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Edge detection of noisy images based on cellular neural networks

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ABSTRACT

This paper studies a technique employing both cellular neural networks (CNNs) and linear matrix inequality (LMI) for edge detection of noisy images. Our main work focuses on training templates of noise reduction and edge detection CNNs. Based on the Lyapunov stability theorem, we derive a criterion for global asymptotical stability of a unique equilibrium of the noise reduction CNN. Then we design an approach to train edge detection templates, and this approach can detect the edge precisely and efficiently, i.e., by only one iteration. Finally, we illustrate performance of the proposed methodology from the aspect of peak signal to noise ratio (PSNR) through computer simulations. Moreover, some comparisons are also given to prove that our method outperforms classical operators in gray image edge detection.

1. Introduction

It is well known that the Hopfield neural network (HNN) requires fully connected and grows exponentially with the size of the array. Thus it is very difficult to implement, even in modest array sizes, as VSLI circuits [1,2]. A novel class of information processing system called cellular neural network (CNN) was proposed by Chua and Yang in 1988, which came from the HNN and cellular automata as an effective combination of both characteristics [3,4]. Moreover, the CNN has two prominent features: real-time signal processing capability and local connection. On one hand, the characteristic of real-time signal processing has been extensively exploited in various applications such as parallel signal processing, image edge detection, connected component detection and various morphology operations (dilation, erosion and hole filling, etc.). On the other hand, the characteristic of local connection makes it applicable to VLSI implementation and allows to operate at a very high speed in real time. With deep submicron technology (0.25 um-0.33 um), an array of 100 × 100 large analog processors array can be implemented on a single chip, whose theoretical computation speed can be at least a thousand times faster than the current digital processor [5]. Some smaller operational test chips have also been designed [6–8]. As a result of this rapid development, the CNNs have been widely studied for practical applications in image and video signal processing, robotic and biological visions and higher brain functions [9–12].

The most important key point of CNNs applications is how to find the satisfactory feedback template "*A*", control template "*B*" and bias "*I*". In recent years, the problem of CNN design for image processing has attracted considerable attention [13–20] and the promising potential of CNN has resulted in the development of several templates design methods. Among studies on the templates design in known literatures, the intuitive way will lead to quick results in several simple cases, but most of the time it does not guarantee to find the desired templates and the main disadvantage is doing lots of experiments. If the desired functions are exactly determined, then an approach for the direct templates design is applied. However, the most widely studied and used way is the templates learning method. These approaches such as LMI-based method [13], classic neural networks learning [11], the heuristic ways such as genetic algorithm [21], differential evolution algorithm [14],

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simulated annealing [23] and particle swarm optimization (PSO) [16] etc., are used to find the correlation between the input and the desired output and obtain the desired templates for specific applications.

Edge in an image is the connected boundary between two different regions. Edge detection is one of the most important and difficult steps in image processing and pattern recognition systems. Its importance arises from the fact that edge often gives an indication of the physical extent of an object within the image. Edge provides sufficient information about the image such that the size of the image data is reduced to the size that is more suitable for image analysis. The performance of the tasks after the edge detection, such as image segmentation, boundary detection, object recognition and classification, and image registration are dependent on the information on the edge. However, noise is a common problem in acquisition, transmission and processing of image, which will decrease image quality seriously [13–15,21,22]. Moreover, it will lead to unexpected results when we process the images with noise by using classical edge detection operators, such as Roberts, Sobel, Prewitt and LOG operators. So in image processing, if we do not reduce the noise influence on images beforehand, the obtained results will be far from our expectation. To the best of our knowledge, edge detection of image with noise based on CNNs has never been involved. Hence, it is our intention to tackle such an important and challenging subject.

In this paper, based on the heuristic level in Ref. [13], we investigated the edge detection of noisy images by employing CNNs and LMI. Our main work focuses on designing and training the templates of noise reduction and edge detection of CNNs. Based on the Lyapunov stability theorem, a criterion for the uniqueness and global asymptotical stabile equilibrium point for noise reduction CNN model is derived. Futhermore, an approach to find the edge detection templates is proposed, which can detect the edge by only one iteration. Both the noise reduction templates and edge detection templates are designed to obtain desirable output by using the property of saturation nonlinearity. It is shown that the problem of noise reduction and edge detection can be characterized in terms of LMIs. By solving a set of LMIs, the templates can be obtained given a certain pair of input and output. Finally, noise reduction templates and edge detection templates are trained by two pairs of input and output images with smaller size, respectively. Using the obtained templates, the edge of noisy image with larger size could be detected precisely. Moreover, some comparisons between the classical edge detection operators and the proposed edge detection methodology are given in detail. The experimental results illustrate that the performance of the proposed edge detection algorithm is better than that of the classical edge detection operators.

The remainder of this paper is organized as follows. In Section 2, we give and review the model of cellular neural networks in brief. Then, we propose a training method, using LMI, to produce the templates for the noise reduction and the edge detection in Sections 3 and 4, respectively. In Section 5, we show performance of the proposed methodology from the aspect of peak signal to noise ratio (PSNR) by means of computer simulations. Moreover, comparisons have also proven that our methodology outperforms the classic edge detection operators in edge detection. Finally, some conclusions are given in Section 6.

2. Model description of cellular neural network and preliminaries

In this section, the model of a two-dimensional CNN is briefly described which is composed of basic processing units called cells. Each cell is connected to its neighboring ones, therefore only the adjacent cells can interact directly with each other. For a CNN array with M rows and N columns on a 2D grid, the dynamics of each cell can be described by the following state equations [3,4]:

$$\begin{cases} \dot{x}_{ij}(t) = -x_{ij}(t) + \sum\limits_{C(k,l)\in N_r(i,j)} A(i,j;k,l)y_{kl}(t) + \sum\limits_{C(k,l)\in N_r(i,j)} B(i,j;k,l)u_{kl} + I_{ij}, \\ y_{ij}(t) = f(x_{ij}(t)) = \frac{1}{2}\left(|x_{ij}(t)+1| - |x_{ij}(t)-1|\right), \end{cases} \tag{1}$$

where $i = 1,2,\ldots,M$, $j = 1,2,\ldots,N$; $x_{ij}(t)$, u_{ij} and $y_{ij}(t)$ are the state, the input and the output of the (i,j)-th cell in the grid. The initial condition $x_{ij}(0) = 0$ and static input $|u_{ij}| \leqslant 1$. $A(i,j;k,l)$, $B(i,j;k,l)$ denote the connection templates from cell $C(k,l)$ to cell $C(i,j)$; I_{ij} represents the bias of (i,j)-th cell in the grid. From Eq. (1), it follows that the state and the output of each cell are affected by the inputs and outputs of its neighboring cells. In Eq. (1), for each cell $C(i,j)$ the following set $N_{i,j}(r)$, named r-neighborhood, can be defined as:

$$N_r(i,j) = \{C(k,l) := \max(|k-i|,|l-j|) \leqslant r, 1 \leqslant k \leqslant M, 1 \leqslant l \leqslant N\}, \tag{2}$$

where r which denotes the neighborhood radius of each cell is a positive integer, and the pairs (i,j) and (k,l) are the indices which express the position of cells, i.e., the rows and the columns of the generic cell and its neighboring ones in the grid, respectively. From a practical point of view, the cells which belong to the r-neighborhood of $C(i,j)$ are arranged in a maximum $(2r+1)\times(2r+1)$ grid whose central element coincides with $C(i,j)$. The working principle of Eq. (1) and the output function are depicted in Fig. 1(a) and (b), respectively.

A space-invariant standard CNN with a 3×3 neighborhood is defined uniformly by a string of 19 real numbers, called the CNN gene, i.e., they include a uniform threshold I, a feedback template A consists of nine feedback synaptic weights and a control cloning template B consists of nine control synaptic weights. The 19 real numbers together with initial condition and static input can completely determine the dynamical properties of the CNN (1). Suppose the templates A, B and the bias I are given by