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Heterogeneous SPCNN and its application in image segmentation

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ABSTRACT

Based on the fact that actual cerebral cortex has different structure, a new heterogeneous simplified pulse coupled neural network (HSPCNN) model is proposed in this paper for image segmentation. HSPCNN is constructed with several simplified pulse coupled neural network (SPCNN) models, which have different parameters corresponding to different neurons. An image is segmented by HSPCNN into several regions according to their gray levels. Moreover, the parameter of HSPCNN is set automatically in this paper, the experimental segmentation results of the gray natural images from the Berkeley Segmentation Dataset (BSD 300) show the validity and efficiency of the proposed segmentation method. Finally, an evaluation index is proposed to measure the segmentation result.

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1. Introduction

Pulse coupled neural networks (PCNN) model was derived from Echorns cortical model [1,2]. It was soon recognized as having significant applications in image processing, after then, large number of improved versions of Echorns cortical model were proposed to make it more suitable for image processing, and these models were collectively known as pulse coupled neural networks. The representative ones are the intersecting cortical (ICM) model proposed by Kinser et al. [3,4], the unit-linking PCNN model [5], the spiking cortical model (SCM) [6], the SPCNN [7] and the fast SCM [8].

PCNN has great potential in image processing field. The last decade has seen the rapid development of PCNN in the image processing field, such as image segmentation [7,9–11], feature extraction [12,13], image fusion [14–16], pattern recognition [17], medical image processing [18,19], etc. However, just like other segmentation algorithms, traditional PCNN is good at processing an image into binary matrix in each iteration. Moreover, the proper parameters of PCNN must set manually or approximately established through a heavy training, which limits the further development of PCNN.

Last but not the least, most of PCNN models generally emphasize on homogeneous architectures of artificial neural networks. But the nervous system of mammal is heterogeneous, which reveals the heterogeneity in constructing elements and their patterns of interconnection [20]. Furthermore, the hierarchies in the visual system [21] also indicates that any artificial networks should heterogeneously in architectures so that well conform to the human visual system. In recent years, Huang et al. [22,23] proposed the conception of heterogeneous PCNN in their researches, and they applied this model in image quantization field, in their research, an image was firstly segmented into background and object region, then a HPCNN was used for performing quantization of these two regions, respectively. Although the HPCNN shows exciting prospect in image quantization field, the development of it is still in infancy, more study should be focus on the theory development and actual application.

A new structure of HSPCNN is proposed in this paper and it has focused on image segmentation. In order to simulate the receptive field of visual area, the proposed HSPCNN is constructed with three SPCNN cells which have different parameters values, and the parameters are set automatically according to the relation between the dynamic properties of neurons and the statistic properties of each input image. Furthermore, the three cells affect each other by linking fields, thus to emulate a mammal cortical system more closely. Finally, the outputs of each SPCNN cell are set different from each other so that the overall outputs of HSPCNN are not binary ones in each iteration. Thus HSPCNN can be used as a tool of multi-regions segmentation just in one iteration.

The rest parts of this paper is divided into four sections. In Section 2, we briefly reviewed the related work on image segmentation field. In Section 3, basic PCNN models include SCM and SPCNN model are described in detail. Section 4 mainly focuses on the analysis of HSPCNN and its parameters setting.

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Section 5 presents the experimental results of the HSPCNN segmentation for several natural gray images of the Berkeley Segmentation Dataset, and the segmentation results evaluations are also conducted in this section. Conclusions and issues for further research are described in Section 6.

2. Related work

Over the past several years, a variety of image segmentation methods have emerged, and we will give a short overview of these works in this section. The existing segmentation approaches can be roughly divided into two categories: interactive and noninteractive segmentation.

Interactive method: Dong et al. [24] deduced the implicit relation of different random walk (RW) algorithms and unified these algorithms. Inspired by the unifying view, they added a set of prior auxiliary nodes to design a sub-Markov random walk algorithms for twigs segmentation, and the noise removal process and leaving probabilities are determined empirically. Shen et al. [25] have developed the lazy random walk for superpixel segmetation, they added the self-loop over the graph vertex to make the RW process lazy to obtain the superpixels, and then optimized the seed superpixels by minimizing an energy function. Their method mainly depends on the target number of superpixels and can achieve better performance in the image containing the complex texture regions. Dong et al. [26] proposed a cosegmentation algorithm utilizing global and local energy optimization. The global energy is used to obtain the information of user scribes, and local smooth energy is based on spline regression used to alleviate the problem that parameters are sensitive in some complex natural images. Shen et al. [27] proposed a new energy framework by adding a smoothing item in the cost function of Laplacian graph energy, their method inherits both the merits of normalized cuts and graph cut and avoids the drawbacks them. In addition, they considered the global prior information into the computation of edge weights so as to achieve more accurate segmentation results. Wang and Shen [28] used likelihood estimation to calculates the probabilities of pixels and obtain a rough segmentation result of image, and then a higher-order energy function which incorporates the rough segmentation as its prior information was presented to achieve final accurate co segmentation results, they also proposed a semi-supervised video segmentation approach based on the spatiotemporal information of the object in multi video frame [29]. Shen et al. [30] utilized the higher-order energy with appearance entropy to achieve image segmentation. They used the Taylor expansion to approximately decompose higher-order function into lower one, and then obtained the minimum solutions of aforementioned lower order function, and thus to achieve the minimization solutions of higher-order energy functions.

Noninteractive method: Cho et al. [31] used the Mahalanobis distance and variances of the chromatic components to modify mean-shift algorithm with global and local information, however, the cluster merge threshold is ambiguous. Chen et al. [32] used a united Markov random field (UMRF) model to incorporate pixel-based information and regional information of image, and then obtained the segmentation result by solve the MAP estimation of UMRF, however, the trade-off between pixel and region is not an easy problem. Wang et al. [33–35] integrated saliency, intra-frame and inter-frame information to obtain estimated object regions, and then converted the video object segmentation task to an object optimization problem. Shen et al. [36] proposed a real time superpixels segmentation method, they used the density based spatial clustering of applications with noise to obtain the initial superpixels, and then utilized color and spatial information to merge the small initial superpixels with their neighbor ones. As convolution neural networks (CNN) have been successfully used in many image processing fields, the segmentation task solved by CNN is becoming increasingly common. Du and Gao [37] used a multi-scale convolutional neural network to segment image and archived feature maps for image fusion. Wang et al. [38] proposed a video salient object detection method based on convolutional neural networks, they fused both static and dynamic saliency into spatiotemporal saliency, and thus generated high-quality salience maps. In addition, their data augmentation method enables the quantity of labeled training data and prevents algorithm's overfitting. Their another research [39] focused on photo cropping problem, they designed a network with two components to predict attention bounding box and analyzing aesthetics, respectively, and thus to obtain a satisfying segmentation result.

3. PCNN models

3.1. Basic PCNN

PCNN is an artificial neural network which only has one single layer, the neurons linked each other and formed a 2-D array. It is verified that this model does not require any training [7]. Ranganath et al. [40] elaborated the basic PCNN and Lindblad et al. [41] described the discrete model as follows:

$$F_{ij}[n] = e^{-\alpha_f} F_{ij}[n-1] + V_F \sum_{kl} M_{ij,kl} Y_{kl}[n-1] + S_{ij} \tag{1}$$

$$L_{ij}[n] = e^{-\alpha_l} L_{ij}[n-1] + V_L \sum_{kl} W_{ij,kl} Y_{kl}[n-1] \tag{2}$$

$$U_{ij}[n] = F_{ij}[n](1+\beta L_{ij}[n]) \tag{3}$$

$$Y_{ij}[n] = \begin{cases} 1, & if \quad U_{ij}[n] > E_{ij}[n-1] \\ 0, & else \end{cases} \tag{4}$$

$$E_{ij}[n] = e^{-\alpha_e} E_{ij}[n-1] + V_E Y_{ij}[n] \tag{5}$$

The (i,j) neuron N_{ij} embedded in a two-dimensional array of neurons contains two main components: feeding input F_{ij} and linking input L_{ij}. Each neuron communicates with its neighboring neurons through the synaptic weights M and W, respectively, and retains its previous state altered by decay factor $e^{-\alpha_f}$ and $e^{-\alpha_l}$. Only the Feeding input F_{ij} receives the input stimulus S_{ij}. The feeding input and the linking input are combined in a second order fashion modulated through linking strength β to create the internal activity U_{ij}. Then the internal activity is compared with a dynamic threshold E_{ij} to yield an output Y_{ij}, and then judge whether the neuron N_{ij} fires or not, i.e. judge the state of Y_{ij} is one or zero. The threshold is dynamic in that when the neuron N_{ij} fires the threshold would increase by amplitude V_E immediately. Otherwise, the dynamic threshold would decay by factor $e^{-\alpha_e}$ until the neuron fires again. The parameters n denotes the discrete iteration time, V_F and V_L are normalized constants denote the amplitudes of feeding input and linking input, respectively. The parameter α^f, α^e and α^l represent the exponential decay coefficients of feeding input, dynamic threshold and linking input, respectively.

3.2. SCM and SPCNN model

In order to retain a lower computational complexity and high accuracy rates, Chen et al. [7] was inspired by Zhan's SCM [6] and derived the SPCNN model in 2011, the discrete models of SCM and SPCNN are described as follows:

SCM:

$$U_{ij}(n) = fU_{ij}(n-1) + S_{ij} \sum W_{ij,kl} Y_{kl}(n-1) + S_{ij} \tag{6}$$

$$E_{ij}(n) = gE_{ij}(n-1) + hY_{ij}(n-1) \tag{7}$$

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