A Cascaded Scheme for Recognition of Handprinted Numerals

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Abstract

This paper proposes a novel off-line handprinted Bangla (a major Indian script) numeral recognition scheme using a multistage classifier system comprising multilayer perceptron (MLP) neural networks. In this scheme we consider multiresolution features based on wavelet transforms. We start from certain coarse resolution level of wavelet representation and if rejection occurs at this level of the classifier, the input pattern is passed to a larger MLP network corresponding to the next higher resolution level. For simplicity and efficiency we considered only three coarse-to-fine resolution levels in the present work. The system was trained and tested on a database of 9000 samples of handprinted Bangla (a major Indian script) numerals. For improved generalization and to avoid overtraining, the whole available data set had been divided into three subsets – training set, validation set and test set. We achieved 94.96% and 93.025% correct recognition rates on training and test sets respectively. The proposed recognition scheme is robust with respect to various writing styles and sizes as well as presence of considerable noise. Moreover, the present scheme is sufficiently fast for its real-life applications.

1. Introduction

Off-line recognition of handwritten characters, in particular numerals has been a topic of intensive research during last few years. The application areas include postal code reading, automatic processing of bank cheques, office automation and various other scientific and business applications.

Automatic recognition of handwritten characters is difficult because of variations in style, size, shape, orientation etc., presence of noise and factors related to the writing instrument, writing surface, scanning device etc. To simplify the recognition scheme, many existing methods put constraints on handwriting with respect to tilt, size, relative positions, stroke connections, distortions etc. In this paper we consider numeral characters written inside rectangular boxes of fixed size.

Enough research papers are found in English [19], Chinese [20], Korean [10], Arabic [1], Kanji [22] and other languages. For example see the review in [17]. However, only preliminary work [16, 2, 3] has been done on a script like Bangla, the second-most popular language and script in the Indian subcontinent and the fifth-most popular language in the world. In the previous census, it was found that only 3% of the educated population of West Bengal, the major Bangla speaking state of India, knows a foreign language (mainly English).

One of the important issues related to handwriting recognition is the determination of a feature set which is reasonably invariant with respect to shape variations caused by various writing styles. To tackle the problem we have chosen a wavelet based multistage approach. Wavelet based approach has been used for handwritten character recognition previously [21, 11, 9] but not in a cascaded manner used by us. In wavelet analysis, the frequency of the basis function as well as the scale can be changed and thus it is possible to exploit the fact that high frequency features of a function are localized while low frequency features are spread over time. Real life images are composed of large areas of similar information but sharp changes at object edges. The biological eyes are more sensitive to object edges rather than minor details inside. Thus, in many situations, wavelet based techniques are suitable for image processing tasks. Moreover, wavelet, as a problem-solving tool fits naturally with digital computer with its basis functions defined by just multiplication and addition operators – there are no derivatives or integrals.

In this paper, a three stage system is proposed where features in the form of wavelet coefficient matrices at different resolution levels are considered at three different stages of the recognition system. MLP networks with different architecture is used as classifiers. In the initial stage, a numeral is subjected to recognition using the low-low part of the wavelet coefficient matrix as the feature set. If the input character is not classified at this level, it is passed to the next stage using wavelet coefficients of the next higher level of resolution. If the pattern is again rejected at this stage, attempt is made by the last stage where the next higher level of wavelet features are considered.

In this scheme, depicted in Fig 1, feature vectors are obtained by convolving the Daubechies-4 wavelets [6] with a character image. Three MLP network architectures are trained using training sets at three coarse-to-fine resolution

(a) (b) (c) (d)

Figure 1: Smooth ... smooth components of wavelet decomposition of a Bangla numeral (one) image at different resolution levels (a) Original image (b) 32×32 resolution level (c) 16×16 resolution level (d) 8×8 resolution level

levels. Also a validation sample set [8] is used to determine the termination of training. The classification strategy is to place an input character to one of the possible 10 categories or reject it. The rejection criterion is chosen interactively so that the misclassification is minimized on the union of training and validation sets. Rejected candidates are given higher representations during the MLP training for the next two recognition stages. This helps in reducing the rejection percentage [14] at the higher stages. The rejection criterion at the final stage is determined by maximizing the correct classification on the above union set.

The rest of this article is organized as follows. Section 2 and 3 respectively provide brief overviews of multilayer perceptron and wavelet transform. We describe the preprocessing, training of the set of MLP networks and the multistage recognition scheme in Section 4. Experimental results are reported in Section 5. Concluding remarks are given in Section 6.

2. Multilayer Perceptron

Multilayer perceptron neural network model is possibly the most well-known neural network architecture [15]. The strengths of connections between nodes in different layers are called weights. Such weights are usually initialized with small random values and in the present application we considered random values between -0.5 to +0.5 obtained from a uniform distribution. The final weights may be obtained in an iterative manner by using the so-called backpropagation (BP) algorithm[18] This training algorithm performs steepest descent in the connection weight space on an error surface defined by

$$E_p = \frac{1}{2} \sum_k (t_{pk} - y_{pk})^2, \tag{1}$$

where $\{t_{pk}\}$, $\{y_{pk}\}$ are respectively, the target and output vectors corresponding to the p-th input pattern. The system error E is defined as

$$E = \frac{1}{P} \sum_p E_p, \tag{2}$$

where P is the total number of patterns in the training set. In classical BP algorithm, weight modification rules are given by

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial E_p(t)}{\partial w_{ij}(t)}, \tag{3}$$

where $w_{ij}(t)$ is the weight connecting a node i and another node j in the next upper layer at time t and $\eta (> 0)$ is a positive constant, called the learning rate.

To tackle the problem of possible local minima and slow convergence, Rumelhart *et al.* suggested the use of momentum term when the weight modification rule (3) becomes

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial E_p(t)}{\partial w_{ij}(t)} + \alpha_m \Delta w_{ij}(t-1), \tag{4}$$

where $\Delta w_{ij}(t-1)$ is the change in the corresponding weight during time $t-1$, and $0 < \alpha_m < 1$ is a constant, called the momentum factor [18].

In many situations, the inclusion of this momentum in the weight modification rule increases the speed of convergence of the algorithm to some extent. However, in real life applications, futher improvement of this learning algorithm is essential and there exits a large number of such modifications of this algorithm in the literature. In fact, in the present application, we used a modified BP algorithm which considers a distinct self-adaptive learning rate corresponding to each individual connection weight. Using such self-adaptive learning rates, the weight modification rule (4) becomes [4]

$$w_{ij}(t+1) = w_{ij}(t) - \beta_{ij} \frac{\partial E_p(t)}{\partial w_{ij}(t)} + \alpha_m \Delta w_{ij}(t-1), \tag{5}$$

where $\beta_{ij} = h(\eta_{ij})$. $h(x) = \frac{d}{1+e^{-x+\frac{d}{2}}}$ is called the effective value function and $d > 0$ is a constant.

The self-adaptive learning rates are modified as follows:

$$\eta_{ij}(t+1) = \eta_{ij}(t) + \Delta_p \eta_{ij}(t) \tag{6}$$

where

$$\Delta_p \eta_{ij}(t) = \frac{\gamma}{d} \frac{\partial E_p(t)}{\partial w_{ij}(t)} \frac{\partial E_p(t-1)}{\partial w_{ij}(t-1)} \beta_{ij}(d - \beta_{ij}),$$

γ is a constant of proportionality.

The learning performance of an MLP network using this modified BP algorithm does not depend much on the choice of γ. The constant d determines the maximum value which can be assumed by a learning rate. In the present application, the value of γ and d are always taken as 0.1 and 4.0 respectively.

3. Wavelet Descriptor for Multiresolution Feature Extraction

In wavelet analysis, an input signal is decomposed into different frequency components and then each component is presented with a resolution matched to its scale. Thus a wavelet provides a tool for time-frequency localization.

A wavelet system is a set of building blocks used to represent a function. It is a two-dimensional set of basis functions $\psi_{jk}(t), where j, k = 1, 2, \cdots$, such that any square integrable function can be expressed as $f(t) = \sum_k \sum_j a_{j,k}\psi_{j,k}(t)$ for some set of coefficients $a_{j,k}$. General wavelet basis functions, ψ_{jk}, may be obtained from a mother wavelet, ψ, by shrinking by a factor of 2^j and translating by $2^{-j}k$, namely

$$\psi_{jk}(x) = 2^{\frac{j}{2}}\psi(2^j x - k), \forall j, k \in Z$$

Here j represents the dilation number and k represents the translation number. The scale factor $2^{\frac{j}{2}}$ normalizes ψ_{jk} so that $||\psi_{jk}|| = ||\psi||$. For certain choices of the mother wavelet function ψ, the set of functions ψ_{jk} form an orthonormal basis and hence any given function f may be approximated by these basis functions.

The first and simplest possible orthogonal wavelet system is the Haar wavelet (Thesis of A. Haar, 1909). However, Daubechies constructed a set of orthonormal wavelet basis function that are perhaps the most elegant. These wavelets are compactly supported in the time-domain and have good frequency domain decay.

The above describes the reason behind our choice of Daubechies' wavelet transform. A particular family of wavelets is specified by a particular set of numbers, called wavelet filter coefficients. The simplest member of the Daubechies' family is the Daubechies4 which has been considered in our implementation. The layout of application of wavelet transform recursively on an image is shown in Figure 2. The successive application of the transform produces an increasingly smoother version of the original image. One most useful aspect of wavelet transform is the existence of fast computation algorithmn by means of multiresolution analysis [13]. Moreover, the algorithm for two-dimensional transform is a straightforward extension of that for the one-dimensional transform.

4. Recognition Scheme

4.1. Preprocessing

As preprocessing, we considered only size normalization. The input grey scale image is first scaled to 64×64 image by using the moment method [5]. No further preprocessing like tilt correction, smoothing etc. are considered.

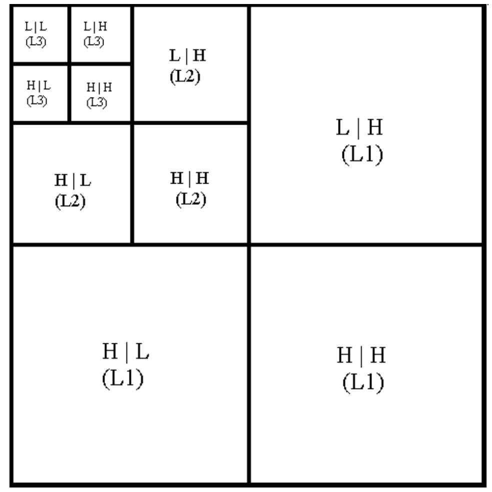

Figure 2: Layout of Wavelet decomposition for an image (L $\rightarrow$ low-pass filter, H $\rightarrow$ high-pass filter, Lj $\rightarrow$ jth level)

4.2. Training of MLPs

Two important aspects of the training of MLP networks are

- Designing the training sets and
- Termination of training

Designing the training set. The recognition performance of an MLP network highly depends on the choice of a representative training set. Manual selection of training samples is definitely a good approach to this problem. However, since this approach is extremely tedious, we have chosen the training set randomly from the available data. In fact, we performed random selections with respect to three different seed values and experimental results will be provided corresponding to the best of these three.

In our simulations, the size of the training set is 20% of the available data size. The MLP network in the first stage, uses this set for its training. However, training sets used for MLP networks of the latter stages are slightly different. We increased the representations of training samples rejected by the MLP of the first stage, by a factor of four to form the sample set for the training of MLP at the second stage. Similarly, the sample set for the training of the MLP at the third stage is formed from the first level training set by increasing the representations of elements rejected at the second level, by a factor of eight. This approach of enhanced representations helps in increasing the correct classification percentage.

Termination of training. There are various termination criteria available in the literature. The recognition performance highly depends on how much training has been given to the network. An effective strategy of judging training adequacy is the use of a validation set. With increased training, the recognition error on the validation set decreases monotonically to a minimum value but then it starts to increase , even if the training error continues to decrease. For better network performance, training is terminated when the validation error reaches its minimum. In our simulations, we considered 15% of the data as the validation set.

4.3. Recognition scheme

The proposed recognition scheme has been simulated on the domain of handprinted Bangla numerals. Ideal Bangla numerals and 70 handwritten samples (7 different numeral characters per class) are shown in Fig. 3.

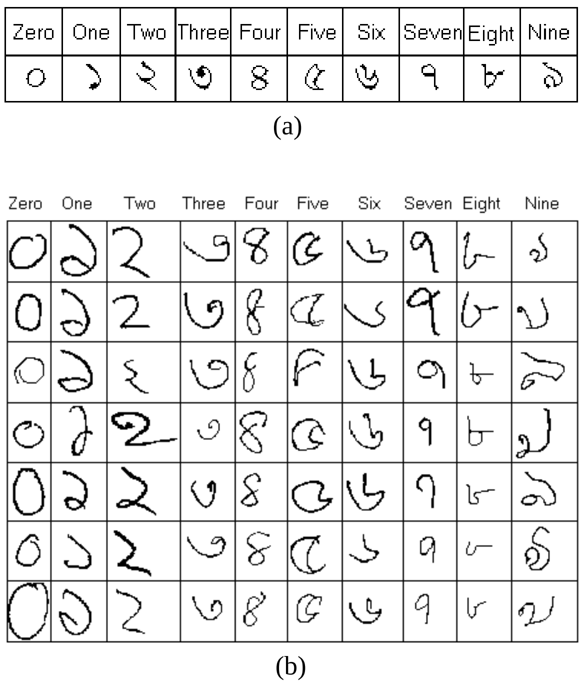

Figure 3: (a) Ideal samples of Bangla numerals (b) A typical sample data subset of handwritten Bangla numerals

The bounding box (minimum possible rectangle enclosing the image) of an input image of a numeral is first computed and then this is normalized to the size 64×64 using the moment method [5]. Wavelet decomposition algorithm is applied to this normalized image recursively for four times to obtain 4×4 smooth. . .smooth approximation of the original image. In this procedure, we also obtain 32×32, 16×16 and 8×8 smooth. . .smooth approximations of the original image. Theoretically, this decomposition algorithm could be applied for the fifth time to obtain 2×2 approximation. However, during our simulations, it is observed that different numerals are not generally distinguishable from these smallest possible approximations.

The above approximations of the original image are gray-valued images and we apply simple thresolding technique to obtain these as binary images. The present scheme is a 3-stage recognition scheme. In the first stage binarized version of 4×4 approximation of the original image is fed to the input layer. Different responses at the nodes of the output layer are compared. Usually the output node with maximum value recognizes the input image. However, in the present problem this approach is not suitable because it leads to unacceptably high misclassification percentage. On the other hand, we interactively determine a thresold value (T) of the diference between the maximum (o_{m1}) and second maximum (o_{m2}) values among the output nodes so that the misclassification from the union of the training and validation sets is minimized. Thus, if corresponding to an input numeral $o_{m1} - o_{m2} > T$ holds, then it is recognized to belong to numeral class correponding to the output node having the value o_{m1}; otherwise the input numeral is said to be rejected by the initial stage of classification. In case of rejection by the first stage of the classification scheme, it is passed to the next stage with 8×8 smooth. . .smooth component of the transformed image. Again similar recognition procedure is followed in this middle level of recognition and if it is rejected for the second time a third and last attempt is made using the 16×16 smooth. . .smooth component of the transformed image. During our simulation runs, it has been observed that by extending the proposed classification scheme into further stages cannot improve the classification accuracy.

5. Experimental Results

The authors do not have information of the availability of any standard database of handprinted Bangla numerals. So, a database has been generated for simulation purposes. In our simulation, we considered a data set of 9000 handprinted Bangla numerals equally distributed over all classes. These data has been collected from different sections of the population of West Bengal, India keeping in mind variations with respect to age, sex, education, place of origin, income group and profession by a number of University students over a period of more than one year. Since there appears variation in the writing style of a single individual at different points of time, each individual has been approached on 4 occassions for the sample.

Out of this set of 9000 data, the training set, validation set and test set consist of 1800, 1440 and 5760 samples respectively. In the first stage of classification scheme, 18.72% of the test data are rejected out of which 67.38% and 2.86% are respectively classified by the second stage and third stage of the classification scheme. The overall rejection percentage is 1.97% and misclassfication is only 5.005%. Thus we achieved 93.025% correct classification accuracy. The confusion matrices at different levels of clas-

Confusion Matrix of the First Stage of Classification

	০	১	২	৩	৪	৫	৬	৭	৮	৯
০	80.1	0.25	0.25	0.5	0.3	0.5	0.2	0.1	0.2	0.1
১	0.1	78.7	1.2	0.2	0.1	0.15	0.3	0.12	0.2	1
২	0.15	3	76.8	0.14	0.18	0.2	0.23	0.1	0.25	0.21
৩	1.1	0.3	0.2	76.3	0.34	0.8	0.26	0.32	0.2	0.1
৪	0.2	0.6	0.1	1.2	74.3	0.3	0.2	0.2	1.1	0.4
৫	0.12	0.1	0.2	2.6	0.1	73.4	0.2	0.3	0.1	0.3
৬	0.14	0.1	0.1	1.6	0.2	0.2	78.7	0.2	0.1	0.6
৭	0.4	0.2	0.3	0.1	1.4	0.3	0.4	80.6	0.3	0.4
৮	0.8	1.2	0.5	0.2	0.7	0.25	0.4	0.3	76.9	0.1
৯	1.1	0.8	0.2	0.3	0.5	0.2	0.3	0.1	0.2	79.6

Confusion Matrix of the Second Stage of Classification

	০	১	২	৩	৪	৫	৬	৭	৮	৯
০	96	0	0.3	0	0	0.7	0	0	0	0
১	0.1	54	0	0.3	0.1	0.4	0	0.4	0.4	0.5
২	0	0.1	63.7	0.5	0	0.6	0	0.8	0	0.25
৩	0	0.2	0	61.3	0	0.5	1.3	0	0	0
৪	0	0	0.3	0	53.6	0	0	2.1	0	0
৫	0	0	0.4	0	0.5	73.8	1.4	0	0.3	0
৬	0	0.5	0	0.4	0.1	0	55.6	0	0	0
৭	0	0	0.9	0	0	0.32	0	82.7	0	1.1
৮	0	0.38	0	0.4	0	0	1.2	0	71.1	0
৯	0	0	0.4	0.5	0	0	1.4	0	0	62

sification and also the overall classification result is given in the Tables below. This recognition performance of the proposed scheme is better than the exiting ones. The correct recognition percentages reported in [16] and [3] are respectively 91.98% and 90.56%. On the other hand, the present approach can recognize sixty numerals per second on a Pentium-IV Desktop Computer which is enough for any real-life applications.

Confusion Matrix of the Third Stage of Classification

	০	১	২	৩	৪	৫	৬	৭	৮	৯
০	54	2.1	0.5	0.6	0	0.4	0	0	0.6	0
১	0.1	62.1	0	0	1.2	0.6	0	1.1	0	0
২	0.3	0.5	44.2	0.7	0	0.4	0	0	0	0.3
৩	0	0.4	0	64.5	0	0	0	1.8	0	0.6
৪	0.2	0	0	0	50.4	0	0.9		0	0.5
৫	0	0.4	0	0	0	35.8	0.7	0	0.8	0
৬	0	0.7	0	0.7	0.8	0	46.8	0	0	0
৭	0.3	0	0	0	1.2	0	0	57.6	0	0.8
৮	0.2	0.3	0	0.7	0.9	0	0	0	44.4	0
৯	0.5	0	0	0	0.6	0	0	0.8	0	47.1

6. Conclusion

Wavelets have been studied thoroughly during the last decade [7] and recently the researchers are applying it in various fields of mathematics and engineering. Its potential in image compression tasks has been already established

Overall Confusion Matrix On The Test Set

	০	১	২	৩	৪	৫	৬	৭	৮	৯
০	97.18	0.36	0.33	0.53	0.3	0.64	0.2	0.1	0.23	0.1
১	0.2	93.26	1.2	0.25	1.06	0.69	0.3	1.06	0.27	1.09
২	0.34	3.05	91.56	0.68	0.18	0.57	0.23	0.25	0.25	0.45
৩	1.1	0.37	0.2	93.4	0.34	0.9	0.52	1.65	0.2	0.54
৪	0.39	0.6	0.16	1.2	90.52	0.3	1.05	0.65	1.1	0.87
৫	0.12	0.12	0.29	2.6	0.21	91.97	0.89	0.3	0.59	0.3
৬	0.14	0.25	0.1	1.73	0.28	0.2	92.41	0.2	0.1	0.6
৭	0.47	0.2	0.44	0.1	1.43	0.35	0.4	94.85	0.3	0.76
৮	0.9	1.29	0.5	0.31	0.75	0.25	0.62	0.3	92.39	0.1
৯	1.4	0.8	0.27	0.38	0.54	0.2	0.53	0.15	0.2	92.76

(a) (b) (c) (d)

Figure 4: Smooth . . . smooth components of wavelet decomposition of a noisy image of a Bangla numeral (one) at different resolution levels (a) Original noisy image (b) 32×32 resolution level (c) 16×16 resolution level (d) 8×8 resolution level

and its applicability in various other image processing problems are getting explored. In this paper we proposed an efficient multistage approach using multiresolution wavelet features and multilayer perceptron clasifiers. As it is seen from the simulation results, the proposed approach can provide very good recognition result on handprinted Bangla numerals. The wavelet based features are also not affected in the presence of moderate noise or discontinuity or small changes in orientation. In Figure 4, we have shown the numeral of Figure $1(a)$ affected by noise and its wavelet-based feature images at different resolution levels. From Figure 4, it is clear that higher resolution levels are more sensitive to noise. During our simulation runs, it is observed that resolution level 16×16 contributes most to recognition.

Here it should be noted that consideration of this multistage classification is useful because if all the test patterns are fed to each of the three individual MLP classifiers, then none of the rejection sets or sets of misclassified samples is a subset of another. On the other hand, considering 4×4 components at the initial stage helps to minimize the average computation time.

Finally, there exists striking resemblance between Quadrature Mirror Filters (QMF) known in subband coding techniques in the field of signal processing and the orthonomal bases of the wavelet analysis. In fact, the wavelet algorithm is a form of subband filtering and most of the computations of wavelets can be implemented using filter banks. Moreover, Lewis and Knowles have also devised a clever idea of quantising the wavelet coefficients in order to build a simple VLSI arhitecture without multipliers [12].

References

[1] A. Amin and H. B. Al-Sadoun, "Hand Printed Arabic Character Recognition System", *12th. Int. Conf. Pattern Recognition*, pp. 536-539, 1994.

[2] U. Bhattacharya, T. K. Das, A. Dutta, S. K. Parui and B. B. Chaudhuri, "Self-organizing Neural Network-Based System for Recognition of Handprinted Bangla Numerals", *Proc. of XXXVI Ann. Convention of Comp. Soc. of India - CSI2001*, Kolkata, 2001, pp. C-92 - C-96.

[3] U. Bhattacharya, T. K. Das, A. Dutta, S. K. Parui and B. B. Chaudhuri, "Recognition of Handprinted Bangla Numerals using Neural Network Models", *Advances in Soft Computing – AFSS 2002*, Springer Verlag Lecture Notes on Artificial Intelligence (LNAI-2275), Eds. N. R. Pal and M. Sugeno, pp. 228-235, 2002.

[4] U. Bhattacharya and S. K. Parui, "Self-Adaptive Learning Rates in Backpropagation Algorithm Improve Its Function Approximation Performance", *Proc. of the IEEE International Conference on Neural Networks*, Australia, pp. 2784-2788, 1995.

[5] R. G. Casey, "Moment normalization of handprinted characters", *IBM J. Res. Develop.*, vol. 14, pp. 548-557, 1970.

[6] I. Daubechies, "The wavelet transform, time-frequency localization and signal analysis", *IEEE Trans. on Information Theory*, vol. 36, no. 5, pp. 961-1005, 1990.

[7] A. Graps, "An introduction to wavelets", *IEEE Computational Science and Engineering*, vol. 2(2), 1995.

[8] M. H. Hassoun, *Fundamentals of Artificial Neural Networks*. Cambridge: The MIT Press, 1995, p. 226.

[9] L. Huang and X. Huang, "Multiresolution Recognition of Offline Handwritten Chinese Characters with Wavelet Transform", *Proc. of Sixth ICDAR*, Seattle, Washington, USA, Sept. 10-13, 2001, pp. 631-634.

[10] S. W. Lee and J. S. Park, "Nonlinear shape normalization methods for the recognition of large-set handwritten characters, *Pattrn Recognition*, vol. 27, pp. 895-902, 1994.

[11] S. W. Lee, C.H. Kim, H. Ma and Y. Y. Tang, "Multiresolution Recognition of Unconstrained Handwritten Numerals with Wavelet Transform and Multilayer Cluster Network", *Pattern Recognition*, vol. 29, no. 12, pp. 1953 - 1961, 1996.

[12] A. S. Lewis, G. Knowles, "A VLSI architecture for the discrete wavelet transform without multipliers", Electronics Letters vol. 27(2), pp. 171-173, 1991.

[13] S. G. Mallat, "A theory for multiresolution signal decomposition : The wavelet representation", *IEEE Trans. on Pattern Anal. and Machine Int.*, vol. 11, no. 7, pp 674 -693, 1989.

[14] T. Masters, *Practical Neural Network Recipes in C++*, New York: Academic Press, 1993, p. 18.

[15] R. Hecht-Nielson, *Neurocomputing*, Addison-Wesley : New York, Chapter 5, 1990.

[16] U. Pal and B. B. Chaudhuri, "Automatic Recognition of Unconstrained Off-line Bangla Hand-written Numerals", *Advances in Multimodal Interfaces, Springer Verlag Lecture Notes on Computer Science (LNCS-1948)*, Eds. T. Tan, Y. Shi and W. Gao. (2000) 371-378.

[17] R. Plamondon, S. N. Srihari, "On-Line and Off-Line Handwriting recognition: A Comprehensive Survey", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 22, no. 1, pp. 63-84, 2000.

[18] D. E. Rumelhart, G. E. Hinton and R. J. Williams, "Learning internal representations by error propagation', *Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Volume 1: Foundations*, D. E. Rumelhart and J. L. McClelland Eds. Cambridge, MA: The MIT Press, pp. 318-362, 1986.

[19] S. N. Srihari, E. Cohen, J. J. Hull and L. Kuan, "A system to locate and recognize ZIP codes in handwritten addresses", *IJRE*, vol. 1, pp. 37-45, 1989.

[20] J. Tsukumo and H. Tanaka, "Classification of Handprinted Chinese Characters Using Nonlinear Normalization Methods", *9th. Int. Conf. Pattern Recognition*, pp. 168-171, 1988.

[21] P. Wunsch and A. F. Laine, "Wavelet Descriptors for Multiresolution Recognition of Handprinted Characters", *Pattern Recognition*, vol. 28, no. 8, pp. 1237-1249, 1995.

[22] H. Yamada, K. Yamamoto and T. Saito, "A non-linear normalization method for handprinted Kanji character recognition – line density equalization", *Pattern Recognition*, vol. 23, pp. 1023-1029, 1990.