

Multilevel Activation Functions For True Color Image Segmentation Using a Self Supervised Parallel Self Organizing Neural Network (PSONN) Architecture: A Comparative Study

Siddhartha Bhattacharyya, Paramartha Dutta, Ujjwal Maulik and Prashanta Kumar Nandi

Abstract—The paper describes a self supervised parallel self organizing neural network (PSONN) architecture for true color image segmentation. The proposed architecture is a parallel extension of the standard single self organizing neural network architecture (SONN) and comprises an input (source) layer of image information, three single self organizing neural network architectures for segmentation of the different primary color components in a color image scene and one final output (sink) layer for fusion of the segmented color component images. Responses to the different shades of color components are induced in each of the three single network architectures (meant for component level processing) by applying a multilevel version of the characteristic activation function, which maps the input color information into different shades of color components, thereby yielding a processed component color image segmented on the basis of the different shades of component colors. The number of target classes in the segmented image corresponds to the number of levels in the multilevel activation function. Since the multilevel version of the activation function exhibits several subnormal responses to the input color image scene information, the system errors of the three component network architectures are computed from some subnormal linear index of fuzziness of the component color image scenes at the individual level. Several multilevel activation functions are employed for segmentation of the input color image scene using the proposed network architecture. Results of the application of the multilevel activation functions to the PSONN architecture are reported on three real life true color images. The results are substantiated empirically with the correlation coefficients between the segmented images and the original images.

Keywords— Color image segmentation, fuzzy set theory, multilevel activation functions, parallel self organizing neural network

I. INTRODUCTION

Segmentation and classification of images are challenging propositions in the image processing community owing to the variety and complexity associated therein. Image segmentation techniques find wide use in the extraction and localization of regions of interest for faithful understanding and analysis of

an image scene. Image segmentation techniques are broadly categorized into two categories [1][2], viz. edge detection based [3], which resort to detection of closed regions in an image scene, and pixel classification based [4][5][6], which use pixel intensity/co-ordinate information for clustering the image data. Several classical approaches including stochastic model based techniques [7][8][9][10][11], morphological watershed based region growing techniques [12], energy diffusion techniques [13] and graph partitioning techniques [14] are reported in the literature.

The problems of image segmentation become more uncertain and severe when it comes to color image segmentation [15]. This is due to the diversity in the color gamut. A color image entails information either in the three primary color components, viz., red, green and blue or their combinations (pure/binary color image) or represents information in all possible combinations of the three primary color components (true color image). In a pure/binary color image, the three primary color components and their combinations appear either with maximum intensity value (255) or with minimum intensity value (0). All possible combinations of intensity values from 0 to 255 for each of the primary color components and their admixtures, form the color spectrum of a true color image. Thus, processing and understanding of a color image scene amount to processing of the primary color component information in a pure color image and processing of all the combinations of these color components in a true color image. A score of works for extraction and indexing of color images can be found in the literature [16][17][18]. Typical color image processing applications include content-based image retrieval systems, image mining applications, traffic sign recognition systems etc [19][20][21][22][23][24][25][26]. Most of these approaches deal with pure color images and assume homogeneity in the color content of the image scene, either explicitly or implicitly. However, real images exhibit a wide range of heterogeneity in the color content. This diversity of color information induces varying degrees of uncertainty in the information content. The vagueness in image information arising out of the admixtures of the color components has often been dealt with the soft computing paradigm. In [27] Chen *et al.* applied fuzzy set theory for proper analysis of uncertainty and vagueness in color image information. Color image segmentation techniques involving fuzzy set theory and fuzzy logic are also available in the literature [28][29][30][31].

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Neural network architectures have also been employed to deal with this task of color image processing. Hart *et al.* used a four-layer fuzzy-neural algorithm for identification of color flag images from natural scenes [32]. They resorted to fuzzy inference engines for segmenting color flag images in HSV color system. A neural network, trained with the segmented color values, was finally used to infer about the color value of the pixels in the test flag images.

Extraction of graded color objects by segmenting a true color image scene has been a major focus of attention in the computer vision community. Such processing tasks involve application of object extraction algorithms preceded by segmentation of the true color images based on object centric features. A single multilayer self organizing neural network (MLSONN) [33] is efficient in extracting binary objects from a noisy binary color image scene. A parallel version of such a network architecture [34] comprising three component single MLSONN networks (for component level processing) can be used for extracting pure color objects from a noisy pure color image scene. Such an architecture when fed with a pure color noisy image scene, produces extracted pure color noise-free homogeneous object regions in the output layer of the architecture. The computational overhead involved in handling the enormous amount of data arising out of the processing of the individual color components of a color image scene has been reduced with the introduction of distributed architectures as well [35].

A parallel version of the self organizing neural network architecture (PSONN) [34], in the present form, is unable to extract graded color objects from a true color image scene. This is due to the fact each of the component single MLSONNs employs the standard bilevel sigmoidal activation function as the characteristic activation function. Since the bilevel sigmoidal activation function produces only binary responses, these component MLSONNs can generate only binary color outputs. So, either an architectural or a functional extension to the existing PSONN architecture is required for producing multiple color responses.

In this article, a functional modification to the PSONN neural network architecture, comprising a source network layer for accepting inputs from the external world, three single three-layer self organizing neural networks for color component level processing and a sink network layer for producing fused component outputs, is proposed. The proposed functional amendment is achieved by introducing a multilevel version of the characteristic activation functions of the three-layer self organizing neural network architectures. A multilevel activation, as the name suggests, is capable of producing multilevel/multipolar outputs corresponding to the inputs. This multipolar feature is incorporated by replicating the functional form of the activation function to form a series of transition lobes, which would respond to the graded and varied intensity inputs to the function. To be precise, varying degrees of intensity level corresponding to varying color values of the inputs, would be handled by the different lobes of the function. The resultant function, thereby, would yield multiple color shades corresponding to the gradation in the color values and induce multiscaling capability to the different component

three-layer self organizing neural network architectures. Several forms of the multilevel activation functions depending on the standard functional form and the number of target classes in the output image scene, and efficient in extracting gray scale objects from a multiscale image scene, can be designed [36][37][38][39][40][41][42]. In the present work, the application of the multilevel activation functions in effecting graded color object extraction through segmentation of a true color image scene by a parallel self supervised three-layer self organizing neural network (PSONN) architecture, has been presented with three different multilevel activation functions, viz. a multilevel sigmoidal (MUSIG) activation function, a multilevel tan hyperbolic (MUTANH) activation and a multilevel tan hyperbolic 15 (MUTANH15) activation. Since the individual component three-layer self organizing neural network architectures operate in self supervision on subnormal fuzzy subsets of color intensity levels, the system errors have been computed using the subnormal linear indices of fuzziness [42] in the color image scene. Results of the proposed segmentation approach are demonstrated using three real life true color image scenes. The standard correlation coefficients between the segmented and the original true color image scenes are used as a figure of merit of the proposed system.

The paper is organized as follows. Section II introduces the basic concepts about fuzzy set theory and fuzzy measures relevant to the task of operation of the PSONN architecture. Section III discusses the dynamics and operation of the PSONN architecture. The different forms of multilevel activation functions used in this article are detailed in Section IV. Section V gives an overview of the proposed true color image segmentation procedure. The results of segmentation of color images are shown in Section VI. Section VII concludes the paper with future directions of research.

II. MATHEMATICAL PREREQUISITES

In this section, a brief overview of fuzzy set theory and the linear index of fuzziness is presented.

A. Fuzzy set theoretic concepts

Fuzzy set theory was introduced by L. A. Zadeh to explain uncertainty in real life situations. A fuzzy set A comprises a collection of elements $x_i, i = 1, 2, 3, \dots, n$ (where n is the number of elements), each of which appearing in the set with a certain degree of membership, $\mu_A(x_i)$ [43][44][45], defined by a membership function $\mu_A(x_i)$. The support of a fuzzy set comprising n such elements is given by

$$S(A) = \{x_i | x_i \in X \text{ and } \mu_A(x_i) > 0, i = 1, 2, 3, \dots, n\} \quad (1)$$

where X is the universe of discourse. The membership value of the elements, defined by $\mu_A(x)$, assumes all possible values $\in [0, 1]$. The closer the membership value of an element is to unity, the greater is the degree of containment of the element in the fuzzy set A , while a lower membership value implies a weaker degree of containment of the element in the set. The maximum membership value of all the elements of a fuzzy set A is referred to as the height (hgt_A) of the fuzzy set [45]. If

$hgt_A=1$, then the fuzzy set A is known as a normal fuzzy set, otherwise, it is a subnormal fuzzy set.

A subnormal fuzzy set A_s can be normalized to its normalized equivalent using the normalization operation defined as

$$Norm_{A_s} = \frac{\mu_{A_s}}{hgt_{A_s}} \quad (2)$$

where μ_{A_s} are the membership values of the elements of the subnormal fuzzy set A_s . The corresponding denormalization operation is given by

$$DeNorm_{A_s} = hgt_{A_s} \times Norm_{A_s} \quad (3)$$

In general, for a subnormal fuzzy set A_s with support $[L, U], 0 \leq L \leq 1$, the normalization and the denormalization operations take the forms as

$$Norm_{A_s} = \frac{\mu_{A_s} - L}{U - L} \quad (4)$$

$$DeNorm_{A_s} = L + (U - L)Norm_{A_s} \quad (5)$$

B. Measures of a fuzzy set

A fuzzy measure is an indicative measure of the fuzziness of a fuzzy set. It determines the relationship between a fuzzy set and its nearest crisp/ordinary counterpart. The index of fuzziness $\nu(A)$ [33], of a fuzzy set A having n elements is a distance metric between the set A and its nearest ordinary set \underline{A} defined as

$$\mu_{\underline{A}}(x) = \begin{cases} 0 & \text{if } \mu_A(x) \leq 0.5 \\ 1 & \text{if } \mu_A(x) > 0.5 \end{cases} \quad (6)$$

The linear index of fuzziness, $\nu_l(A)$, of a fuzzy set A is the Hamming distance version of the index of fuzziness distance metric. It is given by

$$\nu_l(A) = \frac{2}{n} \sum_{i=1}^n [\min\{\mu_A(x_i), 1 - \mu_A(x_i)\}] \quad (7)$$

In the subnormal domain, the subnormal linear index of fuzziness for a subnormal fuzzy set A_s is defined as

$$\nu_l(A_s) = \frac{2}{n} \sum_{i=1}^n [\min\{\mu_{A_s}(x_i) - L, U - \mu_{A_s}(x_i)\}] \quad (8)$$

III. PARALLEL SELF ORGANIZING NEURAL NETWORK (PSOANN) ARCHITECTURE

A single three-layer self organizing neural network [33] is a self supervised neural network architecture, which comprises an input layer, a hidden layer and an output layer of neurons. The input layer neurons accept inputs from the external world and propagate the inputs to the hidden layer through some input-hidden layer interconnection weights (w_{inp_i, hid_j}). The hidden layer neurons similarly process the propagated information and pass it to the output layer neurons via the hidden-output layer interconnection weights (w_{hid_i, out_j}). Both the input-hidden layer and hidden-output layer interconnections follow a second order neighborhood based interconnection topology. If I_{inp_i} are the inputs to each of the input layer

neurons, the net information, I_{hid_j} propagated to each of the hidden layer neurons is given by

$$I_{hid_j} = \sum_i I_{inp_i} w_{inp_i, hid_j} \quad (9)$$

where, the summation is over the i neighboring input layer neurons. The hidden layer neurons process the input information and the processed information, O_{hid_j} at the j^{th} neuron, propagated to the output layer neurons is given by

$$O_{hid_j} = f_{sig}(I_{hid_j}) \quad (10)$$

where, f_{sig} is the standard characteristic bilevel sigmoidal activation function (Fig. 1) given by

$$f_{sig} = \frac{1}{1 + e^{-\lambda(x-\theta)}} \quad (11)$$

The parameters, λ and θ , control the shape and slope of the

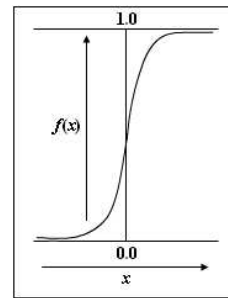


Fig. 1. Bilevel sigmoidal activation function

function.

Keeping in mind the neighborhood topology based interconnection, the inputs to the k^{th} output layer neurons, I_{out_k} is given by

$$I_{out_j} = \sum_i O_{hid_i} w_{hid_i, out_j} \quad (12)$$

The processed outputs at the k^{th} output layer neurons are given by

$$O_{out_k} = f_{sig}(I_{out_k}) \quad (13)$$

where, f_{sig} is the standard characteristic bilevel sigmoidal activation function.

Since the network operates in a self supervised mode and there are no target outputs to compare with, the system error at the output layer neurons are evaluated from the linear indices of fuzziness in the outputs obtained therein. These errors are used to adjust both the hidden-output layer and input-hidden layer weights using the standard backpropagation algorithm. After the weights are adjusted, the outputs obtained at the output layer of the network are fed back to the input layer via the output-input layer neuron-to-neuron interconnection weights for further processing. This processing of the initial input information is carried on until the network system errors fall below some tolerable limit, whereby, segmented outputs are obtained.

A parallel version of the network architecture (PSOANN) (Fig. 2), comprising three independent single three-layer self organizing neural network architectures (for component level

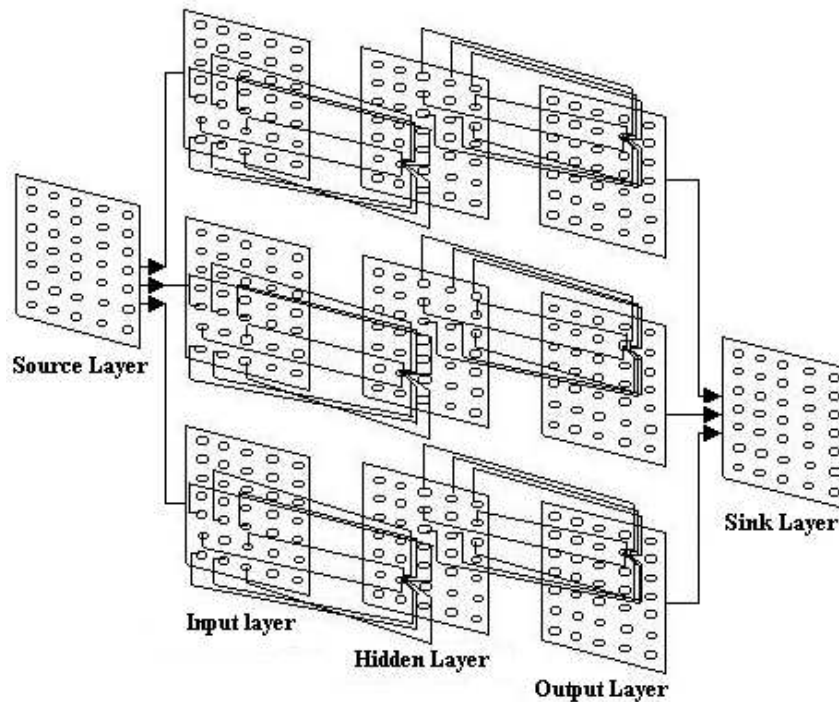


Fig. 2. PSONN architecture comprising a source layer, three independent three-layer self organizing neural network architectures in parallel and a sink layer

processing) apart from a source layer for inputs to the network and a sink layer for generating the final network outputs, can be similarly used for extracting pure color/binary color objects from a pure color image scene [34]. The source layer distributes the primary color component information of the pure color image scene to the three parallel self organizing neural network architectures. Processing at the component level takes place at these three self organizing neural network architectures. Since the three parallel self organizing neural network architectures operate in a self supervised mode on multiple shades of color component information, the system errors are computed from the linear indices of fuzziness of these subnormal color component information obtained at the respective output layers. These subnormal linear indices of fuzziness are obtained by normalizing the subnormal color component information into their equivalent normalized values so as to determine their Hamming distances with the nearest ordinary sets. These distance metrics are then denormalized back to the subnormal domain to result in the system errors. These system errors are used to adjust the respective interlayer interconnection weights using the standard backpropagation algorithm. This method of self supervision is carried on until the system errors at the output layers of the three independent three-layer self organizing neural networks fall below some tolerable limits. At this point, the output layer outputs of the three independent three-layer self organizing neural networks signify segmented color component outputs. These segmented component outputs are finally fused at the sink layer of the PSONN network architecture to produce the final segmented true color output image.

The main drawback of this network architecture is its inability to handle multiscale inputs, i.e. inputs which manifest different heterogeneous shades of color intensity levels. This is solely due to the nature of processing employed at the neurons of each of the network layers. The use of the standard bilevel sigmoidal activation function, which can only generate binary/bilevel outputs, restricts the applicability of this architecture to the graded color domain.

IV. MULTILEVEL ACTIVATION FUNCTIONS

Multicolor responses can be induced in a parallel self organizing neural network (PSONN) architecture by introducing a functional modification of the individual processing neurons of the different layers of the three-layer self organizing neural networks. This can be achieved by adapting a multilevel activation function (capable of producing multiscale outputs) as the characteristic activation function for each of the three independent self organizing neural networks, working in parallel. A multilevel activation function is a functional extension of the generalized activation functions in existence. Several multilevel forms pertaining to several generalized activation functions can be designed. This section discusses the basic design mechanism of the multilevel versions of the standard sigmoidal (MUSIG) activation function, the tan hyperbolic (MUTANH) activation function and the tan hyperbolic 15 (MUTANH15) activation function.

A. MUSIG activation function

The generalized sigmoidal activation function is given by

$$y = f_{\text{sig}}(x) = \frac{1}{\alpha + e^{-\lambda(x-\theta)}} \quad (14)$$

where, α controls the class responses, θ is referred to as the threshold/bias value and λ is the steepness factor of the function. The multilevel form of the sigmoidal function is derived from this generalized form as

$$f_{\text{MUSIG}}(x) \leftarrow f_{\text{sig}}(x) + (\gamma - 1)f_{\text{sig}}(c), (\gamma - 1)c \leq x < \gamma c \quad (15)$$

where, γ represents the color index and $1 \leq \gamma \leq K$, the number of color scale objects or classes. Here, c represents the color scale contribution (assumed to be equal for all classes). Multilevel sigmoidal (MUSIG) activation functions for three and five classes (K) are depicted in Fig. 3 and 4.

The multilevel sigmoidal activation function, exhibiting dif-

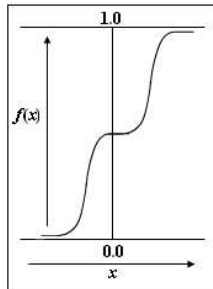


Fig. 3. Multilevel sigmoidal activation function for $K=3$

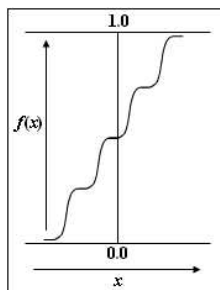


Fig. 4. Multilevel sigmoidal activation function for $K=5$

ferent transition lobes corresponding to the different number of color scales, is thus capable of generating multilevel outputs in response to the input signals by means of the appropriate transitions from one class boundary to the next. In addition, for higher number of classes, higher number of responses can be obtained by varying the α factor. The asymptotic nature of the function can be controlled by the λ parameter of the function. Higher values of λ facilitate the rate at which the different transition lobes of the function reach the class boundaries. The function, however, tends to flatten at lower values of λ . However, the functions always exhibit multipolar responses. All the three attributes of the function i.e. the slope, the threshold value and the class response pertaining to a class can

be varied by changing the values of the λ and the α parameters for that particular class. Moreover, the resulting functions are continuous and differentiable. This is due to the fact that the different transition lobes of the functions preserve continuity at the transition points.

B. MUTANH activation function

Since the input-hidden layer weights and the hidden-output layer weights of the three independent self organizing neural networks change during the self supervision process, it is required that the activations at the different layer neurons should have a mean of zero and a standard deviation of one. The standard sigmoidal activation function has a small asymmetric range from 0 to 1 and has a maximum derivative is 0.25. Thus, the function is not much sensitive to changes in weights effected during the standard backpropagation algorithm and the range of the function does not ensure that the standard deviation would not exceed one. The MUSIG activation function, derived from the generalized form of the sigmoidal activation function also suffers from this limitation. The tan hyperbolic activation function (Fig. 5) is a better alternative to keep things reasonably well-conditioned. It is given by

$$y = f_{\text{tanh}}(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (16)$$

It has a greater range than the sigmoidal activation function.

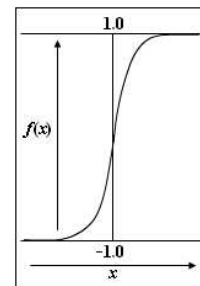
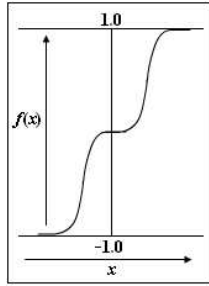
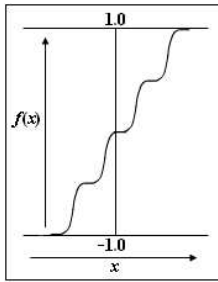


Fig. 5. Bilevel tan hyperbolic activation function

In terms of real numbers, it has a range (-1 to +1) equivalent to double that of the sigmoidal function. This range implies that the standard deviation cannot exceed 1, while its symmetry about zero means that the mean will typically be relatively small. Furthermore, its maximum derivative is also 1, so that backpropagated errors will be neither magnified nor attenuated more than necessary. Thus, the tan hyperbolic activation function would have a greater sensitivity to changes in weights. The generalized form of the tan hyperbolic activation function is given by

$$y = f_{\text{tanh}}(x) = \alpha \tanh(x) = \alpha \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (17)$$

where, α controls the class responses. The multilevel version of the tan hyperbolic function is derived from the generalized form using a recurrence relation similar to equation (15). Multilevel tan hyperbolic (MUTANH) activation functions for three and five classes (K) are depicted in Fig. 6 and 7.

Fig. 6. Multilevel tan hyperbolic (MUTANH) activation function for $K=3$ Fig. 7. Multilevel tan hyperbolic (MUTANH) activation function for $K=5$

C. MUTANH15 activation function

The tan hyperbolic 15 activation function is similar to the tan hyperbolic activation function in terms of the functional form. When used as an activation function of a neural network, it generally increases the rate of learning of the network and speeds up the rate of convergence of the learning procedure. The generalized form of the tan hyperbolic 15 activation function is given by

$$y = f_{\tanh 15}(x) = \alpha \tanh(1.5x) = \alpha \frac{e^{1.5x} - e^{-1.5x}}{e^{1.5x} + e^{-1.5x}} \quad (18)$$

The presence of the weightage term of 1.5 ensures that the function reaches its extrema faster. The multilevel version of the tan hyperbolic 15 function can be generated using relations similar to equation (15).

V. PROPOSED METHODOLOGY

The proposed approach of true color image scene segmentation by a PSONN architecture assisted by multilevel activation functions has been carried out in five phases. The flow diagram is shown in Fig. 8. The different phases are discussed in this section.

A. Designing of MUSIG, MUTANH and MUTANH15 activation functions

The most important part of the true color image segmentation approach lies in inducing multicolor responses into the three independent self organizing neural networks (SONNs). This is achieved by designing appropriate multilevel versions of the sigmoidal, the tan hyperbolic and the tan hyperbolic 15 activation functions from their respective generalized forms. The number of transition lobes of each of the multilevel

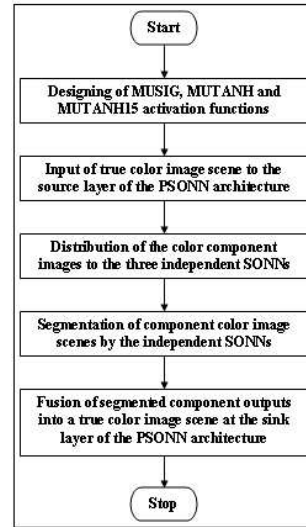


Fig. 8. Flow diagram of the proposed approach

activation functions to be designed, depends on the number of target classes into which the input true color image scene is to be segmented. Assuming equal class responses from contributing classes in the input true color image scene, four different multilevel forms (with number of target classes being 3, 5, 7 and 9), for each of the sigmoidal, the tan hyperbolic and the tan hyperbolic 15 activation functions are designed using equation (15). The resultant MUSIG, MUTANH and MUTANH15 functions are used by the processing units of each layer of the three independent three-layer self organizing neural networks (SONNs) for component level segmentation of the input true color image scene.

B. Input of true color image scene to the source layer of the PSONN architecture

After the multilevel activation functions have been designed and the neurons of the SONNs are activated, the true color image scene to be segmented, is fed as an input to the source layer of the PSONN architecture. The input image pixel true color intensities are assigned to each of the neurons of the source layer for this purpose.

C. Distribution of the color component images to the three independent SONNs

The individual primary color component information are extracted from the input true color image scene and passed on to the three independent three-layer component SONNs. Thus, one SONN accepts the red component, another SONN accepts the green component and the remaining SONN accepts blue component information at their respective input layers through the fixed interconnections with the source layer.

D. Segmentation of component color image scenes by the independent SONNs

The independent SONNs segments the color component information fed to them from the source layer, into different

number of target classes, depending on the number of transition lobes of the multilevel activation functions by means of self supervision. The system errors for each of the SONNs are evaluated at the corresponding output layers based on the subnormal linear indices of fuzziness of the outputs obtained. These errors are used to adjust the interconnection weights between the different layers of the corresponding SONN independently. This self supervision procedure finally results in segmented color component image scenes at the respective output layers of the independent SONNs.

E. Fusion of segmented component outputs into a true color image scene at the sink layer of the PSONN architecture

The segmented outputs obtained at the three output layers of the three independent three-layer SONNs after stabilization of the SONN architectures, are fused at the sink layer of the PSONN architecture to obtain the segmented true color image scene, the number of segments obviously equaling the number of transition lobes of the designed multilevel activation functions used during component level segmentation.

VI. RESULTS

The application of the proposed true color image segmentation approach using multilevel activation functions and a PSONN architecture is demonstrated with a Lena image (Fig. 9a), an Aish image (Fig. 10a) and a cube image (Fig. 11a). Segmentation has been carried out with 3, 5, 7 and 9 number of target classes. The results of segmentation with a MUSIG activation function are shown in Fig. 9(b-e), 10(b-e) and 11(b-e) for the three images respectively. The corresponding segmented images with the MUTANH and the MUTANH15 activation functions are shown in Fig. 9(f-i), 10(f-i), 11(f-i) and Fig. 9(j-m), 10(j-m), 11(j-m) respectively. The standard correlation coefficients between the original and the segmented images for different number of target classes (K) with MUSIG, MUTANH and MUTANH15 activation functions are reported in Tables I, II and III respectively.

TABLE I

STANDARD CORRELATION COEFFICIENTS OBTAINED WITH MUSIG

K	Lena image	Aish image	Cube image
3	0.768755	0.901498	0.935379
5	0.873991	0.950659	0.978707
7	0.897064	0.960225	0.982065
9	0.908066	0.971536	0.984580

TABLE II

STANDARD CORRELATION COEFFICIENTS OBTAINED WITH MUTANH

K	Lena image	Aish image	Cube image
3	0.770469	0.899696	0.936369
5	0.883519	0.956226	0.977580
7	0.897586	0.960606	0.981737
9	0.918973	0.961373	0.982133

From the tables it is evident that the performances of all the multilevel activation functions as regards to the segmentation of the Lena image are comparable. However, the MUSIG

TABLE III

STANDARD CORRELATION COEFFICIENTS OBTAINED WITH MUTANH15

K	Lena image	Aish image	Cube image
3	0.774379	0.899705	0.937297
5	0.883439	0.956260	0.980037
7	0.908828	0.960304	0.981721
9	0.937511	0.969658	0.984662

and the MUTANH15 activation functions outperform the MUTANH counterpart during the segmentation of the Aish and the cube image for higher number of classes. Fig. 12, 13 and 14 show the variation of the standard correlation coefficient with the number of classes for the Lena, Aish and the cube images respectively. This is mainly due to the presence of the darker intensity regions at the background of these images which is absent in the Lena image. Thus it can be inferred that the MUTANH activation function is not so sensitive to finer variations in the darker part of the true color spectrum. These variations are aptly taken care of by the MUSIG and the MUTANH15 activation functions which is reflected by the higher values of the standard correlation coefficients at higher number of classes.

VII. DISCUSSIONS AND CONCLUSION

A parallel neural network architecture for segmentation of true color images is discussed. The architecture is used to segment input color information at the component levels by means of self supervision by three three-layer self organizing neural networks. The constituent network layers of the three-layer self organizing neural networks are activated by multilevel activation functions, thereby exhibiting multicolor responses. The multilevel forms of a sigmoidal (MUSIG), a tan hyperbolic (MUTANH) and a tan hyperbolic 15 (MUTANH15) activation function used by the neurons at the different layers of the PSONN architecture, are designed based on the number of target classes of the segmentation procedure. The performance of the three multilevel activation functions as regards to the segmentation of true color images are compared by evaluating the standard correlation coefficients between the original true color images and the segmented outputs.

The evolution of the PSONN architecture is noteworthy from the implementation point of view. It is clear from the PSONN architecture that the entire segmentation technique can be easily extended in the distributed computing domain, thereby reducing the time complexity of the approach. The authors are currently engaged in this direction.

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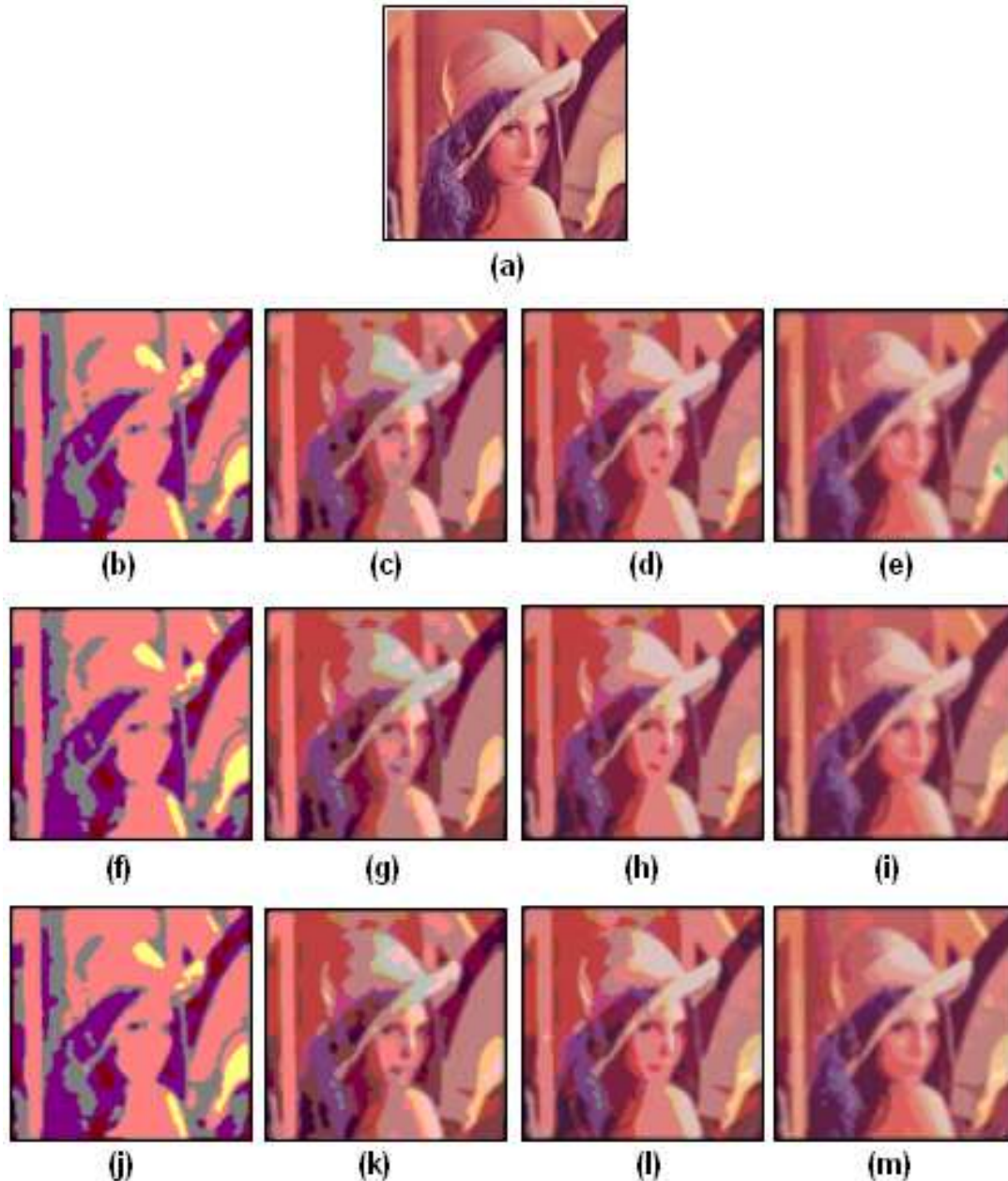


Fig. 9. (a) Lena true color image (b)(c)(d)(e) segmented outputs at 3, 5, 7 and 9 number of classes with a MUSIG activation function (f)(g)(h)(i) segmented outputs at 3, 5, 7 and 9 number of classes with a MUTANH activation function and (j)(k)(l)(m) segmented outputs at 3, 5, 7 and 9 number of classes with a MUTANH15 activation function

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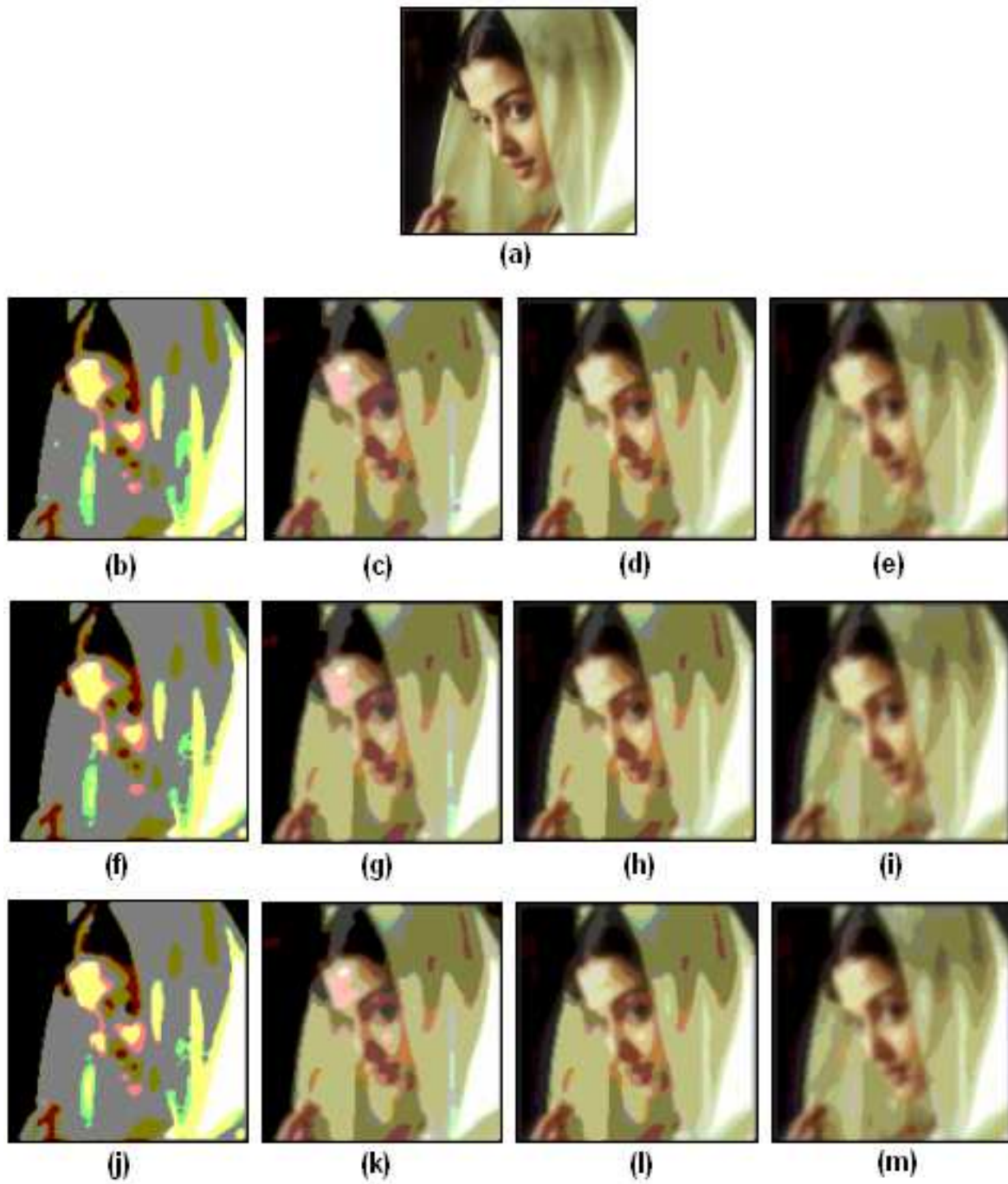


Fig. 10. (a) Aish true color image (b)(c)(d)(e) segmented outputs at 3, 5, 7 and 9 number of classes with a MUSIG activation function (f)(g)(h)(i) segmented outputs at 3, 5, 7 and 9 number of classes with a MUTANH activation function and (j)(k)(l)(m) segmented outputs at 3, 5, 7 and 9 number of classes with a MUTANH15 activation function

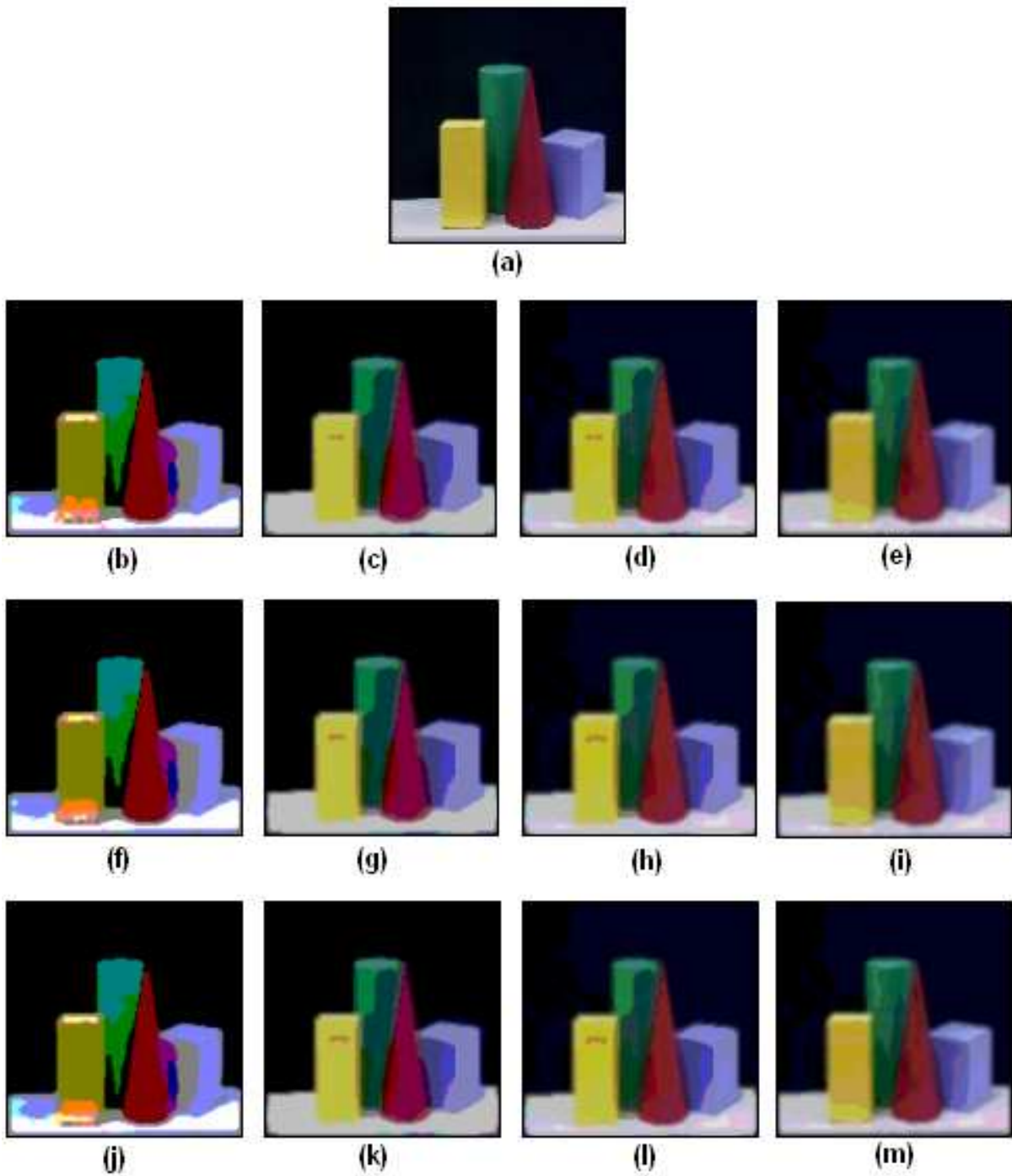


Fig. 11. (a) Cube true color image (b)(c)(d)(e) segmented outputs at 3, 5, 7 and 9 number of classes with a MUSIG activation function (f)(g)(h)(i) segmented outputs at 3, 5, 7 and 9 number of classes with a MUTANH activation function and (j)(k)(l)(m) segmented outputs at 3, 5, 7 and 9 number of classes with a MUTANH15 activation function

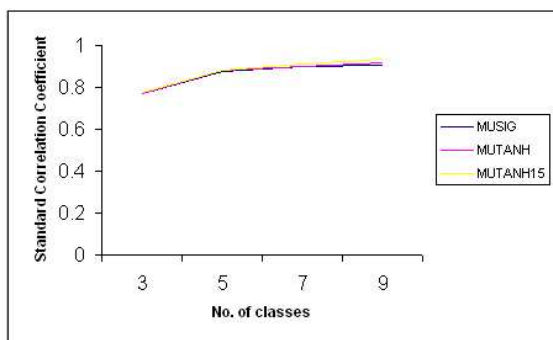


Fig. 12. Variation of the standard correlation coefficient with K for Lena image with MUSIG, MUTANH and MUTANH15 activation functions

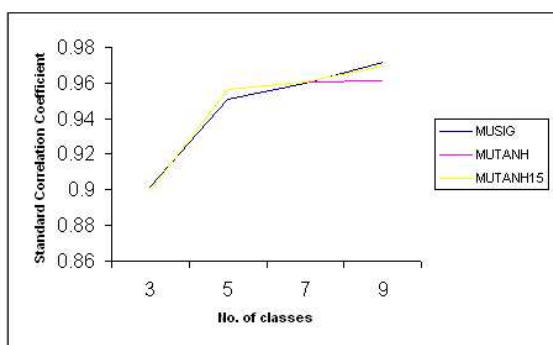


Fig. 13. Variation of the standard correlation coefficient with K for Aish image with MUSIG, MUTANH and MUTANH15 activation functions

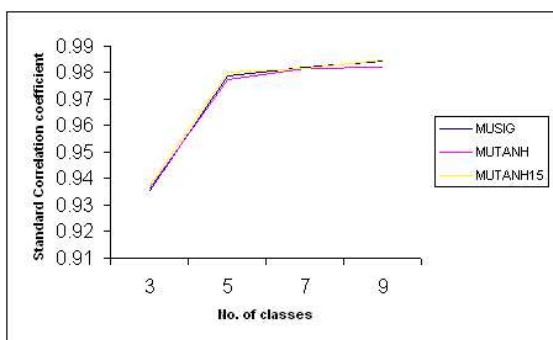


Fig. 14. Variation of the standard correlation coefficient with K for Cube image with MUSIG, MUTANH and MUTANH15 activation functions

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