# Advanced Cellular Neural Networks Image Processing

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# INTRODUCTION

Since its introduction to the research community in 1988, the Cellular Neural Network (CNN) (Chua & Yang, 1988) paradigm has become a fruitful soil for engineers and physicists, producing over 1,000 published scientific papers and books in less than 20 years (Chua & Roska, 2002), mostly related to Digital Image Processing (DIP). This Artificial Neural Network (ANN) offers a remarkable ability of integrating complex computing processes into compact, real-time programmable analogic VLSI circuits as the ACE16k (Rodríguez *et al.*, 2004) and, more recently, into FPGA devices (Perko *et al.*, 2000).

CNN is the core of the revolutionary Analogic Cellular Computer (Roska *et al.*, 1999), a programmable system based on the so-called CNN Universal Machine (CNN-UM) (Roska & Chua, 1993). Analogic CNN computers mimic the anatomy and physiology of many sensory and processing biological organs (Chua & Roska, 2002).

This article continues the review started in this Encyclopaedia under the title *Basic Cellular Neural Network Image Processing*.

## BACKGROUND

The standard CNN architecture consists of an  $M \times N$  rectangular array of cells C(i,j) with Cartesian coordinates (i,j), i = 1, 2, ..., M, j = 1, 2, ..., N. Each cell or neuron C(i,j) is bounded to a sphere of influence  $S_r(i,j)$  of positive integer radius r, defined by:

$$S_{r}(i,j) = \left\{ C(k,l) \left| \max_{1 \le k \le M, 1 \le l \le N} \left\{ \left| k - i \right|, \left| l - j \right| \right\} \le r \right\}$$

$$(1)$$

This set is referred as a  $(2r + 1) \times (2r + 1)$  neighbourhood. The parameter *r* controls the connectivity

of a cell. When r > N/2 and M = N, a fully connected CNN is obtained, a case that corresponds to the classic Hopfield ANN model.

The state equation of any cell C(i,j) in the  $M \times N$  array structure of the standard CNN may be described by:

$$C\frac{dz_{ij}(t)}{dt} = -\frac{1}{R}z_{ij}(t) + \sum_{C(k,l)\in S_{r}(i,j)} \left[A(i,j;k,l) \cdot y_{kl}(t) + B(i,j;k,l) \cdot x_{kl}\right] + I_{ij}$$
(2)

where *C* and *R* are values that control the transient response of the neuron circuit (just like an *RC* filter), *I* is generally a constant value that biases the state matrix  $Z = \{z_{ij}\}$ , and  $S_r$  is the local neighbourhood defined in (1), which controls the influence of the input data  $X = \{x_{ij}\}$  and the network output  $Y = \{y_{ij}\}$  for time *t*.

This means that both input and output planes interact with the state of a cell through the definition of a set of real-valued weights, A(i, j; k, l) and B(i, j; k, l), whose size is determined by r. The cloning templates A and B are called the feedback and feed-forward operators, respectively.

An isotropic CNN is typically defined with constant values for r, I, A and B, implying that for an input image X, a neuron C(i, j) is provided for each pixel (i, j), with constant weighted circuits defined by the feedback and feed-forward templates A and B. The neuron state value  $z_{ij}$  is adjusted with the bias parameter I, and passed as input to an output function of the form:

$$y_{ij} = \frac{1}{2} \left( \left| z_{ij}(t) + 1 \right| - \left| z_{ij}(t) - 1 \right| \right)$$
(3)

The vast majority of the templates defined in the CNN-UM template compendium of (Chua & Roska, 2002) are based on this isotropic scheme, using r = 1 and binary images in the input plane. If no feedback (i.e. A = 0) is used, then the CNN behaves as a convolution network, using *B* as a spatial filter, *I* as a threshold and the piecewise linear output (**3**) as a limiter. Thus,

virtually any spatial filter from DIP theory can be implemented on such a feed-forward CNN, ensuring binary output stability via the definition of a central feedback absolute value greater than 1.

# ADVANCED CNN IMAGE PROCESSING

In this section, a description of more complex CNN models is performed in order to provide a deeper insight into CNN design, including multi-layer structures and nonlinear templates, and also to illustrate its powerful DIP capabilities.

## Nonlinear Templates

A problem often addressed in DIP edge detection is the robustness against noise (Jain, 1989). In this sense, the EDGE CNN detector for grey-scale images given by

$$A = 2, \ B_{EDGE} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}, \ I = -0.5$$
(4)

is a typical example of a weak-against-noise filter, as a result of fixed linear feed-forward template combined with excitatory feedback. One way to provide the detector with more robustness against noise is via the definition of a nonlinear *B* template of the form:

$$B_{CONTOUR} = \begin{bmatrix} b & b & b \\ b & 0 & b \\ b & b & b \end{bmatrix} \text{ where } b = \begin{cases} 0.5 & |x_{ij} - x_{kl}| > th \\ -1 & |x_{ij} - x_{kl}| \le th \end{cases}$$
(5)

This nonlinear template actually defines different coefficients for the surrounding pixels prior to perform the spatial filtering of the input image X. Thus, a CNN defined with nonlinear templates is generally dependent of X, and can not be treated as an isotropic model.

Just two values for the surrounding coefficients of B are allowed: one excitatory for greater than a threshold *th* luminance differences with the central pixel (i.e. edge pixels), and the other inhibitory, doubled in absolute value, for similar pixels, where *th* is usually set around

0.5. The feedback template A = 2 remains unchanged, but the value for the bias *I* must be chosen from the following analysis:

For a given state  $z_{ij}$  element, the contribution  $w_{ij}$  of the feed-forward nonlinear filter of (5) may be expressed as:

$$w_{ij} = -1.0 \cdot p_s + 0.5 \cdot p_e$$
  
= -(8 - p\_e) + 0.5 \cdot p\_e  
= -8 + 1.5 \cdot p\_e (6)

where  $p_s$  is the number of similar pixels in the 3 × 3 neighbourhood and  $p_e$  the rest of edge pixels. E.g. if the central pixel has 8 edge neighbours,  $w_{ij} = 12 - 8 =$ 4, whereas if all its neighbours are similar to it, then  $w_{ij} = -8$ . Thus, a pixel will be selected as edge depending on the number of its edge neighbours, providing the possibility of noise reduction. For instance, edge detection for pixels with at least 3 edge neighbours forces that  $I \in (4, 5)$ .

The main result is that the inclusion of nonlinearities in the definition of *B* coefficients and, by extension, the pixel-wise definition of the main CNN parameters gives rise to more powerful and complex DIP filters (Chua & Roska, 1993).

# Morphologic Operators

Mathematical Morphology is an important contributor to the DIP field. In the classic approach, every morphologic operator is based on a series of simple concepts from Set Theory. Moreover, all of them can be divided into combinations of two basic operators: erosion and dilation (Serra, 1982). Both operators take two pieces of data as input: the binary input image and the so-called structuring element, which is usually represented by a  $3\times3$  template.

A pixel belongs to an object if it is active (i.e. its value is 1 or black), whereas the rest of pixels are classified as background, zero-valued elements. Basic morphologic operators are defined using only object pixels, marked as 1 in the structuring element. If a pixel is not used in the match, it is left blank. Both dilation and erosion operators may be defined by the structuring elements 4 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: www.igi-

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