Early Recurrence Improves Edge Detection

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This paper proposes a computational model of early recurrence for edge detection. The work is motivated by studies of primate vision. Features are perceived through the two pathways with different speeds: the dorsal pathway processes information more rapidly than that of the ventral pathway. It is then likely that results formed at higher-dorsal region influence ventral perception via early recurrent connections [1].

The two pathways are modeled to compute different edge features using 2D Gabors: the ventral layer of V1 computes fine-scale edges and the dorsal layer of V1 computes coarse-scale edges. Higher dorsal area MT integrates V1 energy and sends results to modulate ventral V1 (Fig. 1). Modulated ventral V1 responses are then inhibited by the center-surround self-inhibition [3] to form contour. The whole process can be defined as:

$$R^{V1v} = H(E^{V1v} \cdot Inh_{re}^{MT} - \alpha Inh_{cs}^{V1v}) \tag{1}$$

where R^{V1v} denotes ventral V1 representation. $H(s) = max(s,0)$ is a half-wave rectification function. E^{V1v} denotes ventral V1 responses to feed-forward image stimuli, which have been commonly deemed as the edge representation in most existing works. Inh_{re}^{MT} is the early recurrent inhibition generated from area MT. Inh_{cs}^{V1v} denotes the center-surround self-inhibition, and α is a weighting factor.

The inhibition term Inh_{re}^{MT} is defined as weighted multiplication:

$$Inh_{re}^{MT}(x,y,\theta) = \frac{\sum_{\delta\in\Delta} \omega_{(\delta,\theta)} r_{\lambda,\sigma,\psi}^{MT}(x,y,\theta)}{\|\sum_{\delta\in\Delta} \omega_{(\delta,\theta)} r_{\lambda,\sigma,\psi}^{MT}(x,y,\theta)\|_1}, \tag{2}$$

where $\omega_{(\delta,\theta)}$ is the weighting, denoting strength of connection between MT neuron of orientation δ and ventral V1 neuron of orientation θ. $\sum$ sums MT to all orientations $\delta \in \Delta$. $\|.\|_1$ is L1 norm. By setting $\omega_{(\delta,\theta)}$, two types of early recurrence are derived.

Isotropic inhibition causes fine-scale edge of an orientation inhibited by MT with *all orientations in an equal manner*,where $\omega_{(\delta,\theta)} = 1$ for all orientations. The isotropic representation highlights regions corresponding to low-spatial frequency variations to all orientations and is insensitive to variations caused by high-frequency stimuli.

Anisotropic inhibition suppresses fine-scale edge to a preferred orientation by MT responses to *the same orientation*.

Center-surround inhibition, Inh_{cs}^{V1v} is formalized following [3] as a convolution of the maximum energy map $\hat{E}_{\lambda,\sigma,\psi}^{V1}(x,y,\theta)$ with a Difference of Gaussian function weighting function as:

$$Inh_{cs}^{V1v} = \hat{E}_{\lambda,\sigma,\psi}^{V1v}(x,y) * w_{\sigma}^{V1v}(x,y), \tag{3}$$

where the maximum energy map is calculated as:

$$\hat{E}_{\lambda,\sigma,\psi}^{V1v}(x,y) = \max\{E_{\lambda,\sigma,\psi}^{V1v}(x,y,\theta_i) | i = 1..N\}, \tag{4}$$

To search for the best coarse-scale representation, single-scale representation is extended that employs the interval-tree analysis [5].

To investigate whether the proposed model is a general process for machine vision, our work is applied to 2 popular edge detectors: Canny edge detector [2] and multi-scale Brightness/Texture Gradients (BTG) detector [4]. The proposed recurrent representation fits itself into these models by modulating original edge responses before constructing contour. Result (Fig. 2) indicates the proposed computational model may consistently improve edge detections in real scenes.

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[3] Cosmin Grigorescu, Nicolai Petkov, and Michel A. Westenberg. *IEEE Trans. Image Proc.*, 12(7):729–739, 2003.

[4] D.R. Martin, C.C. Fowlkes, and J. Malik. *IEEE Trans. Image Proc.*, 26(5):530–549, 2004.

[5] A. Witkin. In *ICASSP '84.*, 9, 150–153, 1984.

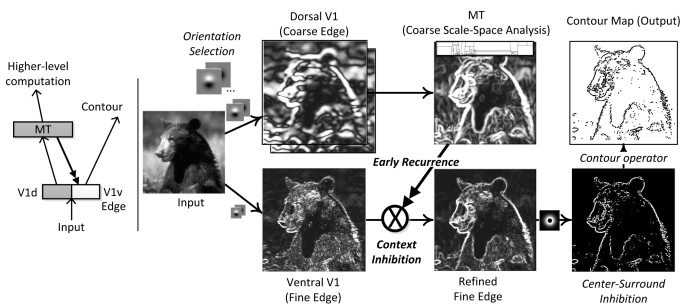

Figure 1: **Model structure. Left:** simplified biological hierarchy. The double arrow denotes the early recurrence. **Right:** an example.

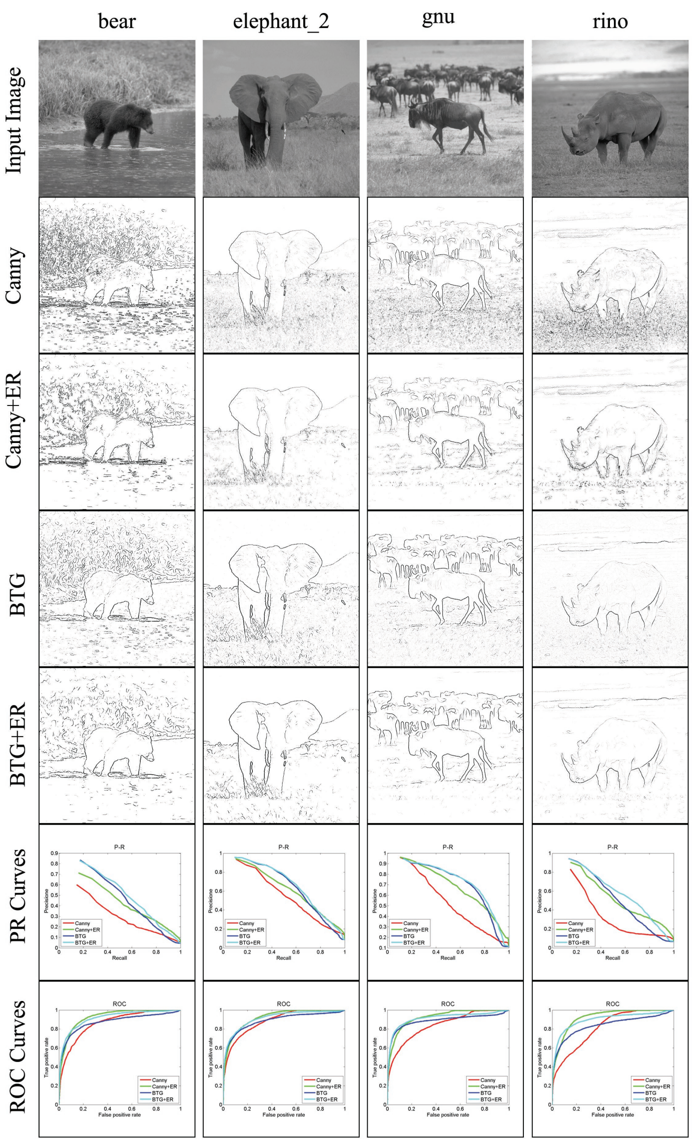

Figure 2: Improved contours.