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Signature Verification Using LDP & LBP with SVM Classifiers

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***Abstract*— *Signature verification is widely used for individual verification. Its many applications include credit card validation, banking security systems etc., but, it has problem of getting destitute for forgery as a consequence an automatic signature recognition and verification system is required. Verification can be accomplished either Online or Offline based application. Offline systems work on the scanned image of a signature. Online systems consider dynamic information like pressure, speed etc. of a signature at the time when the signature is made. The current verification schemes could overlook the signature eventually though it may be genuine. Though diverse techniques are accessible for verification of cheques. In this paper we represent an offline signature recognition and verification technique using different features. First we are going to capture the data and stored in database and then this data are trained and used for signature recognition and verification process. Support Vector Machine (SVM) & chebyshev algorithm are used for verification of signature. This algorithm is used as to verify the signature using features like Local Binary Pattern (LBP) and Local direction Pattern (LDP). LDP is usefully when different pen are used for signature and hence we get more accuracy with LDP.*

***Keywords*— *Offline signature; LDP; LBP; Chebyshev; SVM.*

I. Introduction

Biometrics is a method for identifying an individual. Physical (fingerprint, retina etc) and behavioral (handwritten signature, voice etc) qualities can be recognize by using biometric. There are different biometric method like fingerprint voice and face image but we are going to use Signature as verification of an individual. Handwritten signature is generally used for the identification of the particular person for both authentication and authorization in legal transactions and help in personal identification. It gives confirmation and security to different resources of the underwriter [11]. In the era of advanced technology security is the notable issue to avoid fakes and forgeries. Identification and verification are two different tasks in recognition. Identification determines which user presents a given parameter among a set of known users.

The verification of signature is classified into two categories:

1. On-line signature verification
2. Off-line signature verification.

In Online verification, a signer signs on electronic devices such as Tablet PC, touch screen with an electronic pen, and features like pressure exerted, stroke length, writing speed are noted for the verification in online signature verification.

In offline signature verification, the signature is done on the paper and it is scanned with the help of camera to convert it into digital form and then signature verification is done by comparing the signed signature with the template signature which is already stored in the database at the time of training data [2].

Example of training set of signature is as shown in Fig. 1

Fig. 1. Test signature.

There are two types of variation in the signature, intra variation and inter variation [7]. In intra variation a signature of the same person changes due to abnormal conditions like age, geographic location, illness, etc. whereas the variation in the original and forged signature is termed as inter variation. In case of forgery, a person tries to copy the signature of another person. The forgery signature can be classified into three following way:

- *Random forgery*: In Random forgery the signer knows only the name of the person whose signature is to be signed and uses his own expressive style to sign the document and can be detected by naked eye.
- *Simple forgery*: In this case the signer has seen the signature pattern but does not have any prior experience of signing the signature of the victim.
- *Skilled forgery*: Here the signer knows the signature as well as the pattern very well and has experience in forgery. The signer signs exactly the same as the victim and it is very difficult to compare between original and forged signature [1].

In this paper an off-line signature verification system using support vector machine (SVM) & Chebyshev is proposed. The SVM is a learning method introduced by Vapnik, it tries to find an optimal hyperplane for separating two classes Therefore, the misclassification error of data both in the

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training set and test set is minimized. The best hyperplane for an SVM means the one with the largest margin between the two classes. Margin means the maximal width of the slab parallel to the hyperplane that has no interior data points. The support vectors are the data points that are closest to the separating hyperplane; these points are on the boundary of the slab.

II. Overview of Prior Work

A. *Artificial Neural Network Approach*

Artificial Neural Network Approach describes the wide usability of neural network approach since it is very simple and powerful. There are 2 steps usually. In the first step features representing the signature are extracted. And a classification is performed on the samples. After the classification it is easily possible to determine if a signature is matching with any of the classes.

It performs a study on two approaches. It is basically determination of a class then the match the signature. The two approaches are: 1) The Resilient Back propagation (RBP) neural network. 2) Radial Basic Function (RBF). Around two thousand test signatures are available in the database which is mixture of genuine and forgeries with a ratio of 4:6. [1]

B. *Hidden Markov Models Approach*

Hidden Markov Models Approach describes about an online signature verification system that is based on Hidden Markov Modeling (HMM) technique. Set of localized direction features are extracted from a scanned signature image and this technique is applied on them. There is an elaboration on understanding HMM as stochastic models and their ability to determine distinctness and similarity of the patterns. Also speaks about how HMM states can be varied to analyze the state transition topology. Around samples of 100 users are used containing genuine and skilled random forged signature samples to do the testing [4].

C. *Template Matching Techniques*

Template matching techniques developed a system that uses a closed contour tracing algorithm to represent the edges of each signature with several closed contours. The curvature data of the traced closed contours are decomposed into multiresolutional signals using wavelet transforms. The zero crossings corresponding to the curvature data are extracted as features for matching. A statistical measurement is devised to decide systematically which closed contours and their associated frequency data are most stable and discriminating. Based on these data, the optimal threshold value which controls the accuracy of the feature extraction process is calculated. Matching is done through dynamic time warping. For each experiment, twenty-five writers are used with ten training signatures, ten genuine test signatures, ten skilled forgeries, and ten casual forgeries per writer [10].

D. *Statistical Approach*

Statistical approach performs a study on statistical approach. Here patterns are considered as the features which is nothing; but a point in a Dimensional space. In a d-dimensional feature space the pattern vectors are kept in a close and disjoint regions hence categorizing the pattern vectors separately. A set of properly detached patters is considered as useful. A Hidden Markov Model (HMM) and Bayesian models used for pattern recognition are very popular examples of statistical approach. A Statistical approach is better than template matching approach in detecting even the adept forgeries [3], [4].

III. Proposed Approach

The camera-captured or scanned human signatures are processed using several image processing techniques. Fig. 2 shows the block diagram of proposed system

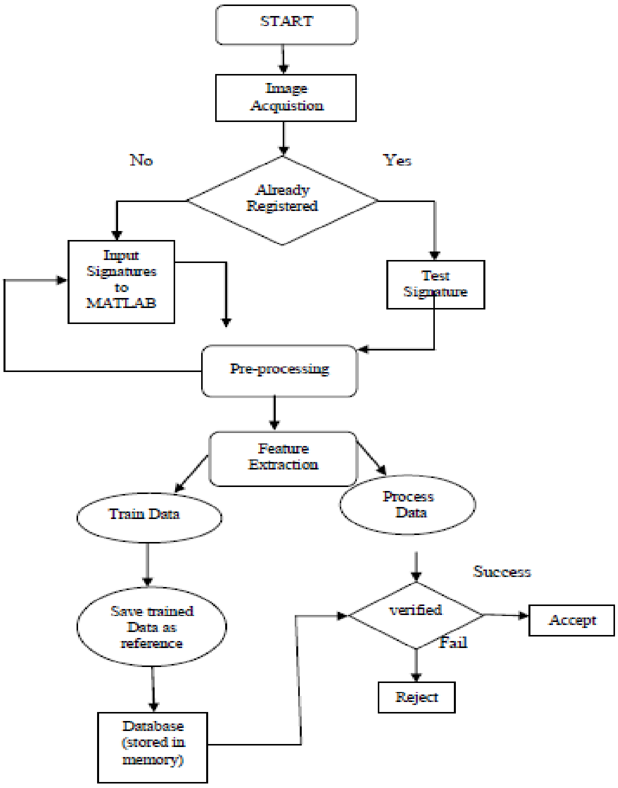

Fig. 2. Steps for signature recognition.

A. *Image Acquisition*

Signature acquisition is the process in which the signature is captured or scanned using a camera of high resolution. The input to the system is the scanned image of the signature [11]. A camera will be a high definition USB portable which is to be initialize in MATLAB.

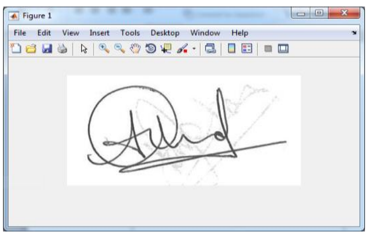
Fig. 3. Image acquired.

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B. Pre-processing

Preprocessing help us to improve the property of signature. The scanned signature image may carry noise and has to be removed to avoid errors and make the signatures ready for feature extraction in both training and testing phase. The prepossessing stage includes following steps.

Step 1: RGB to gray scale conversion

In this step RGB image is converted into gray scale intensity signature image to eliminate the hue and saturation information while retaining the luminance Fig. 4.

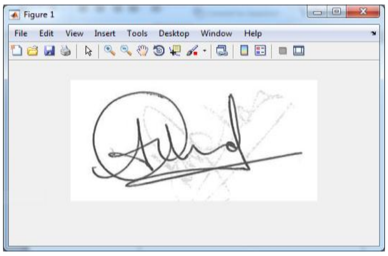

Fig. 4. RGB to Gray converted image.

Step 2: *Background elimination*

Data area cropping must be done for extracting features. In this we use image morphing instead of cropping so that noise reduction in great extent. P-tile thresholding was chosen to capture signature from the background. After the thresholding the pixels of the signature would be "1" and the other pixels which belong to the back-ground would be "0", as shown in fig. 5.

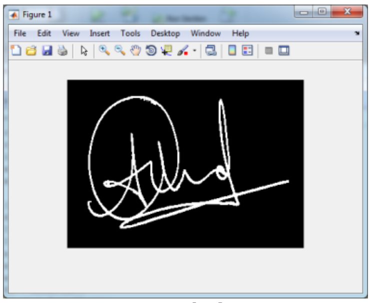

Fig. 5. Morphed image.

Step 4: Resize

Each signature should be of same size, this reduces the area of signature to be used for further processing.

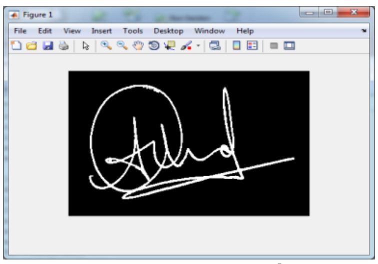

Fig. 6. Image acquired.

C. Feature Extraction

Feature Extraction is an important phase in recognition process. The objective of this phase is to extract the features of the test image that will be compared to the features of original image for verification purpose.

Some extracted features are:-

1) Local Binary Pattern (LBP) and Local Directional Pattern (LDP)

The Local Binary Pattern (LBP) operator is defined as gray level texture measure in a local neighbourhood. The most important property of the LBP operator is its invariance against monotonic gray level changes. Equally important is its computational simplicity. LBP operator describes the surroundings of a pixel. Each ILBP(x, y) code is worked out as follows: the eight neighbouring pixels are binarized using as threshold the center gray level value I(x, y), generating a binary 1 if the neighbour is greater than or equal to the center; otherwise it generates a binary 0. The eight binary number are represented by 8-bit number and saved in ILBP(x, y), the range which is $0 \leq \text{ILBP}(x, y) \leq 255$

$$\text{ILBP.}(x,y)=\sum_{n=0}^{7} s\left(I_N(n)-I(x,y)\right).2^n$$

Where, s(I) =1 if I >0
=0 if I <0

Eg. of LBP operator

Thresholding

235	228	202		1	1	1
112	136	88		0		0
66	89	69		0	0	0

x

1	1	1		128	16	4
0		0		64		2
0	0	0		32	8	1

Hence we get 128+16+4=148
In this case I (x,y) =136.
$I_N(n)$ ={69,88,202,89,228,66,112,235 },
$I_N(n)$ > I(x,y) =1 or else 0.
so we get the set as {0,0,1,0,1,0,0,1},
so ILBP(x,y)=4+16+128=148.

LBP could also be extended to rotation constant operator and generalized gray level operator. The major limitation of LBP is it gets easily susceptible to noise and pen. All the users must use the same pen since LBP is more proficient to gain the distribution of personal ink when all users use the same pen. But when the personal ink distribution involves changes of pen, in such a cases the efficient algorithm could be LDP.

2) Combination of LBP and LDP

LBP components of image are acquired and given as information to Local Directional Pattern and elements are extricated, utilizing these separated elements Hamming Distance is ascertained for match of signature. Blend of LBP and LDP exploits both force data and directional edge reaction [11].

IV. ALGORITHM

1) Support Vector Machine (SVM)

After the feature extraction stage, superiority of features extracted is quantified calculate the accuracy of the classifier. Classification is the final step of signature identification. For classification of signature classes, a layer of SVM classifier has used. An SVM is a classifier derived from statistical learning theory. The number of SVM classifiers in the classification layer is equal to number of signature classes. Vapnik introduced the beginning of SVM in late of 1970's. SVM, based on a solid mathematical foundation, which attempt resolve a universal problem of classification. The basic proposal of SVM is deceptively simple. Given a set of vectors in Rn, labeled +1 or -1 that is separable by a hyper plane, SVM finds the hyper plane with the maximal margin. In this mode, the kernel of SVM classifier is a one order polynomial classifier.

2) Chebyshev

In mathematics, Chebyshev distance (or Tchebychev distance), maximum metric, or L_∞ metric is a metric defined on a vector space where the distance between two vectors is the greatest of their differences along any coordinate dimension. It is named after Pafnuty Chebyshev.

The Chebyshev distance between two vectors or points *p* and *q*, with standard coordinates pi and qi, respectively is

$$D_{Minkowski}(P,Q)=\left(\sum_{i=1}^{m}\left|x_i-z_i\right|^p\right)^{1/p}$$

In the limiting case, when p tends to1, Minkowski distance becomes Chebyshev distance which is given by:

$$D_{Chebyshev}(P,Q)=\lim_{p\to\infty}\left(\sum_{i=1}^{n}\left|x_i-z_i\right|^p\right)^{1/p}=max_i\left|x_i-z_i\right|$$

V. RESULT

LBP (Local Binary Pattern) is efficient when there are a group of signatures to be tested which are signed using the same pen and has less presence of noise. If the signature to be tested is signed with different pens then LDP (Local Directional Pattern) is useful. So LDPs give more accurate result than LBPs when there is no pen dependence.

We proposed offline signature verification based on LBP & LDP using SVM and chebyshev as classifier where we compare the accuracy of both. The accuracy of SVM is higher than the chebyshev.

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