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Writer Independent Offline Signature Recognition based upon HOGs Features

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Abstract: Signature recognition is a behavioral biometric and plays an important role in financial, commercial and legal transactions in authentication of human identity. In this paper, we present a method for offline signature recognition that uses features extracted computing Histogram of Oriented Gradients (HOG) with grid matrix placed over the signature image. Recognition process is carried out using KNN classifier with Euclidean distance as a distance computation measure. The proposed system exhibits good recognition accuracy.
Keywords: HOG, offline signature, KNN, biometric, writer independent.

1. INTRODUCTION

Signature is a well-accepted biometric socially and legally. Handwritten signature is widely used as a means of personal Authentication [1, 2, 3, 4]. Authentication can be performed either Offline or Online based on the application [5]. Touch interface devices use dynamic information of a signature captured at the time signature is made. Offline systems work on the scanned image of a signatures captured offline. The features used include Baseline Slant Angle, Aspect Ratio, Normalized Area, Center of Gravity, number of edge points, number of cross points, and the slope at the joining/corner points in the signature.

The signature recognition is the process of verifying the writer's identity by checking the signature against samples kept in a database. A signature verification system consists of the following steps:

i. Data capture. This initial step consists of locating and extracting the signature from the document. However, for research purpose, specific to the application, set of signature images are captured. This includes genuine signatures, skilled forgery, and forgery signatures. The captured images are digitized. However, there are several database of static signatures developed for academic and scientific research. (SIGMA, GDPS960, MYCT, SigComp) that can be utilized for experimentation.
ii. Pre-processing. This step includes removal of noise and normalization of the digitized images.
iii. Feature extraction. Relevant features are extracted from the digital representation of the signature.
iv. Experimentation The proposed model is subjected to experimentation. The process matches extracted features with templates stored in a database. Usually, the output is decision of signature identification/authentication. The decision step is typically made by using thresholding value which may vary from application to application.
v. Performance evaluation. The outcome of the proposed method is evaluated in terms of parameters like false rejection rate (FRR) of genuine signatures, the false acceptance rate (FAR) of forgery signatures, and Equal Error Rate (EER), a point where FAR equals FRR.

The handwritten signature morphology changes from one person to another. In fact the signatures of the same person may show variations depending on their age, state (physical or moral), and nature of the document (official or non-official). Due to higher errors rates, intra-class variability than other biometric traits, signature authentication is a complex and challenging task.

Several automatic systems for checking the handwritten signature have been proposed; such a system determines the authenticity of a given signature by referring to a beforehand conceived database.

Several feature extraction techniques have been proposed in the literature for signature verification [6]. In [7], a review of the most recent advances in static/offline signature recognition using Computer Vision has been presented. Some new trends and research opportunities such as the generation of synthetic signatures, time drifting, forger and disguise identification and multilingual scenarios have been also discussed.

A machine learning approach to offline signature verification has been presented in [8]. Three steps are proposed towards writer independent approach: 1) Determine the prior parameter distributions for means of both ―genuine vs. genuine and ―forgery vs. known classes using a distance metric. 2) Enrol n genuine and m forgery signatures for a particular writer and calculate both the posterior class probabilities for both classes. 3) When evaluating a questioned signature, determine the probabilities for each class and choose the class with bigger probability. Experiments carried out on images of NISDCC dataset. A system that uses minimal features using sub pattern analysis which leads to less response time in a real time scenario has been presented in [9]. Using training samples, the minimum variance quad-tree components [MVQC] of a signature for a person are listed to be applied on a testing sample. The non-MVQCs and core components were analyzed, initially, by conducting experiment on wavelet decomposed information of the signature.. To characterize the local details Gaussian-Hermite moment was applied. Later Hu moments were applied on the selected subsections. The summation values of the subsections are provided as feature to radial basis function [RBF] and feed forward neural network classifiers. An approach to extract robust Edge Orientation Distance Histogram (EODH) descriptor which effectively reflects signature structure variations is proposed in [10]. In addition, directional gradient density features are employed for skilled forgery verification attempt. To exploit the full capacity of two sets of features, a multilevel weighted fuzzy classifier has been designed that fuse match scores by way of selection priority. Experiments are conducted on a subcorpus of open MCYT signature database which is widely used for performance evaluation. The above methods and studies have suggested the use of single feature as well as multiple features for the biometric recognition systems [11,12,13]. The aim of this paper is to highlight some of the most relevant issues at the frontier of research in the field of automatic signature verification. Throughout the paper, some of the most promising directions of research will be pointed out and discussed. This paper has tried to point out some of the most remarkable directions of recent research in the field of automatic signature verification and suggested investigation of research territories [14].

In the following sections, we present the details of the proposed methodology: database creation, pre-processing, feature extraction, and signature matching process. Section 2 is devoted to the detailing the process of signature collection. Section 3 presents pre-processing and feature extraction steps. Section 4 outlines the recognition process and section 5 describes experimental results and discussions. The conclusion and the perspectives are given in Section 6.

2 COLLECTION OF SIGNATURES

In general, signature recognition systems are learning based, which requires having a large database ideally representing the majority of the target population of the concerned application. The database samples must take into account all the possible variations in the real case of applications such as intrapersonal variations. Different researchers have set up their own databases to validate their signature verification / identification systems. Also, there are several databases of static signatures published for research purpose. However, they lack in representation of all type of signatures, specifically in the Indian context. The origin of some of the static signature database available is presented in table1.

Table 1: Static signature databases

Database	Origin
SIGMA Ahmad et al.[26]	Malaysian
MCYT Ortega-Garcia et al.[27],	Spanish
GPDS960 and 4NSigComp2010 Vargas, J.F.[28], Blumenstein, M. et al.[29]	Spanish
SigCom11 Liwicki, M. et al.[30]	Chinese Dutch
BiosecurID-SONOF DB J. Fierrez, et al. [31]	Spanish
SID Signature Database, Imen Abroug et al.[32]	Tunisian

As part of our research work, we have built a database of offline handwritten signatures. We have proceeded by a collection of signature samples followed by a phase of digitizing and storing data. The signatures are collected from persons on a plain A4 paper, in different sessions, to avoid possible geometric variations. Sixteen samples of signature from each person have been collected. Some statistics of the signatures acquired from various subjects is presented in table2. Sample guanine signatures are shown in figure1.

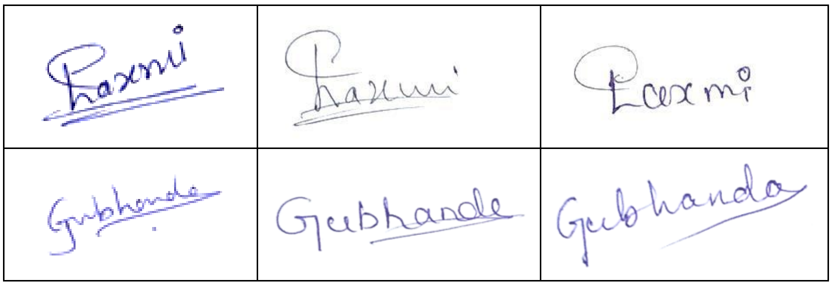
Table 2: Statistics of signatures collected

Subject distribution	Female: 33% Male: 67%
Subject age distribution	18-50
subject category	employee, student, business person

Five different writers were chosen to create the simple and skilled forgery signatures by providing them with a plain A4 paper with one genuine signature on the top-left portion of the page. The person was asked to produce the simple forgery without practicing imitation whereas to produce skilled forgery different static images of the signatures were provided to the writer. The meaning of simple and skilled forgery with respect to acquiring signatures of other persons is defined below.

Unskilled Forgery: The signer creates a signature after observing the signature without any prior experience.

Skilled Forgery: The signer, a professional, replicates a signature after observing the signature carefully and practicing the original signature prior to creating the signature.



(a) (b) (c)

Figure 1. Signatures (a) genuine (b) skilled forgery (c) unskilled forgery (d) random forgery

The database is subdivided into learning phase signatures consisting of 100 signatures (10 of each person) and rest of the signatures (60) as test one. The distribution of samples is given in table 2.

Table2: Statistics of samples for training and testing

Data set	Number of samples	Types of Signatures
Learning	100	Genuine
Test	60	Genuine
	20	Simple forgeries
	20	Skilled-imitated forgeries

The acquired signatures were subject to further process; scanning and digitization. The different pages of the collected signatures are digitized at a 300dpi resolution with 256 gray levels. The individual signature images were extracted from the digitized pages using horizontal and vertical projections and were saved in respective folders; subject_name, skilled_forgery and simple_forgery.

3 PRE-PROCESSING AND FEATURE EXTRACTION

3.1 Pre-processing

In general, pre-processing includes operations like noise removal, contrast enhancement, binarization, skew correction, size normalization and thinning or skelatanization [15]. The acquired signature may contain extra dots which arise as a result of dust in scanning device as well as on paper. These extra dots are removed by using median filter on the captured signature image. The gray scale signature image is then contrast enhanced wherein the contrast of the image is increased by mapping the values of the input intensity image to new values, 1% of the data is saturated at low and high intensities of the input data. The resulting image is then binarized using Otsu's thresholding method [16]. Skew in the image is eliminated using bilinear interpolation technique (Fig 2). Isolated pixels are eliminated and the image is then skeletonized using morphological operations.

Signature dimensions may vary due to the irregularities in the image scanning and capturing process. Also, height and width of the signatures vary not only from one person to another, but sometimes, the same person may draw different size signatures. Hence, we eliminate the size differences and obtain a standard signature size for all the scanned signatures. We used a normalized size of 40x60 pixels for all signatures that will be processed further. During the normalization process, the aspect ratio between width and height of a signature is kept intact. Sample pre-processed images are shown in figure 2.

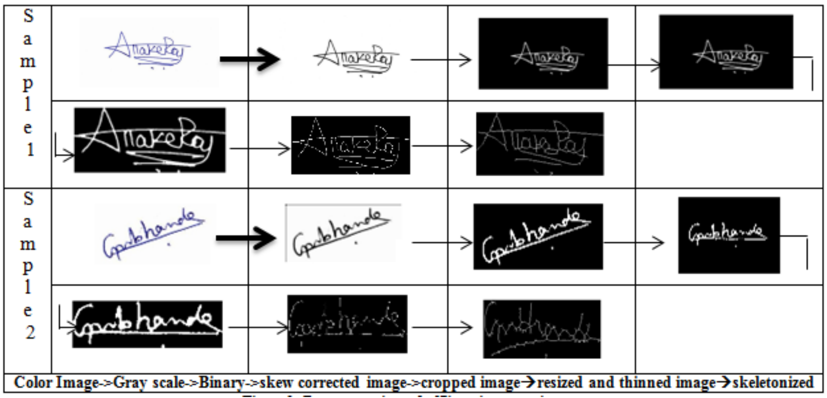


Figure2. Pre-processing of offline signature images

3.2 Feature Extraction

The proposed method consists of two tasks. First one is to identify the signature image as belonging to particular subject and then secondly, to authenticate/reject the signature as belonging/not belonging to the subject identified in the first stage. This calls for efficient feature extraction from the pre-processed gray scale image.

We have adopted Histogram of Oriented Gradient (HOG) features extraction technique to recognize and authenticate the signature image.

HOG was used by Dalal and Triggs[17] for human detection and has been later used as a feature descriptor to detect objects in many applications of computer vision and image processing [18-24]. Primarily, the HOG descriptor technique counts occurrences of gradient orientation in localized portions of an image - detection window, or region of interest (ROI). The basic implementation of the HOG descriptor is as follows:

1. Divide the image into small connected regions (cells), and for each region compute a histogram of gradient directions or edge orientations for the pixels within the cell.
2. Using the gradient orientation obtained, discretize each cell into angular bins.
3. Each cell's pixel contributes weighted gradient to its corresponding angular bin.
4. Adjacent cells are grouped into blocks in the spatial region. This forms the basis for grouping and normalization of histograms.
5. Normalized group of histograms represents the block histogram and the set of these block histograms represents the descriptor.

We have computed HOG features for the signature image using 9 rectangular cells and 9 bin histogram per cell. The nine histograms with nine bins are then concatenated resulting in 81-dimensional feature vector. The HOG features provide us with the edge information of the signature images. The features for all training images are computed and stored in a knowledgebase. The HOG implementation has been done in accordance with the reference [23].

4 RECOGNITION AND AUTHENTICATION

K-NN classifier is used for recognition purpose [25]. The K-NN classifier operates on the premises that classification of unknown instances can be done by relating the unknown to the known according to some distance/similarity function. The assumption is that two instances farther in the instance space defined by an distance function are less likely than two closely situated instances to belong to the same class. The recognition process is shown in Figure 3.

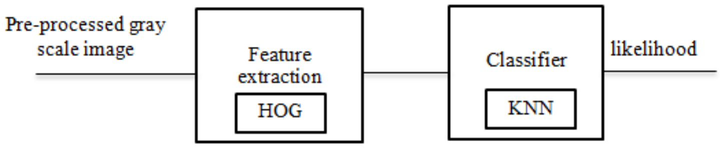


Figure 3. Recognition process

The recognized signature is then processed for its confirmation and rejection. The proposed system for signature verification, classifier calculates distance of the input signature from all sample signatures of claimed class in the feature space. If minimum distance is less than a threshold, identified in the training phase, the input signature is considered to be guanine one; otherwise it will be known as a forgery signature and will be rejected. However, the authentication process is our future work.

5 EXPERIMENTAL RESULTS AND DISCUSSION

The objective is to assess and compare the performance of the approach proposed in this paper for signature recognition. Out of 16 signatures, 10 signatures were selected for training purpose and rest of the other for testing, arbitrarily. Hence, the training set constituted of a total of 100 signatures and that for testing, 60 signatures were available. For all the training samples, HOG features of 81 dimensions were computed and were labelled as belonging to specific subjects, i.e. 10 labels for 100 one dimensional vectors, each vector containing 81 dimension HOG features. For each of the test samples, HOGs of 81 dimensions were computed, without assigning labels. The resulting training vectors and test vectors comprising HOGs as features representing the signature images were input to K-NN classifier. For each reference signature Sr, the corresponding feature vector xr extracted from the signature image is stored in the system's knowledge base during the training phase. In recognition mode, the image of a questioned signature Sq is presented to the system and its feature vector xq, along with the reference set {xr } of signatures of the users enrolled to the knowledge base, are presented to KNN module for recognition. The block diagram of the method followed is presented in Figure 5. Note that in these tests only genuine samples were used.

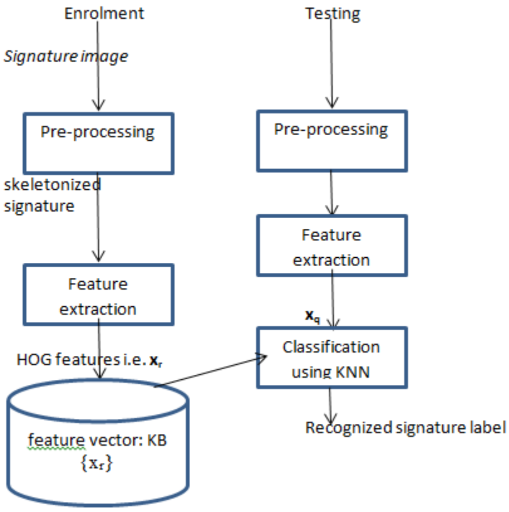
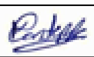
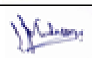


Figure 4. Block diagram of the proposed method

The results of the classifier are presented in Table 1. The results are better for K=1 compared to other values of K.

Table 2: Recognition results using K-NN classifier

Subjects	No. of train/test	Recognition			
		Image size 128x256 pixels		Image size 40 x 60 pixels	
		K=1	K=3	K=1	K=3
	10/6	6	6	5	5
	10/6	6	6	6	6
	10/6	6	6	6	6
	10/6	6	6	6	5
	10/6	5	5	6	5
	10/6	4	5	6	6
	10/6	6	5	5	5
	10/6	6	6	6	5

	10/6	6	6	6	6
Rekha	10/6	2	2	5	4

The confusion matrix is presented in table 3.

Table 3: Confusion matrix (size - 40x60 pixels and 128x256 pixels, respectively)

K=1

Subjects	1	2	3	4	5	6	7	8	9	10
1	5	*	*	*	1	*	*	*	*	*
2	*	6	*	*	*	*	*	*	*	*
3	*	*	6	*	*	*	*	*	*	*
4	*	*	*	6	*	*	*	*	*	*
5	*	*	*	*	6	*	*	*	*	*
6	*	*	*	*	*	6	*	*	*	*
7	*	1	*	*	*	*	5	*	*	*
8	*	*	*	*	*	*	*	6	*	*
9	*	*	*	*	*	*	*	*	6	*
10	*	*	*	*	*	1	*	*	*	5

K=3

Subjects	1	2	3	4	5	6	7	8	9	10
1	5	*	*	*	1	*	*	*	*	*
2	*	6	*	*	*	*	*	*	*	*
3	*	*	6	*	*	*	*	*	*	*
4	*	*	*	5	*	*	1	*	*	*
5	*	*	*	*	5	*	1	*	*	*
6	*	*	*	*	*	6	*	*	*	*
7	*	1	*	*	*	*	5	*	*	*
8	*	*	*	*	*	1	*	5	*	*
9	*	*	*	*	*	*	*	*	6	*
10	*	*	2	*	*	*	*	*	*	4

K=1

Subjects	1	2	3	4	5	6	7	8	9	10
1	6	*	*	*	*	*	*	*	*	*
2	*	6	*	*	*	*	*	*	*	*
3	*	*	6	*	*	*	*	*	*	*
4	*	*	*	6	*	*	*	*	*	*
5	1	*	*	*	5	*	*	*	*	*
6	*	*	1	*	*	4	*	*	*	1
7	*	*	*	*	*	*	6	*	*	*
8	*	*	*	*	*	*	*	6	*	*
9	*	*	*	*	*	*	*	*	6	*
10	*	*	2	*	*	2	*	*	*	2

K=3

Subjects	1	2	3	4	5	6	7	8	9	10
1	6	*	*	*	*	*	*	*	*	*
2	*	6	*	*	*	*	*	*	*	*
3	*	*	6	*	*	*	*	*	*	*
4	*	*	*	6	*	*	*	*	*	*
5	1	*	*	*	5	*	*	*	*	*
6	*	*	3	*	*	3	*	*	*	*
7	*	*	*	1	*	*	5	*	*	*
8	*	*	*	*	*	*	*	6	*	*
9	*	*	*	*	*	*	*	*	6	*
10	*	*	2	*	*	2	*	*	*	2

6 CONCLUSION

In this paper, an efficient approach for offline signature recognition has been presented. HOG is used for feature extraction and K-NN is used for recognition purpose. The results obtained show the efficacy of the proposed system. The next stage of recognition is the authentication process. However, the authentication can have a significant class overlap, especially between genuine signatures and simulated forgeries, and hence require a proper choice of threshold for accepting the recognized signature as authentic. We are working on the same by fine tuning the features and perform the validations in terms of parameters, namely, false acceptance rate and false rejection rate.

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