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RESEARCH ARTICLE

HANDWRITTEN CHARACTER RECOGNITION USING MULTIRESOLUTION TECHNIQUE AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In the present paper, the widely common problem of handwritten character recognition has been tackled with multiresolution technique using discrete wavelet transform and artificial neural networks. The technique has been tested and found to be more accurate and economic in respect of the recognition process time of the system. Features of the handwritten character images are extracted by discrete wavelet transform used with appropriate level of multiresolution technique, then the artificial neural networks is trained by extracted features. The input handwritten character images are recognized by trained artificial neural networks system. The proposed method provides good recognition accuracy for handwritten characters with less training time, less no. of samples and less no. of iterations.

Key words: Multiresolution, Discrete Wavelet Transform, Artificial Neural Network, Feed Forward Back-Propagation**,** Feature Extraction, Handwritten Character Recognition

INTRODUCTION

Handwritten character recognition (HCR) is an area of pattern recognition process that has been the subject of considerable research during the last few decades. The ultimate objective of any HCR system is to simulate the human reading capabilities so that the computer can read, understand, edit and do similar activities as human do with the text. Mostly, English language is used all over the world for the communication purpose, also in many Indian offices such as railways, passport, income tax, sales tax, defense and public sector undertakings such as bank, insurance, court, economic centers, and educational institutions etc. A lot of works of handwritten English character recognition have been published but still minimum training time and high recognition accuracy of handwritten English character recognition is an open problem. Therefore, it is of great importance to develop automatic handwritten character recognition system for English language. In this paper, efforts have been made to develop automatic handwritten character recognition system for English language with high recognition accuracy and minimum training and classification time. Handwritten character recognition is a challenging problem in pattern recognition area. The difficulty is mainly caused by the large variations of individual writing style. To get high recognition accuracy and minimum training and classification time for handwritten character recognition, we have applied multiresolution technique using discrete wavelet transform and artificial neural network. Experimental results show that the proposed method used in this paper for handwritten English character recognition is giving high recognition accuracy and minimum training time. In what follows we briefly describe the different techniques used in our paper.

Multi resolution

Representation of images in various degrees of resolution is known as multi resolution process. In multiresolution process, images are subdivided successively into smaller regions [1,2]. Wavelets are used as the foundation of multi resolution process. In 1987, wavelets are first shown to be the foundation of a powerful new approach to signal processing and analysis called multiresolution theory [2]. Multiresolution theory is concerned with the representation and analysis of images at more than one resolution. We use this technique in HCR.

Artificial neural networks

Neural networks are the simplified models of the biological neuron system. Neural networks are parallel distributed processing systems that are made up of highly interconnected computing elements called neurons. Neurons have the ability to learn and thereby acquire knowledge and make it available for use. The technology, which has been developed as simplified imitation of computing by neurons of human brain, has been termed Artificial Neural Systems (ANS) technology

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026-029or Artificial Neural Networks (ANN) or simply Neural networks [3]. This has been used as an inductive tool in the character recognition process [4-6].

Methodology of the proposed handwritten character recognition system

This paper is divided into four parts. In first part, samples of handwritten characters are collected. In second part, some preprocessing steps are performed on the collected samples of handwritten characters. In third part, pattern vectors are generated using multiresolution technique by applying discrete wavelet transform on preprocessed handwritten characters. In fourth part, feed forward back-propagation algorithm is used to train the artificial neural network with the generated pattern vectors in third part and input handwritten character is recognized by the trained artificial neural network system. A complete flowchart of handwritten English character recognition system is given in the following figure [7].

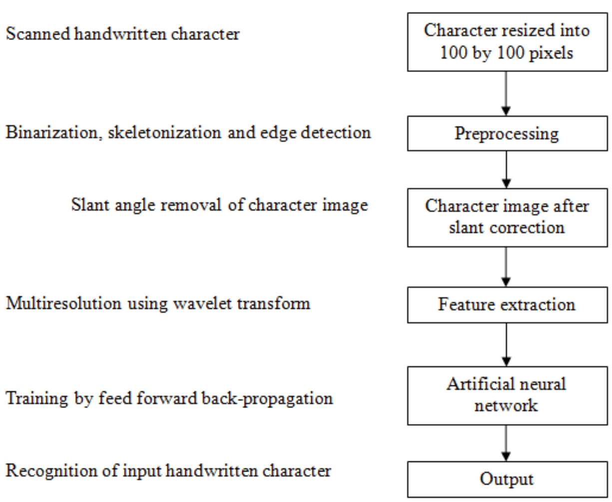

Figure 1. A flowchart of handwritten character recognition system

Data Collection

First of all, the data of English characters is collected in the written form on blank papers by different age groups of persons. These characters are written by different blue/black ball point pen. The collected samples of handwritten characters are scanned by scanner into JPEG format on 600 ppi. Then all the characters are separated and resized into 100 by 100 pixel images. The example of the samples of handwritten characters is given below.

Preprocessing

The separated RGB character images of 100 by 100 pixel resolution obtained in the first part are converted into grayscale images and then the grayscale images is again converted into binary images using appropriate gray scale thresholding. Now, binary image is thinned using skeletonization infinite times. Edges of these thinned images are detected using appropriate thresholding and then further dilated using appropriate structure element. These steps are known as preprocessing and preprocessing steps are given in the following figure.

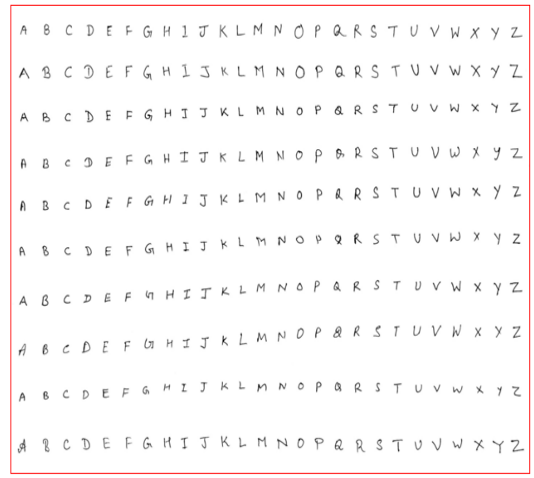

Figure 2. Sample of characters written by 10 different persons

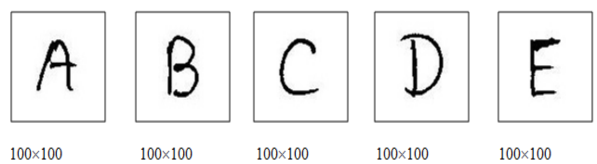

Figure 3. Some separated characters from the sample in figure 1 and resized into 100 by 100 pixel images

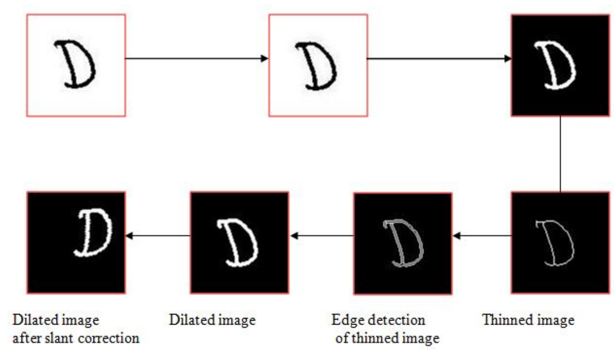

Figure 4. Results of preprocessing steps applying on a handwritten character

Feature Extraction

In this part, multi resolution technique is applied on the dilated images obtained in second part and this is achieved by applying discrete wavelet transform. In this part, pattern vectors are generated that are used to train the artificial neural network [8,9-11]. Discrete wavelet transform has given good results in different image processing applications. It has excellent spatial localization and good frequency localization properties that makes it an efficient tool for image analysis. There are different multi resolution techniques such as image pyramids, subband coding and discrete wavelet transform. We have used discrete wavelet transform in this paper. Discrete wavelet transform maps a function of a continuous variable into a sequence of coefficients. If the function being expanded is a sequence of numbers, like samples of a continuous function *f (x, y)*, the resulting coefficients are called the discrete wavelet transform of *f (x, y)* [1,2]. Discrete wavelet transform of an image *f (x, y)* of size $M \times N$ is defined as

$$W_\varphi(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\,\varphi_{j_0,m,n}(x,y) \qquad \text{......(2.3.1)}$$

$$W_\psi^i(j,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\,\psi^i_{j,m,n}(x,y),\ i=\{H, V, D\} \qquad \text{......(2.3.2)}$$

for $j \ge j_0$ and

$$f(x,y)=\frac{1}{\sqrt{MN}}\sum_{m}\sum_{n} W_\varphi(j_0,m,n)\,\varphi_{j_0,m,n}(x,y)$$

$$+\frac{1}{\sqrt{MN}}\sum_{i=H,V,D}\ \sum_{j=j_0}^{\infty}\sum_{m}\sum_{n} W_\psi^i(j,m,n)\,\psi^i_{j,m,n}(x,y) \qquad \text{......(2.3.3)}$$

where, j_0 is an arbitrary starting scale and

$$\varphi_{j,m,n}(x,y)=2^{j/2}\varphi(2^j x-m, 2^j y-n), \qquad \text{......(2.3.4)}$$

$$\text{and } \psi^i_{j,m,n}(x,y)=2^{j/2}\psi^i(2^j x-m, 2^j y-n),\ i=\{H, V, D\} \qquad \text{......(2.3.5)}$$

where index *i* identifies the directional wavelets that assumes the values H,V and D. Wavelets measure functional variations such as intensity or gray-level variations for images along different directions. Directional wavelets are ψ^H, ψ^V and ψ^D. ψ^H measures variations along columns (like horizontal edges), ψ^V measures variations along rows (like vertical edges) and ψ^D measures variations along diagonals [1,2]. Eqs. (2.3.4) and (2.3.5) define the scaled and translated basis functions. *f (x, y)*, $\varphi_{j,m,n}(x,y)$ and $\psi^i_{j,m,n}(x,y)$ are functions of the discrete variables x = 0, 1, 2, 3, …, M-1 and y = 0, 1, 2, 3, ..., N-1. The coefficients defined in Eqs. (2.3.1) and (2.3.2) are usually called approximation and detail coefficients, respectively. $W_\varphi(j_0,m,n)$ coefficients define an approximation of *f (x, y)* at scale j_0. $W_\psi^i(j,m,n)$ coefficients add horizontal, vertical and diagonal details for scales $j \ge j_0$. We normally let $j_0 = 0$ and select $N = M = 2^j$ so that j = 0, 1, 2, 3, …, J - 1 and m, n = 0, 1, 2, 3, …, 2^j - 1 [1,2]. Eqs. (2.3.3) shows that *f (x, y)* is obtained via the inverse discrete wavelet transform for given W_φ and W_ψ^i of Eqs. (2.3.1) and (2.3.2). Discrete wavelet transform can be implemented using digital-filters and down-samplers [1,2]. The block diagram of multi resolution using discrete wavelet transform is shown in the Fig. 5. We have used MATLAB toolbox for multi resolution by discrete wavelet transform. Discrete wavelet transform is applied 1 to 3 times successively on each dilated character image generated in the second part, and finally the reduced character image is captured into a bounding box using MATLAB toolbox and then, resized into 33 by 22 pixels, 18 by 12 pixels and 12 by 8 pixels images for the study of different cases. The effect of multi resolution (first level) technique on a character obtained in second part is given in the following fig. 5.

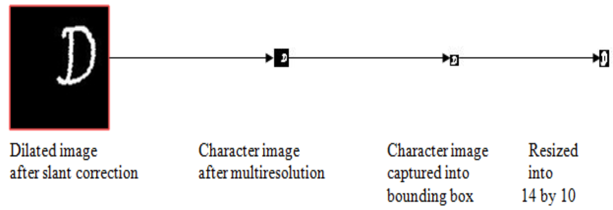

Figure 5. Character image after applying multi resolution technique and captured into bounding box

Classification and Recognition

In this part, feed forward back-propagation algorithm is used to train the artificial neural network with the pattern vectors generated in the section 3 and the input handwritten character is recognized by the trained artificial neural network system [12-18]. The artificial neural network used consists of 2 layers as input layer and output layer. The number of input elements in each pattern vector depends on the resolution of character image after multi resolution technique applied in third part [5-7]. For example, if the character images that are used for training have a resolution of 18 by 12 pixels, then the number of input elements in each pattern vector will be 216. The number of neurons in the output layer is fixed as 26. The first output neuron corresponds to letter A, second corresponds to letter B and so on. The number of neurons in the input layer and hidden layer is taken arbitrarily by trial and error to be 300 each (may change depending upon the resolution of input character image). The training begins with 33 by 22 pixels, 18 by 12 pixels and 12 by 8 pixels images arranged in column vector. There are 390 different pattern vectors to train the artificial neural network. There are 726, 216 and 96 input elements in the pattern vectors of character images of 33 by 22 pixels, 18 by 12 pixels and 12 by 8 pixels respectively. The structure of the artificial neural network for handwritten English character recognition is shown in the figure given below.

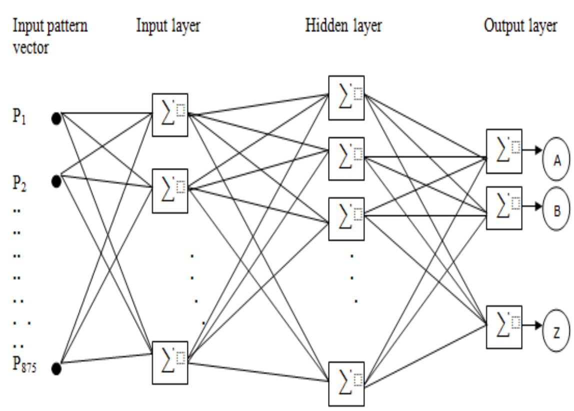

Figure 6. Structure of artificial neural networks for handwritten character recognition

Experimental results

20 samples (520 characters) were collected from 20 persons, 26 from each. First, 15 samples (390 characters) were used to train the artificial neural network and next 5 samples (130 characters) were used to test the artificial neural network. An analysis of experimental results has been performed and shown in the table given below.

Table 1. The simulation results showing the average recognition accuracy. The accuracy measured was 80.77%.

Test Data Set (A – Z)	Level of Multi resolution	No. of Iterations	Training Time (Seconds)	Average Recognition Accuracy (%)
33 by 22 pixels	1	33	9	85.38
33 by 22 pixels	2	32	9	83.85
33 by 22 pixels	3	34	9	73.85
18 by 12 pixels	1	31	4	88.46
18 by 12 pixels	2	32	4	86.15
18 by 12 pixels	3	36	5	76.15
12 by 8 pixels	1	38	3	87.69
12 by 8 pixels	2	37	3	83.08
12 by 8 pixels	3	38	4	80.77

Conclusion

From the above Tab. 1, we observe that the recognition accuracy is high up to a particular level of multi resolution for appropriate resolution of input character images. When average recognition accuracy is optimal (maximum) for a particular level of multi resolution and appropriate resolution of character images, here it is 88.46%, then any further increment in the level of multi resolution results in the decrease of the average recognition accuracy. The resolution of input character image and the level of multi resolution are dependent upon each other so the challenge is to find appropriate relationship between them. Work is going on, we are trying to improve the recognition accuracy using some other methods and techniques.

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