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An adaptive neuro-fuzzy system for color image segmentation

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Abstract

Image segmentation and object extraction plays an important role in image analysis and computer vision. In this paper, we propose a novel technique for color image segmentation called 'adaptive neuro-fuzzy color image segmentation (ANFCIS)'.The proposed system consists of multilayer perceptron (MLP)-like network which performs color image segmentation using multilevel thresholding. Threshold values for detecting clusters and their labels are found automatically using fuzzy C-means (FCM) clustering technique. Fuzzy entropy is used as a tool to decide the number of clusters. ANFCIS uses saturation and intensity planes of HSV (hue, saturation, intensity) color space for segmentation. Neural network is employed to find the number of objects automatically from an image. The major advantage 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. Experimental results have demonstrated the effectiveness and efficiency of the proposed method.

Keywords: Adaptive thresholding, fuzzy entropy, color image segmentation, neuro-fuzzy system, and clustering.

1. Introduction

Computer vision is a novel technology to acquire and analyze the image to obtain information [1]. The core technique in computer vision is image analysis/processing, which can lead to segmentation, quantification and classification of images and objects of interest within images [2]. To understand an image, one needs to isolate the objects in it and find relation among them. The process of partition of objects is referred to as image segmentation. In the past decades, attention had been paid to monochrome image segmentation and many algorithms had been proposed in the literature [3, 4]. Basically, color image segmentation algorithms are frequently based on monochrome image segmentation approaches operating in different color space [5].

Color image segmentation is attracting greater attention. The color perceived by human eye as a combination of tristimuli such as red (R), green (G), and blue (B) are usually called the primary colors. It has long been recognized that the human eye can detect only in the

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neighborhood of one or two dozen intensity levels at any one point in a complex image due to brightness adaptation, but can discern thousands of color shades and intensities [6]. 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 is useful or even necessary for powerful processing in computer vision [7]. Thus applications with color image are becoming increasingly prevalent nowadays [8–10]. In this paper, we propose a system capable of performing adaptive multilevel color image segmentation based on thresholding and FCM clustering technique. Clusters and their labels are automatically found out using FCM clustering technique. The main advantage of this method is that it does not require a priori information to segment a color image. The existing color image segmentation methodologies can broadly be classified into histogram thresholding, region growing, edge detection, neuro-fuzzy based techniques and are briefly discussed here.

Histogram thresholding is one of the oldest, simple and popular techniques for image segmentation [11]. Its underlying assumption is that an image consists of different regions corresponding to the gray-level ranges [12, 13]. It has been used widely as a tool to segment monochrome images, but only a limited amount of work has been published in relation to color images [14]. The main advantage of this technique lies in its simple computation. However, its approaches ignore the spatial relationship information of pixels. Region-growing technique finds the homogeneous regions within an image [15, 16]. Here, we need to assume a set of seed points initially. This technique gathers similar pixels according to some homogeneity criteria and forms a region. However, the difficulty with this technique is its inherent dependence on the selection of initial seed points and the order in which pixels and regions are examined [17, 18]. It is better than histogram thresholding since it considers the spatial relationship between pixels [19].

Edge detection technique is extensively utilized for gray-level image segmentation which is based on the detection of discontinuity in gray level [20, 21]. An edge or boundary is a place where there is a more or less abrupt change in the gray level. An algorithm for edge detection technique using predictive coding model is proposed by Ma and Manjunath [22]. The system is able to recognize the direction of change in color and texture at any point and a given scale. It then forms an edge flow which through propagation converges to the image boundaries.

Artificial neural networks (ANN) is a powerful computing system which consists of number of interconnected, nonlinear computing elements [23, 24]. Its processing capability and nonlinear characteristics are used for classification and clustering [25]. It is widely applied in the area of pattern recognition and computer vision. A fuzzy set-theoretic model provides a mechanism to represent and manipulate uncertainty within an image. Zadeh [26] introduced the concept of fuzzy sets in which imprecise knowledge can be used to define an event. A number of fuzzy approaches for image segmentation are reported [27–29]. FCM is one of the well-known clustering techniques [30–32]. It was first introduced by Dunn [33] and the related formulation and algorithm were extended by Bezdek [34]. However, it has some drawbacks such as:

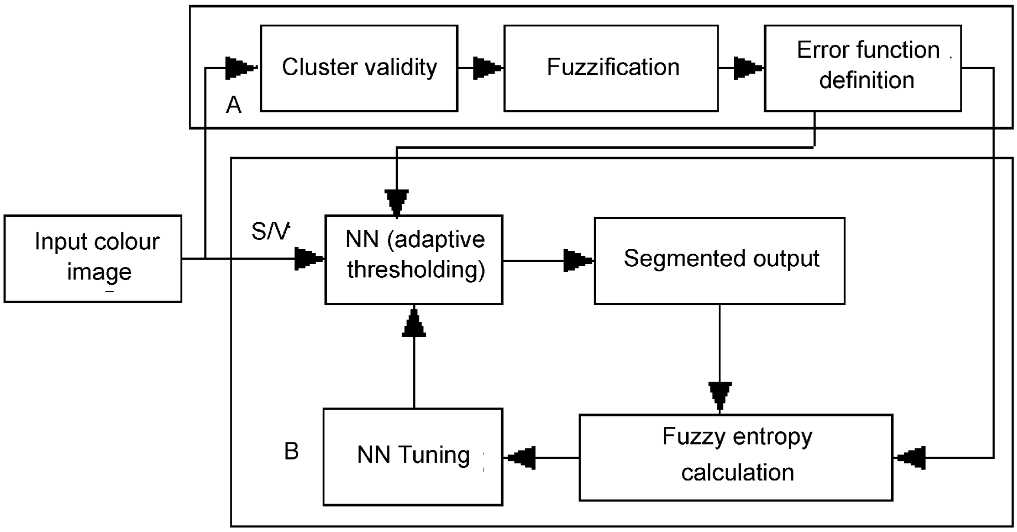

FIG. 1. Block diagram of ANFCIS.

1. It requires the priori knowledge about the number of regions existing in an image.
2. Adjacent clusters often overlap in color space, which causes incorrect pixel classification.

The integration of fuzzy logic and neural networks has emerged as a promising field of research in recent years. This has led to the development of a new branch called neuro-fuzzy computing. Neuro-fuzzy system combines the advantages of both the uncertainty handling capability of fuzzy systems and the learning ability of neural networks.

The present work is an attempt to design an adaptive neuro-fuzzy system capable of performing multilevel segmentation of color images in HSV color space. Clusters (segments) and their labels are found automatically using FCM clustering technique. Neural network is used to detect multiple objects within an image. The network architecture is the same in principle to [35]. It consists of three layers—input, hidden and output layers. Each layer consists of a fixed number of neurons equal to the number of pixels in the image. The activation function of neuron is multisigmoid. The main 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.

The rest of the paper is organized as follows: Section 2 elaborates the proposed system. Section 3 presents experimental results and comparison with other techniques. Section 4 concludes the work.

2. Adaptive neuro-fuzzy system for color image segmentation

Figure 1 shows the block diagram of the proposed ANFCIS system. It uses HSV space for color image representation. This representation is compatible with vision psychology of the human eye and its three components such as hue (H), saturation (S), and intensity (V) are relatively independent. It is better than RGB transformation since there exists a high correlation among the three color components such as R, G, B. ANFCIS uses saturation and intensity planes for color image segmentation since these are the two parameters that may vary and the hue value remains the same. Non-removable singularity near the axis of color cylinder, where a slight change of R, G, B values in the input can cause a large jump in the transformed values is one of the hue's drawbacks. This may create discontinuities and spurious modes in the representation of colors. Also, hue value near the singularity is numerically unstable [36].

Segmentation is carried out separately in each saturation and intensity planes. The final segmentation is achieved by combining the results of these respective planes.

ANFCIS system consists of two main processing sections as shown in Fig. 1.

- Error function definition block (A)
- Adaptive thresholding block (B).

Error function definition block is responsible to generate an error function and provide an adaptive thresholding block. Adaptive thresholding block is used to determine clusters and to compute a multilevel sigmoid function of neurons. The details are explained in subsequent sections.

2.1. *System flowchart*

A general flowchart of the working of the proposed method is depicted in Fig. 2. As ANFCIS is a histogram multithresholding technique, it is essential to find different thresholds to segment the objects in the image. Threshold values are determined by applying FCM algorithm to image histogram in respective planes. After detecting thresholds, labels for the objects are decided. The information about labels is employed to construct network's activation function. Neuron uses a multilevel sigmoid function as an activation function. This function takes care of thresholding and labeling the pixels during recursive training process (Section 2.3).

2.2. *Error function definition block (A)*

Error function definition block consists of cluster validity and fuzzification blocks. The purpose of this block is to generate an objective error function which is used by adaptive thresholding block. In order to calculate an error function, first, cluster validity block determines the number of objects in the input color image of the respective planes. In the proposed work, FCM algorithm is employed to create fuzzy partition (fuzzy sets) as shown in Fig. 3(b). The fuzzification block divides the input color image into different fuzzy sets. An error function is generated by determining the contribution of each gray level to the fuzzy entropy of the partitions as depicted in Fig. 3(c). A cluster validity block automatically determines the number of objects in the input color image. For this, it iterates FCM algorithm for a range of hypothesized number of clusters and chooses the best option based on cluster validity measure. Although cluster validity measures are not very reliable, some of them (Partition coefficient and Partition entropy (PE)) [37] produce good results for most of the color images.

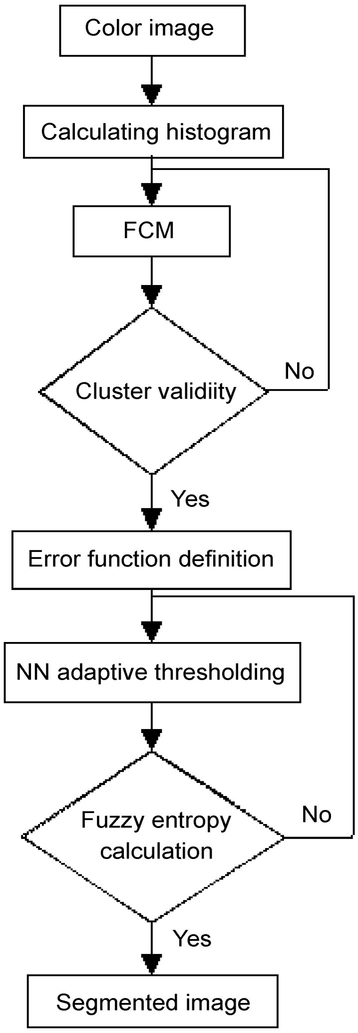

FIG. 2. System flowchart.

2.3 *Adaptive thresholding block (B)*

Adaptive thresholding block consists of adaptive thresholding system itself, fuzzy entropy calculation block and NN tuning block. Its inputs are the input image and the error function generated by error function definition block (A) and its output is the segmented image. The purpose of this block is to find out the number of clusters and the computation of multilevel sigmoid function for neurons. In order to segment objects appropriately, it is essential to determine the number of clusters within an image. The main endeavour here is to find out the number of clusters without a priori knowledge of the image. To achieve this, first the histograms of given color image for saturation and intensity planes are found out. Labels for the objects are found out by applying FCM algorithm to image histogram in respective planes.

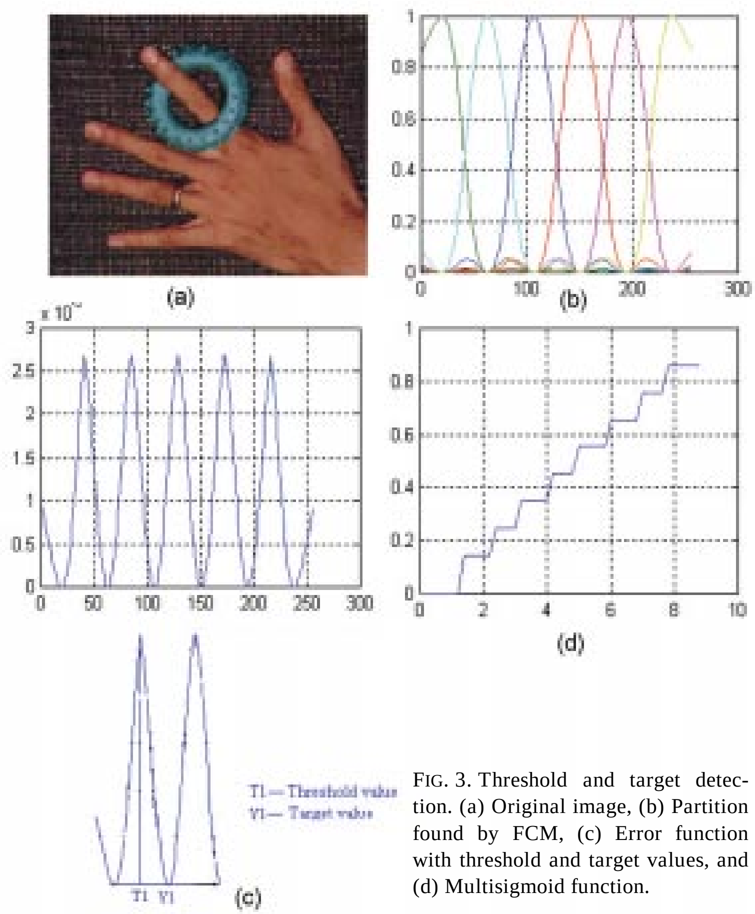

FIG. 3. Threshold and target detection. (a) Original image, (b) Partition found by FCM, (c) Error function with threshold and target values, and (d) Multisigmoid function.

Thresholds and target values are obtained from an error function, as the gray levels with maximum and with minimum levels of fuzziness respectively as depicted in Fig. 3(c). The average value as a target helps to segment object with a color appropriate to its original color. Hence in the ANFCIS 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 [38] as in eqn (1).

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

where u is the step function, θ_k, the thresholds, y_k, the target level of each sigmoid (which will constitute the system labels), θ_0, the steepness parameter, and d, the size of the neighborhood.

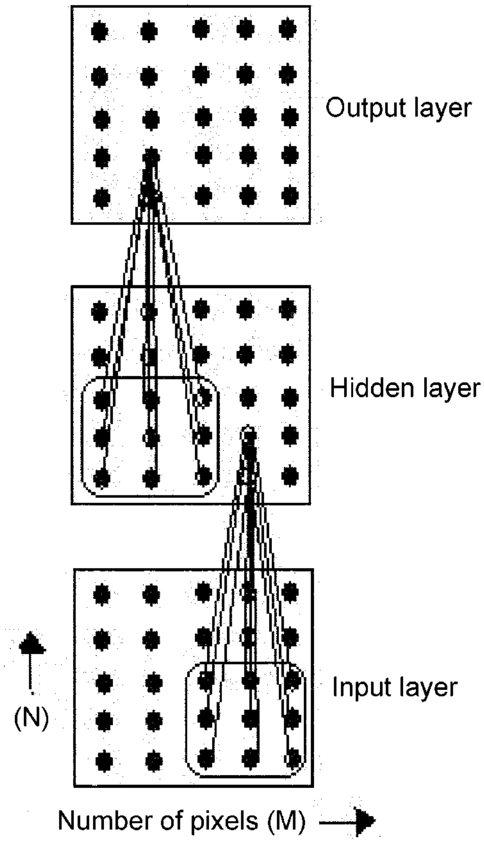

FIG. 4. Neural network architecture.

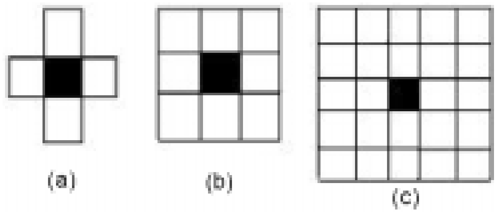

FIG. 5. Neighborhoods of a pixel (a) First- and (b) second-order neighborhood, and (c) Sequence of neighborhood.

2.3.1. *Neural network architecture*

The proposed ANFCIS system consists of two independent neural networks, one each for saturation and intensity planes, respectively. The network has three-layer architecture as depicted in Fig. 4. The layer where the inputs are presented is known as the input layer. On the other hand, the output-producing layer is called the output layer. Besides, the input and output layer, there exists a third layer called the hidden layer. The input to a neuron in the input layer is normalized between [0–1]. The output value of each neuron is between [0–1]. Each layer has a fixed number of neurons equal to the size ($m \times n$) of the image. Each neuron represents a single pixel. All neurons have primary connection weight as 1. Each neuron in one layer is connected to respective neuron in the previous layer with its dth order neighborhood as shown in Fig. 5. Neurons in the same layer do not have any connection among themselves. The output of nodes in one layer is transmitted to the nodes in another layer via links that amplify or inhibit such output 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 (eqn (1)) of the node.

2.3.2. *Fuzzy entropy calculation*

Fuzzy entropy is a function on fuzzy sets. The measure of uncertainty is referred to as the *measure of fuzziness* or *fuzzy entropy*. The concept of entropy, in the frame work of fuzzy sets, was first introduced by Luca and Termini [39]. They define entropy as:

$$H(A) = \frac{1}{n\ln(2)}\sum_{i=1}^{n}\{S_n(\mu_A(x_i))\}. \tag{2}$$

Another definition of fuzzy entropy is given by Pal and Pal [30] as:

$$H(A) = \frac{1}{n(\sqrt{e}-1)}\sum\{S_n(\mu_A(x_i))-1\},$$

with

$$S_n(\mu_A(x_i)) = \mu_A(x_i)e^{1-\mu_A}(x_i) + (1-\mu_A(x_i))e^{\mu_A}(x_i)\,. \tag{3}$$

There have been numerous applications of fuzzy entropy in image segmentation. Cheng *et al.* [40] presented a thresholding approach by performing fuzzy partition on a two-dimensional histogram based on fuzzy relation and maximum fuzzy entropy principle. Zhao *et al.* [41] presented an entropy function by using fuzzy c-partition (FP) and the probability partition (PP) which was used to measure compatibility between FP and PP.

In the proposed work, fuzzy entropy is used to calculate an error of the system. For this purpose, it uses an error function generated by Error function definition block (A) at each training epoch. The PE is calculated using eqn (4) described by Bezdek [37]. Here, the aim of the network is to reduce the degree of fuzziness of the input color image.

$$PE = -\frac{1}{n\ln\left(\frac{1}{C}\right)}\sum_{k=1}^{n}\sum_{i=1}^{C}[\mu ik\ln(\mu ik)]. \tag{4}$$

2.3.3. *Neural network (NN) tuning*

The purpose of NN tuning block is to update the connection weight as in eqn (5) by taking into consideration the output error in the network. A back propagation algorithm [24] is used for training. At every training epoch, error is calculated by taking the difference between the actual output and the desired output of neuron. As discussed earlier, the aim of the network is to reduce error in order to obtain segmentation.

$$\begin{aligned} \Delta Wji = n\left(\frac{-\partial E}{\partial O_j}\right)\frac{\partial O_j}{\partial I_j}O_i\Delta \qquad & \text{Output layer} \\ n\left(\sum k\left(-\frac{\partial E}{\partial Ok}\frac{\partial O_k}{\partial I_k}wkj\right)\right)\frac{\partial O_j}{\partial Ij}Oi \qquad & \text{Hidden layer} \end{aligned} \tag{5}$$

where

Ij = Total input to the *j*th neuron,

Wji = Weight of link from neuron *i* in one layer to neuron *j* in the next layer,

O_i = Output of the ith neuron i in one layer to neuron j in the next layer,
E = Error in the network's output, and
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. 6(d), it can be observed that network tries to label a cluster with an even color spread. We can see that all pixels which represent the ring are assigned to one color label similar to its original color after segmentation. The background is labeled with a color label appropriate to its original color. Segmentation using multiple thresholds is explained with an example in Section 3. The technique to find threshold and target is demonstrated in Fig. 3.

Consider Fig. 3(a) to realize the segmentation process. As a first step, thresholds in saturation (S) and intensity (V) planes are found out. Thresholds and target values are obtained from an error function (Fig. 3(b)) where the gray levels with maximum and minimum levels occur, respectively, as depicted in Fig. 3(c). By using threshold and target values, neuron's activation function is constructed as shown in eqn (1). Figure 3(d) shows the multisigmoid function. Figures 3(b)–3(d) are for the saturation plane. Similar figures are for the intensity plane.

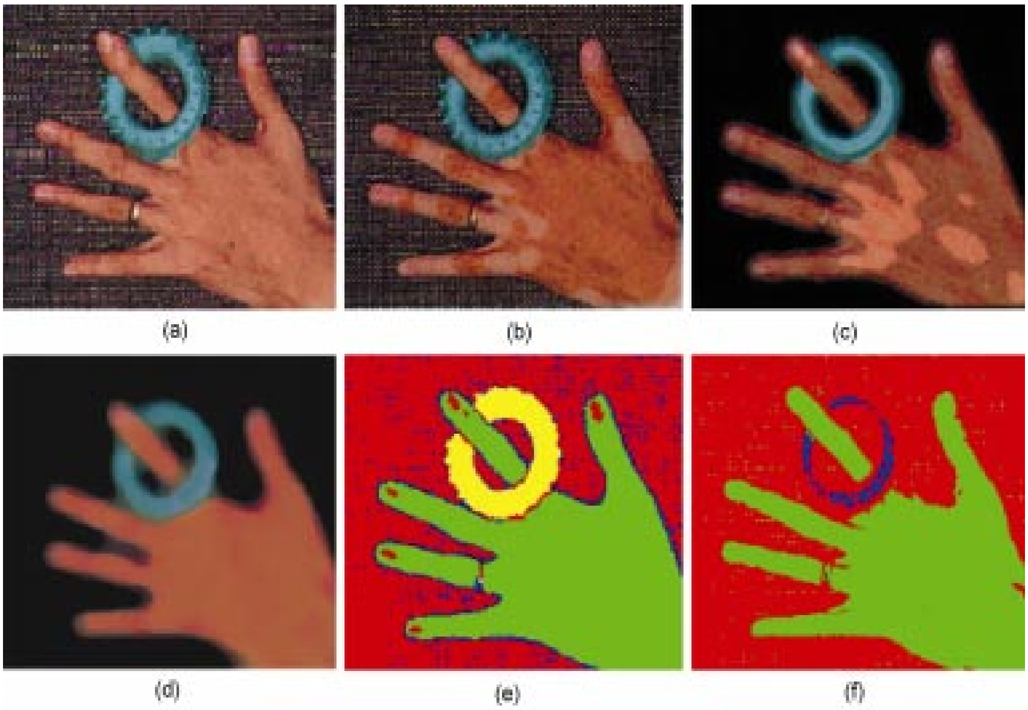

FIG. 6. Comparison of ANFCIS. (a) Original image; segmentation using the proposed method (b) in saturation plane and (c) in intensity plane, (d) final segmentation using the proposed method, (e) segmentation using Busin method, and (f) segmentation using PCA transform.

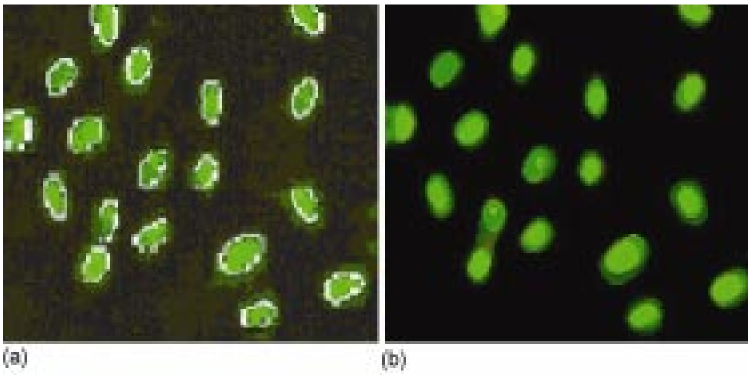

FIG. 7. Bacteria: (a) Original, and (b) Segmented images.

3. Experimental results

Here we discuss the performance of ANFCIS system on different types of color images available on the World Wide Web [42–44]. Experimental results on images such as 'Bacteria', 'Peppers', 'Bird', 'Objects', and 'House' are illustrated here. The proposed algorithm is implemented in MATLAB 5.3 on Pentium IV, 2.8GHz, 256 RAM. We used only 'FCM' a built-in function in MATLAB 5.3, for clustering. We have written the code for MLP (multilayer perceptron) used to carry out actual segmentation of color images. For all experiments, the proposed method uses a second-order (3×3) neighborhood scheme for neuron connection as shown in Fig. 5.

3.1. *Segmentation results*

The comparison between the segmented image obtained by means of the proposed method and some other techniques proposed by Busin *et al.* [45] and PCA-based method proposed by Tominaga [46] are depicted in Fig. 6. Figures 6(b) and (c) show the segmentation result using the proposed method in saturation and intensity plane respectively. Figure 6(d) shows the final segmentation result using the proposed method in combined plane. Figure 6(e) shows the segmentation result using the Busin *et al.* [45] method. In [45], the system

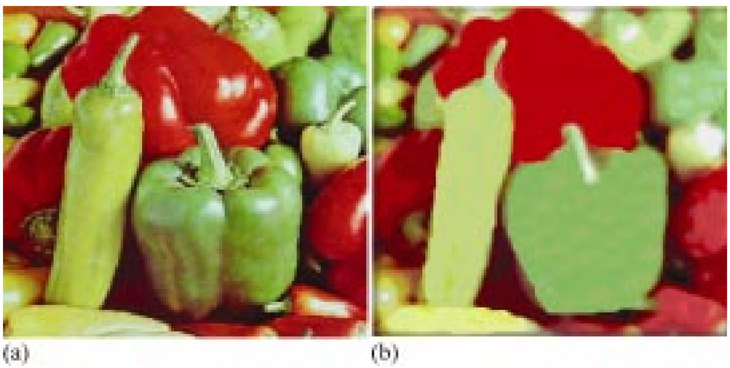

FIG. 8. Peppers: (a) Original, and (b) Segmented images.

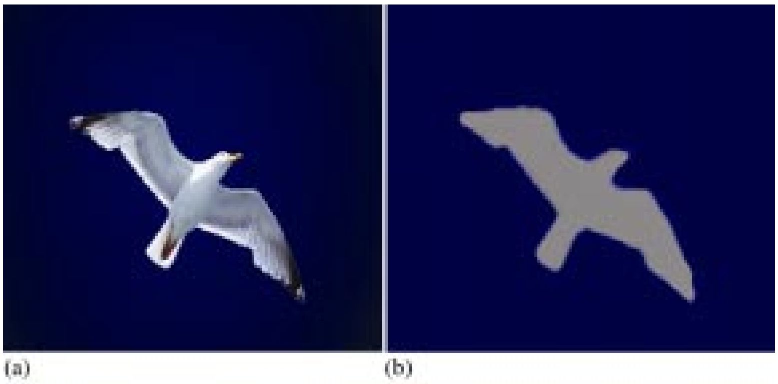

FIG. 9. Bird: (a) Original, and (b) Segmented images.

iteratively constructs the classes by histogram multithresholding. For this purpose, the procedure selects different color spaces in which the modes of 1D-histograms are possibly separated, so that each mode corresponds effectively to a region in the image. Figure 6(e) shows the segmentation result using the Busin [45] method. Tominaga [46] proposes to apply PCA transform on the image at each iteration step to analyze the 1D-histogram of the most discriminating component. The segmented image of Fig. 6(f) is obtained by the technique [46]. Note from Figs 6(b) and (c) that segmentation is not proper and the objects are not labeled correctly when saturation and intensity planes are used individually, whereas from Fig. 6(d), it is observed that segmentation is done uniformly and objects are labeled properly in combined (S+I) planes only. The proposed system produces better segmentation results than [45, 46]. The system maintains the object mean color even after segmentation, whereas for the Busin [45] and Tominaga [46] techniques objects are labeled with colors other than their original color. Maintaining the object colors after segmentation is helpful in computer vision recognition applications.

To see the effectiveness of the proposed method, the algorithm is tested on various color images of different types. The segmentation results for Figs 7(a)–11(a) are depicted in Figs 7(b)–11(b), respectively. It can be observed from Figs 7(b)–11(b) that without a priori

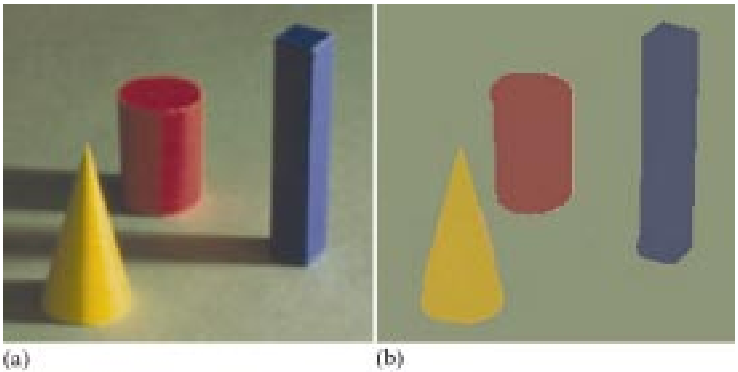

FIG. 10. Objects: (a) Original, and (b) Segmented images.

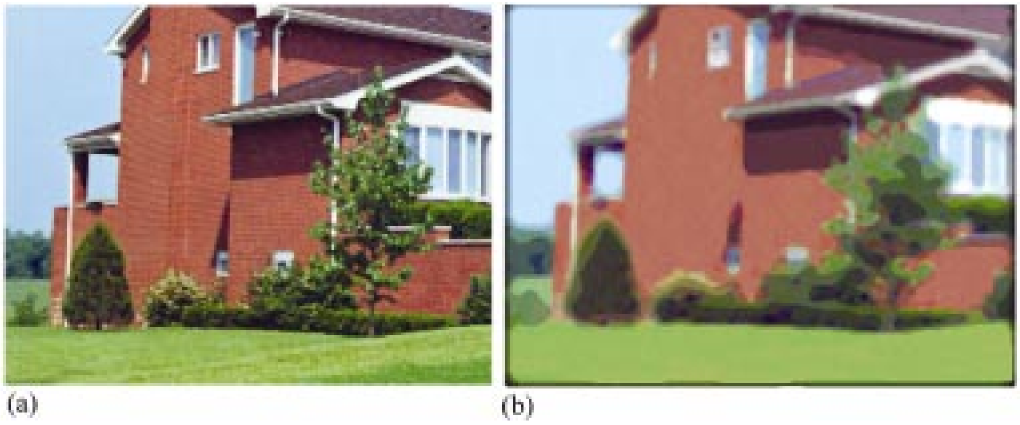

FIG. 11. House: (a) Original, and (b) Segmented images.

knowledge system could isolate the objects properly and can be labeled with their mean colors.

4. 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 FCM algorithm. Neural network with multisigmoid function tries to label the objects with its original color even after segmentation. One of the advantages of this system is that it does not require a priori information about the number of objects in the image. ANFCIS system is tested on several images. Attempts also have been made to compare the performance of the proposed algorithm with other currently available algorithms [45, 46]. From experimental results, the performance of the proposed technique was found satisfactory. It can be used as a primary tool to segment unknown color images. Experimental results show that its performance is robust to different types of color images.

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