Using a gradient of grey scale images, handwritten Odia numerals can be recognised

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Abstract *– The paper presents a system to recognize handwritten Odia numerals in a simple and efficient method with more accuracy. The standard gradient strength and angle are extracted for a gray scale image and are mapped by sine and cosine expansions. These non-linear inputs are fed to a FLANN classifier. The classification shows 98% accuracy in simulation by using different test patterns***.

Keywords*— character recognition, feature extraction, gradient feature, normalisation, principal component analysis gradient feature, curvature feature, principal component analysis, Classifier and artificial neural network*

I. INTRODUCTION

Character recognition means electronic translation of images of handwritten, typewritten or printed text or numerals into machine editable text or numerals. Handwritten character or numerals recognition is difficult as different people have different handwriting styles. So the handwritten character or numerals recognition a difficult yet active area of research. This system consists of two steps (i) representation of the character/numeral as a vector of features and (ii) classify the feature vector into classes.

Various authors have worked on handwriting recognition of Chinese/Japanese and English languages; Indian languages, Hindi, Bangla, Tamil, etc. Odia is one of the major languages used in India which has 10 numerals. Some work for printed Odia character has been carried out to recognize individual characters using a combination of stroke and run-number based features. The authors have reported a classification accuracy of an average of 96.3% [1]. In 2005 three image databases of handwritten isolated numerals of three different Indian scripts namely Devnagari, Bangla and Oriya have been developed [2]. The grayscale images of Odia numerals written by 400 persons have been collected.

which also includes an image database of handwritten Odia numerals [2]. The training and test results of the proposed approach are presented on the basis of this database. In the proposed research the recognition of handwritten Odia numerals 0-9 are used. Each numeral is having 300 data for training and 100 data for testing purpose.

Modified quadratic classifier based scheme for the recognition of off line handwritten numerals of six popular Indian scripts including Odia has been suggested in [3]. The features are obtained from the directional information of the numerals. The curvature feature and quadratic classifier is used for off line Odia handwritten character recognition [4]. The accuracy of classification reported sis 94.6%. Hidden Markov model (HMM) has been proposed in 2006 [5] for recognition of handwritten Odia numerals. The classification accuracy obtained is 90.50%. The neural network is used as classifier in [6] for recognition of off line unconstrained Odia handwritten numerals. Features are mainly considered from the contour of the numerals. In this case the recognition accuracy obtained is 90.38%. An extensive literature survey reveals that little work has been done on recognition of this language. In the present work we propose the functional link artificial neural network (FLANN) based classifier for recognition of handwritten Odia numerals. The gradient and curvature features [7] of the numerals are used separately as the inputs to the FLANN classifier.

The paper is organized into four sections. Section 1 discusses the introduction part. Data collection and feature extraction are dealt in Section 2. In Section 3 a low complexity nonlinear classifier is developed. The performance of the classifier is assessed through simulation study and presented in Section 4. Section 5 provides the conclusion of the investigation.

II. DATA COLLECTION AND FEATURE EXTRACTION

Development of a handwriting recognition system requires a large set of training samples. Further generation of such a data set is always difficult since it is time consuming and labor intensive. Such standard training data sets for any Indian script are not available in public domain. However, a handwritten database have recently been developed

a. Pre-processing of data

A gray scale image is generated from an input binary image of the numerals and the gradient is obtained as follows:

(1) The input image is normalized so that each image has standard width and height of 64 x 64(Fig. 1(a)).

(2) The mean filter of size 3×3 is repeatedly applied number of times to obtain a gray scale image (Fig. 1(b)).
(3) The gray scale image is further normalized so that the mean and the maximum of the gray scale become 0 and 1, respectively.

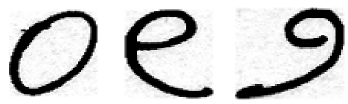

Fig. 1(a) Normalized binary image

Fig. 1(b) Gray scale image

b. Feature extraction

The steps involved in feature extraction process are : gradient calculation, and dimension reduction of the feature vector. Each procedure is dealt one by one.

Calculation of gradient

The Roberts filter [8, 9] is applied to each pixel *g(i, j)* of the normalized image to calculate the gradient by using (1). The strength and gradient so obtained are shown in (Figs. 2(a) and 2(b)) respectively.

$$\left.\begin{aligned} \Delta u &= g(i+1, j+1) - g(i, j) \\ \Delta v &= g(i+1, j) - g(i, j+1) \\ Direction(i,j) &= \tan^{-1}\left(\frac{\Delta v}{\Delta u}\right) \\ Strength(i,j) &= \sqrt{(\Delta u)^2 + (\Delta v)^2} \end{aligned}\right\} \quad (1)$$

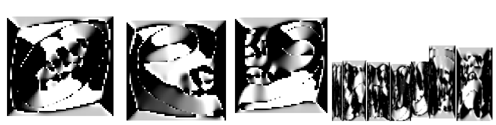

Fig. 2(a) Direction of Gradient

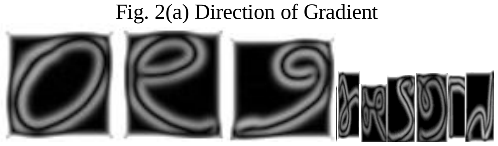

Fig. 2(b) Strength of Gradient

c. Generation of Gradient feature vector

(1) The direction of gradient detected in (1) is quantized to 32 levels with $\pi/16$ interval.

(2) The normalized character image is grouped into 81 (9 horizontal × 9 vertical) blocks.

(3)The strength of the gradient is computed separately in each of 32 directions. Thus 81 local spectra of direction are obtained. This gives rise to feature vector of size 2592 (9x9x32).

(4) To achieve Gaussian like distribution of features a variable transformation ($y = x^{0.4}$) is applied.

d. Feature reduction using PCA

The Principal Component Analysis (PCA) [10] is technique of identifying patterns in data so as to highlight their similarities and differences. The PCA compresses the data by reducing the number of dimensions, without much loss of information. The steps involved in PCA based feature reduction are

Step 1: Get the features
Step 2: Subtract the mean
Step 3: Calculate the covariance matrix
Step 4: Calculate the eigen vectors and eigen values of the covariance matrix.
Step 5: Choose those eigen vectors whose eigen values are greater than or equal to one. These components form a feature vector.
Step 6: Multiply the normalized data set with the feature vector obtained above.
Using this technique the dimension of gradient features has been reduced from 2592 to 66.

III. DEVELOPMENT OF CLASSIFIER

After extracting the features a low complexity single layer network is used for numeral classification. In this network the input pattern is nonlinearly mapped to using trigonometric (sine/cosine) functions. The block diagram of this classifier is shown in Fig. 5. The details of this network along with the learning algorithm are available in [10].

The reduced gradient and curvature features of the Odiya numerals 0, 1 and 2 are used as the inputs to the proposed classifier. The class number is used as the training signal to the classifier. Since in present case the training features belong to three classes according the desired value is applied during training.

In this model the input vector contains 396 x 66 and gradient features and 396 x 64 curvature features for each numeral. Each feature is expanded to three trigonometric terms and then fed to the classifier. The three outputs obtained are compared with training signal to produce three errors. The mean error is used as the cost function for designing the classifier. The epoch based learning of weights is carried out using the delta learning rule [10]. The classification results obtained when test operation are applied are shown in Tables 1-3. The recognition accuracy obtained are 99% (with training dataset) and 98%(with testing dataset) using gradient features . Table 2 compares the classification performance of three different methods with that obtained from the proposed classifier. The new classifier offers comparable performance with the MDQF but it offers low complexity. In addition it is adaptive in nature.

Table 1: Classification results using gradient feature during training

Classified observations	**Class1**	**Class2**	**Class3**
Class1	**97**	0	0
Class2	3	**100**	0
Class3	0	0	**100**

Table 2: Classification results using gradient feature during testing

Classified observations	**Class1**	**Class2**	**Class3**
Class1	**94**	0	0
Class2	5	**100**	0
Class3	1	0	**100**

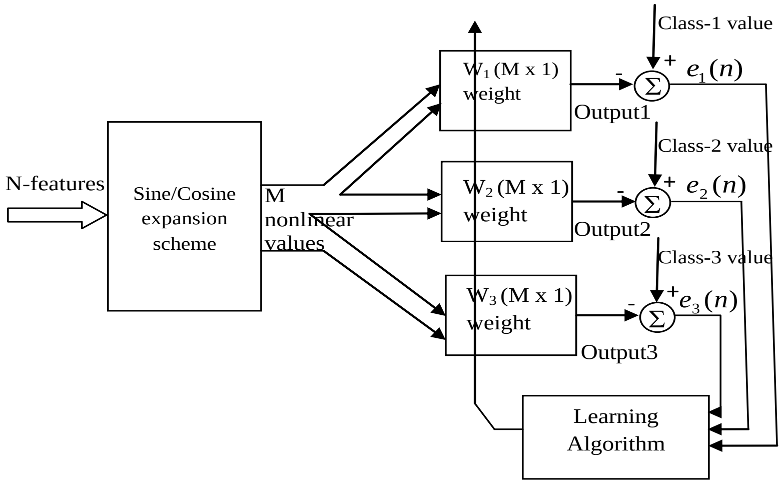

Fig. 1 A low-complexity nonlinear classifier of handwritten Odiya numerals

Table 3: Comparison of recognition accuracy of Odia numerals using different classifiers

Classifier types	**Recognition Accuracy**
Modified quadratic discriminant function(MDQF)	98.04%
Hidden Markov model(HMM)	90.50%
Neural Network(NN)	90.38%
Proposed model	98%

IV. CONCLUSION

In this paper an efficient low complexity nonlinear classifier is developed for recognising handwritten Odia numerals. The details of feature extraction and classifier design are outlined. The simulation results show that the proposed classifier is not only simple but offers performance which is comparable to best available methods. Work is ongoing to recognize the handwritten Odia characters.

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