





# Multi-scale Local Binary Patterns- A Novel Feature Extraction Technique for Offline Signature Verification

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**Abstract.** This paper presents a powerful feature representation method called Multi-scale Local Binary Patterns for offline signature verification. The multi-scale representation oriented local binary patterns can be obtained by changing the radius R value of Local Binary Patterns(LBP) operator and combining the LBP features at different scales. In this proposed approach the LBP operator is applied at 3 different scales by varying the radius R value and at each scale equal number of pixels are considered for the processing. Finally, by cascading a group of LBP operators at 3 different scales over a signature image with fixed number of pixels at each scale and combining their results, a multi-scale representation LBP can be obtained. This essentially represents nonlocal information. Features fusion is performed by the linear combination of the histogram corresponding to 3 different radii results in a multi resolution (scale) feature vector. Support Vector Machine (SVM) is a well known classifier employed to classify the signature samples. Experimental results on standard datasets like CEDAR and a regional language datasets shows the proposed technique's performance. A comparative analysis with few well known methods is also presented to demonstrate the performance of proposed technique.

**Keywords:** Multi-scale Local Binary Patterns · Signature verification · Support Vector Machine · Local binary patterns

## 1 Introduction

Signatures are one of the biometric trait, globally accepted to authenticate individuals. Automatic Signature verification is categorized into two branches based on the way signatures are acquired, which are offline and online signature verification. Offline signature verification method takes the scan of signature which is written on a paper this is static by nature. Offline signature verification works on the static information mainly on texture such as vertical and horizontal projections, line width, orientation etc. Where as online signature verification method takes the signature using digital gadget like digitizing tablets etc

which is dynamic by nature. Online signature verification uses function features and parameter features like x-y coordinates, pen pressure, pen up, pen down, azimuth, pen inclination etc. Considering the nature of forging method forgeries are categorized into three categories namely: *simple, random and skilled forgery*. The simple forgery is one where the forger is aware of the signature name but not its pattern so that there will be variation in his/her own pattern of writing. Random forgery is another type where the forger is not aware of both the signature name and its pattern. Lastly the skilled forgery is one where the forger knows the genuine signature name and its pattern, practices for a while and then imitates. This almost resembles the original pattern and most challenging issue along with high intra class variations in offline signature verification system.

In this work, we made an attempt to exploit the extension of Local Binary Patterns, called Multi-scale Local Binary Patterns. The local binary patterns is a powerful texture descriptor, extending this descriptor to higher scales will helps in capturing nonlocal information. In the literature we found extensive work done on local binary patterns in texture discrimination. Multi-scale local binary patterns also performs well when there is a need for combined local and nonlocal features. Hence, we made an attempt to explore Multi Scale Local Binary Pattern for offline signature verification. The order of this paper with section wise is as follows: Sect. 2 presents a detailed literature of some of the state-of-the-art papers. The elaborated description of the proposed approach is in Sect. 3. Section 4 illustrates the experimental results followed by the discussion. Finally, Sect. 5 represents the conclusion part.

## 2 Review of the Literature

Biometric is extensively used in person authentication. Signature is one of the behavioural traits and can be used to represent a person. The different kinds of signature forgery raises the need for signature verification system which verifies the genuineness of the signature. There are several algorithms used to design offline signature verification system. We have listed few important methods from the literature. Hafemann et al. [3] presents learning features formulations for offline signature verification. Learning features are used to train writer independent classifier using convolution neural networks. Hadjadji et al. [2] proposes an open system based on one-class classifier using curvelet transform along with the principal component analysis. Grid based template matching method by Zois et al. [17] uses the geometric pattern of a signature, which is encoded by grid templates, apparently partitioned as subsets. Yesmine et al. [12] presents Artificial Immune Recognition System for offline signature verification. The proposed method uses two descriptors one is gradient local binary patterns to estimate gradient features from the neighboring local binary patterns and another is longest run feature to describe the signature topology. Score level fusion of classifiers [15] proposed by Mustafa et al., This approach extracts set of features namely, Scale Invariant Feature Transformation (SIFT), Histogram of Oriented Gradients (HoG) and Local Binary Patterns (LBP). Radhika et al. [10] proposed a combined approach of both offline and online signature verification.

Author extracts features such as pen tip tracking from online signatures. Gradient features and projection profile features are extracted from offline signatures. Experiments are conducted separately. The well known classifier Support Vector Machine is employed for classification. Results obtained are combined and verified. Yilmaz et al. [16] proposed a method where signature samples are partitioned in to different zones based on both polar and cartesian coordinate systems. From different zones of both coordinate system histograms are obtained. Classification has been done by employing Support Vector Machine (SVM).

### 3 Proposed Approach

In this work, we propose a Multi-scale Local Binary Patterns (MSLBP) to capture the local as well as global features from the signature image. The LBP features are extracted from signature image at different radii and are stored in the form of histograms. The fusion of histogram features at various scales are performed to form a single feature vector.

The LBP [9] is a gray-scale texture descriptor which describes the local spatial structure of the texture of an image. Based on central pixel value in an image, a code sequence is generated by keeping it as a threshold with its neighborhood pixel values.

$$LBP_{P,R} = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \quad (1)$$

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases}$$

here  $g_c$  represents the central pixel gray value,  $g_p$  neighborhood value,  $P$  represents the number of neighborhood pixels involved and  $R$  represents the radius of the neighborhood pixels. The LBP values are computed for each pixel  $P_{i,j}$  by considering  $N$  neighboring pixels. The  $N$  neighboring pixels of  $P$  are considered in clockwise direction resulting a binary stream  $S$ . In case of  $N = 8$  with  $R = 1$ , the binary stream is defined as follows

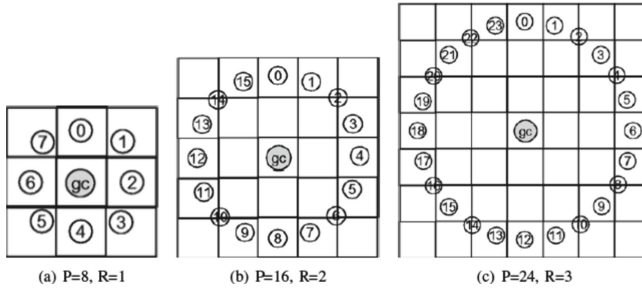
$$S = \{P_{i,j+1}, P_{i+1,j+1}, P_{i+1,j}, P_{i+1,j-1}, P_{i,j-1}, P_{i-1,j-1}, P_{i-1,j}, P_{i-1,j+1}\} \quad (2)$$

Compute the decimal equivalent  $d_i$  of the binary sequence  $S$ . The resulting value  $d_i$  is variant to rotation. To make it invariant to rotation shift  $S$  one bit towards right side by applying right shift operator. This will results in another decimal equivalent  $d_j$  of  $S$ . Repeat the process for all the remaining bits in binary sequence  $S$  to obtain  $N$  decimal equivalent values.

$$D = d_1, d_2, \dots, d_N \quad (3)$$

The minimum decimal value in the set  $D$  is taken as the value for pixel  $P_{i,j}$ . The value of radius  $R$  can be varied. If  $R = 1$  then the neighboring 8

pixels at distance 1 are taken as the binary stream representing the pixel under consideration. The radius can be extended to 2, 3, etc. The neighboring pixels for a given pixel at  $R = 1, 2$  and 3 are shown in the Fig. 1.



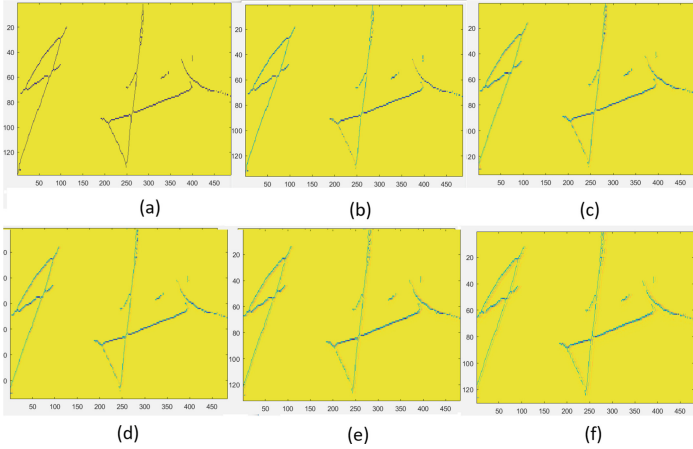
**Fig. 1.** (a) LBP with  $R = 1$  and  $P = 8$  (b) LBP with  $R = 2$  and  $P = 16$  (c) LBP with  $R = 3$  and  $P = 24$  (Image Curtsey : Rassem et al. [11]).

In the proposed approach we have used 3 scales, ( $R = 1, P = 8$ ), ( $R = 2, P = 8$ ), ( $R = 3, P = 8$ ). The input image is applied with LBP( $R = 1, P = 8$ ) operator. The LBP transformed image is converted into an histogram  $H_1$  and stored in a knowledge base. The process is repeated with LBP( $R = 2, P = 8$ ) and LBP( $R = 3$  and  $P = 8$ ) giving rise to two LBP transformed images which are converted to histogram  $H_2$  and  $H_3$  correspondingly and are stored in knowledge base. The Histograms are combined to form a single histogram representing the resultant MSLBP feature vector for input signature image.

The Fig. 2 shows the input signature image and the transformed images after applying the LBP operators LBP( $R = 1, P = 8$ ), LBP( $R = 2, P = 8$ ), LBP( $R = 3, P = 8$ ), LBP( $R = 4, P = 8$ ) and LBP( $R = 5, P = 8$ ) respectively. The classification is done using SVM as follows.

### 3.1 Classification

In this work we have used the well known classifier Support Vector Machine(SVM) to classify signatures samples. The Support Vector Machine is intend to develop a model which learns from training samples based on the extracted features to predict target values of test samples [4,7]. The dataset is divided into training set as well as test set during the classification process. Every sample in the training set having its own target value called class label with set of features known as observed variables. Support vector machines are a bunch of supervised classification and regression algorithms. They are bi-linear by nature and used to classify two class objects. The Multi-SVM can be used to classify more than two class objects, in this case Multi-SVM uses one versus all strategy. The aim of SVM is to separate objects of different class by maximizing



**Fig. 2.** (a) Original image; (b) LBP with  $r = 1$  and  $n = 8$ ; (c) LBP with  $r = 2$ ,  $n = 8$ ; (d) LBP with  $r = 3$ ,  $n = 8$ ; (e) LBP with  $r = 4$ ,  $n = 8$ ; (f) LBP with  $r = 5$ ,  $n = 8$ .

the margin of a hyper plane. The vectors which define the hyper plane are the support vectors.

$$m = 2/(||w||) \quad (4)$$

Where  $m$  is the margin and  $w$  is the width of the hyper plane.

$$w^T X + b = 1 \quad (5)$$

Equation 5 represents the upper boundary of the hyper plane.

$$w^T X + b = 0 \quad (6)$$

Equation 6 represents the center of the hyper plane.

$$w^T X + b = -1 \quad (7)$$

Equation 7 represents the lower boundary of the hyper plane.

For classification of  $N$  classes,  $N$  SVM classifiers are required. Therefore, in the proposed work we employed each SVM classifier for each writer. Here the SVM classifier uses one versus all strategy for classification of signatures.

The next section presents the experimental results in detail.

## 4 Experimentation Results and Discussion

The experiments are conducted on publicly available well-known dataset namely CEDAR (Center for Document Analysis and Recognition) database. Further we continued the experiments also on Local Regional Kannada dataset namely MUKOS (Mangalore University Kannada Offline Signature) corpus. The experiments are carried out using MATLAB tool with version 2016b on DEL laptop with 8 GB ram, 1tb Hard disk and i7 processor on windows 10 operating system (Table 1).

**Table 1.** Datasets details

Datasets	Number of signature contributors	Number of genuine signatures	Number of skilled forgeries	Total number of signatures
CEDAR	55	24	24	2640
MUKOS	30	30	15	1350

The features database contains MSLBP histograms, obtained from both datasets. The MSLBP features are extracted from genuine as well as skilled forgery signatures. The signature samples are categorized into training set and test set from both the dataset. Experiments are carried out in 4 epochs. In epoch-1, we chosen first 10 signatures of both genuine as well as skilled forgeries to train the model and remaining samples are used to test. In set-2, we considered the first 15 genuine samples along with first 15 skilled forgeries to train and remaining samples are used to test. For set-3, 10 genuine along with 10 skilled forgeries are chosen randomly for training and for testing remaining samples are used. Lastly for set-4, again randomly chosen 15 genuine signatures and 15 skilled signatures are considered to train and remaining samples used to test the proposed model. To avoid the impact of randomness, experiments are repeated for set-3 as well as set-4 and finally we considered average results and are tabulated.

### Experiments on CEDAR Dataset

CEDAR is a well-known publicly available database, stands for Center for Document Analysis and Recognition. The database consists 2640 signatures, which are collected from 55 contributors. Each contributor contributed 24 genuine signature samples. 20 randomly chosen contributors are allowed to practice the patterns of genuine signatures and from each of them 24 forge samples are collected. Finally the database contains 48 signature samples, among that 24 genuine and 24 forge. Experiments were started with set-1 along with set-3 where 10 genuine and 10 skilled forge signatures are considered for training and for testing around 14 genuine signatures with 14 skilled forgery signatures are considered. Experiments were continued with Set-2 and set-4 with numerical figures such as first 14 genuine signature samples with first 14 skilled forge signature samples were considered for training and tested against remaining both 9 genuine signature samples with 9 skilled forgery signatures. To overcome from the effect of randomness 5 times experiments are repeated for set-2 and set-4 finally average result is considered. The results are tabulated in Table 2, where FAR and FRR are the metrics.

**Table 2.** Obtained Experimental Results on CEDAR Dataset:

Experiment Set-up	Accuracy	FRR	FAR
Set-1	94.74	4.0	5.6
Set-2	92.72	9.29	5.25
Set-3	90.58	11.94	6.88
Set-4	91.05	10.60	9.2

From the literature, we found the experimental results of few well known approaches on CEDAR dataset. We made an compararision analysis presented in Table 3 shows the improvements in accuracy by the proposed approach.

**Table 3.** Experimentation results on CEDAR dataset

Proposed by	Classifier	Accuracy	FAR	FRR
Kalera et al. [5]	PDF	78.50	19.50	22.45
Chen and Shrihari [1]	DTW	83.60	16.30	16.60
Kumar et al. [8]	SVM	88.41	11.59	11.59
Pattern spectrum [14]	EMD	91.06	10.63	9.4
Surroundedness [8]	MLP	91.67	8.33	8.33
Inter point envelop [6]	SVM	92.73	6.36	8.18
<b>Proposed Approach</b>	<b>SVM</b>	<b>94.74</b>	<b>4.0</b>	<b>5.6</b>

## Experiments on MUKOS Dataset

MUKOS (Mangalore University Kannada Offline Signature) database is a regional language Kannada dataset. The database consists 1350 signatures collected from 30 Signer. There are 30 genuine signature samples and 15 skilled forgeries from each Signer. Contributors had written the signature with black ink pen on a white paper representing 14 boxes. After acquiring genuine signatures, the contributors are allowed to practice the genuine signature pattern for a time interval and contributed skilled forgeries. All experiments are conducted in terms of set-1, set-2, set-3 and set-4. In set-1 and set-2 there are 10 genuine and 10 skilled forgeries are chosen for training and 15 genuine signature and 5 skilled forgeries are chosen for testing. Experiments on set-2 as well as on set-4 we considered 15 genuine signatures and 15 skilled forgeries for training and 15 genuine signatures and 15 skilled forgeries are tested against. Repeat the set-2 and also set-4 experiments 5 times to overcome from the effect of randomness and considering the average result. The metrics FAR and FRR used to measure the accuracy of the our approach. Results obtained for MUKOS dataset is tabulated below (Tables 4 and 5).

**Table 4.** Experimentation on MUKOS database:

Experimental Set-up	Accuracy	FRR	FAR
Set-1	97.73	0.53	4
Set-2	97.25	0.58	4.9
Set-3	97	1.2	4.8
Set-4	98.6	0.8	2.0

**Table 5.** Experiments outcome on MUKOS database- A comparative analysis

Method	Classifier	Accuracy	FAR	FRR
Shape based eigen signature [13]	Euclidean distance	93.00	11.07	6.40
Pattern spectrum [14]	EMD	97.39	5.6	8.2
<b>Proposed Approach</b>	<b>SVM</b>	98.6	0.8	2.0

## 5 Conclusion

In this work we tried to explore Multi-scale Local Binary Patterns for offline signature verification. The Local Binary Patterns is a well known powerful texture descriptor which captures local features. We made an attempt to explore Multi-scale Local Binary Pattern for the purpose of offline signature verification. The MSLBP can effectively represent both local information (micro structure) as well as global information of an image. We conducted extensive experiments on CEDAR database, which is a publicly available well known database. We also conducted experiments on MUKOS data corpus, which is a regional Kannada language offline signature database. Further we made a comparative analysis wherein we found that, the proposed approach performs better than some of the well known approaches on the CEDAR dataset. It is observed experimentally that, the implementation of MSLBP is simple yet gives high accuracy in signature verification task.

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