered and compared with the ultimate samples of the dataset. In Set3, we randomly selected 10 real samples and 10 randomly selected fake samples for training and tested them on the remaining samples in the dataset. Also, in Set4, there are 15 samples randomly selected from each dataset for training, the remaining samples are the sample in question. In order to overcome the influence of randomness, the experiments of Set3 and Set4 are repeated 5 times and the average results are tabulated. Achieved 97 ° and 98 ° accuracy with the CEDAR dataset.

The signature verification efficiency is evaluated by two parameters: (i) false acceptance rate (F A R) and (ii) false rejection rate (F R R). Recognition rate is one more parameter to consider when assessing classifier performance.

Type I error or False Rejection Rate (F R R):

$$\text{FRR} = \frac{\text{No.of genuine signatures identified as forged}}{\text{No.of genuine signature samples}} \times 100\% \qquad (1)$$

Type II error or False Acceptance Rate (F A R):

$$\text{FAR} = \frac{\text{No.of forged signatures identified as genuine}}{\text{No.of forged signature samples}} \times 100\% \qquad (2)$$

Recognition rate: The classifier accuracy is identified by this parameter, which is given by:

$$\text{Recognition rate} = \frac{\text{No.of correctly indentified signature samples}}{\text{No.of signature samples}} \times 100\% \qquad (3)$$

Equal Error Rate (EER): Which is the error when false acceptance rate is equal to false rejection rate.

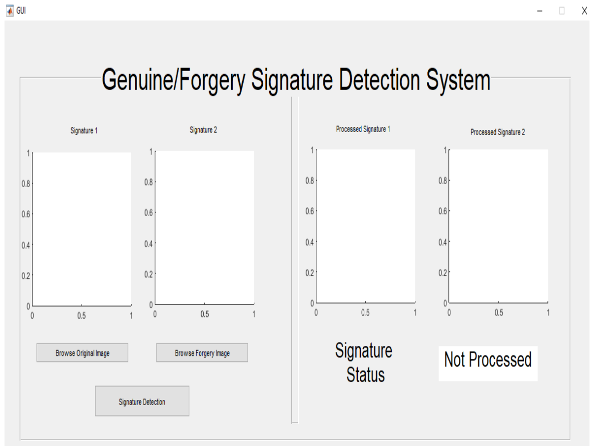

Figure 2: GUI for SVM based Signature Recognition

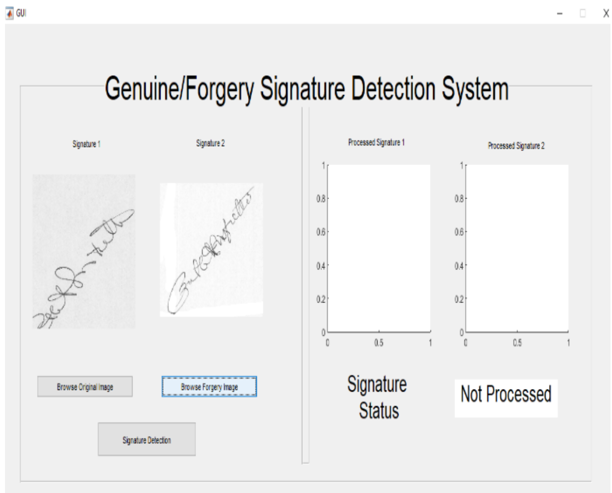

Figure 3: Reading the input forgery/genuine signature

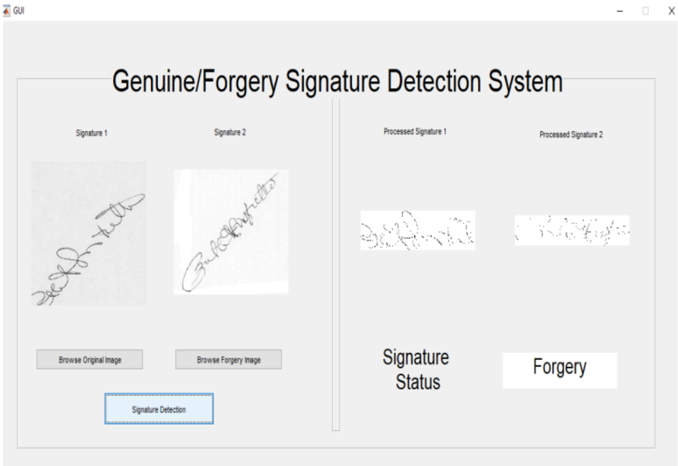

Figure 4: Feature extraction and Forgery Signature Detection Result

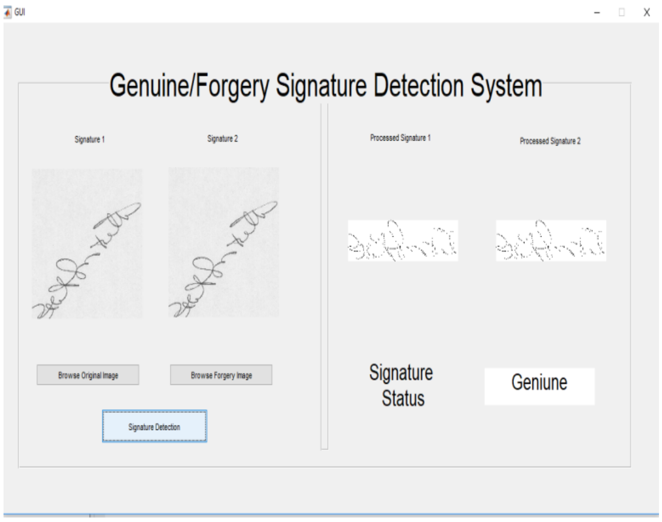

Figure 5: Feature extraction and Genuine Signature Detection Result

For testing the signature detection system. We have considering 50 signatures in that 30 signatures are genuine and 20 signatures are forgery.

Table 1: Results of proposed SVM method

Users	No. of signature	FRR	FAR	Accuracy
User1	50	5/50=10%	3/50=6%	45/50=90%
User 2	50	3/50=6%	4/50=8%	47/50=94%
User 3	50	4/50=8%	2/50=4%	46/50=92%

Table 2: Comparisons with the state-of-the-art works on database SVC2004.

Works	Method	Error Rate (%)
[28]	LNPS+GRU	2.47
[29]	GMM+DTW with SCC	2.63
[30]	DTW+ Warping path alignment	2.53
[31]	Two-stage verification	2.39
[32]	DTW with SCC	2.89
[33]	Spare representation	2.98
Proposed Work	Edge Histogram + SVM	2.37

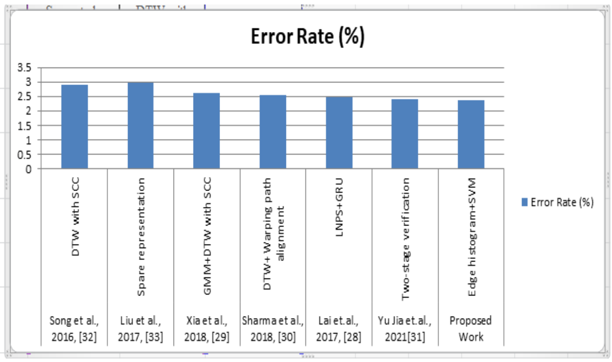

Figure 6: Graphical view of comparative analysis with existing works

Table 2 shows a comparison of the SVC2004 database with the prior art. Due to the different databases, training, tests, etc., it is not easy to make a fair comparison of online signature verification methods. Select some recently published works using the same database (SVC2004). The existing method has a slightly higher EER than our method.

5. Conclusion

Offline signature verification based on edge histograms using a support vector machine system has been proposed. Using techniques such as RGB2Gray conversion, filtering, adjustment, thresholding, and clever edge detection, the signature can be pre-processed. It has been shown here that the proposed method is more efficient and thoroughly tested to detect segmented signatures of the original image with different image processing methods. The proposed work limitation is that the classifier is retrained during the training phase. In Future work, the support vector machine (SVM) is being examined for the discovery task.

Conflict of Interest

The authors declare no conflict of interest.

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