Chapter 6: Adaptive Color Image Segmentation using Fuzzy Min-Max Clustering

"Honest disagreement is often a good sign of progress."

Mahatma Gandhi.
6.1 Introduction

In previous chapter, we discussed the multilevel approach for color image segmentation using derivative of histogram. A survey on image processing with neural networks reported several types of networks such as self organizing feature map (SOM), Hopfield, cellular network that have been applied to the task of image segmentation [1]. Fuzzy set theory that allows to deal with uncertainty and ambiguity has found considerable applications in image segmentation [2]. Computational efficiency of neural networks and capability of fuzzy logic has created a lot of interest in neuro-fuzzy techniques.

There are different clustering algorithms such as K-means, fuzzy c means (FCM) available in literatures for color image segmentation. Among these, FCM is one of the best known clustering algorithms and obtained good result but has some limitations. One of the main drawbacks is that it needs a priori knowledge regarding clusters within an image. To avoid such dependency another clustering algorithm called "Fuzzy Min-max Neural Network" (FMNN) proposed by Simpson is used in the proposed method [3]. FMNN was introduced using a hyperbox fuzzy set concept which is a powerful method to classify linearly non-separable multidimensional data. An $n$-dimensional hyperbox can be defined by stating its min and max vertices. The simplicity in representation and manipulation of hyperboxes are the key factors of its attraction.

This chapter proposes an adaptive neuro-fuzzy technique called "Adaptive color image segmentation using fuzzy min-max clustering" (ACISFMC) adequate to perform multilevel segmentation of color images. ACISFMC uses HSV color space for segmentation. The proposed method is an application of FMMN clustering algorithm to find clusters of pixels with similar color. The clusters (segments) and their labels are automatically found out using FMMN clustering technique. Neural network is used to find multiple objects from an image. The structural design of network is similar in principle to an adaptive color image segmentation [4]. 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 within an image is found out automatically. An application of the proposed method to extract objects from noisy environment is demonstrated. The results obtained are found to be satisfactory.
6.2 FMMN clustering algorithm

Fuzzy sets were first introduced by Zadeh as a means of representing and manipulating data that were not precise, but rather fuzzy [5]. Zadeh’s extension of set theory provided a mechanism for representing linguistic constructs such as ‘many’, ‘few’, ‘often’, and ‘sometimes’. Unlike the traditional theory, which measures the chance with which a given event is expected to occur, fuzzy theory measures the degree to which an event occurs. In situations where a flip of a coin produces one of two possible outcomes, probability theory makes sense. In this situation, the outcome is very decisive. The probability theory fails when attempting to describe non-decisive situations such as the baldness of a person. What is actually required is a measure of the degree to which a person is bald. Fuzzy theory provides the ability to represent measure and manipulate this type of information. A fuzzy set $A$ is represented as [6]

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

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

The evolution of fuzzy logic for clustering is elaborated [7]. The merger of fuzzy logic and neural network for clustering has been reported [8,9]. A similar approach for clustering was proposed by Simpson in FMMN. It was introduced using the hyperbox fuzzy set concept [10]. A hyperbox is a very simple geometrical structure, shown in Figure 6.1. A $n$-dimensional hyperbox can be defined by stating its min and max vertices. The min-max points define the lower and upper limits for each attribute of the points lying inside the hyperbox. By collecting hyperboxes belonging to the same class, one can classify multidimensional data very easily.

![Figure 6.1 Hyperbox.](image-url)
During learning phase, maximum hyperbox size is controlled by a parameter called expansion coefficient (θ). Overlaps created amongst hyperboxes belonging to different classes are removed by the contraction process. 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: 1) Expansion, 2) Overlap test and 3) Contraction of the hyperboxes respectively. The training set \( D \) consists of a set of \( m \) ordered pairs \( \{ x_h, d_h \} \) where \( x_h = (x_{h1}, x_{h2}, \ldots, x_{hn}) \in \mathbb{R}^n \) is an input pattern and \( d_h \in \{1,2,3,\ldots,m\} \) is one of the \( m \) classes.

When a training sample is presented, the network tries to accommodate it in one of the existing hyperboxes of that class provided the hyperbox size is not exceeding the specified maximum limit. After expansion the overlap test checks overlap for the expanded hyperbox with all hyperboxes belonging to other classes. It uses four different tests along each dimension of the two hyperboxes being compared, to verify whether the hyperboxes overlap each other or one hyperbox is contained by another [9]. If no such condition exists along any dimension it indicates that the hyperboxes are isolated and hyperbox contraction is not required. Otherwise hyperbox contraction is performed. If no suitable hyperbox is found to accommodate the applied training sample, a new hyperbox is added to the network. The membership function for the hyperbox is as follows [9].

\[
b_j(A_h, V_j, W_j) = \frac{1}{n} \sum_{i=1}^{n} \min\{(1 - f(a_{hi} - w_{ji}, \gamma)), (1 - f(v_{ji} - a_{hi}, \gamma))\}
\]

Where \( A_h = (a_{h1}, a_{h2}, \ldots, a_{hn}) \in \mathbb{R}^n \) is the \( h \)th input pattern, \( V_j = (v_{j1}, v_{j2}, \ldots, v_{jn}) \) is the min point for \( B_j \), \( w_{ji} = (w_{j1}, w_{j2}, \ldots, w_{jn}) \) is the max point for \( B_j \). \( f(x,y) \) is a two parameter ramp function given by,

\[
f(x, y) = \begin{cases} 
1 & \text{if } xy > 1 \\
x y & \text{if } 0 \leq xy \leq 1 \\
0 & \text{if } xy < 0 
\end{cases}
\]

where \( \gamma \), sensitivity parameter that regulates how fast the membership value decreases as the distance between \( A_h \) and \( B_j \) increases.

Wachs presented an adaptive method for color face segmentation using FMMN clustering technique [11]. Segmentation of face from image background is performed using face color feature information. Skin regions are determined by sampling the skin colors of the face in HSV color model.
A color image segmentation method for wood surface defect detection is presented [12]. The proposed method is called Fuzzy Min-Max neural network for Image Segmentation (FMMIS). The FMMIS method grows the boxes from a set of seed pixels, yields minimum bounded rectangle (MBR) for each defect present in the wood board image. The area recognition rate (ARR) criterion was computed to measure the segmentation quality.

6.3 Adaptive color image segmentation using fuzzy min-max clustering

6.3.1 ACISFMC architecture overview

The proposed block diagram of ACISFMC is depicted in Figure 6.2. ACISFMC uses HSV space for segmentation. As discussed in chapter 2, HSV color representation is compatible with the vision psychology of human eyes and its three components such as hue (H), saturation (S), and intensity (V) are relatively independent. These features make HSV an ideal color model for image processing applications.

Figure 6.2 Block diagram of ACISFMC.

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. The proposed system uses saturation and intensity planes for segmentation. Non-removable singularity is one of hue's drawbacks this may create discontinuities and spurious modes in the representation of colors [13]. The proposed system uses Fuzzy entropy as a tool to measure an 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.

6.3.2 System flowchart

A general flowchart of the proposed algorithm is depicted in Figure 6.3. First, clusters and their labels are automatically found out by applying FMMN clustering to image histogram in respective planes. 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 6.3.3.

![Figure 6.3 System flowchart.](image)

Viewed as a system, ACISFMC consists of two major processing blocks as shown in Figure 6.2.

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

6.3.3 Adaptive threshold selection block (A)

It consists of adaptive thresholding system itself. The purpose of this block is to find out clusters and the 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 using a FMMN clustering technique. The main aspire here is to locate clusters without a priori assumptions 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 the threshold and target values are calculated, a neural network activation function is constructed (Chapter 4, equation 4.6).

6.3.4 Neural network segmentation block (B)

Neural network segmentation block consists of fuzzy entropy calculation block and NN tuning/training block. The proposed ACISFMC system consists of two independent neural networks one each used for saturation and intensity planes. The network structure is same in architecture to Figure 4.5 (Chapter 4). Each node is activated in accordance with the input to the node and the activation function (Chapter 4, equation 4.6) of the node.

A. Fuzzy entropy

Fuzzy set plays an important role in various distributed systems because of their ability to model non statistical ambiguity [14]. Consequently, characterization and quantification of fuzziness are the important issues that affect the management of uncertainty in many system models and designs. It is a function on fuzzy sets that becomes smaller when the sharpness of its argument fuzzy set is improved.
In 1993, Pal and Bhandari introduced a order fuzzy entropy, which uses a order probability entropy form \[15\]. Banks suggested that a fuzzy entropy should satisfy five properties \[2\]. A good survey of fuzzy entropy for finite universal set can be carried out by Pal \[14\].

There have been numerous applications of fuzzy entropy in image segmentation. Cheng proposed fuzzy homogeneity vectors to handle the grayness and spatial uncertainties among pixels and perform multilevel thresholding \[16\]. Cheng defined a new approach to fuzzy entropy used to select fuzzy region of membership function automatically so that an image is able to be transformed into fuzzy domain with maximum fuzzy entropy and implemented a genetic algorithm to find optimal combination of fuzzy parameters \[17\]. Based on the idea of Zhao, Wen-Bing Tao designed a new three-level thresholding method for image segmentation \[18,19\]. He defined new fuzzy entropy formula through probability analysis, fuzzy partition and entropy theory. The image is first partitioned into three parts, namely dark, gray and white part, whose member functions of the fuzzy region are Z-function, P-function and S-function respectively. The width and the attribute of fuzzy region can be decided based on maximum fuzzy entropy; in turn the thresholds can be decided by the fuzzy parameters. For getting optimal thresholds, we must find optimal combination of all fuzzy parameters. Thus, the segmentation problem can be formulated as an optimal problem.

In the proposed work, fuzzy entropy is used to calculate an error of the system. The partition entropy (PE) is calculated using (Chapter 4, equation 4.10) described by Bezdek \[20\]. Here, the aim of network is to reduce the degree of fuzziness of the input color image. From the analysis of results of significant number of tests, it may be concluded that this measure provided a good results for most of color images.

B. Network (NN) Tuning

The purpose of NN tuning block is to update the connection weight by taking into consideration the output error in network. A back propagation algorithm is employed for training \[21\]. At every training epoch, the error is computed by getting a difference between the actual output and the desired output of neuron. The weights are updated using (Chapter 4, equation 4.7). After the weights have been adjusted properly, the output
of neurons in 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.

As the training progresses, a pixel gets the color depending upon its surrounding pixel colors. From the output image shown in Figure 6.4(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 Figure 6.4(a) to understand the segmentation process. As a first step, thresholds in saturation (S) and intensity (V) planes are found out. Figure 6.4(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 the average of two target values is considered as a threshold value. By using threshold and target values, neuron’s activation function is constructed as shown in 6.4. Figure 6.4(d) shows the multisigmoid function. Figure 6.4(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 6.4(c)-6.4(d) are for the saturation plane. Similar Figures are for the intensity plane.

Figure 6.4 Segmentation on test image (a) Original image (b) Segmented output using proposed method.
6.4 Experimental results

We have tested the proposed algorithm by applying it on a variety of images and compared the results with those obtained using Uchiyama and Ahalt [22,23] techniques. The performance of ACISFMC system on different types of color images available on the World Wide Web is discussed [24-26]. Experimental results on images such as ‘Panda’, ‘Horse’, ‘Hand’, ‘Objects’, ‘Biological cell’ and ‘Balloons’ are illustrated here.

6.4.1 Segmentation results

The proposed algorithm is implemented in Matlab environment on a Pentium IV, 2.8GHz, 512MB RAM. For all experiments, the proposed method uses a (3×3) neighborhood scheme for neuron connection scheme as shown in Figure 4.6 (Chapter 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 and Frequency Sensitive Competitive Learning (FSCL) based method proposed by Ahalt are depicted in Figure 6.5 [22,23]. Uchiyama and Arbib presented a segmentation algorithm using a competitive learning (CL) approach [22]. Figure 6.5(b) shows the segmentation result using Uchiyama's method. It is an adaptive version of k-means clustering algorithm [27]. 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 the 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. An extension of k-means clustering algorithm is FSCL which was proposed [23]. 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 Figure 6.5(c) is obtained by Ahalt technique [23]. Figure 6.5(d) shows the segmentation result using proposed method. Note from Figure 6.5(d) that the proposed system produces better segmentation results than [22,23].

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 6.6(a)-6.11(a) are depicted in Figures 6.6(b)-6.11(b) respectively. It can be observed from Figure 6.6(b)-6.11(b) that without a priori knowledge system could isolate the objects properly and are labelled with their mean colors.

![Figure 6.5](image)

Figure 6.5 Comparison of ACISFMC (a) Original image (b) Segmented image obtained using CL approach (c) Segmented image obtained using FSCL (d) Segmented image obtained using proposed technique.
Figure 6.6 Panda: (a) Original image (b) Segmented image.

Figure 6.7 Horse: (a) Original image (b) Segmented image.

Figure 6.8 Hand: (a) Original image (b) Segmented image.

Figure 6.9 Objects: (a) Original image (b) Segmented image.
6.5 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 the segmentation of noisy images is with second order \((3 \times 3)\) neighborhood scheme for neuron connections as shown in Figure 4.6 (Chapter 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 ‘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 6.12(b)-6.14(b) shows the segmentation results of distorted ‘Leaf’ image respectively. Robust performance of the proposed system on noisy images can be observed from the experimental results.
Figure 6.12 Test on Gaussian noise (a) Original image with Gaussian noise (b) Segmented image.

Figure 6.13 Test on Salt & Pepper noise (a) Original image with Salt and Pepper noise (b) Segmented image.

Figure 6.14 Test on Speckle noise (a) Original image with Speckle noise (b) Segmented image.

6.6 Remarks

In this work, a novel technique for color image segmentation is presented using FMMN. 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 \textit{a priori} information about number of objects in the image. ACISFMC system is tested on several images of different types. The performance of the proposed algorithm is compared with other currently available algorithms [22,23]. 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.
References


[25] Informatics Institute of, [http://www.inf.u-szeged.hu](http://www.inf.u-szeged.hu)