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Image Compression and Regeneration based on Different Type of Neurons of Cellular Neural Network

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Abstract

This paper describes Dynamical image compression and regeneration with LIFN (Leaky Integrated Fire Neuron) and FitzHugh-Nagumo (FHN) models in Cellular Neural Network(CNN). The models are action potential of neurons. These models are simplified version of the Hodgkin-Huxley (HH) model which is model in a detailed manner activation and deactivation dynamics of a spiking neuron. If a group of spikes is considered as a pulse train, it is possible to introduce the biological models for CNN instead of $\Sigma\Delta$ modulation. **Keyword:** ADC, CNN, $\Sigma\Delta$ modulation, LIFN and FitzHugh-Nagumo models

1. Introduction

Von Neumann processor was announced in 1945 and this is using in computing. Now computers make it easier to calculate much faster than calculation capacity of human brain. On the other hands, information processing capacity of human brain exceeds computers in few fields. The human brain is composed of nerve cells called neurons.

The LIFN and FHN models represent the qualitative behavior of neurons. The LIFN and FHN models can be described as two-dimensional differential equations. If we choose the parameter values of equations and strong external stimuli, the system will behave characteristically in phase space. This paper describes retinal CNN for image compression and regeneration for the models as AD converters.

2. Cellular Neural Network(CNN)

The CNN is one of neural network. The CNN is connected by each local cell that has simple circuits. The CNN is a nonlinear network using complex spatio-temporal dynamics generated from a combination of the simple cells. The types of CNN are Continuous-time Cellular Neural Network(CT-CNN) and Discrete-Cellular Network(DT-CNN).

3. Sigma-Delta Cellular Neural Network(SD-CNN)

The DT-CNN is defined by difference equations instead of differential equations used in the cellular neural network.[1][2]

The equation of state of the CNN is globally as follows.

$$\boldsymbol{x}(t+1) = \boldsymbol{C}\boldsymbol{x}(t) + \boldsymbol{A}\boldsymbol{y}(t) + \boldsymbol{B}\boldsymbol{u} + \boldsymbol{T} \tag{1}$$

$$\boldsymbol{y}(t+1) = f(\boldsymbol{x}(t+1)) \tag{2}$$

$$\boldsymbol{B} = \mathbf{I}, \boldsymbol{T} = \mathbf{0} \tag{3}$$

where $\boldsymbol{x}(t)$, $\boldsymbol{y}(t)$ and $\boldsymbol{u}$ are the variable of states, the output and the input, and $\mathbf{I}$ is unit matrix. Moreover, the A-template and the C-templates are defined as

$$A(i,j;k,l) = -\frac{1}{2\pi\sigma^2}\exp\left(-\frac{(k-i)^2+(l-j)^2}{2\sigma^2}\right) \tag{4}$$

$$C(i,j;k,l) = \begin{cases} \frac{2}{2l\pi\sigma^2} & \text{if } k=i \text{ and } l=j \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

σ is a standard deviation of the Gauss function. For SD-CNN, the nonlinear function $f_{(x)}$ can be built locally as the sum of pulse sequences as

$$x_{n+1} = f(x_n) \equiv x_n - Q(x_n) + u \quad for\ 0 \le n < l \tag{6}$$

$$y_n = Q(x_n) = \begin{cases} 1 & for\ \ x_n \ge 0 \\ 0 & for\ \ x_n < 0. \end{cases} \tag{7}$$

Using the available output sequence $\{y_0, \cdots, y_{p-1}\}$ with length p, the decoder produces an estimate $\tilde{u}$.

$$\tilde{u} = \frac{1}{p}\sum_{n=0}^{p-1} y_n \tag{8}$$

$$u - \tilde{u} = \frac{1}{p}(x_p - x_0) \tag{9}$$

The local connection is important to change from analog field to digital field without same bits DD(Digital to Digital) conversion. The average sum of the pulse train is equivalent to the value of $f_s(x)$, the value of stair is the point on the linear region of formula [-1,1][3].

$$f_s(x) = \begin{cases} 1 & (x \geq \xi) \\ \frac{1}{\xi} g(x) & (-\xi < x < \xi) \\ -1 & (-\xi \geq x) \end{cases} \tag{10}$$

where $g(x)$ is given by

$$g(x) = \begin{cases} \Delta\left(\left[\frac{x}{\Delta} + \frac{1}{2}\right]\right) & (l\, is\, odd) \\ \Delta\left(\left[\frac{x}{\Delta}\right] + \frac{1}{2}\right) & (l\, is\, even) \end{cases} \tag{11}$$

$$\Delta = \frac{2\xi}{l-1} \tag{12}$$

Also, Δ and l are respectively the width and the number of levels for each stair step function, shown in Fig.1. Next,

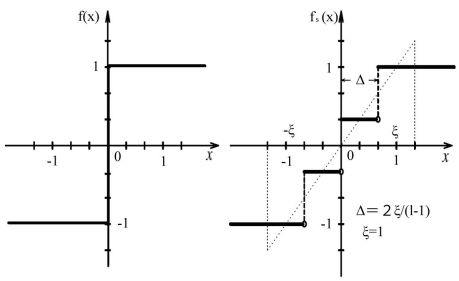

Figure 1. Multi step function CNN

we describe the temporal-spatial dynamics of SD-CNN. Fig.2 shows the mechanism to restore the image using the analog input SD-CNN. The top of the Fig.2 represents train generation mechanism by CNN, the input analog image is modulated to a digital pulse train by the dynamics of the SD-CNN. Bottom of the Fig.2 is the system as the average processing train. The system has global and local dynamics.

Since the average value of a digital pulse train is calculated by this system, we obtain the original analog image made by Gaussian Filter. Each cell has the neighborfood binding coefficient. The C-template works as a weight to create the integral effect.

4. Leaky Integrate-and-Fire Neuron CNN

The neurocomputer that assumes human neural circuit (encephalon) to be a model is one of the exemplary and important researches in the pulse train information processing field. The nonlinear dynamics information processing which is done on

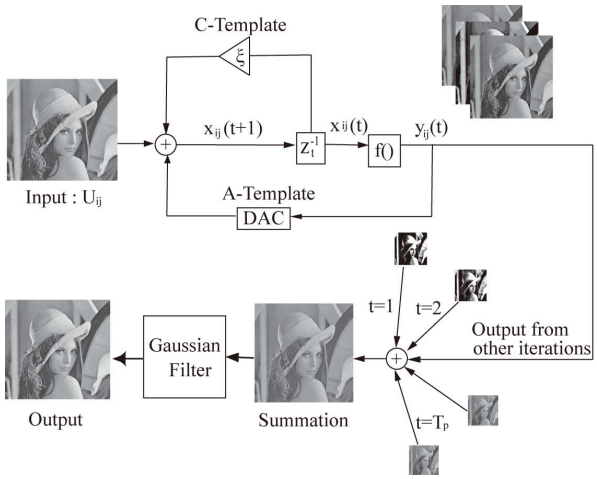

Figure 2. The dynamics by SD-CNN

3 dimensional structure is a binary pulse train generated by using the single cell of the excitatory and the inhibitory cells. The information processing by CNN is done by dynamics of cells in the neighborhood is like retina system. The processes are complex, parallel, advanced pulse train information.

When we describe complex dynamics of the neural differential equation, the equation can be replaced with the circuit model by which the neuron and the ion channel are assumed to be a capacitor and conductance. The neural circuit model treated by this paper is a neuronal firing model named LIFN. The LIFN model can be described with a following two-dimensional differential equations.

$$\tau \frac{dx}{dt} = -x - r_m G_r (x - E_k) + R_M I \tag{13}$$

$$\frac{G_r}{dt} = -\frac{G_r}{\tau} \tag{14}$$

$$lim_t \rightarrow t_f \tag{15}$$

where x and $I(t)$ are membrane potentials and the stimulation currents of the input, .

Gr is a time-variance, τ is membrane time constant, E_k is negative reversal potential, R_M is a linear resistor and t_f is firing time.

A time-variance Gr depends on the time. The voltage rises by integrating the synaptic input. The spike is generated when the voltage exceeds a certain threshold value, and membrane potential is reset in a certain negative value. In that case, time strange parameter Gr increases only by a prescribed amount.

The LIFN is a concept of accumulation of the input with attenuation and the neuronal firing. And the LIFN has three important characteristics as a neuron named Spike Rate Adaptation[5]. Spike Rate Adaptation is an adaptability in the neuronal firing. It is a phenomenon that the ignition frequency

decreases gradually in the process that the neural circuit repeats the ignition. In the neuronal firing, time strange parameter Gr increases, and this phenomenon happens.

The LIFN draws Fig.3 and 4 shape of waves.

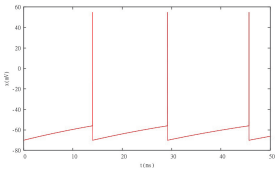

Figure 3. characteristic of LIFN(I=500)

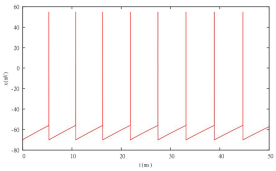

Figure 4. characteristic of LIFN (I=800)

Fig 5 shows that I and pulse density make multiple values step function. It is possible to introduce the FHN model instead of $\Sigma\Delta$ modulation because of Fig 5.

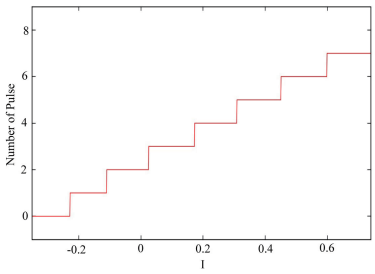

Figure 5. step function of pulse

5. FitzHugh-Nagumo models(FHN model)

The FHN model can be described with a following two dimensional differential equations.

$$\frac{du}{dt} = c\left(-v + u - \frac{u^3}{3} + I\right) \tag{16}$$

$$\frac{dv}{dt} = u - bv + a \tag{17}$$

where u is the membrane potential, v is inactivation, I is the outer stimulus current. a, b and c are parameters which are chosen as any value. Those parameters carry out specific behavior in phase space in case of strong outer stimulus. They are corresponding to Depolarization in spike of neural cell and Re-polarization.

This system was suggested by Richard FitzHugh, and the equivalent circuit by Jinnichi Nagumo.

The excitation of the membrane potential is done by the variable of u and v. When a neuron is excited, physiological process in the cell will cause the neuron to recover from the excitation.

The FHN equations are a system for activity behavior of the neurons. A neuron can be stimulated with an input I. After the stimulus current, the neuron is exited. The motivation for the FHN model was to isolate conceptually the essentially mathematical properties of excitation and propagation from the electrochemical properties of sodium and potassium ion flow. Two equations have an important characteristic. The equations of FitzHugh-Nagumo models shows the waveforms such as Fig.3 and Fig.4 for the LIFN.

6. Experiment

Experiments are used to verify the performance of the original image regeneration for LIFN-CNN, FHN-CNN and SD-CNN. The experiment which verifies the original signal reproducibility of an image is shown the number of each original image is 8bit and the number of output image is 3bit per pixel. The image is given as an input u of LIFN-CNN or FHN-CNN. The image restoration is evaluated using the PSNR. In this case, the system of neighborhoods is $5 \times 5(r = 2), \xi = 1$, and the standard deviation of the Gaussian function is changed as $0.25, \cdots, 0.95$. The evaluiation is done by their PSNR's. The input picture is the standard gray image "Sailboat"(512*512,8bit).

The table 1 shows PSNRs of the restored image for each value of standard deviation σ of the Gaussian function

Table 1: The PSNR[dB] of restored image for each CNN

σ	SD	FHN	LIFN
0.20	6.81564	7.85247	7.7308
0.25	17.8721	18.62636	19.31335
0.30	25.38458	25.46602	24.27153
0.35	20.86954	20.31727	20.27208
0.40	20.63888	20.32213	20.19603
0.45	21.6771	21.40652	21.26182
0.50	24.46701	24.25502	24.01677
0.55	27.10761	27.0891	26.70718
0.60	30.30771	30.08123	30.0062
0.65	33.71081	34.41542	33.80077
0.70	33.68466	34.29928	34.00048
0.75	32.90819	33.55189	33.43777
0.80	32.02842	32.79314	32.50385
0.85	31.44995	32.10817	32.0232
0.90	30.84657	31.22873	31.04718
0.95	30.51234	30.70207	30.43343

The largest PSNR by SD-CNN is 33.71081($\sigma = 0.65$). The largest PSNR by FHN-CNN is 34.41542($\sigma = 0.65$). The largest PSNR by LIFN-CNN is 34.00048($\sigma = 0.70$). Fig.6 and Fig.7 are restoration images($\sigma = 0.70$). 2 change from 8

bits to 3 bits for each pixel. This figures show that FHN-CNN and SD-CNN have high restoration.

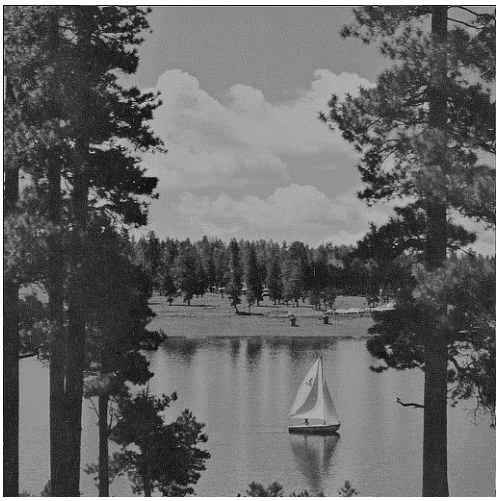

Figure 6. Sum of halftone images(FHN-CNN)

Figure 7. Regeneration analog image by Gaussian template(FNH-CNN)

7. Conclusion

In this paper, we evaluated the image restoration of the CNN which have LIFN and FHN models in local and global dynamics. This result shows that we get higher resolution for some σs. On the other hand, by using a sequencial machine, the processing speed of the CNN which has FHN model is more slowly than that of the Σ Δmodulation. However, it's worth studying biological systems which have LIFN and FHN models in local dynamics. It is also important to use HH model in future. We would like to use the high resolution input image which should be approaching to the analog image.

References

[1] L.O. Chua and L. Yang, "Cellular Neural Networks: Theory", IEEE Trans. Circuits Syst., vol.35, no.10, pp.1257-1272, Oct. 1988.

[2] H. Harrer and J. A. Nossek, "Discrete-time cellular neur-al networks", Int. J. Circuits Theory Applicat., vol.20, pp.453-467, 1994.

[3] JACEK FLAK, DENSE IMPLEMENTATIONS OF BINARY CELLULAR NONLINEAR NEURAL NETWORKS; FROM CMOS TO NANOTECHNOLOGY, TKK Dissertation 79 Espoo 2007, 2007.

[4] M.Tanaka, and K.Kenya, "Conversion of Resolution and Intensity using Cellular Neural Networks", Research report of Grant-in-Aid for Scientific Research (KAKENHI)., 49, pp. 1-22, Oct 2010.

[5] S. Maezawa, H. Aomori and M. Tanaka, "Image Processings of a Leaky Integrated-and-Fire Neuron by Cellular Neural Network", NLP, vol. 111, no. 106, pp. 113-118, 2011.

[6] H. Aomori, T. Otake, N. Takahashi and M. Tanaka, "A Spatial Domain Sigma-Delta Modulation via Discrete-Time Cellular Neural Network", Neural Networks, vol. 21, pp.349-357, 2008.