BLOCKWISE BINARY PATTERN: A ROBUST AND AN EFFICIENT APPROACH FOR OFFLINE SIGNATURE VERIFICATION

B. H Shekar[a], Bharathi Pilar[b,*], Sunil Kumar D S[a]

[a] Department of Computer Science, Mangalore University, Mangalore, Karnataka, India. bhshekar@gmail.com, dssunil6@gmail.com
[b] Department of Computer Science, University College Mangalore, Karnataka, India. bharathi.pilar@gmail.com

Commission II, WG II/5

ABSTRACT:

This paper presents a variant of local binary pattern called Blockwise Binary Pattern (BBP) for the offline signature verification. The proposed approach has three major phases : Preprocessing, Feature extraction and Classification. In the feature extraction phase, the signature is divided into 3 x 3 neighborhood blocks. A BBP value for central pixel of each block is computed by considering its 8 neighboring pixels and the 3 x 3 block is replaced by this central pixel. To compute BBP value for each block, a binary sequence is formed by considering 8 neighbors of the central pixel, by following the pixels in a anti-clockwise direction. Then the minimum decimal equivalent of this binary sequence is computed and this value is assigned to the central pixel. The central pixel is merged with the neighboring 8 pixels representing the 3 X 3 neighborhood block. This method is found to be invariant to rotation, scaling and shift of the signature. The features are stored in the form of normalized histogram. The SVM classifier is used for the signature verification. Experiments have been performed on standard signature datasets namely CEDAR and GPDS which are publicly available English signature datasets and on MUKOS, a regional language (Kannada) dataset and compared with the well-known approaches to exhibit the performance of the proposed approach.

1. INTRODUCTION

Signatures have been widely accepted by society as a convenient personal attributes to authenticate individuals. Unlike other authentication schemes using PIN or password, smartcard or fingerprints, signatures cannot be forgotten, stolen, or lost. Hence there is a growing demand for the faster and more accurate automatic signature verification system which is a real challenge. The handwritten signature verification can be performed automatically either on-line or off-line. On-line signature verification needs special instruments such as a tablet, stylus, or digitizer, where as off-line verification employs the static image of a signature. Off-line signatures are already popular as it does not require any special devices and can be performed in the absence of the signer. A forged signature (forgery) is the imitation of the genuine signature to the level of acceptance without the knowledge of the genuine signer. Based on the knowledge of the forger about the signature and the signer, forgery can be broadly classified into three types such as: *skilled, random and simple forgery*. In simple forgery, the forger knows the name of the signer but not the genuine signature pattern and hence produces his/her own pattern of strokes. Random forgeries occur when the forger neither knows the name of the signer nor the signature pattern, where as the skilled forger will have the access to the genuine signature sample pattern and also the name of the signer, hence resulting as the major threat for verification and authentication of a person through signature.

Apart from the forge threat, there are many other instances, such as the intra class deviation of the signature sample, i.e variation of the signature by the genuine signer due to age, illness, orientation of the document used to sign, pen width, deteriorated signatures, illegible signatures and so on which needs greater attention in signature verification (Pal et al., 2011).

*Corresponding author

Generally, the selection of dominant and important features for the representation of the sample is crucial in offline signature verification approaches. A feature extraction technique can be a global or local. A global technique is usually computed from the whole input signature, where as local feature extraction involves partitioning of the image into different partitions and hence features from each partition is accumulated to represent the whole signature. In this paper, we present a local approach namely Blockwise binary pattern, in which the signature is divided into 3 x 3 blocks. Each block is replaced by a single pixel with a minimal decimal value of binary sequence comprising the neighborhood pixel. A histogram is computed for these decimal values computed for each block forming the feature vector. For verification purpose, we have considered a well known SVM classifier.

The remaining part of the paper is organized as follows. In section 2, the review of the related works are brought down. In section 3, the proposed approach is presented in detail. In section 4, the experimental set-up along with the discussion of the results are brought out and conclusion is given in section 5.

2. LITERATURE REVIEW

To improve the efficiency of the signature verification systems, researchers have tried different methods with various approaches. Some of them have employed two or three expert systems that evaluate the signature in two/three different ways and verify whether it is genuine or forge. The Writer-independent (Kumar et al., 2012) approach is based on surroundedness property of a signature. The proposed method mainly concentrates on shape of a signature. It considers spatial distribution of a black pixel around candidate pixel. This approaches uses two popular classifiers Multi-layer Perceptron and Support Vector Machine. The Polar feature descriptor (Pushpalatha et al., 2013) for signature contains radon transform and Zernike moments. Multiclass Support

Vector Machine is used for verification. Regression score is obtained by applying PLS regression on sample against all samples in the database. Hidden Markov Model is used to calculate log likelihood of the sample against all samples. Shikha et al. (Shikha and Shailja, 2013) proposed an offline signature recognition system, which is based on Multi-layer percepron (MLP) and Self Organizing Map groups of neural networks (SOM).

In Local morphological pattern spectrum (Shekar et al., 2013) based approach the signature image is partitioned into eight equally sized vertical grids and for each grid a structured morphological pattern spectra obtained. The Eigen-signature (Shekar and Bharathi, 2011a) approach makes use of eigenvalue and the eigen vector to form eigen-sign knowledge base. In Chain Code Histogram based approach (Bharathi and Shekar, 2013) the feature vectors are enhanced through Laplacian of Gaussian filter for off-line signature verification. Bhattacharyaa et al., (Bhattacharya et al., 2013) have proposed an off-line signature verification and recognition system using pixel matching technique (PMT). The PMT is used to verify the signature of the user with the sample signature which is stored in the database. Kumar and Puthan (Kumar and Puhan, 2014) proposed a method, which employs inter point envelope based distance moments for offline signature verification. It exposes two types of features namely DC- Line and Envelope to Envelope. The high dimensional inter point distances are used to estimate centralized moments such as the variances, skewness, kurtosis and mean. The resultant moment features are applied for training SVM classifier.

Kruthi and Shet (Kruthi and Shet, 2014) proposed off-line signature verification system using Support Vector Machine. SVM is a tool for classification and regression prediction. The main aim of SVM is to draw a decision plane among a set of objects belonging to different classes and classify them. Yasmine et al., (Guerbai et al., 2015) propose a design of handwritten signature verification by using one class support vector machine i.e. OC-SVM. This method takes only genuine signature model. The Deep Multitask Metric Learning (DMML) (Soleimani et al., 2016) approach is based on the nature of similarities and dissimilarities of both the genuine and forge signature. The DMML uses both the writer dependent and writer independent approaches. Its shared layer acts as writer independent and separate layers to learn writer dependent features.

Although, we have seen plethora of algorithms for offline signature verification, devising an efficient and accurate offline signature verification method is still a challenging issue. Hence, we were motivated to develop robust and an efficient approach for offline signature verification.

3. PROPOSED APPROACH

In this work, unique structural features are extracted from the signature through the use of a novel approach called Blockwise Binary Pattern (*BBP*). The proposed approach has three major phases : Preprocessing, Feature extraction and Classification. In the preprocessing phase, the given signature image is binarized using Otsus binarization method. The noise intruded due to binarization is eliminated using morphological filter operations. We have normalised the thickness of the strokes in signature image by a series of thinning and dilating operation. The feature extraction and Classification process is presented in detail in the following section.

3.1 Block Based Binary Pattern

In this section, we present in detail the steps involved in the process of feature extraction of the signature using *BBP* approach. In this approach, we have divided the signature into 3 x 3 neighborhood blocks as shown in the Figure 1. The eight pixels are merged into single pixel and the value of this pixel which represents the 3 X 3 block is computed as follows.

Divide the signature into 3 x 3 neighborhood blocks. Let $P_{i,j}$ be the central pixel. Obtain the binary stream of the block say,

$$B = \{P_{i-1,j-1}, P_{i-1,j}, P_{i-1,j+1}, P_{i,j-1}, P_{i,j+1}, P_{i+1,j-1}, P_{i+1,j}, P_{i+1,j+1}\} \quad (1)$$

Here, B is nothing but binary stream. Obtain the decimal value of the binary stream. This decimal value is the representation of the binary values in the Block. But this value is rotation variant. To make this rotation invariant, we have used the following procedure. The binary stream B is shifted one position right and the decimal value of the binary stream is obtained. The above procedure is repeated for all the bits in the binary stream resulting in 8 decimal values. The smallest decimal value is the rotational invariant block representation value. This value replaces the block.

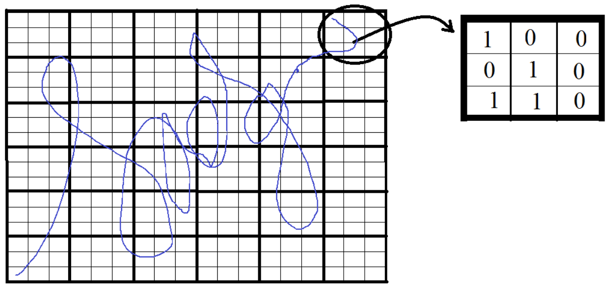

Figure 1. Block Based Binary pattern on a Signature

The above process is repeated for all the blocks. The resulting image containing the *BBP* values are stored in the form of normalized Histogram in the knowledge base.

3.2 Feature extraction by *BBP* method

The Local Binary Pattern (*BBP*) of the signature is calculated as follows.

1. Divide the signature into 3 X 3 block. For every shape pixel p, identify the 8 neighbors of the pixel by following the pixels in a anti-clockwise forming the *BBP* sequence s, for p.
2. Compute the decimal equivalence $d1$ of binary string s.
3. Perform circular right shift by 1, of s and compute the decimal equivalent of the resulting string, say dk.
4. Repeated the above step for 7 more times obtaining di, for i = $2 \ldots 8$.
5. Store the binary string corresponding to smallest decimal value as the BBP value of pixel p.
6. Represent the *BBP* values thus obtained for each shape pixel, in the form of histogram H.

Repeat the above process for every signature in the training set forming the *BBP* based knowledge base. Thus every signature is described by *BBP* features forming a knowledge base. The Support Vector Machine (SVM) classifier is used as the verification tool.

3.3 Classification based on SVM

Recent research in the field of machine learning focuses on the design of efficient classifiers. The main characteristics of any classifier is to correctly classify unseen data which were not present in the training set. Several applications have been developed based on one of the accurate classifier called Support Vector Machine(SVM). The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes [(Hsu et al., 2003), (Kumar et al., 2010a)] . Any classification task usually involves separating data into training and testing sets. Each instance in the training set contains one target value (i.e. the class labels) and several attributes(i.e. the features or observed variables). Given a set of n training samples $\{(x_i; y)\}_{i=1}^n$ where $x_i \in R^L$ is drawn from a domain X and each of the label y_i is an integer from $Y = \{0, 1\}$. The goal of the binary-class classification in SVM is to learn a model that assigns the correct label to an unseen test sample. This can be thought of as learning a function f : $X \rightarrow Y$ which maps each instance x to an element y of *Y*. Let S be the covariance matrix defined as follows:

$$S = \frac{1}{n}(X - ce^T)(X - ce^T)^T, \tag{2}$$

where $X = [x_1; x_2; ....; x_n]$ is the data matrix, c is the centroid of X and e is the vector of all ones. Assuming the data is separable, the hard margin SVM looks for some hyperplane:

$$f(x) = (x, w) + b = 0; \tag{3}$$

which separates the positive from the negative examples. Here *w* is normal to the hyperplane, $(x, w) = (x^T w)$ is the inner product between x and *w*, and $|b|/\|w\|_2$ is the perpendicular distance from the hyperplane to the origin. For the linearly separable case, the hard margin SVM simply looks for the separating hyperplane with the largest margin. The optimal hyperplane is computed by minimizing $\|w\|_2$ subject to the constraint that:

$$y_i((x_i, w) + b) \geq 1, \forall i \tag{4}$$

A test point x is assigned to the positive class, if $(w, x) + b > 0$, and to the negative class otherwise. The above formulation can be extended to deal with non separable data by introducing the slack variables and a tuning parameter $C > 0$. This is known as the soft margin SVM. Hence, for a given instance label pairs $(x_i, y_i), i = 1, \ldots, l$ where $x_i \in R^n$ and $y \in \{0, 1\}^l$, the SVM requires the solution for the following optimization problem:

$$min_{(W,b,\xi)} \frac{1}{2} W^T W + C \sum_{i=1}^{l} \xi_i \tag{5}$$

Subjected to

$$y_i \left(W^T \phi(x_i) + b \right) \geq 1 - \xi_i \tag{6}$$

and

$$\xi_i \geq 0. \tag{7}$$

Here training vectors x_i are mapped into a higher dimensional space by the function ϕ. The SVM finds a linear separating hyperplane with the maximal margin in the higher dimensional space. $C > 0$ is the penalty parameter of the error term. In order to transform a data from lower dimensional to higher dimension, kernel trick is used, which is defined as $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$. Few of the basic kernels used are :

- linear : $K(x_i, x_j) = x_i^T x_j$.
- polynomial : $K(x_i, x_j) = \left(\gamma x_i^T x_j + r\right)^d, \gamma > 0$.
- radial basis function : $K(x_i, x_j)$ =exp$\left(-\gamma \parallel x_i - x_j \parallel^2\right), \gamma > 0$.
- sigmoid: $K(x_i, x_j)$ =tanh$\left(\gamma x_i^T x_j + r\right)$.

Dataset	No. of Signers	Genuine Signatures	Skilled Forgery	Total Signatures
CEDAR	55	24	24	2640
GPDS-160	160	24	30	8640
MUKOS	30	30	15	1350

Table 1. Number of samples in the datasets

Here γ, r and d are kernel parameters. The parameter selection to train the SVM is a challenging issue and could be decided based on the feature and sample size used for training. In our experimentation, we have considered a maximum of 100000 iterations, with linear kernel function for polynomial of order 2. Since SVM is a binary classifier (can categorize two classes) for classification of N classes, N SVM classifiers are needed. Hence, in the proposed work number of SVM classifiers is equal to the number of writers. Each SVM classifier is used for identification of one writer signatures against all other writers (one against all strategy). The Experimentation process is presented in detail in the following section.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section presents the analysis of the experimental results conducted on the well known publicly available datasets. The proposed approach is experimented on standard off-line english signature datasets namely: CEDAR and GPDS-160 (A sub-corpus of GPDS-300). In addition, we have also extended the experiments on our regional language off-line signature corpus called MUKOS (Mangalore University Kannada Off-line Signature). Each dataset has varying number of signers, genuine and forge samples. The total number of signature samples considered in each dataset is tabulated in Table 1 . All experiments are conducted using MATLAB tool and tested on Pentium(R) dual core CPU with 3GB RAM on windows-7.

The knowledge base contains the BBP of every signature in the data set including both genuine and skilled forge samples. For each dataset, the signature samples are divided into two groups: training sample set and testing sample set with varying number of samples. We have carried out four sets of experiments. In Set-1, first ten genuine and first ten skilled forgeries are considered as training samples and tested against the remaining samples of the respective datasets, where as in Set-2, we have taken first 15 samples of genuine and first 15 samples of skilled forgery for training and tested with remaining samples. In Set-3, randomly chosen 10 genuine and randomly chosen 10 forge samples are considered for training, and tested with the remaining samples,

Experimental Set-up	Accuracy	FRR	FAR
Set-1	91.55	10.12	6.75
Set-2	93.54	6.06	6.86
Set-3	90.45	10	9.09
Set-4	93.64	8.68	4.04

Table 2. Experimental Results obtained for CEDAR Dataset:

and in Set-4, 15 samples are chosen randomly from the respective datasets for training and remaining samples are considered for testing. In order to over come the effect of the randomness, Set-3 and Set-4 experimentations are repeated five times and the average result is tabulated.

Experimentation on CEDAR dataset

The Centre of Excellence for Document Analysis and Recognition (CEDAR), at SUNY Buffalo, has built the off-line signature dataset with 55 signers, a total of 2640 signature samples. 24 genuine signature samples were collected from each signer and later, to obtain the forgeries (skilled), 20 arbitrary chosen signers skilfully forged the signature in the dataset each with 24 samples. Hence for each signer, 24 genuine and 24 skilled forge samples, a total of 48 signature samples were collected. The CEDAR signature dataset is available on (object dataset, available from:, n.d.a).

We started experimenting with set-1 and set-3 configurations, where the training set consists of 10 genuine and 10 skilled forgery sample features and tested with remaining 14 genuine and 14 skilled forged sample features. Set-2 and set-4 test configuration had 15 genuine and 15 skilled forge sample features for training and tested against the remaining 9 genuine and 9 forge samples. Set-3 and set-4 experimental set-up is repeated five times in order to overcome the effect of the randomness. The metrics FAR and FRR obtained are given in Table 2.

From the literature we observed that, Kalera et al., (Kalera et al., 2004), Chen and Shrihari (Chen and Srihari, 2005) and Kumar et al., (Kumar et al., 2010b) have experimented on CEDAR dataset and hence a comparative analysis is given in Table 3.

Experimentation on GPDS-160 dataset

Digital Signal Processing Group (GPDS) of the Universidad de Las Palmas de Gran Canaria, has comeout with a good scale dataset called GPDS-300 corpus. GPDS-300 is a dataset of 300 signers signature samples with 24 genuine and 30 forge of each, summing to a total of 16200 samples. For our experimentation, a subset of 160 signers, starting from the first signer to 160th signer is extracted from the corpus and named GPDS-160 with 8640 signature samples including both genuine and forge signatures.

Here we have conducted experimentation with set-1 and set-3 test configuration where we considered 10 genuine and 10 skilled forgery sample features and tested with remaining 14 genuine and 20 skilled forge. Extending the experimentation, set-2 and set-4, considering 15 genuine and 15 skilled forge sample features for training and tested with remaining 9 genuine and 15 skilled forge sample features of all 160 signers in the corpus. The set-3 and set-4 experiment was conducted with 5 random instances. Thus, the results in terms of FAR and FRR on GPDS-160 dataset are tabulated in Table 4. As GPDS-300 is another well known publicly available off-line signature dataset and considered by many researchers, we have provided a comparative analysis with the state-of-the-art work in Table 5.

Table 4. Experimental Results obtained for GPDS-160 Dataset:

Experimental Set-up	Accuracy	FRR	FAR
Set-1	95.38	4.72	4.46
Set-2	97.29	2.33	3.33
Set-3	94.19	5.9	5.67
Set-4	97.27	3.167	2.014

Experimental Set-up	Accuracy	FRR	FAR
Set-1	97.39	5.6	8.2
Set-2	97.25	0.58	4.9
Set-3	96.08	0.8	6.95
Set-4	97.1	0	5.80

Table 6. Experimental Results obtained for MUKOS Dataset:

Experimentation on MUKOS dataset:

MUKOS [Mangalore universiry Kannada Off-line Signature] is a corpus with signatures in Kannada, a regional language. It consists of 1350 signatures from 30 signers where we have collected 30 genuine signatures and 15 skilled forgeries from each signer. Each genuine signature was collected using black ink on A4 size white paper featuring 14 boxes on each paper. Once the genuine signatures were collected by all thirty signers, the forgeries were produced imitating a genuine signature from the static image of the genuine after a time gap where they were allowed to practice the genuine sample of other signers. These signatures were acquired with a standard scanner with 75 dpi resolution in an 8-bit gray scale image.

The experimentation is conducted considering set-1 and set-3 test configuration with 10 genuine and 10 skilled forgery samples to obtain feature vectors and further classification is achieved by the remaining 15 genuine and 5 skilled forgery samples of each signer. Similar experimentation is carried out with test configuration set-2 and set-4, where we have considered 15 genuine and 15 skilled forge samples to yield the feature vectors. Here the remaining 15 genuine and all 15 skilled forge samples of all signer's are considered for testing. The classification accuracy due to set-1 to set-4 experimental configurations are tabulated in Table 6. Here the experimental results for set-2 and set-4 is the average of 5 instances of experimentations, where the samples are chosen randomly for training the system. A comparative analysis on the MUKOS dataset with our earlier work is tabulated in Table 7.

Method	Classifier	Accuracy	FAR	FRR
Shape based eigen signature (Shekar and Bharathi, 2011b)	Euclidean distance	93.00	11.07	6.40
Pattern Spectrum (Shekar et al., 2013)	EMD	97.39	5.6	8.2
Proposed Approach	**SVM**	94.02	7.35	5.98

Table 7. Experimental Results for MUKOS dataset- A comparative analysis

5. CONCLUSION

In this work, we have designed an efficient and robust approach namely Blockwise binary pattern for offline signature verification. The input image is pre-processed and the dominant features

Proposed by	Classifier	Accuracy	FAR	FRR
Kalera et al., (Kalera et al., 2004)	PDF	78.50	19.50	22.45
Chen and Shrihari (Chen and Srihari, 2005)	DTW	83.60	16.30	16.60
Kumar et al., (Kumar et al., 2010b)	SVM	88.41	11.59	11.59
Pattern Spectrum (Shekar et al., 2013)	EMD	91.06	10.63	9.4
Surroundedness (Kumar et al., 2012)	MLP	91.67	8.33	8.33
Inter Point Envelop (Kumar and Puhan, 2014)	SVM	92.73	6.36	8.18
Proposed Approach	**SVM**	**93.64**	**8.68**	**4.04**

Table 3. Experimental Results obtained for CEDAR Dataset - A comparison:

Model Proposed	**Classifier type**	**Accuracy**	**FAR**	**FRR**
Ferrar et al., (Ferrer et al., 2005)	SVM HMM	86.65 –	13.12 12.60	15.41 14.10
Vargas et at., (Vargas et al., 2011)	SVM +LBP	87.28	6.17	22.49
Solar et al., (Ruiz-Del-Solar et al., 2008)	Bayseian	84.70	14.20	16.40
Surroundedness (Kumar et al., 2012)	MLP	86.24	13.76	13.76
Pattern Spectrum (Shekar et al., 2013)	EMD	91.06	10.63	9.4
Proposed Approach	**SVM**	**97.27**	**3.167**	**2.014**

Table 5. Experimental result obtained for GPDS-300/160 dataset : A comparative analysis

are obtained using BBP method. The features are represented using normalized histogram. The classification is done using SVM classifier. Extensive experimentation is conducted on well known publicly available signature dataset :CEDAR and GPDS-160 (a sub-corpus of GPDS-300) and a regional language signature dataset called MUKOS. In order to highlight the superiority of the proposed approach, a comparative analysis is provided with the state-of-the-art off-line signature methods on CEDAR and GPDS-160 dataset. It is found that the proposed approach is simple to implement, computationally efficient and accurate in terms of classification.

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