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Kohonen neural network based Kannada numerals recognition system

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Abstract- In spite of several advancement in technologies pertaining to optical character recognition (OCR), the process of pattern recognition pose quiets a lot of challenges especially in recognizing hand-written scripts of different languages in India. Handwriting continues to persist as means of documenting information for day today life especially in rural areas. In this paper we proposed a novel approach for feature extraction in spatial domain to recognize segmented (isolated) Kannada numerals using Kohonen neural networks. Artificial neural systems represent the promising new generation of information processing networks to develop intelligent machines which can be used as classifier.. Handwritten numerals are scan converted to binary images and normalized to a size of 30 x 30 pixels. The features are extracted using spatial co ordinates and are given to Kohonen neural network classifier. Kohonen SOM used Euclidean distance to determine best-matching unit and utilized two-dimensional layer map. Higher degree of accuracy in results has been obtained with the implementation of this approach on a comprehensive database.

Index terms- Handwritten Kannada numerals, Artificial Neural Network,, Feature Extraction, Pattern Classification, Kohonen Neural Network, Self Organizing Feature Map.

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1. INTRODUCTION

Pattern recognition encompasses two fundamental tasks: description and classification. Given an object to analyze, a pattern recognition system first generates a description of it (i.e., the pattern) and then classifies the object based on that description (i.e., the recognition).

Character extraction and recognition techniques have potential application in any domain where a large mass of document image-bearing texts must be interpreted or analyzed. Conventionally, such images are processed by human operators who act according to what has been written or simply key in what they read onto a computer system that carries out further processing, say of postal address [1] This process can be automated using computer popularly known as pattern recognition system.

The essential problem of pattern recognition is to identify an object as belonging to a particular group. Assuming that the objects associated with a particular group share common attributes more so than with objects in other groups, the problem of assigning an unlabeled object to a group can be accomplished by determining the attributes of the object (i.e., the pattern) and identifying the group of which those attributes are most representative (i.e., the recognition). This can be done by artificial neural networks.

The main thing missing in computers when compared to humans is the ability to think and take decisions as human brain does. One of the ways of making computers brainy is to simulate a human brain in the computer. The brain learns by experience (i.e., through examples). In order to simulate a brain in the computer, we have to make the computer to learn by examples and use this knowledge in future.

Pattern recognition is becoming more and more important in modern world. It helps humans ease their jobs and solve more complex problems. The recognition of handwritten numerals has been the subject of much attention in pattern recognition because of its number of applications such as bank check processing, interpretation of ID numbers, vehicle registration numbers and pin codes for mail sorting.

The penetration of Information Technology (IT) becomes harder in a country such as India where the majority people read and write in their native language. Therefore, enabling interaction with computers in the native language and in a natural way such as handwriting is absolutely necessary [4]. The need for OCR arises in the context of digitizing Kannada documents from the ancient and old era to the latest, which helps in sharing the data through the Internet [5]. Kannada, the native language of a southern state in India i.e, Karnataka has several million speakers across the world and is received cultural status from central government very recently.

The Kannada language is one of the four major south Indian languages. It is spoken by about 50 million people in the Indian states of Karnataka, Tamilnadu, Andhra Pradesh and Maharashtra. The Kannada alphabet consists of 16 vowels and 36 consonants. It also includes 10 different symbols representing the ten numerals of the decimal number system as shown in figure1.

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1. 1.1 Kannada Numeral Set

Figure1. Kannada numerals 0 to 9

In the literature, many papers have been published with research detailing new techniques for the classification of handwritten characters and promising feature extraction methods have been identified in the literature for recognition of characters and numerals of many different scripts. These include template matching, projection histograms, geometric moments, Zernike moments, contour profile, Fourier descriptors, and unitary transforms. A brief review of these feature extraction methods is found in [1]. Various methods have been proposed, and high recognition rates are reported, for the recognition of English handwritten digits [8 - 10]. The task of classification is to partition the feature space into regions corresponding to source classes or assign class confidences to each location in the feature space. Statistical techniques, neural networks, and more recently support vector machine (SVM) have been widely used for classification due to the implementation efficiency [1-5].

From the literature survey, it is evident that the work on handwritten Kannada numeral recognition is still in infant stage. This has motivated us to design a recognition system for handwritten Kannada numerals.

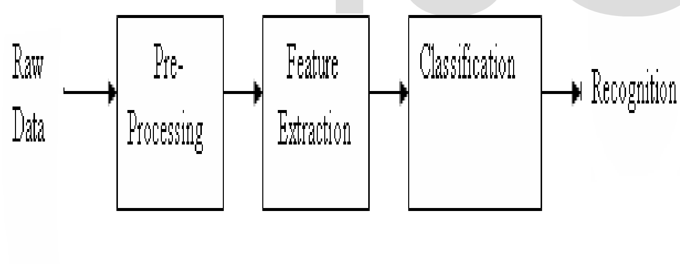

Fig 2. Typical pattern recognition system

2. NUMERALS RECOGNITION SYSTEM

A typical pattern recognition system consists of three stage processes as shown in figure 2. The first stage is Pre-processing, second stage is Feature extraction and the third stage is Classification.

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4. 2.1 Pre-processing

Pre-processing involves normalizing the raw data given to the computer so that the further processing is easier. The typical preprocessing operations involves noise reduction, size normalization, slant estimation and correction, thinning, segmentation etc.,

5. 2.2 Feature Extraction

When the input data to an algorithm is too large to be processed and it is suspected to be redundant then the input data will be transformed into a reduced representation set of features. Transforming the input data into the set of features is called features extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. The set of features that are used makes up a feature vector, which represents each member of the population. Then, character recognition system classifies each member of the population on the basis of information contained in the feature vector [6].

Selection of a feature extraction method is probably the single most important factor in achieving high recognition performance in character recognition systems. The features that are extracted are fed to the Classifiers for further processing. Bar code method used to extract features of numerals in our system.

2.2.1 Barcode Method

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which over fits the training sample and generalizes poorly to new samples.

Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Best results are achieved when an expert constructs a set of application-dependent features.

In barcode feature extraction method pattern may be divided into number of boxes as given in fig 2. which suits the given pattern. Advantage of this method is its flexibility, that is, we may choose any number of boxes out of given pattern. Then the features of pattern can be extracted by choosing suitable boxes (the darken boxes as in the Fig 2.) We may choose any number of boxes for feature extraction. Selection of boxes for feature extraction will decides the pattern recognition rate. Optimum number of features at optimum places of pattern gives us high rate of recognition as such. In our system we extracted 17 features out of given pattern assuming the pattern has

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under gone all pre processing procedures like thinning, normalizing, tilting rotation etc.,

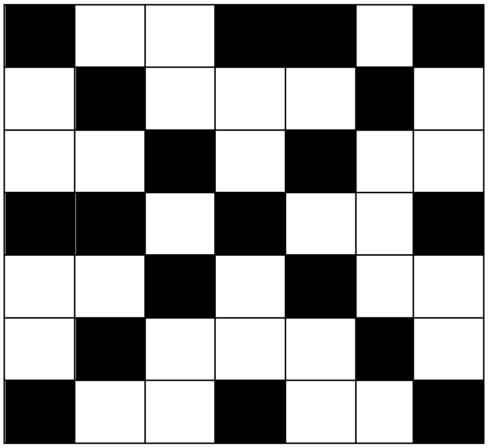


Fig 2. Pattern's feature areas

Thus the feature values F1; F2; : : : ; F17 are evaluated and stored in a feature array.

Algorithm:

1. Read the pattern in bmp format.
2. Choose suitable number of boxes out of whole pattern
3. For each box area, count number of 'ON'cells and total number of cells present in that box.
4. Feature value F is
 sum of values of 'ON' cells / sum of values of all the cells.
5. Repeat this for all the chosen boxes in the patterns.

The pattern is bmp image which normally contains 1's and 0's based on shape of pattern. The bmp image value for the pattern '1' is given in Fig 3.

0	0	0	1	1	0	0	0
0	0	1	0	0	1	0	0
0	1	0	0	0	0	1	0
0	1	0	0	0	0	1	0
0	1	0	0	0	0	1	0
0	1	0	0	0	0	1	0
0	1	0	0	0	0	1	0
0	1	0	0	0	0	1	0

Fig 3. BMP Image values

Consider the 3x3 box in a given pattern as in Fig 4. From which a feature vector is calculated as:

F1=number of ON cells / total number of cells.

0	0	0
0	0	1
0	1	0

Fig 4. Feature Vector Area

i.e., F1=2/9=0.2222

6. 2.3 Classification

Classification is a step in numerals recognition which accepts extracted features from the feature extraction step and identifies the pattern written. A large number of classifiers are available: parametric and nonparametric statistical classifiers, neural networks, support vector machines (SVMs), hybrid classifiers etc [9]. Kohonen Neural Network has been used as a classifier in our system.

7. 2.3.1 Artificial neural network (ANN)

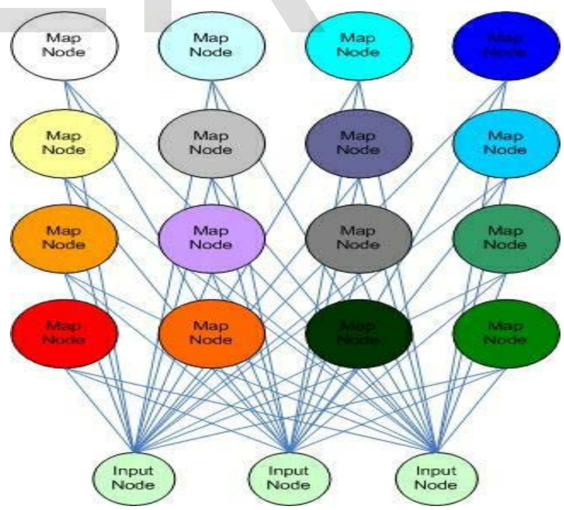
Artificial neural network systems have great ability to learn by experience and generalize the inputs to produce reasonable outputs for inputs that were not encountered during learning (training).

8. 2.3.2 Kohonen Self organizing map

Two-dimensional (m x n) input and weight vector are employed to the application. The two-dimensional lattice of map produces random values for the initial weight vector For the learning rate and the neighbourhood size (radius of neighbourhood) is initialized with the maximum value. Morever, kohonen neural network learning with SOM algorithm where the require neurons to be competitive to become a winner in the layer map. Thus, the minimum Euclidean distance is used to determine the winner.

9. Network Architecture

The network is created from a 2D lattice of 'nodes', each of which is fully connected to the input layer. Figure 5 shows a very small Kohonen network of 4 X 4 nodes connected to the input layer representing a two dimensional vector.



10. Figure 5 A simple Kohonen network.

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13. Each node has a specific topological position (an x, y coordinate in the lattice) and contains a vector of weights of the same dimension as the input vectors.

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That is to say, if the training data consists of vectors, V, of n dimensions:

V1,V2,V3,………………Vn;

Then each node will contain a corresponding weight vector W, of n dimensions:

W1,W2,W3……………………Wn;

There are no lateral connections between nodes within the lattice.

Learning Algorithm Overview

A SOM does not need a target output to be specified unlike many other types of network. Instead, where the node weights match the input vector, that area of the lattice is selectively optimized to more closely resemble the data for the class the input vector is a member of. From an initial distribution of random weights, and over many iterations, the SOM eventually settles into a map of stable zones. Each zone is effectively a feature classifier. Any new, previously unseen input vectors presented to the network will stimulate nodes in the zone with similar weight vectors.

Training occurs in several steps and over many iterations:

1. Each node's weights are initialized.

2. A vector is chosen at random from the set of training data and presented to the lattice.

3. Every node is examined to calculate which one's weights are most like the input vector. The winning node is commonly known as the Best Matching Unit (BMU).

4. The radius of the neighbourhood of the BMU is now calculated. This is a value that starts large, typically set to the 'radius' of the lattice, but diminishes each time-step. Any nodes found within this radius are deemed to be inside the BMU's neighbourhood.

5. Each neighbouring node's (the nodes found in step 4) weights are adjusted to make them more like the input vector. The closer a node is to the BMU, the more its weights get altered.

6. Repeat step 2 for N iterations.

Calculating the Best Matching Unit

To determine the best matching unit, one method is to iterate through all the nodes and calculate the Euclidean distance between each node's weight vector and the current input vector. The node with a weight vector closest to the input vector is tagged as the BMU.

The Euclidean distance is given as:

$$Dist = \sqrt{\sum_{i=0}^{i=n} (V_i - W_i)^2}$$

Equation 1

where V is the current input vector and W is the node's weight vector

Determining the Best Matching Unit's Local Neighbourhood

Each iteration, after the BMU has been determined, the next step is to calculate which of the other nodes are within the BMU's neighbourhood. All these nodes will have their weight vectors altered in the next step. A unique feature of the Kohonen learning algorithm is that the area of the neighbourhood shrinks over time. This is accomplished by making the radius of the neighbourhood shrink over time

$$\sigma(t) = \sigma_0 \exp\left(-\frac{t}{\lambda}\right) \qquad t = 1, 2, 3..$$

Equation 2

where the Greek letter sigma, σ0, denotes the width of the lattice at time t 0 and the Greek letter lambda, λ, denotes a time constant. t is the current time-step.

Adjusting the Weights

Every node within the BMU's neighbourhood (including the BMU) has its weight vector adjusted according to the following equation:

$$W(t+1) = W(t) + L(t)(V(t) - W(t))$$

Equation 3

Where t represents the time-step and L is a small variable called the learning rate, which decreases with time. Basically, what this equation is saying, is that the new adjusted weight for the node is equal to the old weight (W), plus a fraction of the difference (L) between the old weight and the input vector (V).

The decay of the learning rate is calculated each iteration using the following equation:

$$W(t+1) = W(t) + L(t)(V(t) - W(t))$$

Equation 4

14. 2.5 Recognition

Once the artificial neural network is trained to form various clusters for given set of numerals (training data set), it is ready to use for recognizing new digits (testing data set) in the numerals recognition system. Trained neural network finds winning neuron using SOM algorithm explained earlier. Then the cluster to which the winning neuron belongs will be identified. During recognition phase, Artificial Neural Network has the capacity to generalize and identify the numerals written with little variations when compared to the numerals used for training

3. Results and Conclusion

The proposed system describes a novel procedure which uses spatial features and Kohonen neural network as classifier to recognize hand written Kannada numerals. We have used 100 samples of each numeral from the created data base includes 1000 samples in total. Sample patterns of which shown in figure 6. Out of which 80 patterns used for training phase and 20 samples for testing phase. We achieved considerably good recognition rate and is evident in table 1.

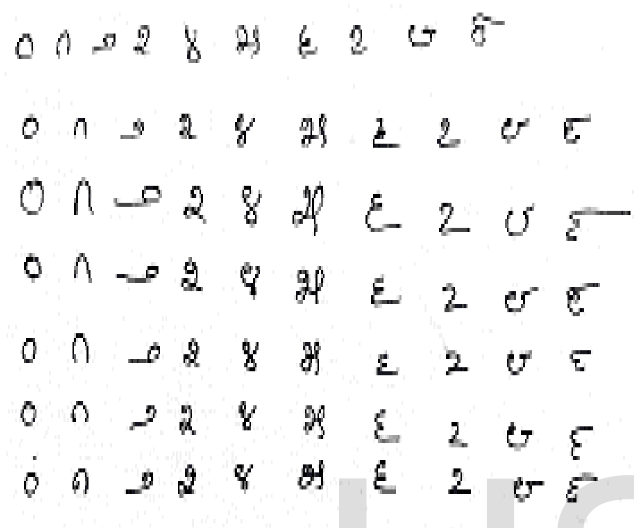

Figure 6. A sample patterns of Kannada Handwritten numerals 0 to 9

Numerals	Recognition rate in %
0	100
1	90
2	100
3	90
4	70
5	90
6	80
7	100
8	80
9	90
Average recognition rate	89

Table 1

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