

Recognition of Bangla Handwritten Number Using Combination of PCA and FIS with the Aid of DWT

Samsunnahar Khandakar¹, Md. Imdadul Islam¹, Fahima Tabassum², Risala T. Khan²

¹Department of Computer Science & Engineering, Jahangirnagar University, Dhaka, Bangladesh

²Institute of Information Technology, Jahangirnagar University, Dhaka, Bangladesh

Email: nahar43cse2000@gmail.com, imdad@juniv.edu, fahima@juniv.edu, risala@juniv.edu

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Abstract

The structure of any Bangla numerical character is more complex compared to English numerical character. Two pairs of numerical character in Bangla resembles to be closed and they are: “one and nine” and “five and six”. We found that, handwritten Bangla numerical character cannot be recognized using single machine learning algorithm or discrete wavelet transform (DWT). Above phenomenon motivated us to use combination of DWT, Fuzzy Inference System (FIS) and Principal Component Analysis (PCA) to recognize numerical characters of Bangla in handwritten format. The four lowest spectral components of a preprocessed image are taken using DWT, which is considered as the feature vector to recognize the digits in first phase. The feature vector is then applied to FIS and PCA separately. The combined method provides recognition accuracy of 95.8% whereas application of individual method gives less rate of accuracy. Instead of storing the images itself in a folder, if we can store the feature vector of images achieved from DWT in tabular form. The records of table can be applied in FIS, PCA or other object detection algorithm. Although the technique used in the paper can detect objects with moderate rate of accuracy but can save huge storage against a benchmark database of images. If a tradeoff is made between storage requirements and accuracy of recognition, the model of the paper is preferable compared to other present state-of-art. Another finding of the paper is that, the spectral components of images acquired by DWT only matched with FIS and PCA for classification but do not match properly with unsupervised (K-mean clustering) and supervised (support vector machine) learning.

Keywords

Spectral Components, Recognition Accuracy, De-Noising, Thinning Scheme,

1. Introduction

Huge number of works relevant to object detection and recognition using machine learning is found in recent literature. In this section, we will search some works pertinent to DWT, FIS and PCA in image classification or identification. Nawaf Hazim Barnouti *et al.*, discussed about combination of DWT and DCT that has been used for embedding and extraction copyright protection by using digital watermarking method in [1]. This two method DWT + DCT applied on two-dimensional images and works in frequency domain which seems to be more robust as found in its result section. Pooja B. Minajagi *et al.*, proposed a method about segmentation of brain MRI image using Fuzzy c means clustering (FCM) and DWT in [2]. The paper provides level set segmentation using fuzzy c means based on special features (SFCM) and segmentation of brain MRI images using DWT algorithm. The performance evaluation is done by computing mean square error, peak signal to noise ratio (PSNR), maximum difference, absolute mean error etc.

Another work in combination of DWT and DCT in digital watermarking of color image is found in [3] by Ravinder Singh *et al.* The watermarking technique of the paper selected one color component from RGB image, is applicable in embedded watermarking since it requires only red component as discussed in [3]. T. Sridevi *et al.*, implemented a robust watermarking using fuzzy logic approach based on DWT and SVD algorithm in [4]. The fuzzy logic decided how much of watermark has to be added to the cover image, which is based on the image properties as shown clearly in [4].

A classifier based on fuzzy if-then rules that allows the incorporation of weighted training patterns is proposed in [5]. The antecedent part of fuzzy if-then rules are specified by partitioning each attributes into fuzzy sets while the consequent class and the degree of certainty are determined from the compatibility and weights of training patterns. A learning method which adjusts the degree of certainty to improve performance of classification and reduce costs as introduced in [5]. In [6] fuzzy logic-based image processing is used for accurate and noise free edge detection and Cellular Learning Automata (CLA) is used to enhance the previously-detected edges with the help of the repeatable and neighborhood considering nature of CLA. The different results of edge detection technique are compared with fuzzy edge detected and resulting edge is enhanced using CLA. The authors in [7] deal with Fuzzy logic for the automatic analysis of X-ray images of industrial products for defect detection. A to stage algorithm is presented based on the feature analysis of the radiographic images obtained from the inspected product.

In [8], authors developed a semi-automated fuzzy inference system to detect the internal architecture of a mass transport complex (MTC) in seismic images.

The characteristics of a MTC were expressed as fuzzy if-then rules consisting of linguistic values associated with fuzzy membership functions. Ashwini B Yargall *et al.*, in [9] discussed about Handwritten Character Recognition using deep learning where Convolutional Neural Network (CNN) has been used to train a model and Long Short Term Memory networks (LSTM) has been used to construct bounding boxes for each character. Chandrika Saha *et al.*, in [10] proposed Deep Convolutional Neural Network (DCNN) to recognize Bangla handwritten digits. Authors used seven layered D-CNN containing three convolution layers, three average pool layers and one fully connected layer. In this paper we avoid CNN to reduce process time of recognition. None of above papers used the combination of DWT and FIS. The spectral components of images of Bangla digits acquired from DWT are found random on its scatterplot. A lot of points correspond to a particular class of image are found in the middle of the region of another class of image. The support vector machine (SVM) and k-means clustering fails to identify image from the spectral data of an image. We found that DWT + FIS combination only works to achieve reasonable rate of accuracy of recognition. Application of PCA in object detection is found in recent literature, for example upper part of human body is detected by PCA in [11]. The performance of PCA is compared with HOG, BDPCA and Haar cascade, where no combined scheme is used. In [12], authors claim that CNN has inherent problem of over-fitting and to overcome the problem they combined PCA with CNN for object detection and recognition in robot-aided visual system. Analyzing all the previous works mentioned here, we found two research gaps. None of above papers finds the matching of spectrum of DWT with FIS and PCA in object recognition. Another finding of the paper is that, DWT has mismatch with K-mean clustering and SVM in object recognition. This paper for the first time applies DWT + FIS + PCA to recognize handwritten Bangla digits including image enhancement and morphological operation. We successfully recognize Bangla handwritten digits and compare our results with some previous works and got better accuracy of recognition, mentioned at the end of the result section.

The rest of the paper is organized as: Section 2 deals with basic theory of DWT, FIS and PCA along with experimental setup of object recognition, Section 3 provides results based on analysis of Section 2. Finally Section 4 concludes entire analysis.

2. Methodology

In this paper image recognition is done using DWT, FIS and PCA. This section will deal with basic theory of wavelet transform, FIS and PCA then the experimental setup to combine above three methods.

2.1. Wavelet Transform

Wavelet is an oscillatory function of finite duration. If the sinusoidal wave

$y(t) = A \cos \omega_c t$ is modulated by a smooth Gaussian window function $g(t) = e^{-t^2}$, the modulated wave, $\psi(t) = g(t)y(t) = Ae^{-t^2} \cos(\omega_c t)$ is an wavelet over the interval $[\infty, -\infty]$ but almost all of its energy is confined within a small interval.

The continuous-time wavelet transform (CWT) of an integrable function $f(t)$ is expressed as [13] [14],

$$W(a, b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|a|}} \psi^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

where a and b are real (scaling and shifting parameter) and $*$ denotes conjugation.

If scaling (a) and shifting (b) are chosen based on powers of two then the analysis will be much more efficient and accurate like CWT. Such analysis of WT is called the discrete wavelet transform (DWT) expressed as,

$$d(m, n) = \frac{1}{2^m} \int_{2^m n}^{2^m(n+1)} y(t) \psi(2^{-m}t - n) dt \quad (2)$$

Here $d(m, n)$ is equivalent to continuous wavelet transform $W(a, b)$ when $a = 2^m$ and $b = n2^m$.

2.2. Fuzzy Inference System

FIS is a nonlinear mapping by means of fuzzy logic, from a given set of input value to one or more output values. To produce the expected outputs, it takes inputs and processes them based on the pre-specified rules. Fuzzy rules and fuzzy arithmetic is used in the internal processing. In the fuzzy inference system, real value is used in both the input and output units. The basic structure of a fuzzy inference system consists of a set of conceptual components as shown in **Figure 1** as mentioned in [15] [16].

2.3. Principal Component Analysis

PCA is widely used in objection recognition or detection with reduction of variable. In this paper the feature vector derived from DWT is applied in PCA to enhance accuracy of object recognition. The steps of PCA algorithm is given below as [17] [18].

1) Let feature vectors of images derived from DWT are: $F_1, F_2, F_3, \dots, F_M$ each of size $1 \times N$

2) The average of feature vectors is, $\Phi = \frac{1}{M} \sum_{i=1}^M F_i$ and difference vectors, $D_i = F_i - \Phi$; $i = 1, 2, 3, \dots, M$

3) The covariance matrix is evaluated as: $C = \frac{1}{M} \sum_{i=1}^M D_i^T D_i$.

4) The M orthogonal Eigen vectors U_k , where $U_k^T U_j = \delta_{k,j}$ and corresponding Eigen values λ_k are selected from the covariance matrix C indicate the principle components of data.

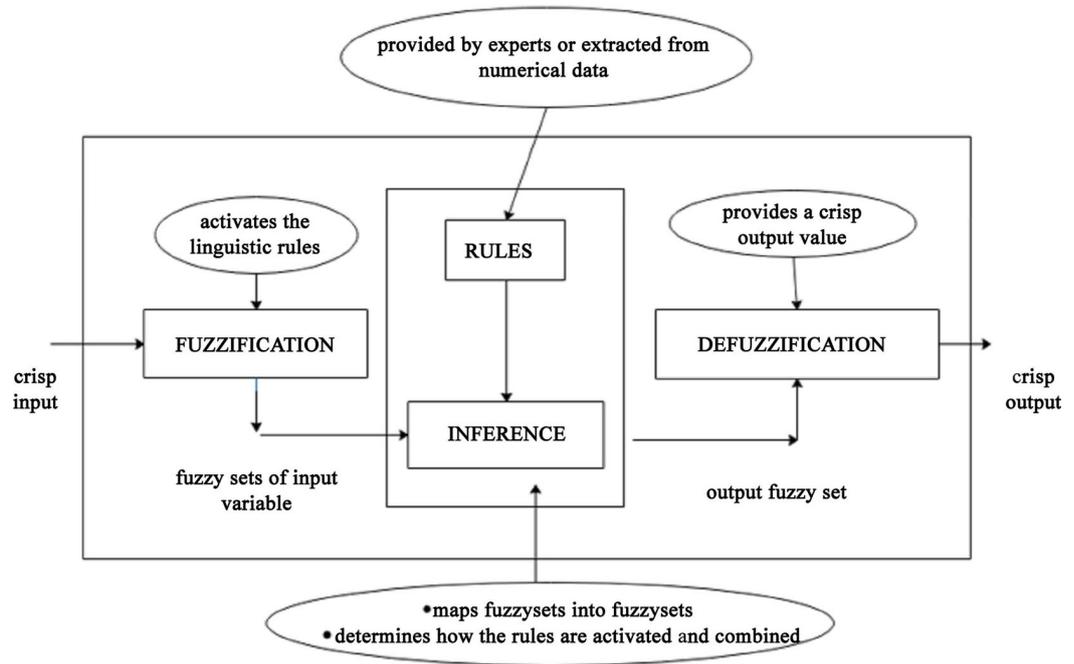


Figure 1. Structure of fuzzy inference system.

5) Let us now select a new test image and determine its vector F_r . The projection of F_r on Eigen vector space is: $U_i^T (F_r - \Phi) = U_i^T D_i = \omega_i$ is called weight of object i . Let us define weight vector, $\Omega_i = [\omega_1 \ \omega_2 \ \dots \ \omega_k]$, where we consider k Eigen vector corresponding to k largest Eigen values.

6) If Ω_i is the weight vector of i th training image then the Euclidean distance: $\varepsilon_i = \|\Omega_i - \Omega_r\|$ is measured and if the distance is less than a threshold value θ then the test image is under the category of i th training image.

7) If the distance is greater than θ , then check for other category of object repeating all the previous steps.

2.4. Implementation

The steps of preprocessing of image consists of RGB to grayscale conversion, de-noising of image using filter, enhancement of image and finally thinning scheme as shown in **Figure 2**. The signal vector of the image is extracted using row and column wise DWT, the corresponding algorithm is given in subsection 2.5. Actually each row of the preprocessed image is applied in a filter bank of **Figure 3** consists of lowpass (LP) filter of impulse response $h(n)$ and highpass (HP) filter of impulse response $g(n)$ like [19]. Each of the filtered signal is down sampled by a factor of two hence the length of the signal vector of output of the sampler is half of its input. The HP filter generates detail component and the LP provides the approximate component. The approximate component is further split into approximate and detail components.

One dimensional DWT is applied on each row of the preprocessed image until reducing to one element. The single element from each row forms a signal vector, which is again applied to one dimensional DWT until getting a column

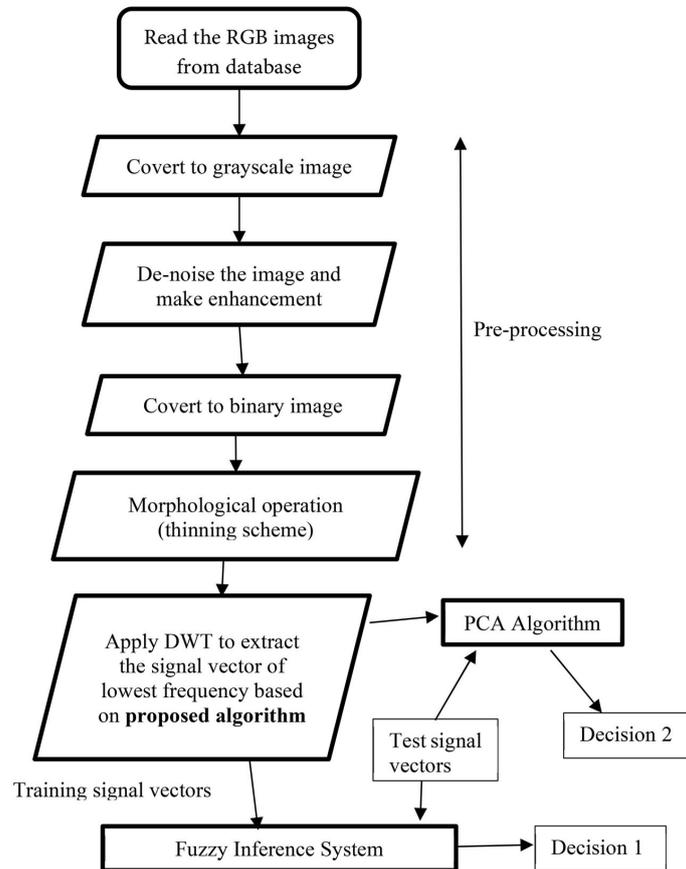


Figure 2. Experimental setup of image recognition.

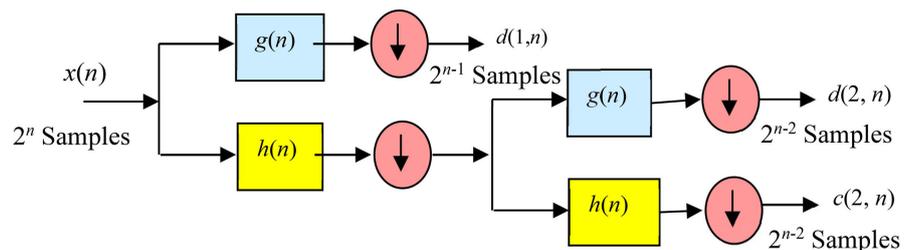


Figure 3. Decomposition of signal under filter bank.

matrix, $V = [a \ b \ c \ d]^T$ of 1×4 , which is actually contains the low frequency components of the image. The numerical values of elements of V is shown in **Table 1** for nine “0”, “1” and “2”. The scatterplot of a - b and c - d are shown in **Figure 4(a)** and **Figure 4(b)**. The region of digits “0”, “1” and “2” on a - b and c - d using k -means clustering are shown in **Figure 4(c)** & **Figure 4(d)**. The corresponding scatterplot using SVM are shown in **Figure 4(e)** & **Figure 4(f)**.

2.5. Proposed Algorithm of Extracting Four Lowest Spectral Components

M is the binary image of $N \times N$ after preprocessing

for $i = 0:N-1$,

{ $s = M(i, :)$; %ith row the of the image matrix, M

Table 1. Co-efficients of DWT.

DWT Co-efficient for Digit "0"				DWT Co-efficient for Digit "1"				DWT Co-efficient for Digit "2"			
<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>
1.000	0.754	0.785	0.876	0.837	1.000	0.837	0.848	1.000	0.658	0.627	0.939
1.000	0.592	0.701	0.738	1.000	0.808	0.876	0.732	0.881	1.000	0.966	0.786
0.934	0.899	0.893	1.000	1.0000	0.921	0.929	0.997	0.941	1.000	0.996	0.930
0.976	0.849	1.000	0.990	0.803	1.000	0.726	0.849	0.879	0.910	0.724	1.000
1.0000	0.797	0.834	0.985	1.000	0.883	0.686	0.929	0.896	1.000	0.924	0.881
0.794	0.880	0.884	1.000	0.923	0.813	0.668	1.000	1.000	0.897	0.884	0.944
0.756	0.561	0.702	1.000	0.982	0.943	0.768	1.000	0.942	1.000	0.733	0.889
1.000	0.992	0.995	0.995	0.998	1.000	0.999	0.989	1.000	0.994	0.995	0.994
0.993	0.999	1.000	0.998	0.996	1.000	0.994	0.998	1.000	0.997	0.999	0.999

Select orthogonal LP and HP filter bank (for example Daubechies wavelet filter)

Take DWT on the row vector s and extract approximate component i.e. the output of LP filter u .

$y =$ Under sample of u like figure 3

while $\text{length}(y) > 1$

Continue step 1 to 4

$r(i) = y$ %single element derived from i th row

}

Apply DWT on vector, $r = [r(0) \ r(1) \ r(2) \ \dots \ \dots \ \dots \ r(N-1)]$, m times

Plot the resultant vector of length $N/2^m$

Both the K -mean clustering and SVM algorithms fail to segregate the digits in three different regions i.e. the algorithms failed to match the profile of spectral components due random location of points visualized from **Figures 4(c)-(f)**. We got better matching using FIS and PCA, which is highlighted in next section.

3. Results

Few images of Bangla handwritten numerical character are shown in **Figure 5** (before preprocessing) taken from benchmark Indian database (Character Databases of Indic Scripts). The URL of the database is:

(<https://www.isical.ac.in/~ujjwal/download/database.html>) taken on 30th December 2018. The original image, enhanced image, image with thinning scheme and the result of the proposed algorithm is shown in **Figure 6** for four image of each character taken randomly from the database. Here we resize each grayscale image as 256×256 and apply DWT on each row of the image until getting a single value against each row. The output of DWT now will be a column vector of size 256×1 . Next we apply DWT on the final column vector 3 times, therefore the size of the feature vector becomes, $256/2^3 = 32$ as mention in subsection 2.5.

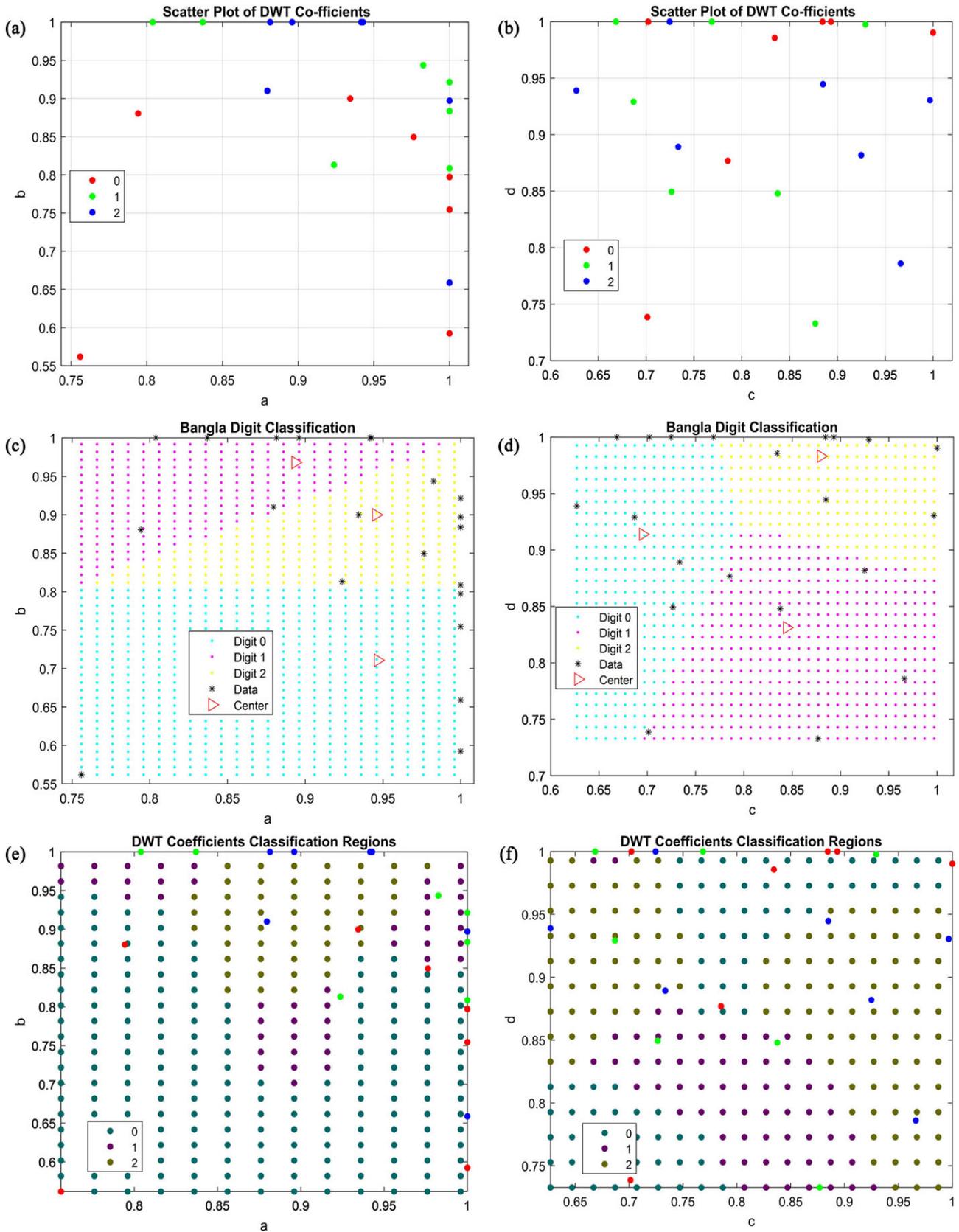


Figure 4. Scatterplot of spectral components. (a) Scatterplot of $a - b$; (b) Scatterplot of $c - b$; (c) Region of digits on $a - b$ using K-means; (d) Region of digits on $c - d$ using K-means; (e) Region of $a - b$ using SVM; (f) Region of $c - d$ using SVM.

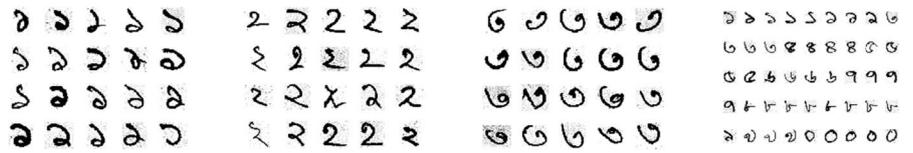


Figure 5. Few numerical character before preprocessing.





Figure 6. Output of proposed algorithm.

Taking the one “dimensional DWT vector” of co-efficient of length 16, we get the profile like **Figure 7**. Here we consider only five image of digit 1, 2, 3, 4 and 5. Each digit reveals distinct feature. Reducing the length of vector of length four we get the following data (**Table 1**) against digit 1, 2 and 3. Here each vector is presented as, $V = [a \ b \ c \ d]$. We next apply FIS on the data of **Table 1**. The basic diagram of FIS, signal flow diagram and few Fuzzy rules are shown in **Figures 8(a)-(c)** respectively like [20]. The variation of variable a , b , c and d of input vector, $V = [a \ b \ c \ d]$ is shown in **Figure 9**. Verification of relation of input and output of FIS is shown in **Figure 10** under four examples of, ($V = [0.941 \ 1 \ 0.996 \ 0.93]$, output = 2), ($V = [0.803 \ 1 \ 0.726 \ 0.849]$, output = 1), ($V = [0.976 \ 0.849 \ 1 \ 0.99]$, output = 0) and ($V = [0.9428 \ 1 \ 0.7336 \ 0.8893]$, output = 2).

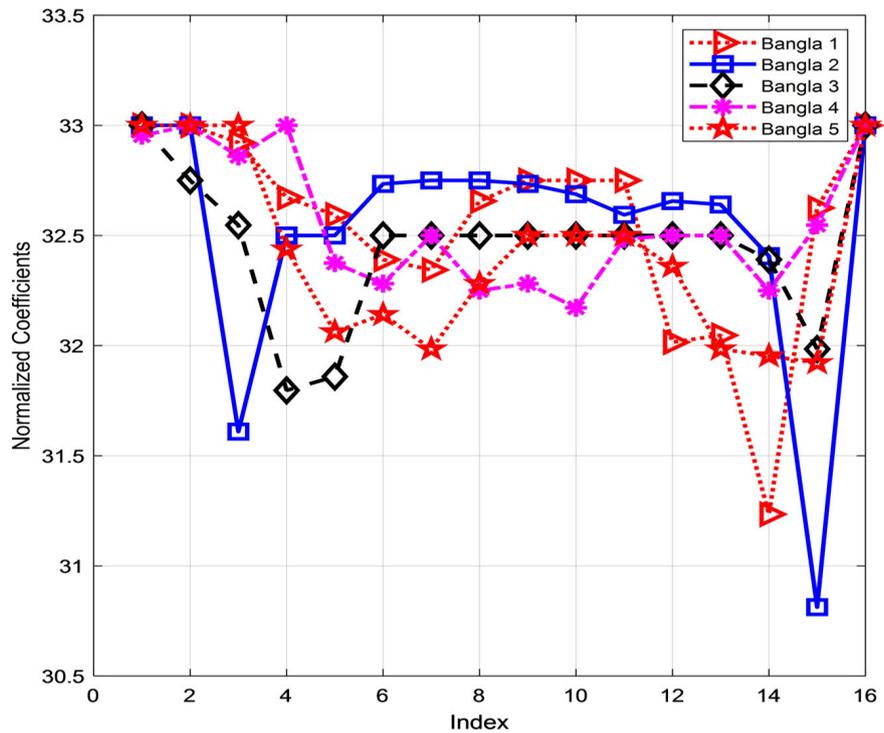
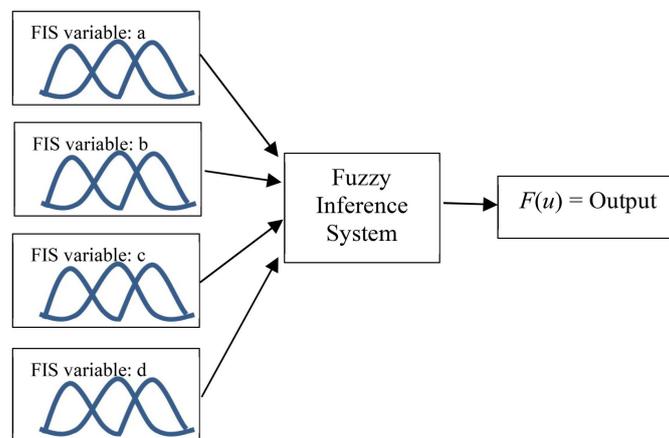
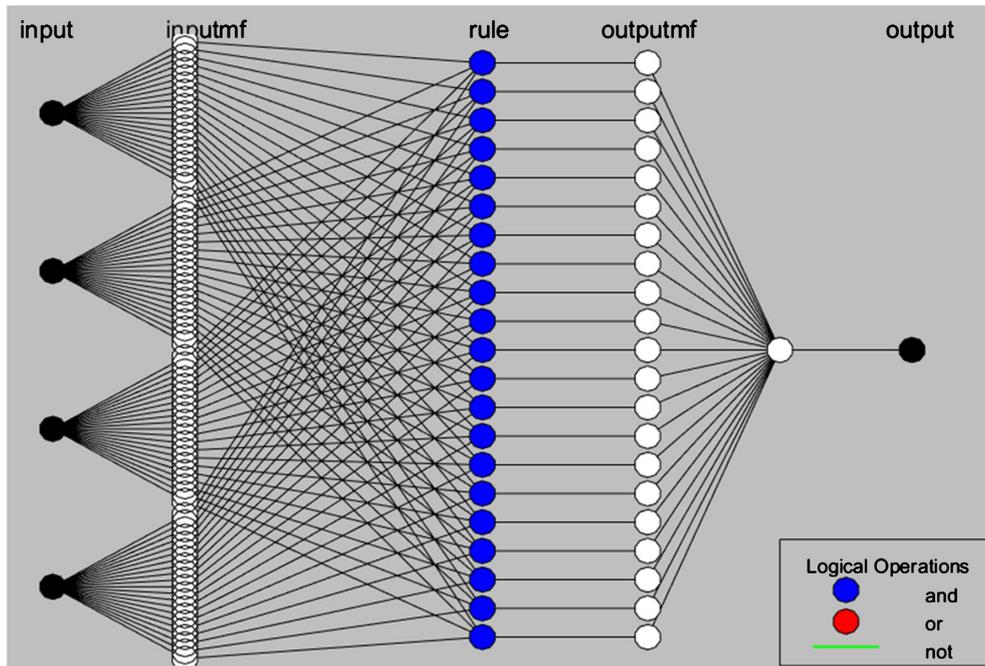


Figure 7. Profile of coefficient vectors of DWT.



(a)

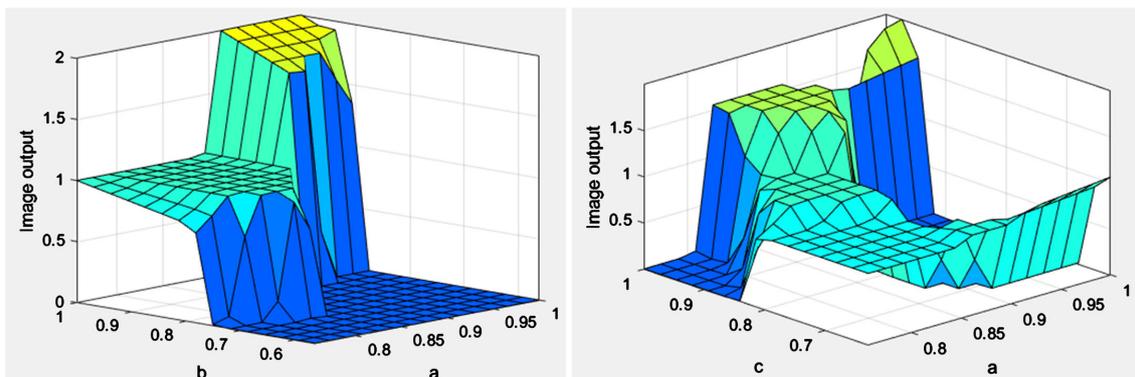


(b)

1. If (aa is in1cluster1) and (bb is in2cluster1) and (cc is in3cluster1) and (dd is in4cluster1) then (Image output is out1cluster1) (1)
2. If (aa is in1cluster2) and (bb is in2cluster2) and (cc is in3cluster2) and (dd is in4cluster2) then (Image output is out1cluster2) (1)
3. If (aa is in1cluster3) and (bb is in2cluster3) and (cc is in3cluster3) and (dd is in4cluster3) then (Image output is out1cluster3) (1)
4. If (aa is in1cluster4) and (bb is in2cluster4) and (cc is in3cluster4) and (dd is in4cluster4) then (Image output is out1cluster4) (1)
5. If (aa is in1cluster5) and (bb is in2cluster5) and (cc is in3cluster5) and (dd is in4cluster5) then (Image output is out1cluster5) (1)
6. If (aa is in1cluster6) and (bb is in2cluster6) and (cc is in3cluster6) and (dd is in4cluster6) then (Image output is out1cluster6) (1)
7. If (aa is in1cluster7) and (bb is in2cluster7) and (cc is in3cluster7) and (dd is in4cluster7) then (Image output is out1cluster7) (1)
8. If (aa is in1cluster8) and (bb is in2cluster8) and (cc is in3cluster8) and (dd is in4cluster8) then (Image output is out1cluster8) (1)
9. If (aa is in1cluster9) and (bb is in2cluster9) and (cc is in3cluster9) and (dd is in4cluster9) then (Image output is out1cluster9) (1)
10. If (aa is in1cluster10) and (bb is in2cluster10) and (cc is in3cluster10) and (dd is in4cluster10) then (Image output is out1cluster10) (1)
11. If (aa is in1cluster11) and (bb is in2cluster11) and (cc is in3cluster11) and (dd is in4cluster11) then (Image output is out1cluster11) (1)
12. If (aa is in1cluster12) and (bb is in2cluster12) and (cc is in3cluster12) and (dd is in4cluster12) then (Image output is out1cluster12) (1)
13. If (aa is in1cluster13) and (bb is in2cluster13) and (cc is in3cluster13) and (dd is in4cluster13) then (Image output is out1cluster13) (1)
14. If (aa is in1cluster14) and (bb is in2cluster14) and (cc is in3cluster14) and (dd is in4cluster14) then (Image output is out1cluster14) (1)
15. If (aa is in1cluster15) and (bb is in2cluster15) and (cc is in3cluster15) and (dd is in4cluster15) then (Image output is out1cluster15) (1)
16. If (aa is in1cluster16) and (bb is in2cluster16) and (cc is in3cluster16) and (dd is in4cluster16) then (Image output is out1cluster16) (1)
17. If (aa is in1cluster17) and (bb is in2cluster17) and (cc is in3cluster17) and (dd is in4cluster17) then (Image output is out1cluster17) (1)
18. If (aa is in1cluster18) and (bb is in2cluster18) and (cc is in3cluster18) and (dd is in4cluster18) then (Image output is out1cluster18) (1)
19. If (aa is in1cluster19) and (bb is in2cluster19) and (cc is in3cluster19) and (dd is in4cluster19) then (Image output is out1cluster19) (1)
20. If (aa is in1cluster20) and (bb is in2cluster20) and (cc is in3cluster20) and (dd is in4cluster20) then (Image output is out1cluster20) (1)
21. If (aa is in1cluster21) and (bb is in2cluster21) and (cc is in3cluster21) and (dd is in4cluster21) then (Image output is out1cluster21) (1)

(c)

Figure 8. FIS model of digit recognition. (a) Basic FIS; (b) Signal flow; (c) Fuzzy rules of the system.



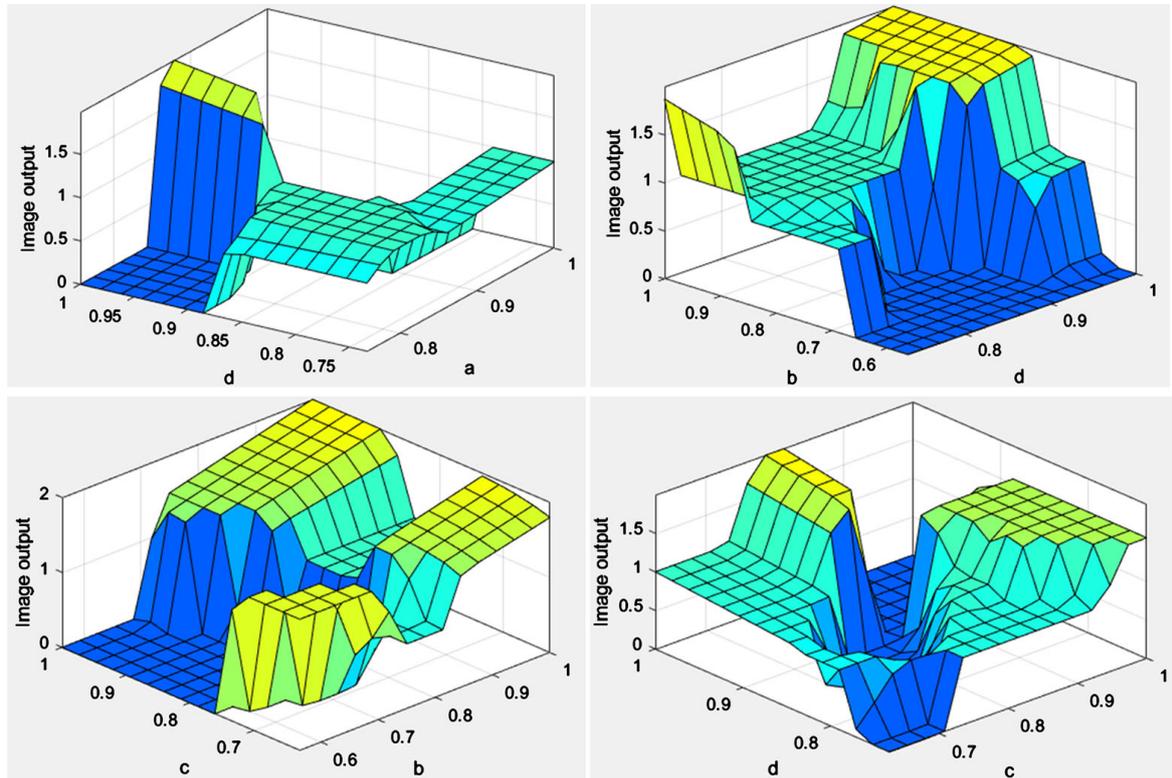


Figure 9. Surface plot of coefficients of DWT.

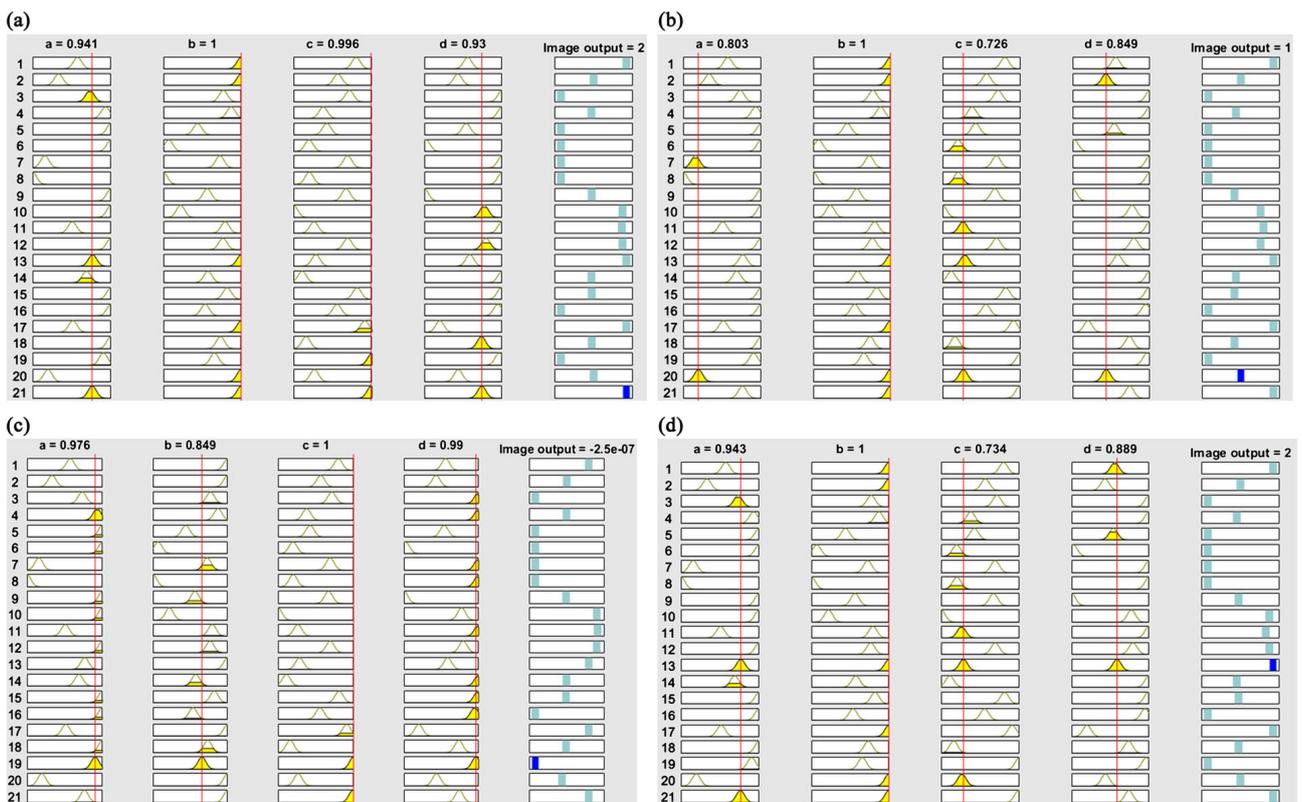


Figure 10. Verification of Fuzzy input and output of the FIS. (a) $V = [0.941 \ 1 \ 0.996 \ 0.93]$; (b) $V = [0.803 \ 1 \ 0.726 \ 0.849]$; (c) $V = [0.976 \ 0.849 \ 1 \ 0.99]$; (d) $V = [0.9428 \ 1 \ 0.7336 \ 0.8893]$.

The combination of DWT and PCA are also properly matched in object detection as found in this paper. Taking the DWT co-efficient of **Table 1** against three digits: 0 (object-1), 1 (object-2) and 3 (object-3), we determine four principal components of each object as shown in **Figures 11(a)-(d)** separately. Each of the four principal components are widely separated and shows better separation compared to **Figure 7** hence combination of DWT and PCA works better than DWT alone.

The impact of size of vector V of DWT and the size of preprocessed image on accuracy of recognition is shown in **Table 2**. The accuracy of recognition of ten objects (Bangla digits) are determined by four techniques as: DWT of [21], PCA + DWT under the concept of [22] [23], FIS + DWT using the technique of [24] and FIS + PCA + DWT as the proposed method. The accuracy increases with increase in size of vector V and that of image for all four cases. The PCA + DWT shows better result compared to FIS + DWT for larger V or size of image. The combination of three schemes outperforms compared to other three cases of **Table 2**. Three techniques of object recognition are combined using entropy

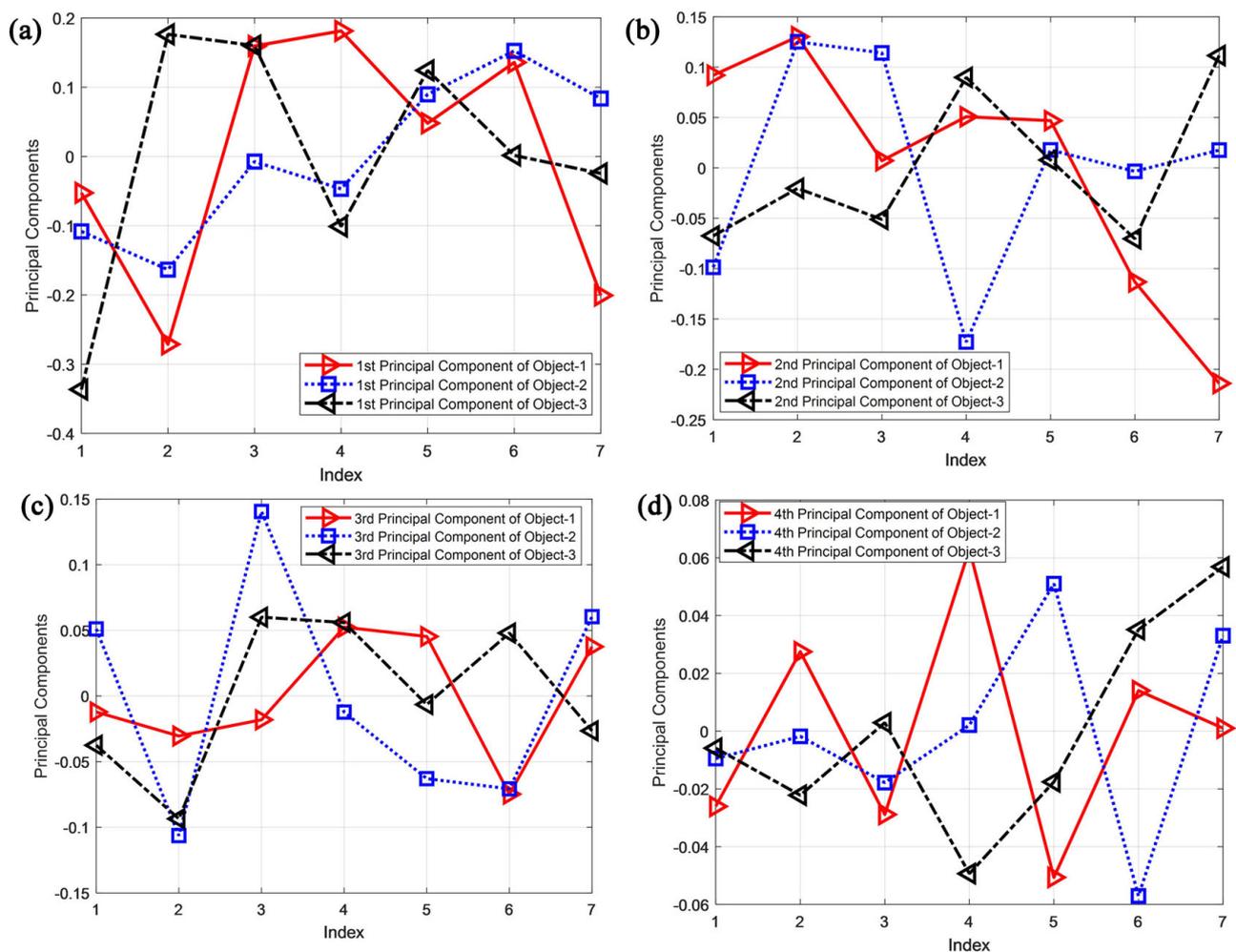


Figure 11. Profile of PCA of three objects taking spectrum of DWT as the input. (a) First principal components; (b) Second principal components; (c) Third principal components; (d) Fourth principal components.

Table 2. Comparison of recognition accuracy.

length of V for DWT	Size of image for FIS	Accuracy of recognition (DWT) [21]	Accuracy of recognition (PCA + DWT) [22] [23]	Accuracy of recognition (FIS + DWT) [24]	Accuracy of recognition (FIS + PCA + DWT)
4	8×8	0.814	0.872	0.886	0.891
6	16×16	0.835	0.897	0.902	0.933
8	32×32	0.844	0.942	0.939	0.947
10	64×64	0.863	0.951	0.944	0.958

based algorithm of [25]. We worked on the machine: Processor \rightarrow Intel(R), Core(TM) i7-8550U, RAM \rightarrow 8.00 GB and use Matlab 18. Taking the size of image: 64×64 we get the process time of 500 ms for DWT, 1.8S for PCA + DWT, 2.7S for FIS + DWT and 4.6S for FIS + PCA + DWT against each object.

4. Conclusion

In this paper, we recognize Bangla handwritten digits using combination of PCA and FIS, taking the feature vector of DWT. We compare the results of our proposed method with some previous works of object recognition and we get better accuracy of recognition. One limitation of the paper is that we did not compare the process time or complexity of algorithms. In future, we will combine more object recognition algorithm to recognize Bangla vowels, consonants and digits all together. The concept of the paper is applicable in any kind of object detection/recognition, although the accuracy of recognition may vary for different type of objects and quality of image. Inclusion of DWT will save the memory against storing the database of images. Still we have the scope to use other object recognition algorithms like, PCA, LDA, SURF, HOG and CNN for comparison in context of accuracy of recognition and process time so that we can select appropriate algorithm for real time operation of computer vision.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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