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FEATURE EXTRACTION AND DIMENSIONALITY REDUCTION IN PATTERN RECOGNITION USING HANDWRITTEN ODIA NUMERALS

[1]PRADEEPTA K. SARANGI, [2]KIRAN K. RAVULAKOLLU

[1]Asstt Prof., School of Computer Science, Apeejay Institute of Technology, Greater Noida, U.P, India
[2]Asst. Prof., Sharda University, Greater Noida, U.P, India
E-mail: [1]pradeepta_sarangi@yahoo.com, [2]kiran.ravulakollu@sharda.ac.in

ABSTRACT

Feature extraction is the initial and critical stage which needs to be carried out very carefully for any recognition system that uses pattern matching. In order to reduce the feature extraction complexity, dimensionality reduction is applied. This also increases the performance and recognition accuracy. This paper proposes the concept of a new feature extraction and dimensionality reduction method based on a set of linear transformation of the character image. The verification of the method has been carried out by implementing a simple recurrent neural network (RNN) with a data set consisting of 1500 isolated handwritten Odia numerals. An accuracy of 92.41% is reported. Experimental results show that the proposed method has the potential to be used as a feature extraction method for handwritten Odia numerals.

Keywords: *Handwritten Recognition, Odia Numerals, Recurrent Neural Network, Feature Extraction*

1. INTRODUCTION

Odia is a regional language derived from the Devanagari script and commonly used in north-eastern States of India. It is one of the many official languages of India and mainly spoken in Odisha and in some parts of West Bengal. Although, Odia is one of the many official languages, the research on Odia character recognition system is not so advanced as on other Indian languages. The condition for handwritten characters is even worse. Whatever research works have been done so far or the ongoing researches in progress are mainly the application of various existing techniques either single or combined. Research on handwritten Odia characters has not been much explored as only a few research centers at national level are involved in exploring Odia script. Utkal University, Bhubaneswar is the only center in the State (Odisha) reported to be engaged in research on Odia script [1]. This provides a lot of scope available for researchers in this area. Here, we present some of the related and recent developments on handwritten Odia numerals by various researchers (table-1) including our own previous works [3, 6, and 10].

Data set is another key factor for any successful OCR system design. Availability of a standard data set helps researchers to easily implement new methods /techniques in the field and compare results. However, in this research, we have used our own collection of data. Handwritten numerals have been collected from several people on a plain paper. The respondents were of different qualifications, age groups and professions. Each respondent was asked to write each numeral five times as shown in the figure-1.

Table-1: Summary Of Related And Recent Works

Authors	Classifier	Recognition
Pal et al. [2]	MQC	98.40
Sarangi et al.[3]	Hop Field	95.40
Jindal et al.[4]	MLP	94.20
Mahato et al. [5]	ANN	93.20
Sarangi et al. [6]	Naive Bayes	92.75
Mishra et al. [7]	BPNN	92.00
Bhowmik et al.[8]	HMM	90.50
Roy et al. [9]	Quadratic	90.38
Sarangi et al.[10]	Neural Network	85.30

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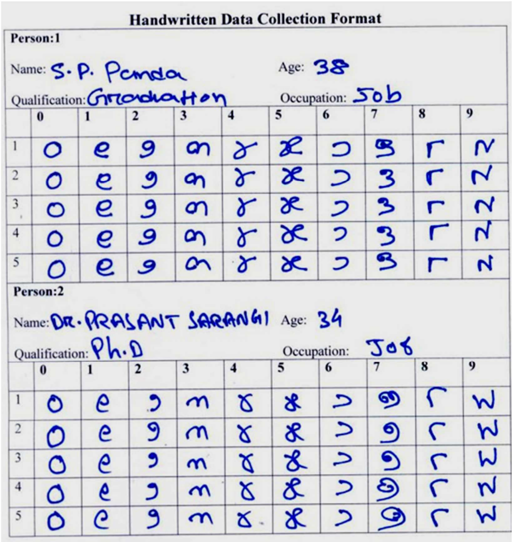

Fig-1: Sample Data Set Collected From Two Persons

A total of 1500 different numerals for all ten classes (0 to 9) consisting of 150 numerals of each class have been collected from 30 people. The data set has been divided into training patterns and test patterns.

The following sections of this article describe the general concept of feature extraction & state-of-the-art, the architecture of the proposed method, step-wise description and finally verification of the method by implementing recurrent neural network as the classifier.

2. FEATURE EXTRACTION

Feature extraction (FE) is the process of finding a smaller set of elements (feature vector) that represents the original object in a miniature form. Feature vector represents the inherent properties of the original image. Too many parameters in the feature vector may not solve the purpose at all and at the same time very few parameters may not be able to represent the original object in the appropriate form. Feature extraction is highly subjective in nature and depends on the type of problem we are trying to handle. No generic feature extraction method is available to work for all cases. It is also almost impossible to rank an algorithm as the best for feature extraction. It all depends on the application at hand. Since no standard feature extraction method exists, researchers have to develop or adopt suitable feature extraction method depending on the nature and properties of the data set. A list of feature extraction methods used in various pattern recognition systems is found in [11]. In case of handwritten Odia numeral recognition system, no knowledgeable work is reported towards proposition of new feature extraction method. The authors have mainly put their efforts towards using existing feature extraction techniques except our own work [6, 10]. Here, we present some of the feature extraction methods used in handwritten Odia numeral recognition [table-2].

Table-2: FE Techniques In Odia OCR

Authors	Features
Pal et al. [2]	Directional
Sarangi et al. [3]	Binary image
Jindal et al.[4]	Zernike moment
Mahato et al. [5]	Quadrant mean
Sarangi et al. [6,10]	LU Factors
Mishra et al. [7]	DCT and DWT
Bhowmik et al. [8]	Scalar
Roy et al. [9]	Chain Code Histogram
D. Padhi[12]	Zone centroid distance and standard deviation
Pal et al.[13]	Curvature feature

This review reveals that research on handwritten Odia characters has not been much explored. Only a few works are reported towards the handwriting recognition of Odia numerals. This seems to be a potential area, where a lot of scope for innovation is available for researchers .

3. MOTIVATION

The basic questions that motivate to propose this new feature extraction method are:

i. Are all feature extraction methods based on mathematical/logical derivations?

ii. Is minimum size of the image a relevant factor for particular feature extraction method?

iii. What relationship exists between the feature vector and the original image?

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iv. Is it possible to reconstruct the original image from the feature vector?

Non-availability of sufficient literature to give a satisfactory answer to these questions motivated us to propose a new feature extraction method, which could probably answer these questions maintaining the basic objectives of feature extraction along with efficiency and accuracy.

4. FEATURE EXTRACTION: PROPOSED METHOD

The proposed method is based on the row wise decimal conversion of the elements using binary matrix of the image. The block diagram of the proposed method is given in figure-2

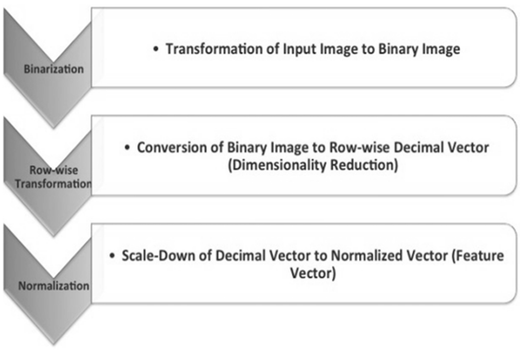

Fig-2: Block Diagram Of The Proposed Method

The main characteristics of this method are:

- It is very simple to calculate the feature values. Only three steps are required to extract the feature values.
- The feature values are extracted by a set of inter-connected logical steps.
- The size of the feature vector depends directly on the size of the image. If the image-size increases, then the size of feature vector also increases. However, there is no need of using large image size as an image of size as low as of '8 x 8' could effectively represent the original image.
- The original image could be reconstructed from the feature vector by back-tracking the steps.
- A one-to-one relationship exists between the original image and the feature vector.

The steps involved in feature extraction for this proposed method are given below:

i. Pre-process the extracted numeral image (cropping & resizing).

ii. Convert the input gray scale image to binary image.

iii. Calculate the row wise decimal values considering one row in the binary image as one binary number.

iv. Finally, scale down the decimal values to the range of 'zero' to 'one' using suitable formula.

Here, we have used the following formula:

$$\text{Scaled-Down-Value} = (\text{Actual-Value} - X) * \frac{Y}{Z} \qquad \text{...........Eq.(1)}$$

where, the X is the lower bound of the data set, Y is the value calculated based on the difference of upper bound and lower bound of data set and Z is one unit based on the value of Y. Each image has a fixed binary representation. If we take each row in the binary image as a binary number and convert it to decimal values then we will get a set of decimal values. Each of these decimal values represents one row in the binary image. For example, if we take an image size of '8 X 8' then we will get 'eight' rows of decimal values. Then converting these decimal values to the range from 'zero' to 'one', we will get the desired feature vector. An explanation is given in figure-3.

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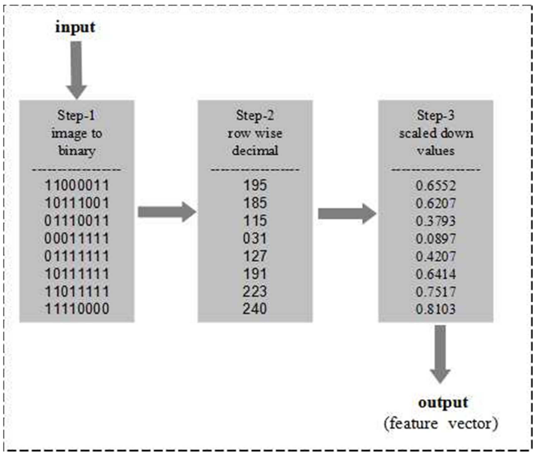

Fig-3: FE Using The Proposed Method

The above diagram describes a pictorial representation of an example of implementation of the proposed feature extraction method.

5. EXPERIMENTAL VERIFICATION

Selection of a suitable classifier is an important aspect in the performance of any OCR system. However, no standard rules are available to decide the classifier. All these have to be done only on experimental basis based on the nature of the script and characters. Since this research deals with handwritten Odia numerals, the implementation strategy has been designed keeping in mind the nature of the data set. A simple recurrent neural network (also known as Elman Network) has been used as the classifier for this research. An Elman network is an MLP with a single hidden layer and in addition it contains connections from the hidden layer's neurons to the context units. The context-units store the output values from the hidden neurons in a time unit and these values are fed as additional inputs to the hidden neurons in the next time unit. [14]. RNNs use their internal memory to process arbitrary sequences of inputs. This makes them applicable to handwriting recognition, where they have achieved the best-known results [15]. The main characteristic of RNN is the internal feedback or time-delayed connections. A simple structure of RNN [14] is given in figure-4 .

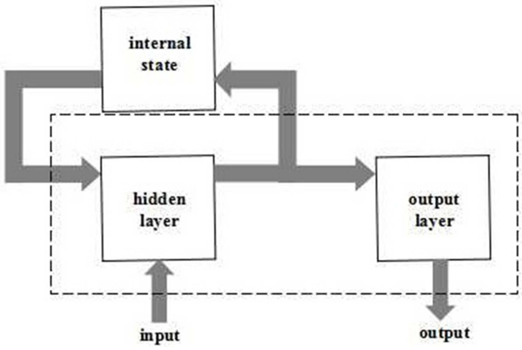

Fig-4: A Simple Elman Network

The diagram above represents a simple structure of an Elman network. The dotted box (lower one) represents a simple MLP and the upper box (out side the dotted line) represents the internal state that stores the time delay.

5.1 Training Algorithm

Training procedure of a recurrent neural network is similar to the case of MLP training where the network's output is compared with the target output. The square error is used to update the network's weights according to the error back propagation algorithm. If X^n is the vector produced by the union of input and context vectors, then the training algorithm for an Elman network is very similar to the algorithm for an MLP network training and is described below [14]:

1. Initialize the weight vector $w(0)$ with random values in (1,1), the learning rate η, the repetitions counter (*k=0*). Initialize the context nodes at 0.5.

2. Let $W(k)$ be the network's weight vector in the beginning of epoch *k*

   i. Start of epoch *k*. Store the current values of the weight vector $W_{old} = W(k)$

   ii. For *n=1, 2, 3, …N*

   a. Select the training example (X^n, t^n) and apply the error back propagation in order to compute the partial derivatives $\frac{\partial E^n}{\partial w_i}$

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b. Update the weights

$$w_i(k+1) = w_i(k) - \eta \frac{\partial E^n}{\partial w_i}$$

c. Copy the hidden nodes' values to the context units.

iii. *End of epoch* k Termination check. If true, terminate.

3. *k=k+1.* Go to step-2.

5.2 Implementation

A simple recurrent neural network (SRN) with back propagation learning has been implemented. The network structure and various parameters used in this implementation are as under:

Architecture: 8-8-10

Type: Recurrent neural network

Input patterns: Feature vectors (8 elements)

No. of test patterns: 1200

Learning algorithm: Back propagation

Performance: Mean Squared Error (MSE)

An example of the network structure is given in figure-5.

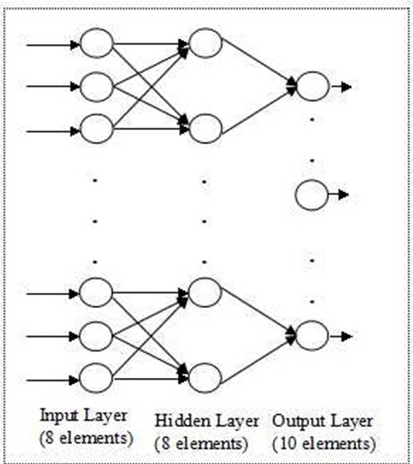

Fig-5: An Example Of The Network Structure

The diagram above represents a simple structure of an MLP consisting of one input layer (8 elements), one hidden layer (8 elements) and one output layer (10 elements).

5.3 Result Analysis and Discussion

Once the training was over, the target patterns were presented to the network one by one and the output was noted. The results are summarized in table-3.

Table-3 : Network Output For Test Patterns

Input Class	Correct Classifications	Recognition Accuracy
0	113	94.16
1	102	85.00
2	105	87.50
3	108	90.00
4	110	91.66
5	116	96.66
6	116	96.66
7	109	90.83
8	116	96.66
9	114	95.00

A total of 1200 patterns for all ten classes (120 patterns for each class) have been tested on the network. The confusion matrix is given in table-4 below.

Table-4: Confusion Matrix

Class	0	1	2	3	4	5	6	7	8	9
0	113	4	3	0	0	0	2	0	0	0
1	1	10	12	0	2	0	3	0	0	0
2	2	11	105	0	0	0	0	2	0	0
3	0	1	2	108	4	0	2	0	1	2
4	1	2	1	0	110	3	0	2	1	0
5	0	0	0	0	3	116	0	1	0	1
6	1	0	2	0	0	0	116	0	0	1
7	1	1	4	2	0	0	2	109	0	1
8	0	0	0	0	0	0	1	0	116	3
9	0	0	0	0	0	0	1	1	4	114

Here, we observe that the incorrect classifications are more between '1' and '2' and the reason is that the characters 1 and 2 in Odia language are just mirror image of each other. This problem could be resolved if we consider the column decimal values instead of row decimal values.

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5. CONCLUSION

A new feature extraction method is proposed which is based on set of linear transformation. The method has been verified by implementing a simple recurrent neural network. An overall recognition accuracy of 92.41% is reported. When we compare the recognition accuracy with other similar works (table-1), this result stands at sixth best position. This does not imply that this method is inefficient because recognition accuracy differs for different languages, even if the same feature extraction and classification methods are used. Here we just propose a new method and it is in the beginning stage. It is also too early to say that the method will be universally applicable to all types of scripts. More experiments and researches are required to test the suitability of this method applicable for other languages. Even for handwritten Odia numerals, the applicability of this proposed feature extraction method needs to be tested with a larger size data set and with Odia alphabet also. Another approach could also be considered by taking column-wise elements instead of row-wise.

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