Yide Ma
Kun Zhan
Zhaobin Wang

Applications of Pulse-Coupled Neural Networks

脉冲耦合神经网络及应用

高等教育出版社
HIGHER EDUCATION PRESS

Yide Ma
Kun Zhan
Zhaobin Wang

Applications of Pulse-Coupled Neural Networks

脉冲耦合神经网络及应用

MAICHONG OUHE SHENJING WANGLUO JI YINGYONG

With 161 Figures

常州大学图书馆
藏书章

高等教育出版社·北京
HIGHER EDUCATION PRESS BEIJING

Authors

Yide Ma
School of Information Science and Engineering
Lanzhou University
Gansu 730000, P. R. China
E-mail: ydma@lzu.edu.cn

Kun Zhan
School of Information Science and Engineering
Lanzhou University
Gansu 730000, P. R. China
E-mail: ice.echo@gmail.com

Zhaobin Wang
School of Information Science and Engineering
Lanzhou University
Gansu 730000, P. R. China
E-mail: wangzhaobin@126.com

图书在版编目 (CIP) 数据

脉冲耦合神经网络及应用 = Applications of Pulse Coupled Neural Networks : 英文 / 马义德，绽琨，王兆浜著. —北京: 高等教育出版社, 2010.6
ISBN 978-7-04-027978-8

Ⅰ. ①脉··· Ⅱ. ①马···②绽···③王··· Ⅲ. ①神经网络—英文 Ⅳ. ①TP183

中国版本图书馆 CIP 数据核字 (2010) 第 103299 号

策划编辑 陈红英　**责任编辑** 陈红英　**封面设计** 张 楠
责任印制 陈伟光

出版发行	高等教育出版社	购书热线	010-58581118
社　　址	北京市西城区德外大街 4 号	咨询电话	400-810-0598
邮政编码	100120	网　　址	http://www.hep.edu.cn http://www.hep.com.cn
		网上订购	http://www.landraco.com http://www.landraco.com.cn
经　　销	蓝色畅想图书发行有限公司	畅想教育	http://www.widedu.com
印　　刷	涿州市星河印刷有限公司		
开　　本	787×1092　1/16	版　　次	2010 年 6 月第 1 版
印　　张	13.25	印　　次	2010 年 6 月第 1 次印刷
字　　数	300 000	定　　价	49.00 元

本书如有缺页、倒页、脱页等质量问题，请到所购图书销售部门联系调换。

版权所有　侵权必究

物料号 27978-00

Not for sale outside the mainland of China

Yide Ma
Kun Zhan
Zhaobin Wang

Applications of Pulse-Coupled Neural Networks

Preface

There is no more complicated, advantaged and powerful device than the mammalian primate cortical visual system for image processing in nature. The pulse-coupled neural network (PCNN) is inspired from the investigation of pulse synchronization within the mammalian visual cortex, and has been widely applied to image processing and pattern recognition.

Visual cortex is the passage for brain to acquire information from eyes and a part of brain central nervous system. Several biological models based on visual cortex were proposed through investigation of cat cortex and had been applied to image processing.

The PCNN emulates the mammalian visual cortex, which is supposed to be one of the most efficient image processing methods. The output of the PCNN is a series of pulse images which represent the fundamental features of original stimulus, such as edge, texture, and segment. Neurons receive inputs from other neurons through synapses and are fired synchronously in certain regions, that is why the PCNN can be applied to image segmentation, smoothing, and coding. Another important feature of the PCNN is that the pulse images are able to be characterized to a unique invariant signature for the image retrieval.

This book analyzes the PCNN in detail and presents some special applications and corresponding results based on our own researches.

Contributions of the book have come from Hongjuan Zhang, Rongchang Zhao, Maojun Su, Dongmei Lin, Xiaojun Li, Guanzhu Xu, Xin Wang, Zaifeng Zhang, Xiaowen Feng, Haibo Deng, Li Liu, Xiaozhe Xu, Chunliang Qi, Chenghu Wu, Fei Shi, Zhibai Qian, Qing Liu, Min Yuan, Jiuwen Zhang, Yingjie Liu, Xiaolei Chen, and our graduate students at Circuit and System Research Institute of Lanzhou University.

This work was supported by the National Natural Science Foundation of China under the No.60872109, Program for New Century Excellent Talents

此为试读，需要完整PDF请访问：www.ertongbook.com

in University under the No.NCET-06-0900, National Natural Science Foundation in Gansu Province under the No.0710RJZA015, and the Subproject of 985-3rd for Lanzhou University.

We would like to give many thanks to Ms. Hongying Chen for her excellent support, help, and suggestion for the publication of this book.

Yide Ma, Kun Zhan, Zhaobin Wang
14 May 2010

Contents

此为试读，需要完整PDF请访问：www.ertongbook.com

Chapter 1 Pulse-Coupled Neural Networks

The image captured by eyes is transmitted to brain by the optic nerve, and the image signal is transferred in the fiber pathways and finally processed by the primate visual cortex dominantly. The primate visual cortex is devoted to visual processing, and nearly all visual signals reach the cortex via the primary visual cortex. The primary visual cortex is the largest and most important visual cortical area, and does so when neurons in the cortex fire action potentials as stimuli appear within their receptive fields. Signal produced in neurons is transferred to their neighbors by means of localized contact of synapses, which are located on the dendrites and also on the neuron cell body. Electrical charges produced at the synapses propagate to the soma and produce a net postsynaptic potential. If the postsynaptic potential is large enough to exceed a threshold value, the neuron generates an action potential. Synchronized Gama oscillations ($30-100$ Hz) were found in the primary visual cortex of mammalian [1, 2]. In Ref. [2], the linking field model was proposed based on the hypothesis that neuronal pulse synchronizations can be partitioned into two types: stimulus-forced and stimulus-induced synchronizations. Stimulus-forced synchronizations are directly driven by stimulus transients and establish fast but crude sketches of association in the visual cortex, while stimulus-induced synchronizations are believed to be produced via process among local neural oscillations that are mutually connected. The feeding and the linking create the membrane potential. A single feeding input of a neuron is connected to a spatially corresponding stimulus, and the linking inputs of each neuron are connected to the output of the neighboring neurons within the same predetermined radius. Based on the studies of the linking field model, the pulse-coupled neural network (PCNN) were developed and applied to image processing and pattern recognition [3, 4].

1.1 Linking Field Model

The fundamental components of the model [2] are different leaky integrators shown in Fig. 1.1. A leaky integrator is realized as first-order recursive digital filter. The impulse response of a leaky integrator is

$$I(t) = V_x \exp(-t/\tau_x), \tag{1.1}$$

where x denotes certain leaky integrator; V_x is the amplification factor; and τ_x is the decay time constant. For certain V_x and τ_x, $I(t)$ is of exponential decay with time t.

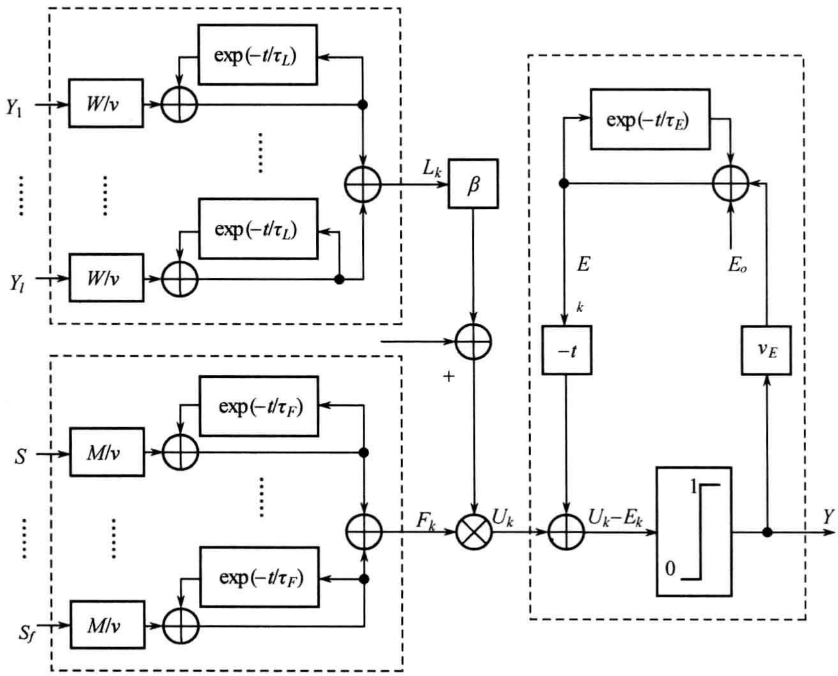

Fig. 1.1. Linking Field Model

The feeding F and linking L are combined together as neuron's internal activity U. Neuron receives input signals via feeding synapse M, and each neuron is connected to its neighbors such that its output signal modulates the activity of its neighbors via linking synapses L.

$$\begin{cases} F_{jk}[n] = F_{jk}[n-1]\exp(-t/\tau_F) + V_F S_j[n] M_{jk}, \\ F_k[n] = \displaystyle\sum_{j=1}^{f} F_{jk}[n]; \end{cases} \tag{1.2}$$

$$\begin{cases} L_{ik}[n] = L_{ik}[n-1]\exp(-t/\tau_L) + V_L Y_i[n-1] M_{ik}, \\ L_k[n] = \displaystyle\sum_{i=1}^{l} L_{ik}[n]; \end{cases} \tag{1.3}$$

$$U_k[n] = F_k[n](1 + \beta L_k[n]); \tag{1.4}$$

where n is the time index; i is the index of neuron on linking input; j is the index of neuron on feeding input; k is the counting index of neuron; τ_F and τ_L are the time constants; V_F and V_L are the magnitude adjustments; and β is the linking strength of the PCNN.

The pulse is able to feed back to modulate the threshold, raising the threshold by magnitude V_E that decreases with τ_E. The threshold and output are generally given by Eqs. (1.5) and (1.6), respectively.

$$E_k[n] = E_k[n-1]\exp(-t/\tau_E) + V_E Y_k[n-1]; \tag{1.5}$$

$$Y_k[n] = \begin{cases} 1 & U_k[n] > E_k[n], \\ 0 & \text{Otherwise.} \end{cases} \tag{1.6}$$

If U is the physical intensity of a stimulus, then it is a constant C for a single neuron. Putting $U = C = E$ into Eq. (1.5), then the time when the pulses occur can be computed by

$$t = \tau_E \ln(V_E/C) + m\tau_E \ln(1 + V_E/C), \quad m = 0, 1, \dots . \tag{1.7}$$

Thus neuron's firing frequency is

$$f = \frac{1}{\tau_E \ln(1 + V_E/C)}. \tag{1.8}$$

1.2 PCNN

As shown in Fig. 1.2, the PCNN neuron accepts the feeding input F and the linking input L and then generates the internal activity U. When U is greater than the dynamic threshold E, the PCNN produces sequential pulse sequence Y.

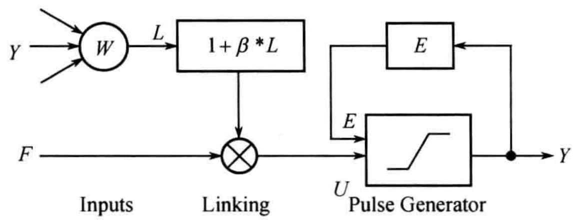

Fig. 1.2. The basic PCNN neuron

For the convenience of simulation, the PCNN is modified [3, 4]. Its model is as follows:

$$F_{ij}[n] = \mathrm{e}^{-\alpha_F} F_{ij}[n-1] + V_F \sum_{kl} M_{ijkl} Y_{kl}[n-1] + S_{ij}; \tag{1.11}$$

$$L_{ij}[n] = \mathrm{e}^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} W_{ijkl} Y_{kl}[n-1]; \tag{1.12}$$

$$U_{ij}[n] = F_{ij}[n](1 + \beta L_{ij}[n]); \tag{1.13}$$

$$E_{ij}[n] = E_{ij}[n-1]\mathrm{e}^{-\alpha_E} + V_E Y_{ij}[n-1]; \tag{1.14}$$

$$Y_{ij}[n] = \begin{cases} 1 & U_{ij}[n] > E_{ij}[n], \\ 0 & \text{Otherwise}. \end{cases} \tag{1.15}$$

where α_F, α_L, and α_E are the time constants; V_F, V_L, and V_E are the magnitude adjustments; β is the linking strength of the PCNN.

Each neuron is denoted with indices (i, j), and one of its neighboring neurons is denoted with indices (k, l). Feeding F is combined with linking L as neuron's internal activity U. The neuron receives input signals via feeding synapse M, and each neuron is connected to its neighbors such that the output signal of a neuron modulates the activity of its neighbors via linking synapse W. The pulse is able to feed back to modulate the threshold E via a leaky integrator, raising the threshold by magnitude V_E that decreases with time constant α_E. During iterations when a neuron's internal activity U exceeds its dynamic threshold E, pulse is generated.

In order to analyze single neuron's firing periodicity, we suppose that there is no coupled stimulus induced, and then the internal activity would be described by

$$U_{ij}[n] = \mathrm{e}^{-\alpha_F} F_{ij}[n-1] + S_{ij} = F_{ij}[0]\mathrm{e}^{-n\alpha_F} + \frac{1-\mathrm{e}^{-n\alpha_F}}{1-\mathrm{e}^{-\alpha_F}} S_{ij}. \tag{1.16}$$

Notice the relation between the internal activity and its iteration time n,

$$U_{ij}[n] = \left(F_{ij}[0] - \frac{S_{ij}}{1-\mathrm{e}^{-\alpha_F}}\right)\mathrm{e}^{-n\alpha_F} + \frac{S_{ij}}{1-\mathrm{e}^{-\alpha_F}}. \tag{1.17}$$

Eq. (1.16) can be shown as Fig. 1.3.

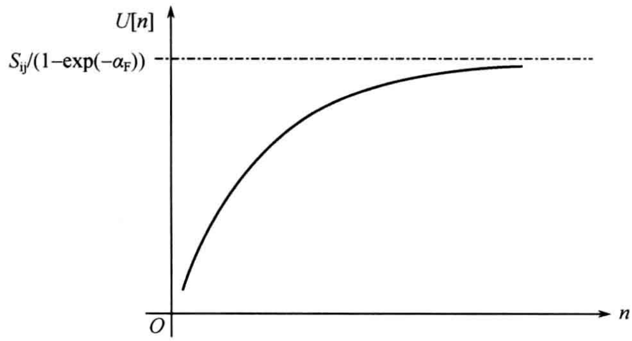

Fig. 1.3. The schematic representation of internal activity without stimulus induced

The static threshold can be described by

$$E_{ij}[n] = E_{ij}[0]\mathrm{e}^{-n\alpha_E}. \tag{1.18}$$

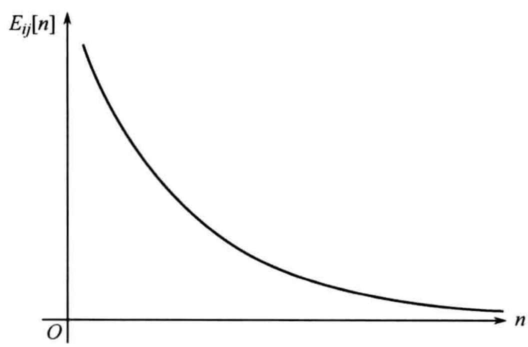

Fig. 1.4. The schematic representation of dynamic threshold while no pulse occurs

Therefore, the internal activity of neuron is compared with the dynamic threshold to decide whether to produce output pulse or not. Combining Fig.

1.3 with Fig. 1.4 we can obtain the pulse output of the PCNN as shown in Fig. 1.5.

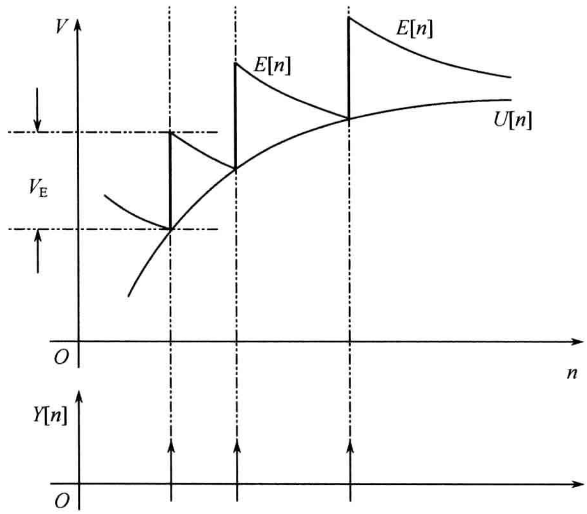

Fig. 1.5. The schematic representation of output of the PCNN without stimulus induced

So the $(k+1)$ times pulse occurs at the iteration number n_k:

$$n_k = \frac{1}{\alpha_E} \ln\left(\frac{E[0]}{U[n_1]}\right) + \sum_k \frac{1}{\alpha_E} \ln\left(\frac{U[n_{k-1}] + V_E}{U[n_k]}\right). \tag{1.19}$$

If the internal activity is equal to its stimulus when neuron receives a constant in the network, from Eq. (1.19) we can obtain the firing frequency of PCNN as follows:

$$f_{ij} = \frac{\alpha_E}{\ln(1 + V_E/S_{ij})}. \tag{1.20}$$

1.3 Modified PCNN

Three modified models are introduced in this section. They are the intersection cortical mode, the spiking cortical model, and the multi-channel PCNN, respectively.

此为试读，需要完整PDF请访问：www.ertongbook.com