Long-Range Inhibition in Reaction-Diffusion Algorithms Designed for Edge Detection and Stereo Disparity Detection

A. Nomura, M. Ichikawa, K. Okada & H. Miike Yamaguchi University & Chiba University Japan

# Outline

- Introduction
- Motivation
- Reaction-diffusion algorithms
  - Edge detection
  - -Stereo disparity detection
  - Experimental results
- Proposal on the stereo algorithm
  - Anisotropic strong inhibitory diffusion
- Conclusion

- Chemical reaction system
  - Belousov-Zhabotinsky (BZ) reaction
- Biological system
  - Amoeba: Dictyostelium discoideum
- Self-organized dynamic patterns



Numerical simulation of Belousov-Zhabotinsky reaction Keener & Tyson, *Physica D*, 1986



Numerical simulation of Dictyostelium discoideum Höfer et al., *Physica D*, 1995

Introduction:

## A Reaction-Diffusion System

Diffusion equation with a source term

$$\frac{\partial u}{\partial t} = D_u \nabla^2 u + S$$

 $D_u$ : diffusion coefficient S: source term

 General form of a reaction-diffusion system  $\frac{\partial u}{\partial u} = D_u \nabla^2 u + f(u, v)$  $\partial t$  $\frac{\partial v}{\partial t} = D_v \nabla^2 v + g(u, v)$ 

diffusion terms reaction terms

 $D_{\mu}$ ,  $D_{\nu}$ : diffusion coefficients

#### Strong Inhibitory Diffusion in Biological Systems

- Turing scenario in biological systems
  - Turing, Phil. Trans. Roy. Soc., 1952
    - Strong inhibitory diffusion induces spatial periodic waves.
  - Gierer & Meinhardt, Kybernetik, 1972
    - Realistic models of biological pattern formation
  - Kondo & Asai, Nature, 1995
    - Pattern on fish skin is caused by the Turing scenario
- Key point: Strong inhibitory diffusion

 $\Leftrightarrow$  Long-range inhibition?

Does the Turing pattern exist in biological systems ?

#### Introduction:

# Long-Range Inhibition in Biological Vision

- DoG filter
  - Marr & Hildreth, Proc. Roy. Soc. Lond., 1980
- Mach bands effect
  - human visual system
    - Mach, Akademie der Wissenschaften, 1865
  - lateral eyes of Limulus (crab)
    - Ratliff & Hartline, J. Gen. Physiol., 1959



DoG: difference of two Gaussians







Is the Hermann grid illusion due to long-range inhibition?

#### Motivation

- Image processing with a reaction-diffusion system (photo-sensitive chemical reaction)
  - Kuhnert et al., *Nature*, 1989

- Long-range inhibition in nature and in visual systems.
- ⇒ We confirm how long-range inhibition or rapid inhibitory diffusion works in reaction-diffusion algorithms in edge detection and stereo disparity detection.

Reaction-diffusion algorithm: preliminaries

#### The FitzHugh-Nagumo Reaction System

• Single reaction system (ODE)

$$\begin{cases} \frac{\mathrm{d}u}{\mathrm{d}t} = \frac{1}{\varepsilon} \left[ u(u-a)(1-u) - v \right] \\ \frac{\mathrm{d}v}{\mathrm{d}t} = u - bv \end{cases}$$

a,b,e: constants

°>>3>0

• Reaction-diffusion system (PDE)

$$\begin{cases} \frac{\partial u}{\partial t} = D_u \nabla^2 u + \frac{1}{\varepsilon} \left[ u(u-a)(1-u) - v \right] \\ \frac{\partial v}{\partial t} = D_v \nabla^2 v + u - bv \end{cases}$$

Time-evolving equations starting from initial states of u(x,y,t=0) and v(x,y,t=0).

#### Reaction-diffusion algorithm: preliminaries

System Behaviour of the FitzHugh-Nagumo ODE System



## **Spatially Coupled Uni-stable Reaction Systems**

- Uni-stable ODE systems placed at image grids
  - Nomura et al., J. Phys. Soc. Jpn., 2003
  - Kurata et al., Phys. Rev. E, 2009

$$\frac{\mathrm{d}u_{i,j}}{\mathrm{d}t} = \frac{D_u}{\delta h^2} \left[ \overline{u_{i,j}} - 4u_{i,j} \right] + \frac{1}{\varepsilon} \left[ u_{i,j} (u_{i,j} - a)(1 - u_{i,j}) - v_{i,j} \right]$$
$$\frac{\mathrm{d}v_{i,j}}{\mathrm{d}t} = \frac{D_v}{\delta h^2} \left[ \overline{v_{i,j}} - 4v_{i,j} \right] + u_{i,j} - bv_{i,j}$$
Spatial coupling  $\overline{u_{i,j}}$ : average in the nearest four points.

• Strong inhibition:  $D_u << D_v$ 

 $\Rightarrow$  Stationary pulse at an edge position

• Weak inhibition:  $D_u > D_v$ 

 $\Rightarrow$  Propagating pulse in space



j+1

*i*-1

δł

*i*-1

*i*+1

# Examples for a Real Image

- Initial states:
  - $u_{i,j}(0)$ ="image intensity distribution" and  $v_{i,j}(0)$ =0.0 for any *i,j*.
- Pulses are self-organised at edges.
  - $D_u << D_v$  : pulses are stationary at the edges.
  - $D_u > D_v$  : pulses propagates and develop as spiral waves.



 $D_{v}=0.0$  and  $\delta h=1/5$ 



 $u_{i,j}(t=10)$  with  $D_v=5.0$  and  $\delta h=1/2$ 

Real image (512×512 pixels) Initial state of  $u_{i,j}$ (t=0).

Courtesy of Heath et al.: "Edge detector comparison", http://marathon.csee.usf.edu/edge/edge\_detection.html Other parameter settings:  $D_{t}=1.0, a=0.05, b=1.0, \epsilon=1.0 \times 10^{-2}, \delta t=1/10000$ 

## **Examples for Real Images**



## Reaction-Diffusion Stereo Algorithm

- Multi-layered network of bi-stable reaction-diffusion systems
  - Nomura et al., Mach. Vis. Appl., 2009

$$\begin{array}{l} \begin{array}{l} \text{Reaction} \\ \text{Diffusion} \\ \text{Eqs.} \end{array} \left\{ \begin{array}{l} \displaystyle \frac{\partial u_n}{\partial t} = D_u \nabla^2 u_n + f(u_n, v_n, u_{\max}) + \mu C(x, y, d_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \end{array} \right. \\ \left. \begin{array}{l} \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n + g(u_n, v_n) \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial t} = D_v \nabla^2 v_n \\ \displaystyle \frac{\partial v_n}{\partial$$

• Disparity map:

$$M(x, y, t) = \underset{n \in \{0, 1, \cdots, N-1\}}{\operatorname{arg\,max}} u_n(x, y, t)$$

 $\mu$ : constant

N: total number of disparity levels  $d_n$ : disparity level at the *n*th network  $C(x,y,d_n)$ : matching cost function

#### Diagram of the Stereo Algorithm

Reaction-diffusion systems:

$$\frac{\partial u_d}{\partial t} = D_u \nabla^2 u_d + f(u_d, v_d, u_{\max}) + \mu C_d$$
$$\frac{\partial v_d}{\partial t} = D_v \nabla^2 v_d + g(u_d, v_d)$$

*d*: disparity level *C<sub>d</sub>*: matching cost function

Disparity map:  $M(x, y, t) = \arg \max_{d} u_{d}(x, y, t)$ 



A pair of stereo images overlapped with several possible disparity levels *d*. Correlation maps computed for overlapped stereo images. A multi-layer network of  $u_{\text{reaction-diffusion systems}}$  mutually connected via  $a(u_{\text{max}})$ .

A stereo disparity map obtained with the argmax  $u_d$ .

- Propagating waves realise a filling-in process.
- Wave speed depends on  $D_{v}$ .



- The Middlebury stereo vision page provides
  - stereo image pairs,
  - ground-truth data of disparity maps,
  - definition of areas (occlusion area & depth discontinuity area),
  - scores of other stereo algorithms
- Example of stereo image pairs (left reference image)

(a) CONES 450X375 pixels 60 disparity levels (b) TEDDY 450X375 pixels 60 disparity levels (c) TSUKUBA 384X288 pixels 15 disparity levels

(d) VENUS 434X383 pixels 30 disparity levels

Courtesy of Scharstein & Szeliski: "Middlebury Stereo Vision Page", http://vision.middlebury.edu/stereo/

#### Reaction-diffusion algorithm: stereo disparity detection Dependence of Inhibitory Diffusion on Performance



 Imposing strong inhibitory diffusion D<sub>v</sub>(x,y) at around depth-discontinuity areas.

$$\begin{cases} \frac{\partial u_n}{\partial t} = D_u \nabla^2 u_n + f(u_n, v_n, u_{\max}) + \mu C(x, y, d_n) \\ \frac{\partial v_n}{\partial t} = \nabla \cdot \left[ D_v(x, y) \nabla v_n \right] + g(u_n, v_n) \end{cases}$$



# Diagram of the Proposed Stereo Algorithm



A pair of stereo images overlapped with several possible disparity levels *d*. Correlation maps computed for overlapped stereo images. A multi-layer network of  $u_{\text{reaction-diffusion systems}}$  mutually connected via  $a(u_{\text{max}})$ .

A stereo disparity map obtained with the argmax  $u_d$ .

#### Reaction-diffusion algorithm: stereo disparity detection

#### Results on the Stereo Image Pair VENUS



(Anisotropic diffusion)

Error distributio (Original)

#### Conclusion

- Reaction-diffusion algorithms for edge detection and stereo disparity detection.
- Strong inhibition works for stable results in edge detection.
- Strong inhibitory diffusion brings better result in depth discontinuity areas in stereo disparity detection.

Acknowledgment:

The present study was supported in part by the Grant-in-Aid for Scientific Research (C) (No. 20500206) from the Japan Society for the Promotion of Science.

#### Thank you for your attention!

#### Appendix:

Reaction-Diffusion System with Chua's Circuit

- Ordinary Differential Equation (ODE) System:
  - Matsumoto, IEEE-CS, 1984
  - Chua et al., *IEEE-CS*, 1995

$$\begin{cases} C_{1} \frac{\mathrm{d}v_{1}}{\mathrm{d}t} = G(v_{2} - v_{1}) - g(v_{1}) \\ C_{2} \frac{\mathrm{d}v_{2}}{\mathrm{d}t} = G(v_{1} - v_{2}) + i_{3} \\ L \frac{\mathrm{d}i_{3}}{\mathrm{d}t} = -v_{2} \end{cases} \xrightarrow{\mathsf{F}_{1}} \left[ \begin{array}{c} \mathbf{v}_{1} \\ \mathbf{v}_{1} \\ \mathbf{v}_{2} \\ \mathbf{v}_{2} \\ \mathbf{v}_{1} \\ \mathbf{v}_{2} \\ \mathbf{v}_{2} \\ \mathbf{v}_{1} \\ \mathbf{v}_{2} \\ \mathbf{v}_{1} \\ \mathbf{v}_{2} \\ \mathbf{v}_{3} \\ \mathbf{v}_{4} \\ \mathbf{v}_{5} \\ \mathbf{v}_{$$

Spatially coupled Chua's circuits realise a reaction-diffusion system.

#### Appendix:

Performance Evaluation of Edge Detection Algorithms

- Tested algorithms:
  - Reaction-diffusion algorithm
  - Canny algorithm
- Error measures:

$$E_{c} = \frac{1}{|M_{c}|} |M_{c} \cap \overline{M_{o}}| \times 100 \,(\%)$$
$$E_{o} = \frac{1}{|M_{o}|} |M_{o} \cap \overline{M_{c}}| \times 100 \,(\%)$$

	E <sub>c</sub> (%)	E <sub>o</sub> (%)
Reaction-Diffusion algorithm	23.07	11.44
Canny algorithm	8.20	8.08



#### Appendix:

#### Performance Evaluation with BMP and RMS error measures

	Algorithm	Reaction-diffusion stereo algorithm						Adapting BP
version		Original (Nomura et al., <i>Mach.</i> Vis Appl. 2000)		IIEI (Nomura et al., <i>Proc.</i> <i>VISA PP</i> , 2000)		Anisotropic inhibitory diffusion		(Klaus et al., <i>Proc. ICPR</i> , 2006)
Image pair	Area	BMP (%)	RMS (pixel)	BMP (%)	RMS (pixel)	BMP (%)	RMS (pixel)	BMP (%)
TSUKUBA	nonocc.	<u>6.77</u>	<u>1.42</u>	8.51	1.54	7.02	1.47	1.11
	all	<u>8.53</u>	<u>1.61</u>	10.23	1.72	8.54	1.64	1.37
	disc.	18.68	<u>2.47</u>	19.42	2.52	<u>18.55</u>	2.60	5.79
VENUS	nonocc.	2.81	0.75	3.17	0.77	<u>1.21</u>	<u>0.59</u>	0.10
	all	3.97	0.92	4.33	0.92	<u>2.44</u>	<u>0.80</u>	0.21
	disc.	21.64	2.01	19.62	1.88	<u>8.12</u>	<u>1.52</u>	1.44
TEDDY	nonocc.	14.26	<u>2.19</u>	<u>14.00</u>	2.38	14.56	2.29	4.22
	all	20.26	<u>3.23</u>	<u>20.00</u>	4.36	20.64	3.32	7.06
	disc.	29.19	<u>3.36</u>	28.89	3.48	<u>27.98</u>	3.45	11.8
CONES	nonocc.	<u>5.03</u>	1.94	5.08	<u>1.85</u>	5.21	1.88	2.48
	all	<u>12.13</u>	<u>3.08</u>	12.35	5.45	13.34	3.15	7.92
	disc.	14.06	3.34	<u>13.67</u>	<u>3.03</u>	14.08	3.17	7.32

nonocc.: non-occlusion area, all: all area, disc.: depth discontinuity area BMP: Bad-Match-Percentage, RMS: Root Mean Squares

Courtesy of Scharstein & Szeliski: "Middlebury Stereo Vision Page", http://vision.middlebury.edu/stereo/