DYNAMIC IMAGE SEGMENTATION SYSTEM WITH MULTI-SCALING SYSTEM FOR GRAY SCALE IMAGE

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Keywords: Dynamic image segmentation, Coupled system, Chaotic neurons, Gray scale image, Multi-scaling of gray levels.

Abstract: In this paper, we describe an image segmentation technique for a gray scale image by utilizing the nonlinear dynamics of two respective discrete-time dynamical systems. The authors have proposed a discrete-time dynamical system that consists of a global inhibitor and chaotic neurons that can generate oscillatory responses. By utilizing oscillatory responses, our system can perform dynamic image segmentation, which denotes segmenting image regions in an image and concurrently exhibiting segmented images in time series, for a binary image. In order that our system can work for a gray scale image, we introduce a multi-scaling system as a pre-processing unit of our system. It is also made of a discrete-time dynamical system and can find an image region composed of pixels with different gray levels by multi-scaling gray levels of pixels. In addition, it can compute the proximity between pixels based on their multi-scaled gray levels. Computed proximity becomes significant information for designing parameters in our system. We demonstrated that our dynamic image segmentation system with the multi-scaling system works well for a gray scale image.

1 INTRODUCTION

Image segmentation is the first essential and important step in a low-level vision system and a computer-aided diagnosis support system. A lot of frameworks that provide static image segmentation have been developed (Pal and PAL, 1993).

In contrast to static image segmentation techniques, a locally excitatory globally inhibitory oscillator network (LEGION) (Wang and Terman, 1995) can perform image segmentation dynamically, which denotes segmenting isolated image regions in a static image and concurrently exhibiting the segmented images in time series. A LEGION has a global inhibitor and the same number of oscillators as pixels in an input image, and its dynamics is described by ordinary differential equations. Dynamic image segmentation is based on oscillatory responses of oscillators, which is a nonlinear phenomenon observed in a LEGION.

Dynamic image segmentation using a LEGION needs a high computational cost in a digital computer, since it is a continuous-time dynamical system. As a more suitable dynamic image segmentation system for digital computing, the authors have developed a discrete-time dynamical system (Fujimoto et al., 2008) with a global inhibitor and chaotic neurons (Aihara et al., 1990) that can generate an oscillatory response. The architecture of our system is similar to a LEGION, and our system can perform dynamic image segmentation based on oscillatory responses of chaotic neurons. We analyzed suitable parameter values and demonstrated that our system works well for a binary image (Fujimoto et al., 2009).

In this paper, as a pre-processing system of our system, we consider introducing a discrete-time dynamical system (Zhao et al., 2003), which functions as a multi-scaling system (degradation system) for gray levels of pixels like a K-means technique (Hartigan and Wong, 1979), so that it can yield successful dynamic segmentation for a gray scale image. The multi-scaling system not only gradate a gray scale image but also compute the proximity between pixels, i.e. their connections, based on their multi-scaled gray levels concurrently. Computed proximity is significant for designing parameter values of our system.

Fujimoto K., Musashi M. and Yoshinaga T. (2010).
DYNAMIC IMAGE SEGMENTATION SYSTEM WITH MULTI-SCALING SYSTEM FOR GRAY SCALE IMAGE.
In *Proceedings of the Third International Conference on Bio-inspired Systems and Signal Processing*, pages 159-162
DOI: 10.5220/0002689701590162

2 SYSTEM DESCRIPTION

Our dynamic image segmentation system (Fujimoto et al., 2008) was designed for a binary image. In this paper, we consider introducing a multi-scaling system (Zhao et al., 2003) into our original system so that it can work well for a gray scale image.

2.1 Multi-scaling System of Gray Levels

In segmentation of a gray scale image, a fundamental task is to find an image region (connected components) that consists of pixels with different gray levels. As an approach, a multi-scaling technique for a gray scale image has been proposed (Zhao et al., 2003). The scheme consists of degradation of a gray scale image like a K-means technique (Hartigan and Wong, 1979) and concurrent computation of the proximity between pixels based on their gradated gray levels. Moreover, it has an interested feature that it needs no setting of the number of centroids and their initial arrangements unlike the K-means method.

The scheme is performed by utilizing nonlinear dynamics of the following discrete-time dynamical system. Let $p_i(\tau)$ be the ith pixel value normalized in the range $[0,1]$. It is updated according to

$$p_i(\tau+1) = \begin{cases} 0 & \text{if } p_i(\tau)+\eta F_i(\tau) \le 0 \\ p_i(\tau)+\eta F_i(\tau) & \text{if } 0 < p_i(\tau)+\eta F_i(\tau) < 1 \\ 1 & \text{if } p_i(\tau)+\eta F_i(\tau) \ge 1 \end{cases} \tag{1}$$

and

$$F_i(\tau) = \frac{1}{S_i(\tau)} \sum_{j\in\Delta_i(\tau)} \frac{p_j(\tau)-p_i(\tau)}{|p_j(\tau)-p_i(\tau)|} e^{-\gamma|p_j(\tau)-p_i(\tau)|}, \tag{2}$$

where $p_i(0)$ is given as the normalized gray level of the ith pixel in an input image; $\Delta_i(\tau)$ denotes a set of pixels with approximately the same value as $p_i(\tau)$; and the sign $|\cdot|$ expresses the absolute value. $S_i(\tau)$ represents the number of elements in $\Delta_i(\tau)$ and is counted based on the proximity level $q_{ij}(\tau)$ between the ith and jth pixel values at every iteration. It is updated as

$$q_{ij}(\tau+1) = \beta q_{ij}(\tau) + (1-\beta) H\left(e^{-\gamma|p_j(\tau)-p_i(\tau)|} - \psi\right), \tag{3}$$

where H denotes the Heaviside step function and returns zero or one if its argument value is negative or non-negative, respectively. η, γ, β, and ψ are positive parameters, and the each value except for γ is set as less than one. Therefore, the value of $q_{ij}(\tau)$ gradually converges to the return value of H, e.g., $q_{ij}(\tau+1)$ approaches one when the values of $p_i(\tau)$ and $p_j(\tau)$ are close. Based on the values of $q_{ij}(\tau)$, the values of $p_i(\tau)$ are also converged to several clusters gradually, and eventually, a multi-scale image is obtained.

According to the values of p_i and q_{ij} after sufficient iteration, couplings between adjacent chaotic neurons are determined so that the ith and kth chaotic neurons are coupled only if $q_{ik} = 1$, where $k \in L(i)$.

2.2 Coupled System of Chaotic Neurons

Our dynamic image segmentation system (Fujimoto et al., 2008) consists of a global inhibitor and the same number of chaotic neurons (Aihara et al., 1990) as pixels of an input image. A chaotic neuron can generate an oscillatory response under adequate values of system parameters. Dynamic image segmentation is performed based on oscillatory responses.

The architecture of our system and dynamic image segmentation scheme are illustrated in Fig. 1. Chaotic neurons are arranged in a two-dimensional grid so that one corresponds to a pixel. Chaotic neurons corresponding to high-gray-level pixels in an image region are coupled and also have a positive self-feedback coupling. The global inhibitor connects to all chaotic neurons and suppress their activity levels when one or more chaotic neurons fire. The dynamics of the ith chaotic neuron with two state variables (x_i, y_i) is described as

$$x_i(t+1) = k_f x_i(t) + I_i + C_i(t) \tag{4}$$

$$y_i(t+1) = k_r y_i(t) - \alpha g(x_i(t)+y_i(t), 0) + a, \tag{5}$$

where t denotes the discrete time. I_i takes a value from 0 to 2, and we set the value of I_i as the value of $\lim_{\tau\to\infty} 2p_i(\tau)$. $C_i(t)$ represents the sum of external stimuli from chaotic neurons including itself in the same image region and the global inhibitor. It is described as

$$C_i(t) = \sum_{k\in L(i)} \frac{W}{M(i)} g(x_k(t)+y_k(t), 0) - W g(z(t), 0.5), \tag{6}$$

where $L(i)$ denotes a set of chaotic neurons corresponding to almost the same gray levels of pixels as the ith pixel in its four-neighborhood. $M(i)$ is the number of elements in $L(i)$ and be calculated as the number of chaotic neurons satisfying $q_{ik} = 1$ in which $k \in L(i)$. g denotes the output function of a chaotic neuron or the global inhibitor and is defined as

$$g(u(t), \theta) = \frac{1}{1+\exp(-(u(t)-\theta)/\varepsilon)}. \tag{7}$$

The dynamics of the global inhibitor with a state variable (z) is expressed as

$$z(t+1) = \phi\left\{ g\left(\sum_{i=1}^{N} g(x_i(t)+y_i(t), W), 0 \right) - z(t) \right\}, \tag{8}$$

where N denotes the number of chaotic neurons.

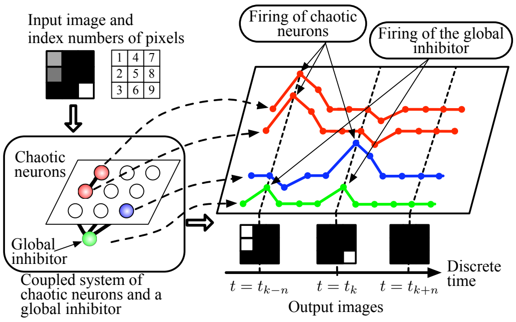


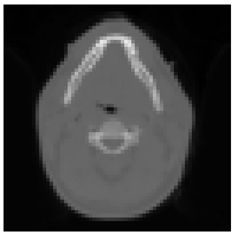
Figure 1: System architecture and dynamic image segmentation scheme.

Let us explain dynamic image segmentation scheme using a multi-scaling system and our system. Now, we treat a gray scale image with 3×3 pixels shown in Fig. 1. A multi-scaling system provides a multi-scaled image and connections between pixels in the processed image. As the results, it has two high-gray-level image regions: one is composed of the first and second pixels and the other is the ninth pixel. Therefore, only the three chaotic neurons can oscillate. In addition, based on computed connections, the first and second chaotic neurons are coupled and can oscillate in phase. When one or more chaotic neuron fire, the global inhibitor also fires and suppresses the activity levels of all chaotic neurons at the next time. Owing to the suppression, chaotic neurons in different image regions can fire separately. By assigning high gray levels to pixels that correspond to fired chaotic neuron every discrete time, individual segmented images are output and are exhibited in time series.

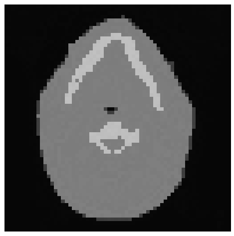
3 EXPERIMENTAL RESULTS

We treated an 8-bit computed tomography (CT) image with 64×64 pixels at a human head shown in Fig. 2(a). It is provided from the public database of the visible human project (Ackerman, 1991). From visual evaluation for the image, it has one mid-intensity image region and two isolated high-intensity image regions. The mid-intensity region corresponds to soft tissues, the upper high-intensity region denotes teeth and the mandible bone, and the lower one represents a cervical spine, roughly.

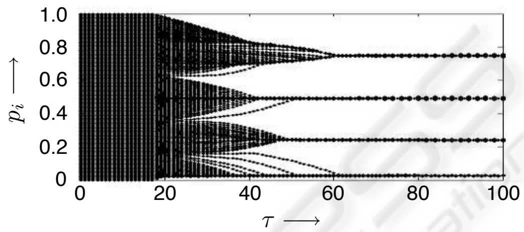
At first, to obtain a multi-scale image of the original image, the multi-scaling procedure was performed, where we set the parameter values in Eqs. (1)–(3) as $\eta = 0.01$, $\gamma = 5$, $\beta = 0.1$, and $\psi = 0.5$. Figure 2(c) shows the multi-scaling process. Its abscissa denotes the iteration number (discrete time) and



(a) 8-bit original image



(b) multi-scaled image



(c) process of multi-scaling.

Figure 2: 8-bit CT image and its multi-scaling based on the nonlinear dynamics described in Eqs. (1)–(3).

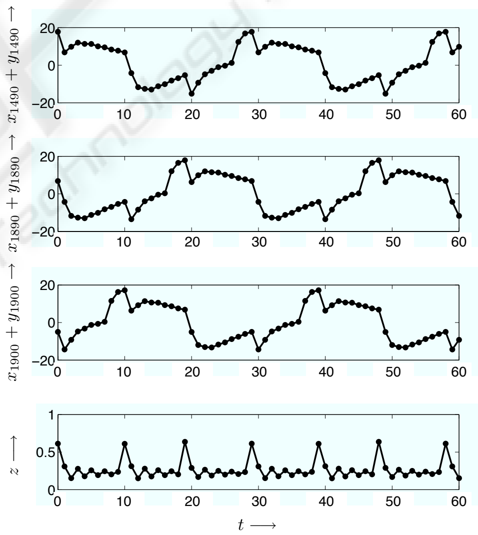


Figure 3: Oscillatory responses of chaotic neurons and the global inhibitor.

dots at every discrete time represent the distribution of all pixel values. Although the normalized pixel values were distributed throughout $[0, 1]$ at $\tau = 0$, they gradually converged to four clusters based on the dynamics of Eqs. (1)–(3). As the result, we obtained a multi-scaled image shown in Fig. 2(b). It consists of four gray-levels and has three high-gray-level image regions that correspond to the aforementioned image regions from our visual evaluation.

The next, using our system consisting of 4096 (64×64) chaotic neurons and a global inhibitor, dy-

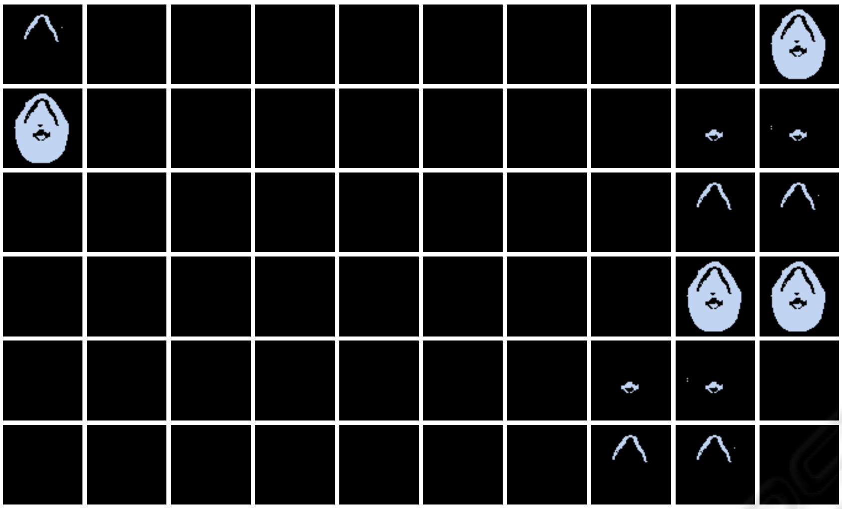


Figure 4: Results of dynamic image segmentation performed by our framework for a gray scale image.

namic image segmentation was performed for the image. According to our analyzed results (Fujimoto et al., 2009), we set as $k_f = 0.5$, $k_r = 0.885$, $\alpha = 4$, $a = 0.5$, $W = 15$, $\varepsilon = 0.1$, $\phi = 0.8$, and $I_i = 2p_i(100)$. By giving certain initial values to all chaotic neurons and the global inhibitor, chaotic neurons corresponding to the three image regions oscillated separately in steady state. Figure 3 shows oscillatory responses of three chaotic neurons and the global inhibitor. The 1490th, 1890th, and 1900th chaotic neurons correspond to a part of teeth and the mandible bone, the cervical spine, and soft tissues, respectively. Moreover, owing to suppression of the global inhibitor, their oscillatory responses were out-of-phase each other, i.e., it is a three-phase oscillatory response. Note that we expediently set the start time of simulation as $t = 0$.

Figure 4 shows snapshots of dynamically segmented images based on output values of the all chaotic neurons every discrete time, where the ith pixel value at t was assigned to $200 \cdot g(x_i(t) + y_i(t), W)$. The snapshots sequentially appear from the top-left to the bottom-right. Moreover, their appearances in each line also start from the left. The three isolated image regions appeared separately, and therefore, it was demonstrated that our system with a multi-scaling system worked well for a gray scale image.

4 CONCLUDING REMARKS

We have proposed a dynamic image segmentation system for a binary image. In this paper, we considered applying our system to a gray scale image by introducing a multi-scaling system for gray levels as a pre-processing. Through experiments for a gray scale image, we demonstrated that the composite system consisting of the multi-scaling system and our dynamic image segmentation system works well.

This work was partially supported by the Ministry of Education, Culture, Sports, Science and Technology, Japan, Grant-in-Aid for Young Scientists (B), No. 20700209.

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