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Adaptive Color Image Segmentation Using Fuzzy Min-Max Clustering

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Abstract- **This paper proposes a novel system for color image segmentation called "Adaptive color image segmentation using fuzzy min-max clustering (ACISFMC)". The present work is an application of Simpson's fuzzy min-max neural network (FMMN) clustering algorithm. ACISFMC uses a multilayer perceptron (MLP) like network which perform color image segmentation using multilevel thresholding. Threshold values used for finding clusters and their labels are found automatically using FMMN clustering technique. FMMN clustering technique uses a hyperbox fuzzy set concept. In the proposed work, Fuzzy entropy is used as a tool to decide number of clusters. ACISFMC uses saturation and intensity planes of HSV (hue, saturation, intensity) color space for segmentation. Here, neural network is used to find the number of objects automatically from an image. One of the good feature of this method is that, it does not require a *priori* knowledge to segment a color image. The algorithm is found to be robust and relatively computationally inexpensive for large variety of color images. One application of the proposed method is demonstrated here. Experimental evaluation demonstrates the performance of ACISFMC is robust for noisy images also.**

Index Terms- **Adaptive thresholding, Color image segmentation, Fuzzy min-max neural network, Neuro-fuzzy system.**

I. INTRODUCTION

Segmentation is a process of grouping an image into units that are homogeneous with respect to one or more characteristics. It is an important task in image analysis [1]. In past decades, attention has been focused on monochrome image segmentation whose goal is to separate individual objects in the perception of the scene. A common problem in segmentation of monochrome image occurs when an image has a background of varying gray levels such as gradually changing shades [2]. This problem is inherent, since intensity is the only available information from monochrome images. It has long been recognized that the human eye can detect only in the neighborhood of one or two dozen intensity levels at any one point in a complex image due to its brightness adaptation but can discern thousands of color shades and intensities [3].

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Color is a perceptual phenomenon related to human response to different wavelengths in the visible electromagnetic spectrum [4]. Color is perhaps, the most dominant and distinguishing feature in many applications. Three psychological attributes namely hue, saturation and intensity are generally used to represent a color. Compared to monochrome image, a color image provides in addition to intensity, the additional information (hue and saturation) in the image. In fact, human beings intuitively feel that color is an important part of their visual experience and color is useful or even necessary for powerful processing in computer vision [5]. In computer vision, researchers have attempted to utilize this additional information. Thus, applications with color image are becoming increasingly prevalent nowadays [6],[7]. In this paper, we propose a system capable to perform adaptive multilevel color image segmentation based on thresholding and FMMN clustering technique. Clusters and their labels are automatically found out using FMMN clustering technique. The main advantage of this technique is that, it does not require a *priori* information to segment a color image.

Color image segmentation techniques can be roughly classified into four types such as histogram based approaches, neighborhood based approaches, clustering based approaches and hybrid based approaches as discussed below.

Histogram thresholding is a popular technique that looks for the peaks and valleys in histogram [8]. It assumes that images are composed of regions with different gray level ranges. The histogram of an image can be separated into a number of peaks (modes), each corresponds to one region, and there exists a threshold value corresponding to the valley between two adjacent peaks. The major advantage of this technique lies in its simple computation. However, this method lacks the spatial relationship information of the pixels [9]. The neighborhood based approach usually uses the uniformity criteria to segment regions in the image [10]. E.g. Region based techniques. These techniques consider that neighboring pixels within same region should have similar values (e.g. intensity, color, and texture). Here, we need to assume a set of seed points initially. However, the difficulty with this technique is the selection of initial seed points and the order in which pixels and regions are examined [11]. Moreover, it is better than histogram thresholding techniques since it considers the spatial relationship between pixels.

Clustering based approach generally uses a fuzzy logic to define membership of the pixels [12]. Regions are formed by inspecting the membership values of pixels using partition method e.g. Fuzzy C-means (FCM) algorithm. Huntsberger [13] define a regions if the membership value is above "α -cut off". For clustering based approach, fuzzy model of the image is a crucial factor for the successful implementation. Hybrid based techniques improve the segmentation result by combining all above methods for segmentation. Harries [14] presented a segmentation algorithm using watershed algorithm and region merging. The technique uses a watershed transform to initial partition of the image into primitive regions. The output of watershed algorithm is used as an input for hierarchical (bottom-up) region merging process, which produced the final segmentation.

The present work is an attempt to design an adaptive neuro-fuzzy system adequate to perform multilevel segmentation of color images in HSV color space. The proposed method is the application of FMMN clustering algorithm to find number of clusters of pixels with similar color [15],[16]. The clusters (segments) and their labels are automatically found out using FMMN clustering technique. Neural network is used to find multiple objects in the image. The network architecture is similar in principle to [17]. The network consists of three layers such as input layer, hidden layer and output layer. Each layer consists of fixed number of neurons equal to number of pixels in the image. The activation function of neuron is a multisigmoid. The major advantage of this technique is that, it does not require a priori information of the image. The number of objects in the image is found out automatically. One application of the proposed method is also demonstrated here. The network has been employed to extract objects from noisy environments. The results obtained are found to be satisfactory.

The rest of the paper is organized as follows. Section II introduces a FMMN clustering algorithm. Section III elaborates the description of the proposed method. Section IV presents experimental results and comparison with other techniques. Section V presents an application of the proposed method. The final section concludes with summary.

II. FMMN CLUSTERING ALGORITHM

Zadeh [18] first introduced the concept of fuzzy sets in which imprecise knowledge can be used to define an event. A fuzzy set A is represented as

$$A = \{\mu_A(x_i)/x_i, i = 1,2,......,n\} \qquad (1)$$

Where,

$\mu_A(x_i)$ gives the degree of belonging the element x_i in the set *A*.

The relevance of fuzzy set theory in pattern recognition problems has adequately been addressed in the literature [19],[20],[21]. A fuzzy set theory, that allows to deal with uncertainty and ambiguity has found considerable applications in image segmentation [22],[23]. The integration of fuzzy logic with neural network has emerged as a promising field of research in recent years. This has lead to the development of a new branch called neuro-fuzzy computing, such as FMMN clustering algorithm [15],[16].

FMMN clustering technique uses a hyperbox fuzzy set concept. In FMMN [15],[16] algorithm, hyperboxes are defined by a pair of min-max points and a membership function is defined with respect to these points. The membership function for each hyperbox fuzzy set must describe a degree to which the pattern fits within a hyperbox.

FMMN learning algorithm has three steps namely Expansion, Overlap test and Contraction of the hyperboxes respectively. The training set *D* consists of a set of *m* ordered pairs $\{x_h, d_h\}$ where $x_h = (x_{h1}, x_{h2},...., x_{hn}) \in I^n$ is the input pattern and $d_h \in \{1,2,,3,......,m\}$ is one of the *m* classes.

When a training sample is presented to network, the algorithm tries to search a hyperbox for the same class which can expand to include the input. If no suitable hyperbox is found to accommodate the applied training sample, a new hyperbox is formed and added to the neural network. After expansion, overlap test find out the overlap between expanded hyperbox with all other class hyperboxes. When the overlap occurs between hyperboxes representing the same class, the overlap is not removed. But when the overlap occurs between hyperboxes that represents the different classes, the overlap is eliminated using contraction process. The contraction process only eliminates the overlap between those portions of the hyperboxes from separate classes that are having full membership. The membership function for the hyperbox is as follows (2).

$$b_j(A_h) = \frac{1}{2n}\sum_{i=1}^{n}\begin{bmatrix}\max\left(0,1-\max\left(0,\gamma\min\left(1,a_{hi}-w_{ji}\right)\right)\right)\\ +\max\left(0,1-\max\left(0,\gamma\min\left(1,v_{ji}-a_{hi}\right)\right)\right)\end{bmatrix} \qquad (2)$$

Where,

$A_h = (a_{h1}, a_{h2},...., a_{hn}) \in I^n$ is the h^{th} input pattern

$V_j = (v_{j1}, v_{j2,},...., v_{jn})$ is the min point for B_j

$\gamma =$ Sensitivity parameter.

III. ADAPTIVE COLOR IMAGE SEGMENTATION USING FUZZY MIN-MAX CLUSTERING

A. ACISFMC architecture overview

The proposed block diagram of "Adaptive Color Image Segmentation Using Fuzzy Min-Max Clustering (ACISFMC)" is as depicted in Fig. 1. ACISFMC uses HSV color space for the color image segmentation. HSV color representation is compatible with vision psychology of human eyes and its three components such as hue (H), saturation (S), and intensity (V) are relatively independent [5]. It is better than RGB transformation since there exists a high correlation among three color components such as red (R), green (G), and blue (B) which makes these three components dependent upon each other and associate strongly with intensity. Hence, RGB color space is very difficult to discriminate highlights, shadows and shading in color images [9]. HSV color space can solve this problem. HSV color model is having following advantages.

1. Hue is an invariant to certain types of highlights, shading, and shadows.
2. HSV color model decouples the intensity component from color information (hue and saturation) in a color image.

ACISFMC system consists of a multilayer neural network which performs adaptive, multilevel thresholding of the color image. Clusters and their labels are automatically found out by applying FMMN clustering algorithm on image histogram in saturation and intensity plane respectively. ACISFMC uses saturation and intensity planes for color image segmentation since these are the two quantities that may vary and hue value remains same also, non-removable singularity is one of hue's drawbacks this may create discontinuities and spurious modes in the representation of colors [4].

Fuzzy entropy is used as a tool to measure the error of the system. Given an input image, system is forced towards a minimum fuzzy entropy state in order to obtain segmentation. Segmentation is carried out independently in each plane respectively. The final segmentation is achieved by combining the results of these planes.

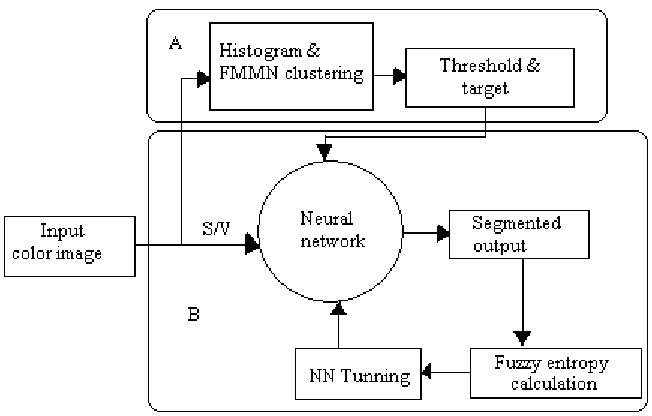


Fig. 1. Block diagram of ACISFMC.

B. System flowchart

A general flowchart of the proposed algorithm is depicted in Fig. 2. First, clusters and their labels are automatically found out by applying FMMN clustering algorithm on image histogram in respective plane respectively. ACISFMC is a histogram multithresholding technique hence it is necessary to find different thresholds and target to segment objects in the image. Once the clusters are found out, average of two cluster center in respective planes is taken as a threshold value. After detecting thresholds, labels for the objects are decided. The information about labels is used to construct network's activation function. Neuron uses a multilevel sigmoid function as an activation function. This activation function takes care of thresholding and labeling the pixels during training process. The details are given in section C.

Viewed as a system, ACISFMC consists of two major processing blocks as shown in Fig. 1.

- Adaptive threshold selection block (A)
- Neural network segmentation block (B)

Adaptive threshold selection block is responsible to determine clusters and compute a multilevel sigmoid function of neurons. Neural network segmentation block does the actual segmentation based on the number of objects found out by adaptive threshold selection block.

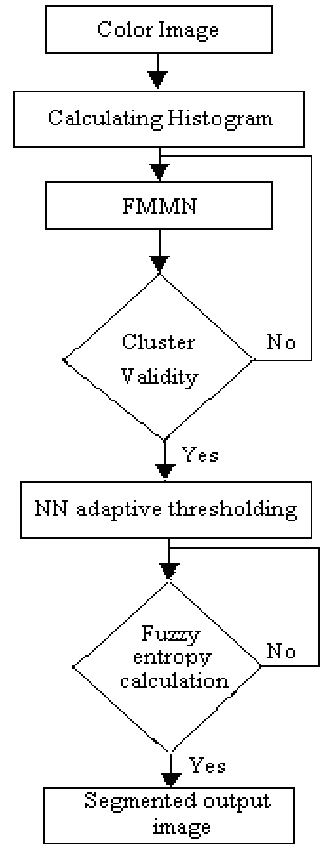


Fig. 2. System Flowchart.

C. Adaptive threshold selection block (A)

Adaptive threshold selection block consists of adaptive thresholding system itself. The purpose of this block is to find out number of clusters and computation of multi-level sigmoid function for neurons. With the aim of keeping the system totally adaptive, there is a need of an automatic way to determine number of clusters. In the proposed work, this was done by using a FMMN clustering technique. The main aspire here is to locate the number of clusters without a priori knowledge of the image. To accomplish this, first the histogram of given color image for saturation and intensity planes are found out. Clusters and their labels for the objects are found out by applying a FMMN clustering algorithm to image histogram in respective planes. Threshold and target values are obtained from the clusters. Cluster centers are considered as a target while the average of two targets is considered as a threshold. The average value as a threshold helps to segment the objects with a color appropriate to its original color. Hence in ACISFMC system, objects are colored with their mean color i.e. system tries to maintain the color property of the object even after segmentation. This can be helpful in image post-processing. Once threshold and target values are calculated, a neural network activation function is constructed [24] as in (3).

$$f(x) = \sum_k \left(\frac{y_k - y_{k-1}}{1 + e^{-(x-\theta_k)/\theta_0}} + y_{k-1} \right) \times \left[\mu\left((x - y_{k-1}) \times d^2\right) - \mu\left((x - y_k) \times d^2\right) \right] \quad (3)$$

Where,

- u Step function
- θ_k Thresholds
- y_k Target level of each sigmoid, will constitute the system labels
- θ_0 Steepness parameter
- d Size of neighborhood.

D. Neural network segmentation block (B)

Neural network segmentation block consists of fuzzy entropy calculation block and NN tunning/training block.

The proposed ACISFMC system consists of two independent neural networks one each used for saturation and intensity planes respectively. In Fig. 3, we depict the three layered proposed network architecture. The layer where the inputs are presented is known as the input layer. On the other hand the output producing layer is called as output layer. Besides, the input and output layer, there exists a third layer called as a hidden layer. Each layer is having a fixed number of neurons equal to the size (M x N) of image. Each neuron in a layer represents a single pixel. The input to a neuron in the input layer is normalized between [0-1]. The output value of each neuron is between [0-1]. All neurons are having primary connection weight as 1. Each neuron in a layer is connected to the corresponding neuron in the previous layer and to its neighbors over N^d neighborhood as shown in Fig. 4. So for N^1 neighborhood connection scheme, a neuron has five links, representing "1" as depicted in Fig. 4. Whereas for N^2 neighborhood connection scheme, there are nine links associated with every neuron representing "1" and "2" and so on. Neurons in the same layer do not have connection among themselves. The output of the nodes in one layer is transmitted to the nodes in another layer via links that amplify or inhibit such outputs through weighting factors. Except for the input layer nodes, the total input to each node is the sum of weighted outputs of the nodes in the previous layer. Each node is activated in accordance with the input to the node and the activation function (3) of the node.

D.1. Fuzzy entropy

Fuzzy set plays an important role in various distributed systems because of their ability to model non statistical ambiguity [20]. Consequently, characterization and quantification of fuzziness are important issues that affect the management of uncertainty in many system models and designs. The entropy of a fuzzy set is a measure of fuzziness of that fuzzy set. The first fuzzy entropy formula without reference to probabilities was proposed in 1972 in the work of Luca and Termini [25], who defined entropy using Shannon's functional form. He defined fuzzy entropy as:

$$H(A) = \frac{1}{n\ln(2)} \sum_{i=1}^{n} \left\{ S_n\left(\mu_A(x_i)\right) \right\} \quad (4)$$

In 1993, Pal and Bhandari [26] extended Luca and Termini's formula, and introduced α order fuzzy entropy, which uses α order probability entropy form.

Another definition of fuzzy entropy is given by Pal and Pal in [27] as:

$$H(A) = \frac{1}{n\left(\sqrt{e}-1\right)} \sum \left\{ S_n\left(\mu_A(x_i)\right) - 1 \right\}, with$$
$$S_n\left(\mu_A(x_i)\right) = \mu_A(x_i) e^{1-\mu_A}(x_i) + \left(1 - \mu_A(x_i)\right) e^{\mu_A}(x_i) \quad (5)$$

There have been numerous applications of fuzzy entropy in image segmentation. Cheng [28] presented a thresholding approach by performing fuzzy partition on a two-dimensional histogram based on fuzzy relation and maximum fuzzy entropy principle. Zhao [29] presented an entropy function by using fuzzy partition (FP) and the probability partition (PP) which was used to measure the compatibility between FP and the PP.

In the proposed work, fuzzy entropy is used to calculate the error of the system. The partition entropy (PE) is calculated using (6) described by Bezdek in [30]. Here, the aim of network is to reduce the degree of fuzziness of the input color image.

$$PE = -\frac{1}{n \ln\left(\frac{1}{C}\right)} \sum_{k=1}^{n} \sum_{i=1}^{C} \left[\mu ik \ \ln\left(\mu ik\right) \right] \quad (6)$$

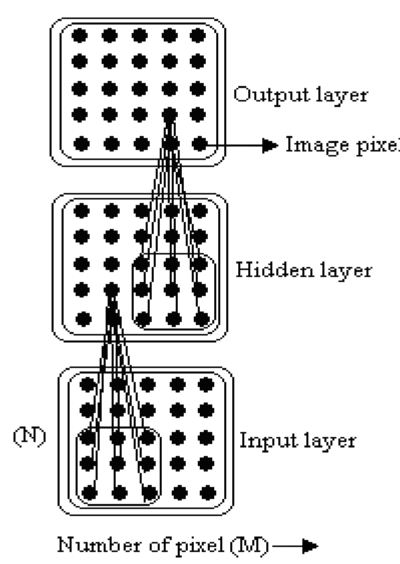


Fig. 3. Neural network architecture.

			6			
	5	4	3	4	5	
	4	2	1	2	4	
6	3	1	1	1	3	6
	4	2	1	2	4	
	5	4	3	4	5	
			6			

Fig. 4. Neighborhood system.

D.2. Neural Network (NN) Tunning

The purpose of NN tunning block is to update the connection weight as in (7) by taking into consideration the output error in network. A back propagation algorithm [31],[32] is employed for training. At every training epoch, error is computed by getting a difference between the actual output and the desired output of neuron. The weights are updated using (7). After the weights have been adjusted properly, the output of the neurons in the output layer is fed back to the corresponding neurons in the input layer. The second pass is then continued with this as an input. The iteration (updating of weights) is continued until the network stabilizes; i.e. the error value (measure of fuzziness) becomes minimum in order to obtain segmentation. As discussed before, the intention of network is to reduce the error in order to obtain segmentation.

$$\begin{aligned} \Delta w_{ji} &= n\left(\frac{\partial E}{\partial o_j}\right)\frac{\partial o_j}{\partial I_j} o_i \quad \textit{Output layer} \\ & n\left(\sum k\left(-\frac{\partial E}{\partial o_k}\frac{\partial o_k}{\partial I_k} w_{kj}\right)\right)\frac{\partial o_j}{\partial I_j} o_j \, \textit{Hidden layer} \end{aligned} \tag{7}$$

Where,

Ii Total input to the i^{th} neuron
Wji Weight of link from neuron *i* in one layer to neuron *j* in the next layer
O_i Output of the i^{th} neuron i in one layer to neuron j in the next layer
E Error in the network's output
n Learning rate.

As the training progresses, a pixel gets the color depending upon its surrounding pixel colors. From the output image shown in Fig. 5(b), it can be observed that network tries to label a cluster with an even color spread. The segmentation using multiple thresholds is explained with an example in the next section.

Consider Fig. 5(a) to understand the segmentation process. As a first step, thresholds in saturation (S) and intensity (V) planes are found out. Fig. 5(c) shows the histogram of the image. Clusters are automatically found out by applying a FMMN clustering algorithm to image histogram in respective planes. Thresholds and target values are obtained from the clusters. Cluster centers are considered as a target whereas average of two target values is considered as a threshold value. By using threshold and target values, the neuron's activation function is constructed as shown in (3). Fig. 5(d) shows the multisigmoid function. Fig. 5(b) shows the segmented output using proposed method. The main advantage of this technique is that, it does not require a priori knowledge to segment regions. Following Figures 5(c)-5(d) are for the saturation plane. Similar Figures are for the intensity plane.

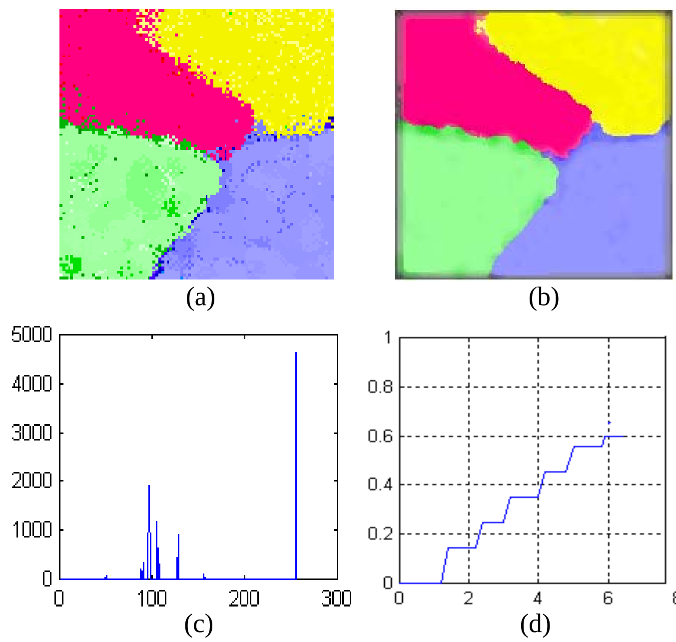


Fig. 5. (a) Original image (b) Segmented output using proposed method (c) Histogram of the image (d) Multisigmoid function.

IV. EXPERIMENTAL RESULTS

We have tested the proposed algorithm by applying it on a variety of images and compared the results with those obtained using [33],[34] techniques. The performance of ACISFMC system on different types of color images available on the World Wide Web such as [35],[36],[37] is discussed here. Experimental results on images such as "Panda", "Horse", "Hand", "Objects", "Biological cell" and "Balloons" are illustrated here.

A. Segmentation results

The proposed algorithm is implemented in matlab environment on a Pentium IV, 2.8GHz, 256 RAM. For all the experiments, the proposed method uses a (3 x 3) neighborhood scheme for neuron connection scheme as shown in Fig. 4.

To demonstrate the segmentation performance of ACISFMC system, we do some experiments. The comparison between the segmented image obtained by means of proposed method and some other techniques proposed by Uchiyama and Arbib [33] and Frequency Sensitive Competitive Learning (FSCL) based method proposed by Ahalt [34] are depicted in

Fig. 6. Fig. 6(b) shows the segmentation result using [33] method. Uchiyama and Arbib [33] presented a Segmentation algorithm using competitive learning (CL) approach. It is an adaptive version of K-means clustering algorithm [38]. It is based on the least sum of squares criterion. Although k-means and CL learning algorithm can successfully accomplish data clustering in some situations, it suffers from several drawbacks. First, there is a *dead-unit* problem. That is, if some units are initialized far away from the input data set in comparison with the other units, they immediately consider as a dead unit without any winning chance in the forthcoming competitive learning process. Second, it needs to pre-determine the cluster number. When pre-determined cluster number equals to true cluster number, then and then only k-means algorithm correctly find out the cluster center.

(a) (b)

(b) (d)

Fig. 6. (a) Original image (b) Segmented image obtained using CL approach (c) Segmented image obtained using FSCL (d) Segmented image obtained using proposed technique.

An extension of k-means clustering algorithm is FSCL which was proposed in [34]. In FSCL algorithm, the winning chance of a seed point is penalized along with the increase of past winning frequency, and vice versa. FSCL clustering technique can successfully assign one or more seed points to each cluster without a dead-unit problem. But its cluster performance decreases when cluster number is incorrectly selected in advance. The segmented image of Fig. 6(c) is obtained by Ahalt [33] technique. Fig. 6(d) shows the segmentation result using proposed method. Note from Fig. 6(d) that the proposed system produces better segmentation results than [33],[34].

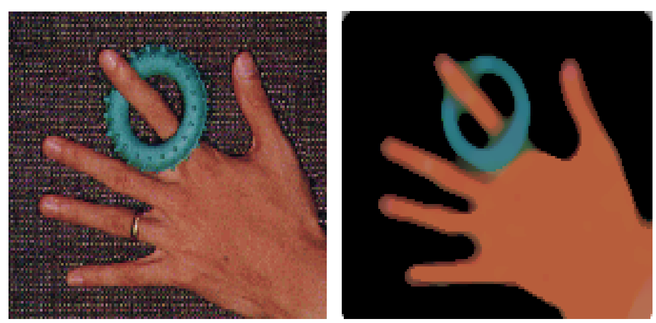
To see the effectiveness of the proposed method, the algorithm is tested on various color images of different types. The segmentation results for the Figures 7(a)-12(a) are depicted in Figures 7(b)-12(b) respectively. It can be observed from the Fig. 7(b)-12(b) that without a priori knowledge system could isolate the objects properly and are labeled with their mean colors.

(a) (b)

Fig. 7. (a) Original image (b) Segmented image.

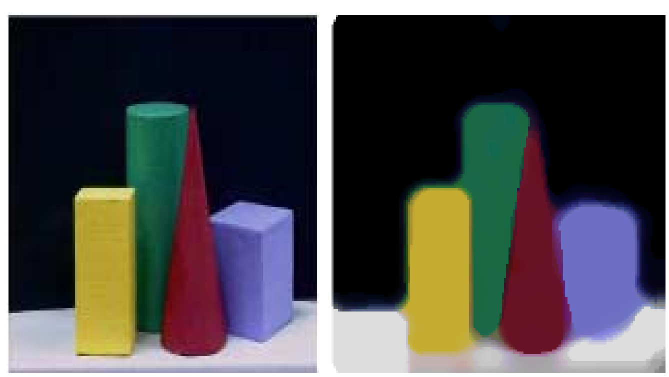
(a) (b)

Fig. 8. (a) Original image (b) Segmented image.



(a) (b)

Fig. 9. (a) Original image (b) Segmented image.



(a) (b)

Fig. 10. (a) Original image (b) Segmented image.

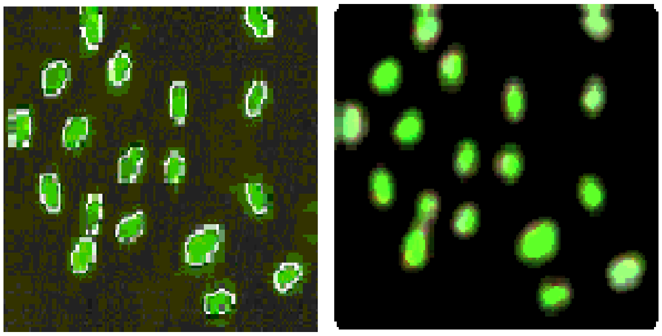

(a) (b)

Fig. 11. (a) Original image (b) Segmented image.


(a) (b)

Fig. 12. (a) Original image (b) Segmented image.

V. APPLICATION

Application of the proposed system is demonstrated here. The proposed system has been employed in object extraction problem from noisy environments. The system used for segmentation of noisy images is with second order (3x3) neighborhood scheme for neuron connections (Fig. 4). The neuron thus gets the input from nine neurons in the previous layer. The algorithm has been implemented on a set of noisy images of different types. The Effectiveness of ACISFMC system on noisy images such as “Panda”, “Leaf” is illustrated here. The images are distorted with different types of noise immunity such as “Gaussian”, “Salt & Pepper”, and “Speckle” with mean 0 and variance 0.1, 0.01, 0.02 respectively. Figures 13(b)-18(b) shows the segmentation results of distorted “Panda” and “Leaf” image respectively. Robust performance of the proposed system on noisy images can be observed from the experimental results.


(a) (b)

Fig. 13. (a) Original image with Gaussian noise (b) Segmented image.


(a) (b)

Fig. 14. (a) Original image with Salt and Pepper noise (b) Segmented image.


(a) (b)

Fig. 15. (a) Original image with Speckle noise (b) Segmented image.

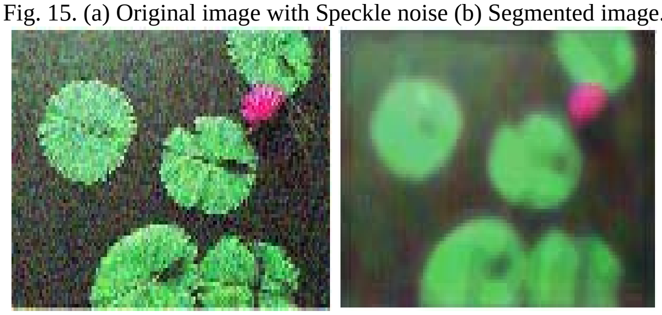

(a) (b)

Fig. 16. (a) Original image with Gaussian noise (b) Segmented image.

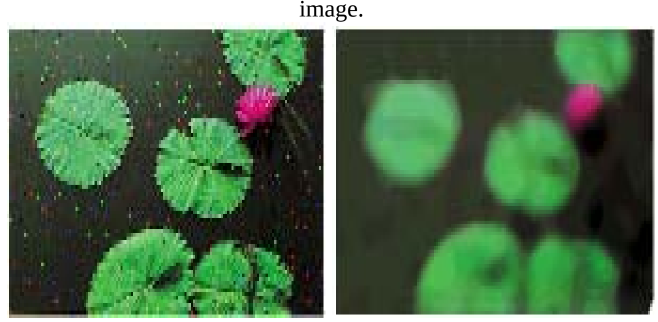

(a) (b)

Fig. 17. (a) Original image with Salt and Pepper noise (b) Segmented image.

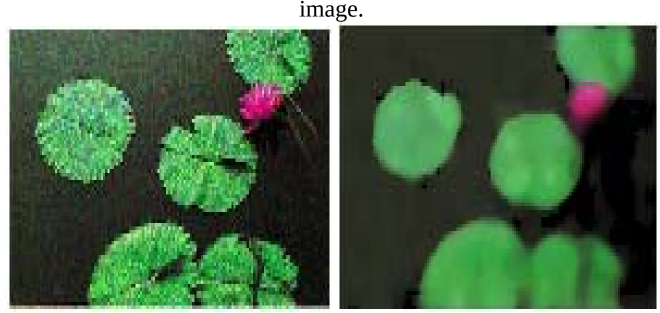

(a) (b)

Fig. 18. (a) Original image with Speckle noise (b) Segmented image.

VI. CONCLUSION

In this paper, a novel segmentation technique for color images is presented. The segments in images are found automatically based on adaptive multilevel threshold approach and FMMN clustering algorithm. The neural network with multisigmoid function tries to label the objects with its original color even after segmentation. One of the good features of the proposed system is that it does not require *a priori* information about number of objects in the image. ACISFMC system is tested on several images of different types. The performance of proposed algorithm is compared with other currently available algorithms such as [33],[34]. Experimental results show that the performance of the proposed technique is found satisfactory. The system can be used as a primary tool to segment unknown color images. The algorithm has been implemented on a set of noisy images. Results show that the system performance is robust to different types of noisy images also.

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