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# COLOR CELL IMAGE SEGMENTATION USING PYRAMIDAL CONSTRAINT SATISFACTION NEURAL NETWORK

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**Abstract**

*Automatic analysis of medical cell images has been gaining more importance in pharmacology and toxicology research. Segmentation of cell bodies is the crucial step in their analysis since result of segmentation directly affect the following quantitative analysis steps. On the other hand, various smoothing representations of cell bodies are desired to calculate different parameters of the cells. In this work, a new version the Constraint Satisfaction Neural Network (CSNN) algorithm is used to segment the cell images in various details. This is accomplished by incorporating in the CSNN algorithm a multiresolution scheme using pyramid structure.*

## 1. Introduction

Image segmentation, perhaps the most important step in image analysis, is the process of dividing the given image into uniform and homogenous regions called segments. This process aims to partition the image into regions homogenous with respect to certain features, and which hopefully correspond to real objects in the actual scene [1]. Performance of the segmentation process directly effects the performance of the subsequent processing steps. There is a continuing interest in the segmentation problem. The main segmentation paradigms are measurement based techniques, methods based on region growing varieties, discontinuity or boundary driven methods and the Bayesian methods [1]. It has been observed however, that hybrid technique that exploit the tools of more than one method give superior performance [7].

Automated analysis of medical cell images has been gaining more importance in pharmacology and toxicology practice. Extraction of accurate quantitative data about the cell morphology is a critical task for biologists. An automated procedure for analysis of cell images is highly desirable since there may exist a hundreds of images for each patient. and the analysis by hand is very time-consuming and tedious[8]. In such an automated analysis system, the most critical step is the correct segmentation of cell bodies which are then used obtain quatitative data. In this paper, a novel segmentation algorithm based on multiresolution approach is proposed to segment the cell images. The algorithm is derived from the Constraint Satisfaction Neural Network (CSNN) algorithm [2]. The novelities brought in the CSNN algorithm are the following:

a) A multiresolution approach that enables to control the smoothness and details of the segments
b) Addition of a cluster validity scheme to determine automatically the number of clusters.

## 2. The Constraint Satisfaction Neural Network Segmentation

The segmentation implemented via CSNN can be interpreted as a fuzzy region growing instrumented by means of a neural network that is forced to satisfy certain constraints [2][3]. The neural network structure used in all the resolution levels is depicted in Figure 1 [2]. The fuzzy measure attached to the pixels is their probability to belong to a certain segment. The spatial constraints imposed can be in the form of edge information, neighborhood constraints or multiresolution inheritance constraints. The label probabilities grow or

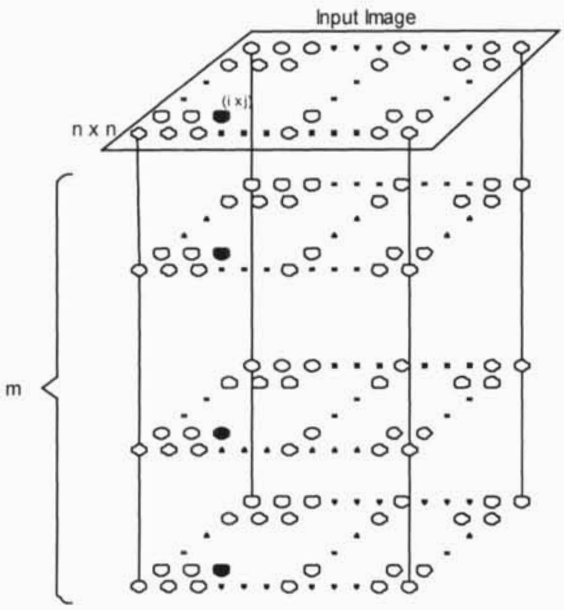


**Figure 1.** Constraint satisfaction neural network topology. Each layer represents the segments. $(i,j)^{th}$ neuron in each layer holds the probability that $(i,j)^{th}$ pixel belongs to the segment represented by the layer.

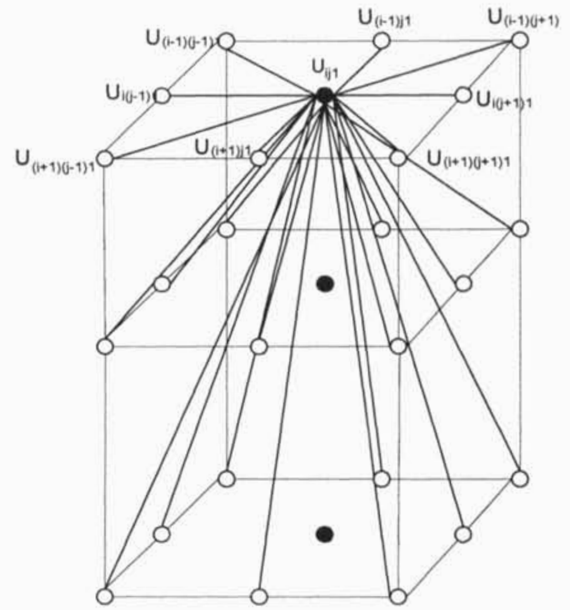

**Figure 2.** Connection between a neuron and its neighbors. The weights of these connections are interpreted as constraints.

diminish in a winner-take-all style as a result of contention between segments. The global satisfaction of the label assignment in the image domain give rise to the final segmentation.

More specifically every layer in this topology corresponds to a segment. Neurons in the layers hold the probability that the pixel belongs to the segment represented by corresponding layer. As shown in Figure 2, each neuron synapses to eight neighborhood neurons in the same layer as well as all the other layers. Snaptic weights represent evidences or counter-evidences for segment decisions. They are updated in such a manner that a neuron excites those neurons that represent the same label, and inhibits the ones that represent the significantly different labels. The synaptic weights must be determined to guarantee the convergence of the network.

In the method proposed by Lin et.al. the number of segments is assumed known based on some a-priori knowledge. An initial label assignment is performed according to the gray level distribution of the image. Probabilities of each pixel to belong to different segments are determined and presented to the constraint satisfaction neural network as the initial conditions. These segment probabilities are updated by taking into account their neighborhood labels and the spatial constraints [2]. The network converges to a solution which also satisfies the given constraints. After converging, the label which holds the largest

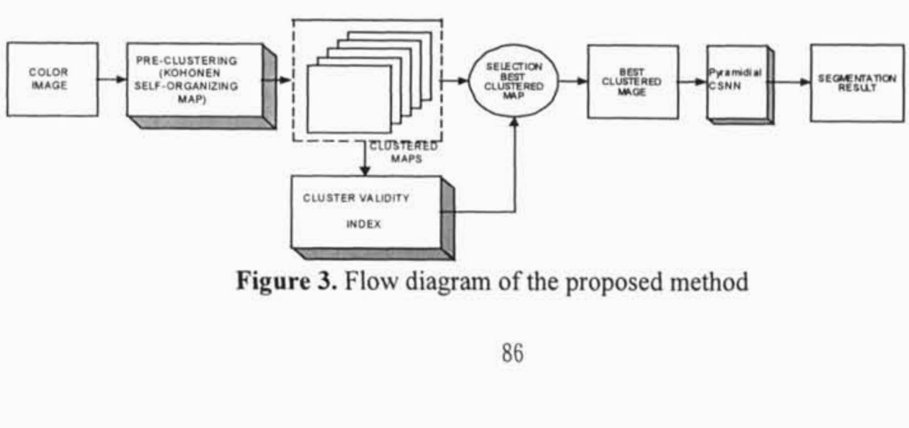


**Figure 3.** Flow diagram of the proposed method

probability value is assigned to the corresponding pixel.

## 3. Proposed Modification: Pyramidal Constraint Satisfaction Neural Network

The flow chart of the pyramidal CSNN segmentation scheme is depicted in Figure 3. The Constraint Satisfaction Neural Network (CSNN) proposed by Lin et.al. [2] is extended in the following ways.

In the initialization step of the CSNN, the initial labeling is obtained by clustering the pixels in the color space.

The first improvement is the automated determination of the the number of segments from the given image. This information may not be available in many applications. To this purpose the Normalized Akaike Information Criteria (N-AIC) cluster validity index measure is adopted to determine the number of segments [6]. Thus the feature vectors of a given image is clustered with the number of segments varying from two to a selected maximum, by using Kohonen self-organizing map. Then N-AIC index is calculated for every clustered data. The index of minimum N-AIC value is chosen as the correct number of segments in the given image.

The second and the main contribution is the enhancement of the CSNN with multiresolution capability. This is accomplished by defining a new neural network structure based on pyramid of data as shown in Figure 4. Notice that the pyramid is constructed in the label space obtained from the full resolution image. Each level of the pyramid consists of a separate CSNN structure but with interconnections across resolution levels. This pyramid structure is established in the initialization step. The clustered map obtained from pre-clustering and validity step is used for this purpose. This clustered map which has the original image dimensions is taken as the base of the pyramid structure ($0^{th}$ level). It is fuzzified as defined in [2] and is used to condition the CSNN in the $0^{th}$ level. Then the segmentation label map is transformed to $1^{st}$ level label map using an approach suggested by Burt et.al [9]. In this approach, a parent pixel in the upper level is related its 16 child pixels in the lower level. A child pixel in the lower level has also 4 parent pixels in the upper level. A voting among the child pixels is performed and the maximum encountered segment label of the child pixels is assigned to the parent pixel. This a new label map forming $1^{st}$ level is used to generate the $2^{nd}$ level label map, and so on.

After initialization of the pyramidal CSNN as described above, the neural network

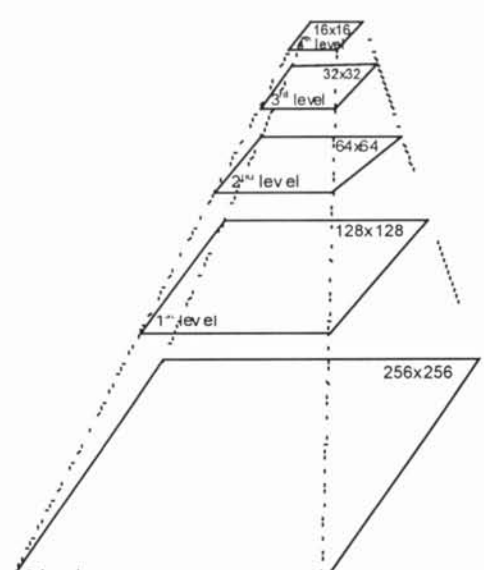


**Figure 4.** Structure of Pyramidal CSNN. Each level represents a CSNN which consists of number of segments layers.

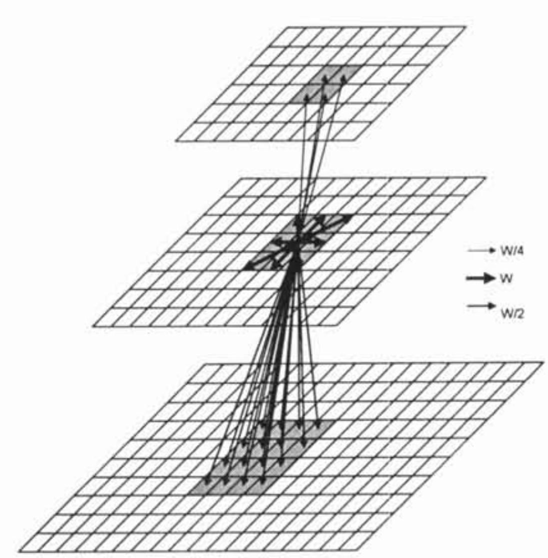


**Figure 5.** Connections between levels. These connection weights can be adjusted to obtain more smoothed or more detailed segmentation result.

runs to a segmentation result which must satisfy the all constraints in the system. The constraints are determined by the snaptic weights between neurons in the CSNN. Notice that each neuron synapses to

a) 16 child sites in the lower resolution level,
b) 4 parent sites in the higher resolution level,
c) 8 neighboring sites in the same resolution level.

Each site contains 8x(the number of segments) neurons in the segmentation levels as depicted Figure 2. The weights of these connections determines the constraints and the dynamic structure of the neural network. For example, if high connection weights is attributed to lower-upper synapses more smoothed segments will be obtained because smoothed pixels have dominant role in this scheme. On the contrary, if high connection weight is chosen for upper-lower synapses more detailed segments will be obtained. Consequently, the proposed method gives the user flexibility to tune the algorithm for user's demand.

Finally, CSNN algorithm is extended to use color information since segmentation of color images has recently been gaining importance[4] [5]. The main motivation behind using color information in image processing is that color can sometimes be a powerful feature in the identification of the objects.

**4. Application to Cell Images**

The proposed image is applied to the several color cell images and satisfactory results are obtained. In Figure 6-a, a cell image is depicted. The cells are painted purple by chemical mean. Desired information from this cell image is a) The morphology of the cell ( Perimeter, area, form factor, etc.), b) The irregular area in the nucleoid. These two tasks are carried out successfully by the pyramidal CSNN by its tuning the connection weights. In Figure 6-b, a more smooth segmentation is obtained for calculation of the morphology of the cells. The more detailed segmentation which exposes irregular areas is used for examination of the nucleoid as depicted in Figure 6-c.

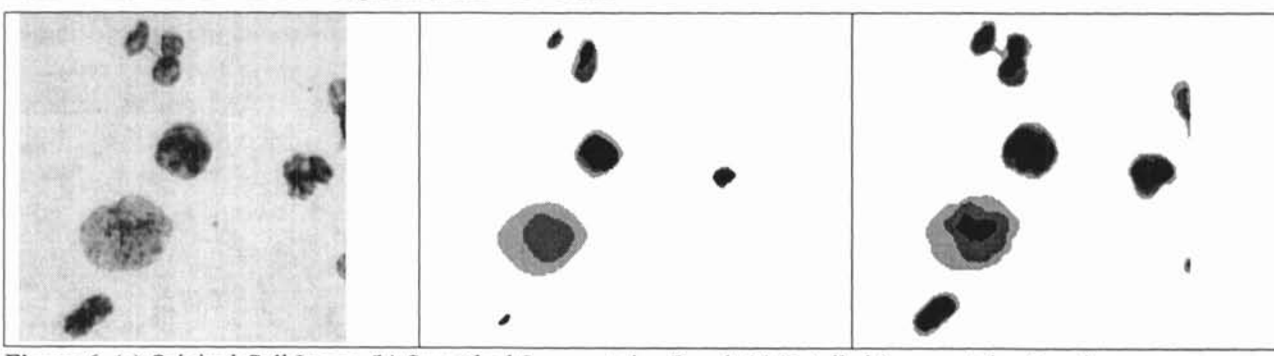

**Figure 6.** (a) Original Cell Image (b) Smoothed Segmentation Result (c) Detailed Segmentation Result


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