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# Handwritten Numeral Recognition using Local Intensity Order Pattern of Popular South Indian Scripts

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**ABSTRACT :** Multi-lingual multi-script often poses various challenges in handwritten numeral classification. In this paper, we present a method for classification of off-line handwritten numerals of three popular Indian scripts. Here we consider Kannada, Telugu and Tamil scripts for our experiment. The features used in the classifier are obtained from local intensity order patter descriptor. For feature computation, Local Intensity Order Pattern (LIOP) is used. Basically LIOP encodes the local ordinal information of each pixel and the overall ordinal information is used to divide the local patch into sub-regions which are used for accumulating the LIOPs respectively. Therefore, both local and overall intensity ordinal information of the local patch are captured by the LIOP descriptor so as to make it a highly discriminative descriptor. LIOP descriptor features are not only invariant to monotonic intensity changes, image rotation but to many other geometric and photometric transformations such as viewpoint change, image blur issues are effectively addressed in our experiments [7]. A five-fold cross validation technique with numeral network classifier has been used for result computation and we obtained 98.34%, 98.40%, and 97.51% accuracy for Kannada, Telugu, and Tamil scripts respectively.

**KEYWORDS –** local intensity order pattern, Multi-lingual, Numeral Recognition, Neural network, South-Indian Script

## I. INTRODUCTION

The Recognition of handwritten numerals has been a popular research area for many years because of its various application potentials, such as Postal automation, Bank cheque processing, Automatic data entry etc. There are many notable works towards handwritten recognition of Roman, Japanese, Chinese and Arabic scripts, and various approaches have been proposed by the researchers towards handwritten numeral recognition [1]. Many published papers are available towards postal automation of non-Indian language documents and sorting systems are also available for postal automation in several countries like USA, UK, Japan, Germany etc. To the best of our knowledge there is no such sorting system is available for Indian post. System development towards postal automation for a country like India is difficult because of its multi-lingual and multi-script behavior.

The numeral recognition is an active subarea of character recognition field since many decades but still it carries variety of challenges which still need to be addressed. Many issues such as dealing with classification in multilingual scripts, variety in writing style, skew correction and many other are still open area of research.

## II. LITERATURE REVIEW

A statistical learning approach to Document image analysis by [1] have explained in the field of computer analysis of document images, the problems of physical and logical layout analysis and these problems have been approached through a variety of heuristic, rule-based, and grammar-based techniques. In this paper they investigate the effectiveness of statistical pattern recognition algorithms for solving these two problems, and report results suggesting that these more complex and powerful techniques are worth pursuing. First, they developed a new software environment for manual page image segmentation and labeling, and used it to create a dataset containing 932 page images from academic journals. Next, a physical layout analysis algorithm based on a logistic regression classifier was developed, and found to outperform existing algorithms of comparable complexity. Finally, three statistical classifiers were applied to the logical layout analysis problem, also with encouraging results [1]. On developing High accuracy OCR systems for Telugu and other Indian scripts [2], they list a number of factors that are important in achieving high recognition accuracy in OCR system for Telugu and other Indian scripts. They stated that it is easy to obtain 85% to 93% accuracy but difficult to improve the performance. They used their factors and achieved accuracy of nearly 97% with OCR system for Telugu script. These factors work for all other Indian scripts in general and south Indian Scripts in particular. In the work [3][6] a new chain-code quantization approach enabling high performance handwritten recognition based on multi-classifier schemes was proposed by S.Hoque and et.al,. They proposed a novel approach to classify handwritten character based on a directional decomposition of the corresponding chain code representation. This was alternative to previous transformation of the chain-codes proposed, namely the ordered and random decomposition of the bit-planes resulting from the binary representation of the chain-codes. The results obtained through a series of cross-validation experiments show that proposed fusion scheme not only outperforms its constituent's parts and number of other successful classifiers, but also enables significant savings in memory requirements compared to the original sntuple-based recognition system. In [4] authors have presented a review paper on OCR system which covers various methods for recognition and classification of characters as well as numerals. In [5], a precise programmatic approach for classifying handwritten characters is presented. OCR is age old problem but still there is lot more research issues are present. An advanced feature extraction, recognition and classification ideas are being addressed on numeral recognition

## III. DATASET

Dataset has been collected for all the three scripts. Handwritten samples are collected from various age groups covering even illiterate people as well. We had showed them the character template sample asked them to copy the graphics like image. This is done in order to capture all possible variation in the dataset. The same above said procedure is carried out for collecting the data sample for all the three scripts. Once the samples are collected on the paper, they are digitized by flatbed scanner at lowest possible conventional resolution to the highest conventional resolution (150 dpi for black and white, 300 dpi for intermediate quality and 600 dpi for high resolution quality). Thus we end up at creating sufficiently large dataset having a 12k samples for Kannada, 8k samples for Telugu and 6k samples for Tamil.

The collected dataset is divided into two subsets. The first subset randomly picks 70% of numeral characters for each class (each numeral corresponds to one class. Since there are 10 numerals available in each script including zero, thus 10 classes are created, with zero class repeated in the three scripts). This subset is used for training our classifier. The left over 30% of samples are put into other subset and we use this as validation set.

We have used printed as well as handwritten numerals for testing samples. The procedure followed for recognition of numerals is as follows: we first collected the much challenged samples for testing data in our model. Charted printed and written on the cheques, railway tickets, bus tickets, postal department forms and other information leaf where handwritten numerals are all collected. Later we scanned those images and segmented the numeral part in it. Using this we have collected nearly 600 samples for Kannada, 350 samples for Telugu and 275 numeral samples for Tamil scripts. The numeral characters collected from these sources comprises of various fonts, formats and different size (usually very small fonts). This efficiently gives lot of challenging for testing our proposed model.

## IV. PROPOSED METHOD

We had mentioned in the earlier section that, LIOP descriptor are being used to extract the features and neural network classifier with RBF kernel is used for recognition purpose. Our overall idea is depicted in the figure1

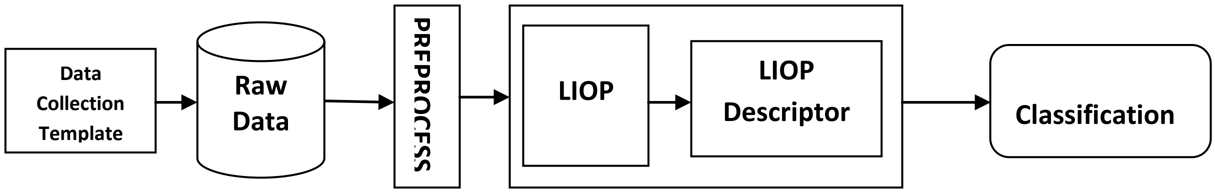


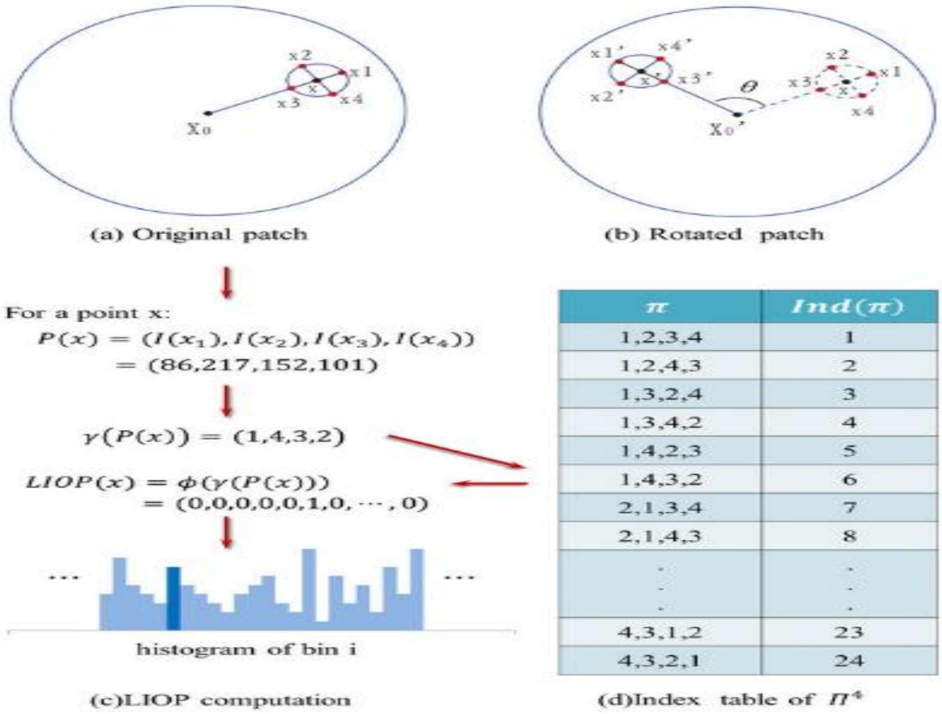

**Figure 1: Our method for handwritten numeral recognition**

In the following section, we discuss our effort in extrapolating LIOP feature descriptor for numeral character recognition problem. LIOP has been proven to be a very effective method to capture the local intensity variation and use it as a feature descriptor. We had employed a couple of preprocessing steps to remove noise in the raw dataset. We have used Gaussian filter to remove the noise and used the Otsu method to get the binary image out of TIFF format.

## V. LIOP FEATURE DESCRIPTOR

Local Intensity Order Pattern for feature description effectively exploits the local information by using the intensity order of all the sampled neighboring points [7]. It makes use of a rotation invariant sampling to avoid the estimation of the local consistent orientation. Thus, higher discriminative power is expected. The descriptor is constructed by accumulating the LIOPs of points in each ordinal bin respectively, then by concatenating them together. LIOP descriptor computation is shown in Figure 3. Mathematically, the LIOP descriptor of the local patch is computed as:

$$LIOP\ descriptor = (des_1, des_2, \cdots, des_B)$$
$$des_i = \sum_{x \in bin_i} LIOP(x)$$




| $\pi$ | $Ind(\pi)$ |
|---|---|
| 1,2,3,4 | 1 |
| 1,2,4,3 | 2 |
| 1,3,2,4 | 3 |
| 1,3,4,2 | 4 |
| 1,4,2,3 | 5 |
| 1,4,3,2 | 6 |
| 2,1,3,4 | 7 |
| 2,1,4,3 | 8 |
| ⋮ | ⋮ |
| 4,3,1,2 | 23 |
| 4,3,2,1 | 24 |

**Figure 2: (a) Original patch – numeral image (b) Rotated Patch with theta degree (c) LIOP Computation (d) Index table**

The feature vector obtained from LIOP descriptor are augmented as row vectors and preserved as feature vectors. In the next stage a simple neural network with 2 hidden layers is used for training the classifier. The parameters used for neural network are as follows. Stochastic gradient descent algorithm is used with back propagation for learning phase. A log-loss error function is considered. Learning rate and momentum are set to 0.001 and 0.9 respectively.

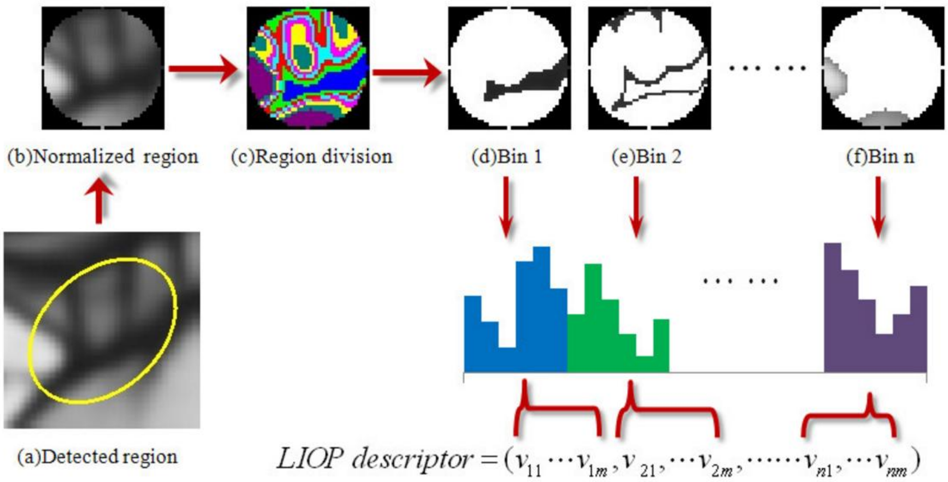



**Figure 3: (a) Intensity detected region (b) Normalized Image (c) Region Division (d)Bin1 (e)Bin2 (f) Bin n (corresponding descriptor shown as histogram)**

## VI. RESULTS AND DISCUSSION

In this section we present the recognition results obtained from our model in table1. From our experiments we noted that LIOP features yield results irrespective of the scripts used. However we trained different model on each script but the results seems to be within the model. In our future work we aim to consider 30 class problems instead of 3 different 10 class problem. We have compared our results with some recent research papers on the numeral recognition and we found that our method meets the state of art results.

Table 1: Results

| Script | Recognition Rate (%) |
|---|---|
| Kannada | 98.34 |
| Telugu | 98.47 |
| Tamil | 97.51 |

## VII. CONCLUSION

In this paper, we present an idea of inheriting the popular texture based method, local intensity order pattern to utilize on the handwritten numeral recognition. The results obtained from our experiments clearly states that LIOP features can be one of the good feature descriptor for handwritten numeral recognition task. India is a multi-lingual and multi-script country comprising of 18 official languages. But not much work has been done towards off-line handwriting recognition of south Indian scripts such as Kannada, Telugu and Tamil languages. In this case considering all the scripts at once and posing the problem of classifying large classes will produce script independent results and this is very much required to efficiently address the multilingual script recognition task. In this regard we aim to take up this task in near future work.

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