

# ULTRASOUND IMAGE SEGMENTATION WITH GROWING CELL STRUCTURE

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## ABSTRACT

**In this study, Growing Cell Structure (GCS) is proposed for the segmentation of ultrasound images. Elements of the feature vectors are formed by the fast Fourier transform (FFT) of image intensities in 4×4 square blocks. Two neural networks, Kohonen map and GCS are comparatively examined for segmentation of two ultrasound images. It is observed that GCS gives the best segmentation performance.**

## I. INTRODUCTION

Segmentation is often an important step in the analysis of medical images. A correct segmentation promises a more accurate extraction of clinical information from ultrasound (US) images for clinical applications. However, US image segmentation in practice is a very hard problem due to the complex nature of US images. To accomplish US image segmentation more efficiently and accurately, a computerized approach would be an ideal choice for clinical use.

Kohonen's Self-Organising Maps (SOM) [1] generate mappings from high-dimensional signal space to lower dimensional topological structures. Their main features are formation of topology-preserving feature maps and approximation of the input probability distribution.

Incremental artificial neural networks grow as they learn, and shrink as they forget. It is observed that incremental artificial neural networks and competitive learning are widely used in the literature [2 - 4]. Fritzke [2] proposed a growing cell structure (GCS) for self-organizing clustering and topology preserving. To its simplicity, the competitive Hebbian rule has been used for topology learning in the growing neural gas (GNG) [3] and dynamic cell structure [4]. The GCS has three main advantages over SOM: First, the network structure is determined automatically by the input patterns; secondly, the network size needs not to be predefined; and thirdly, all parameters of the model are constant.

In this study, Kohonen network and GCS are comparatively examined for the segmentation of ultrasound images.

## II. METHODS

The feature extraction method used in a previous study [5] is also realized in this study. The ultrasound image is splitted into square blocks of 4×4 pixels, and 2D-FFT of each block is computed. 2D-FFT coefficients of a 4×4 block are shown in Figure 1. In the proposed method, only four coefficients ( $F_{11}$ ,  $F_{12}$ ,  $F_{21}$  and  $F_{22}$ ) which are shown inside a bold-bordered square are used to form the codewords.

The global scheme for the segmentation of the ultrasound images is described in Figure 2. After vectorization (transformation of image blocks into vectors), the 2D-FFT coefficients are computed in the second stage to form codewords. Codeword vectors are formed by using the absolute values of the complex  $F_{ij}$  coefficients. In the third stage, the codewords are presented to an artificial neural network (ANN) for the learning process.

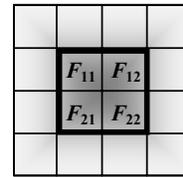


Figure 1. Selected FFT coefficients for a block of 4×4 pixels.

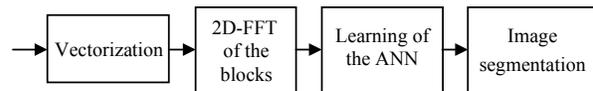


Figure 2. Segmentation process.

### III. GROWING CELL STRUCTURE (GCS)

The goal of a GCS network is to create a mapping of vector space  $V$  with a  $n$ -dimensional probability distribution  $P(\xi)$  onto a discrete  $k$ -dimensional topological structure  $A$ . This mapping should have the following properties: First, similar input signals are mapped onto topologically close elements of  $A$ ; secondly, topologically close elements in  $A$  should have similar signals being mapped onto them; thirdly, regions of  $V$  where the probability density of the input vector distribution is higher should be represented by correspondingly more elements in  $A$ . The initial topology of network is a  $k$ -dimensional simplex. During self-organisation new cells are added to the network and superfluous cells are removed.

In two dimensions, GCS performs the Delaunay triangulation of input vector space according to an unknown input vector density distribution  $P(\xi)$ .

#### LEARNING OF THE GCS NETWORK

1. Start with  $k$ -dimensional simplex. The  $(k+1)$  vertices are initialized to random vectors in  $\mathbb{R}^n$ .
2. Choose an input signal  $\xi$  according to the input distribution  $P(\xi)$ .
3. Determine the best-matching unit  $s$  (the unit with the nearest reference vector):

$$\|w_s - \xi\| \leq \|w_c - \xi\| \quad (\forall c \in A)$$

4. Add the squared distance between the input signal and the best-matching unit  $s$  to a local error variable  $E_s$ :

$$\Delta E_s = \|w_s - \xi\|^2$$

5. Move  $s$  and its direct topological neighbours towards  $\xi$  by fractions  $\varepsilon_b$  and  $\varepsilon_n$ , respectively, of the total distance:

$$\Delta w_s = \varepsilon_b (\xi - w_s)$$

$$\Delta w_i = \varepsilon_n (\xi - w_i)$$

(With  $N_c$  we denote the set of topological neighbours of a unit  $c$ , i.e. those units which are connected to  $c$  by an edge.)

6. If the number of input signals generated so far is an integer multiple of a parameter  $\lambda$ , insert a new unit as follows.

- Determine the unit  $q$  with the maximum accumulated error:

$$E_q \geq E_c \quad (\forall c \in A)$$

- Insert a new unit  $r$  by splitting the longest edge emanating from  $q$ , say an edge leading to a unit  $f$ . Insert the connections  $(q, r)$  and  $(r, f)$  and remove the original connection  $(q, f)$ . To rebuild the structure such that it again consists only of  $k$ -dimensional simplices, the new unit  $r$  is also connected

with all common neighbours of  $q$  and  $f$ , i.e. with all units in the set  $N_q \cap N_f$ .

- Interpolate the reference vector of from the vectors of  $q$  and  $f$ :

$$w_r = 0.5(w_q + w_f)$$

- Decrease the error variables of all neighbours of  $r$ :

$$\Delta E_i = -\frac{\alpha}{|N_r|} E_i \quad (\forall i \in N_r)$$

- Set the error variable of the new unit  $r$  to the mean value of its neighbours:

$$E_r = \frac{1}{|N_r|} \sum_{i \in N_r} E_i$$

7. Decrease the error variables of all units:

$$\Delta E_c = -\beta E_c \quad (\forall c \in A)$$

8. If a stopping criterion (e.g. net size or some performance measure) is not yet fulfilled, continue with step 2.

### IV. COMPUTER SIMULATIONS

In this study, two ultrasound images are segmented by using GCS and Kohonen networks. The ultrasound images of kidney cyst and bladder are shown in Figures 3 (a) and (b), respectively. All simulations are performed on Pentium IV-2.4 GHz PC using MATLAB 6.0.

The ultrasound images are splitted into square blocks of  $4 \times 4$  pixels. Codewords are formed by using 2D-FFT of the square blocks. Training set consists of codewords formed by all the square blocks in the image.

The topology of the Kohonen network is estimated before the training. In the study, two different topologies of the Kohonen network are determined after 10 different trials with the same training set. Figures 4 (a) and (b) show segmented kidney cyst and bladder images by using the Kohonen network, respectively. The structure of the Kohonen network is determined as  $5 \times 5$  and  $6 \times 6$  for segmentation of the kidney cyst and bladder images in Figures 4 (a) and (b), respectively.

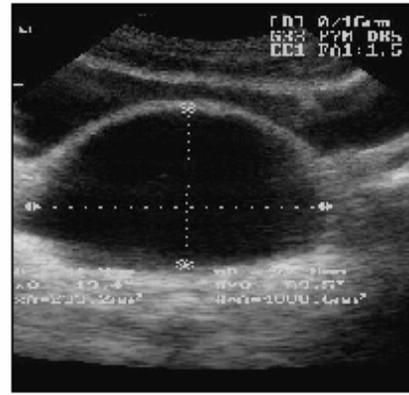
Figures 4 (c) and (d) show segmented ultrasound images by using the GCS. In contrast to Kohonen network, there is no need to specify the network size of the GCS in advance. All parameters are constant. To specify the parameters, it runs with several variations of parameters. In the study, the parameters are selected for both kidney cyst and bladder images as follows;

$$\varepsilon_n = 0.05, \varepsilon_b = 0.0006, \lambda = 200, \alpha = 0.5, \beta = 0.0005$$

Both ultrasound images, kidney cyst and bladder, in Figures 3 (a) and (b) are segmented into six tissues, respectively.



(a)

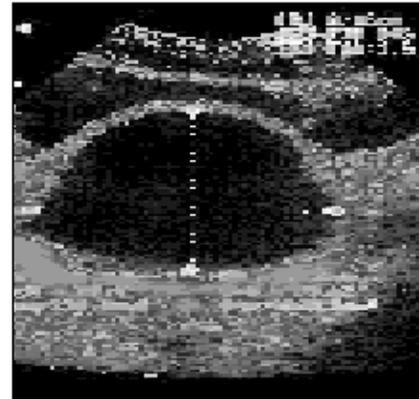


(b)

Figure 3. Ultrasound images of (a) kidney cyst, and (b) bladder.



(a)

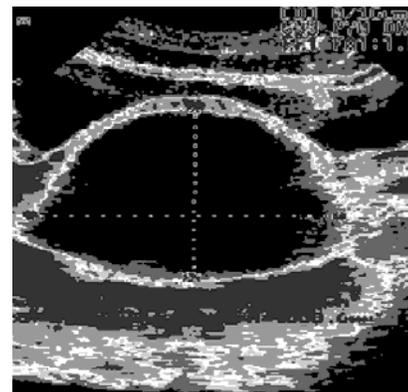


(b)

Figure 4. (a) and (b) Segmented ultrasound images by the Kohonen network.



(c)



(d)

Figure 4. (c) and (d) Segmented ultrasound images by the GCS network.

## V. CONCLUSION

In this study, two neural networks are compared for the segmentation of US images, kidney cyst and bladder. During the training of the GCS, the number of nodes of the network is determined automatically. However, the topology of the Kohonen network must be estimated before training. After 10 different trials with the same training set, the structure of the Kohonen network are determined as 5x5 and 6x6 for segmentation of the kidney cyst and bladder images, respectively. However, for segmentation of both US images with GCS, number of nodes is only six. It is observed that GCS give better segmentation performance than Kohonen network for both US images.

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