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Handwritten Bangla Numeral Recognition using Local Binary Pattern

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***Abstract*—Local Binary Pattern (LBP) is a simple yet robust texture descriptor that has been widely used in many computer vision applications including face recognition. In this paper, we exploit LBP for handwritten Bangla numeral recognition. We classify Bangla digits from their LBP histograms using K Nearest Neighbors (KNN) classifier. The performance of three different variations of LBP – the basic LBP, the uniform LBP and the simplified LBP was investigated. The proposed OCR system was evaluated on the off-line handwritten Bangla numeral database CMATERdb 3.1.1, and achieved an excellent accuracy of 96.7% character recognition rate.**

Keywords*—*Local Binary Pattern, Bangla Optical Character Recognition, Handwritten Character Recognition, Digit Recognition

I. Introduction

Optical Character Recognition (OCR) is a well-known computer vision problem that has been studied by many researchers. An OCR system detects and recognizes characters from document images, and facilitates text processing. It has a number of applications including digitizing scanned pages of texts. The scanned text can be either printed or handwritten. Handwritten character recognition is considered more challenging due to the higher degree of variation in writing styles. However, automatic recognition of handwritten characters has many special applications such as archiving ancient handwritten manuscripts or Human Computer Interaction (HCI) using pen-computing in hand-held mobile devices like cell phones.

With more than 200 million native speakers, Bangla is ranked the fifth most spoken language in the world. It is the national language of Bangladesh, and a large number of people in India speaks in Bangla as well. Consequently, automatic recognition of handwritten Bangla characters will find many applications, and play an important role in Bangla language processing. Due to its demographic diversity, writing patterns of Bangla script can vary quite a bit. As a result, handwritten Bangla character recognition is not only an important research topic, but also can be a challenging task.

This paper focuses on the recognition of handwritten Bangla numeric characters. Handwritten digit recognition has specific applications including reading postal codes, automatic data entry and bank check processing. Liu et al. [1] applied gradient direction based features along with state of the art classifiers to benchmark Bangla numeral recognition, and achieved an unprecedented accuracy of 99.4% on a standard database, namely the ISI database. Das et al. [2] exploited genetic algorithm based region sampling for local features selection, and achieved 97% accuracy on the handwritten Bangla numeral data set CMATERdb. Basu et al. [3] achieved 95.1% accuracy using combination of classifiers. An accuracy of 94% was achieved in Bangla digit recognition using Sparse Representation Classifier by Khan et al. [4]. Xu et al. [5] applied hierarchical Bayesian network and achieved 87.5% accuracy. Surinta et al. [6] used character contour computed by 8-directional codes along with nonlinear SVM classifier and achieved 86.8% accuracy. In this paper, we exploit Local Binary Pattern (LBP) for handwritten Bangla numeral recognition. To our best knowledge, LBP has never been used in Bangla character recognition. We evaluate the performance of LBP on a standard character data set of Bangla numerals. Initial investigation reveals a promising accuracy of close to 97%.

The rest of the paper is organized as follows: Section II introduces Local Binary Pattern, and Section III summarizes the proposed character recognition system. In Section IV experimental results are analyzed, and finally, concluding remarks are made in Section V.

II. Local Binary Pattern

Local Binary Pattern (LBP) is a simple yet robust texture descriptor [7], [8]. It describes the local texture pattern, and can be exploited for texture classification. One of the most significant characteristics of LBP is its robustness to monotonic gray-scale changes caused by varying illumination conditions. Another important property is its computational simplicity, which makes it suitable for real-time applications. As a result, LBP has been successfully used in a wide variety of computer vision applications including face recognition [9], human detection [10], moving object detection [11] and medical image analysis [12].

LBP operates on each pixel by thresholding its neighbor pixels with the value of the center pixel itself. This results into binary outcomes, 0s and 1s, where 0 indicates that the gray scale value of the neighbor pixel is lower than that of the center pixel, while 1 indicates the contrary. The concatenated bit stream from all the neighbors is then converted to a decimal number, and is defined as the LBP value of the center pixel. This process is explained with the following mathematical expressions:

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

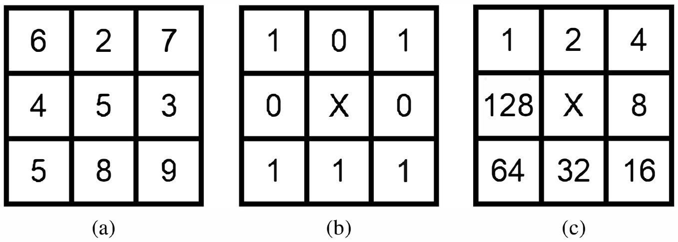

Fig. 1. Illustration of Local Binary Pattern (LBP) calculation (a) example image, (b) binary pattern by thresholding and (c) weight matrix.

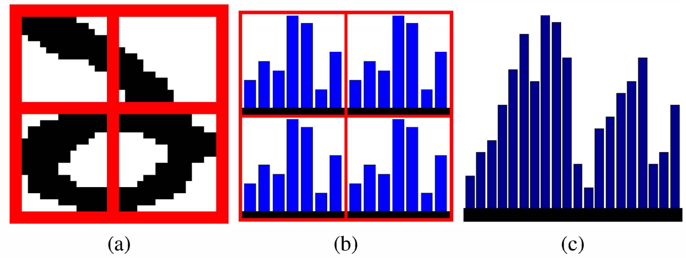

Fig. 2. Illustration of LBP feature extraction (a) 2×2 zoning, (b) corresponding local LBP histograms and (c) concatenated histogram.

$$LBP = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{2}$$

where $s(x)$ is the threshold function, and g_c and g_p represent the gray-scale value of the center pixel and the p-th neighbor respectively. Hence, the binary value of the p-th neighbor is multiplied by its corresponding weight 2^p. LBP is computed by summing up these weighted binary values. This is illustrated in Figure 1 which shows that the binary pattern 01110101 is converted to LBP $= 1 + 4 + 16 + 32 + 64 = 117$.

Depending on the position - the distance (or radius) and the orientation of the sampling points (neighbors), many different forms of Local Binary Patterns can be realized. In the following sections, we describe three of the most popular variations of LBP: basic LBP, uniform LBP and simplified LBP.

A. *Basic LBP*

It is the most commonly used pattern for LBP. In basic LBP, a 3×3 neighborhood is considered around the center pixel, and LBP is calculated using the eight neighbor pixels. Hence, basic LBP can represent $2^8 = 256$ unique patterns.

B. *Uniform LBP*

It is an extended version of the basic LBP. The uniform LBP places all binary patterns with more than two transitions from 0 to 1 and 1 to 0 in a single category, called the non-uniform LBP. In contrast, every binary pattern that has two or less transitions is called the uniform pattern, and is assigned a unique LBP value. For example, the binary pattern 00110100 has four transitions, hence it is a non-uniform pattern. On the other hand, the binary pattern 00110000 has two transitions, so it is a uniform pattern. The idea behind uniform LBP is that non-uniform patterns occur so rarely that their probability cannot be estimated properly. Consequently, non-uniform patterns should be discarded as a useful feature. Uniform LBP provides a significant feature reduction, and can improve the classifier performance.

C. *Simplified LBP*

Simplified LBP or S-LBP is introduced by Lui et al. [13]. S-LBP uses only three sample points. However, the position of these points are empirically determined. S-LBP has demonstrated promising results.

Once Local Binary Pattern is computed for all pixels, the LBP converted image is split into a number of zones or blocks. Local histogram of each block is then calculated separately. Finally, these local histograms are concatenated and exploited as features for image classification. This process is illustrated in Figure 2.

III. Methodology

Figure 3 demonstrates the block diagram of the proposed OCR system. At first, the input image is pre-processed. Next, features are extracted from the pre-processed character images, and finally, the character images are classified using a classifier.

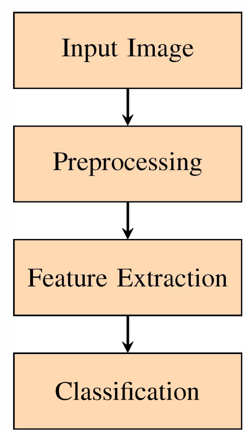

Fig. 3. Block diagram of the proposed character recognition system.

A. *Preprocessing*

The input image is passed through a series of initial steps that helps to improve the character recognition rate. In this work, we perform the following pre-processing: noise reduction, slant correction and size normalization.

1) Noise Reduction: Noise reduction improves image quality. Different approaches including morphological operation and image filtering can be employed to remove the image noise. In this paper, we exploit Gaussian Low Pass filter for image smoothing and noise reduction.

2) Slant Correction: Automatic detection and correction of character slant is performed on the image. Slant correction reduces the variability due different writing styles. We used KSC algorithm [14] for slant detection and correction.

Fig. 4. Sample character images: column 1 indicates the actual digit class and columns 2–6 illustrate some randomly selected images of the digit.

3) Size Normalization: All input images are normalized to a standard size. This is done through image scaling by either down-sampling or up-sampling of the input image. Size normalization is a critical prerequisite for many feature extraction steps.

B. Feature Extraction

Different features can be exploited to represent and identify the character image. These features include statistical features, structural features, moment based features, global transform based features etc. However, in this paper, we exploit Local Binary Pattern for handwritten Bangla numeral recognition. We apply three different variations of LBP: basic LBP, uniform LBP and simplified LBP, for character recognition, and evaluate their performance.

C. Classification

A number of standard classifiers including KNN (K Nearest Neighbors), ANN (Artificial Neural Network) and SVM (Support Vector Machine) can be exploited to classify the character images. We use Euclidean distance Nearest Neighbor classifier (that is, KNN classifier with K=1) for character recognition. Even though, more sophisticated classifiers such as ANN or SVM are likely to result into a higher recognition rate, Nearest Neighbor classifier was chosen for initial benchmarking of LBP features due to the simplicity of this classifier.

IV. Experiments and Results

A. Data Set

We evaluate the proposed method on the Handwritten Bangla Numeral Database CMATERdb 3.1.1 collected from CMATERdb [2]. This data set contains total 6000 images of unconstrained handwritten isolated Bangla numerals. The data set is evenly distributed into ten classes from zero to nine, each class containing 600 binary images of 32×32 pixels. For the evaluation of the character recognition algorithm, we split the data set into test set and train set. The test set contains 1000 randomly selected character images - 100 test images per digit, while the train set contains the remaining 5000 images. In Figure 4, few sample images from the data set are demonstrated. The character images have no visible noise. However, there is high degree of variation due to different writing styles.

TABLE I. Overall accuracy for character recognition

Zones	Basic LBP	Uniform LBP	Simplified LBP
2×2	92	92.1	91.6
4×4	96.5	96.6	96.4
8×8	96.7	96.6	96.5

B. Result Analysis

We evaluate the performance of three different types of LBP features with different zoning. Results are shown in Table I. The results demonstrate that for each of the LBP features (basic, uniform, and simplified LBP), the OCR system performs the best for 8×8 zoning. The basic LBP achieves the highest accuracy for character recognition of 96.7%. Both uniform and simplified LBP features perform quite similar, and achieve 96.6% and 96.5% accuracy respectively. This accuracy is marginally reduced for 4×4 zoning. However, the performance of the OCR system declines significantly for 2×2 zoning. In general, across different zoning, both basic and uniform LBP consistently outperform simplified LBP. The performance of the simplified LBP, nevertheless, is very much comparable with that of the others.

TABLE II. Class–wise recognition rate for 8×8 zones

Digit	Basic LBP	Uniform LBP	Simplified LBP
1	98	98	97
2	100	100	100
3	98	98	98
4	99	99	99
5	98	98	96
6	92	92	92
7	98	98	98
8	100	100	100
9	85	84	86
0	99	99	99

Table II demonstrates the class-wise classification accuracy for different LBPs using 8×8 zoning. It is obvious that some classes (such as class two and class eight) are classified more accurately than the others (such as class six and class nine). While the OCR system achieves 100% accuracy for classes two and eight, it achieves only 85% recognition rate for class nine. This variation in character recognition rate is most likely due to the inherent patterns of the characters.

The confusion matrix presented in Table III demonstrates the correlation between different character classes. For instance, class one is highly correlated with class nine – with more than 15% confusion between them. Similarly, there is significant amount of confusion between class three and class six, and between class five and class six. A closer look at Figure 4 reveals that class one and class nine have very similar pattern. Likewise, the left halves of class three and class six are quite similar as well. Again, class five and class six have similar bottom halves.

TABLE III. CONFUSION MATRIX FOR BASIC LBP USING 8×8 ZONING

		Predicted Class									
		1	2	3	4	5	6	7	8	9	0
Actual Class	1	98		1						1	
	2		100								
	3			98							2
	4				99				1		
	5					98	1				1
	6			6		2	92				
	7		2					98			
	8								100		
	9	15								85	
	0					1					99

One possible approach to overcome the challenge of correlated characters could be to combine character specific features with LBP. For example, in order to differentiate between class five and class six (with highly correlated bottom half), we could exploit features that give emphasis on the top half of the character image.

Another interesting observation is that even though simplified LBP uses only three sampling points or neighbor pixels ($2^3 = 8$ binary patterns), it can achieve quite similar performance to basic LBP (with 8 sampling points or $2^8 = 256$ binary patterns). Therefore, simplified LBP can have advantage in real-time applications such as license plate recognition from traffic videos where computational cost is a concern.

C. Comparison

Table IV demonstrates the character recognition accuracy achieved by different methods on CMATERdb. It is observed that Local Binary Pattern based features are able to achieve state of the art character recognition rate. The accuracy of the proposed method is comparable to that of the Genetic Algorithm based approach, and is identical to the Simulated Annealing and the Hill Climbing based approaches. The proposed method achieves higher accuracy than the rest of the methods presented in Table IV.

TABLE IV. COMPARISON OF CLASSIFICATION ACCURACY

Classification method	Accuracy
proposed method	96.7
Genetic Algorithm (GA) [2]	97
Simulated Annealing (SA) [2]	96.7
Hill Climbing (HC) [2]	96.7
Classifier Combination [3]	95.1
Sparse Representation Classifier [4]	94
Hierarchical Bayesian Network [5]	87.5

V. CONCLUSION

We propose a novel method for classification of handwritten Bangla numerals using LBP features. We evaluate this approach by using three different variations of LBP (the basic LBP, the uniform LBP, and the simplified LBP) using different zoning. The characters are classified using the Nearest Neighbor classifier. The initial inspection reveals a promising result. However, exploitation of more sophisticated classifiers is likely to result into an even better accuracy. Likewise, combining LBP features with other conventional features may also improve the recognition rate. Therefore, LBP features for classifying Bangla handwritten numerals should be investigated further.

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