

A Joint Bioinspired Architecture for Fast Optic Flow and Two-dimensional Disparity Estimation

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Motivation and major contribution of the work

The major contributions of this work are:

- (1) the development of a distributed neuromorphic architecture for the estimation of motion and 2D (horizontal and vertical) disparity fields in a sequence of binocular stereo pairs, by mimicking the sharing of computational resources evidenced in cortical areas;
- (2) the handling of both horizontal and vertical disparities;
- (3) the application of such bioinspired approach in real-world situations;
- (4) a good compromise between reliability of the estimates and execution time;
- (5) performances comparable to the state-of-the-art algorithms (also not bioinspired).

The joint neural architecture

The proposed population approaches for the computation of horizontal and vertical disparities and optic flow share a joint algorithmic structure:

- (1) the distributed **coding** of the features across different orientation channels through a filtering stage (that resembles the filtering process of area V1);
- (2) the **decoding** stage for each channel;
- (3) the **estimation of the features** through channel interactions: the aperture problem is tackled by combining the estimates of velocity and disparity for each spatial orientation;
- (4) the **coarse-to-fine refinement**: the features, obtained at a coarser level of the pyramid, are expanded and used to warp the sequence of the spatially convolved images, then the residual optic flow and disparity are computed.

POPULATION CODING STRATEGY: $N \times K \times M$ CELLS

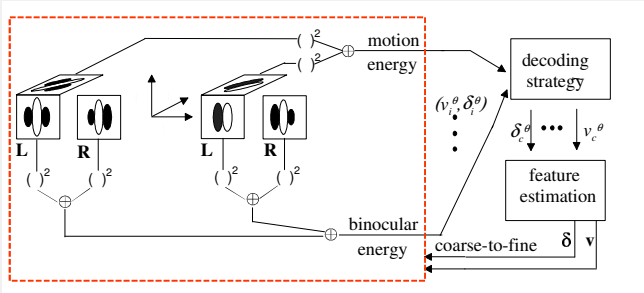
N oriented channels

K disparity tuned cells for each orientation δ_i^θ

M velocity tuned cells for each orientation v_i^θ

SINGLE CELL RECEPTIVE FIELD (3D spatio-temporal Gabor filter)

$$h(x, y, t; \theta, \psi, \omega) = g(x, y; \theta, \psi) f(t; \omega) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2}} e^{j(\omega_0 x_\theta + \psi)} e^{-\frac{t^2}{2\sigma_t^2}} e^{j\omega t} 1(t)$$



POPULATION DECODING STRATEGY (center of gravity)

$$\delta_c^\theta(x_0) = \frac{\sum_{i=1}^K \delta_i^\theta E(x_0; \delta_i^\theta)}{\sum_{i=1}^K E(x_0; \delta_i^\theta)} \quad v_c^\theta(x_0, t) = \frac{\sum_{i=1}^M v_i^\theta E(x_0, t; v_i^\theta)}{\sum_{i=1}^M E(x_0, t; v_i^\theta)}$$

MOTION ENERGY [Adelson&Bergen, 1985]

$$Q(x_0, t; v^\theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x_0 - x, t - \tau; \theta, v) I(x, \tau) dx d\tau$$

$$E(x_0, t; v^\theta) = |Q(x_0, t; v^\theta)|^2 = \left| \int_0^t Q(x_0, \tau; v^\theta) e^{-j\omega_0 \tau} d\tau \right|^2$$

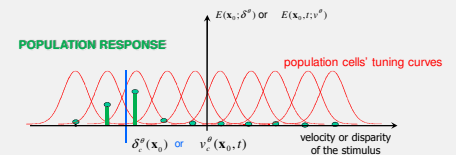
where $\omega_0 = \omega_0 v^\theta$

BINOCULAR ENERGY [Ohzawa et al., 1990]

$$Q(x_0; \delta^\theta) = \int_{-\infty}^{\infty} g^L(x_0 - x; \theta, \psi^L) I^L(x) dx + \int_{-\infty}^{\infty} g^R(x_0 - x; \theta, \psi^R) I^R(x) dx$$

where $\Delta\psi = \psi^L - \psi^R = \delta^\theta \omega_0$

$$E(x_0; \delta^\theta) = |Q(x_0; \delta^\theta)|^2 = |Q^L(x_0; \delta^\theta) + e^{-j\Delta\psi} Q^R(x_0; \delta^\theta)|^2$$



Optic flow estimation

(Middlebury benchmarking dataset)

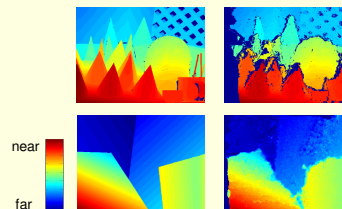


ground truth

estimate

Disparity estimation

(Middlebury benchmarking dataset)

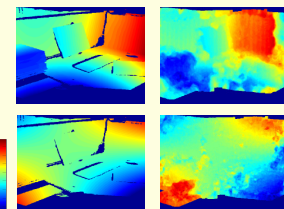


ground truth

estimate

Disparity estimation

(Active vision system with vergent axes)



ground truth

estimate

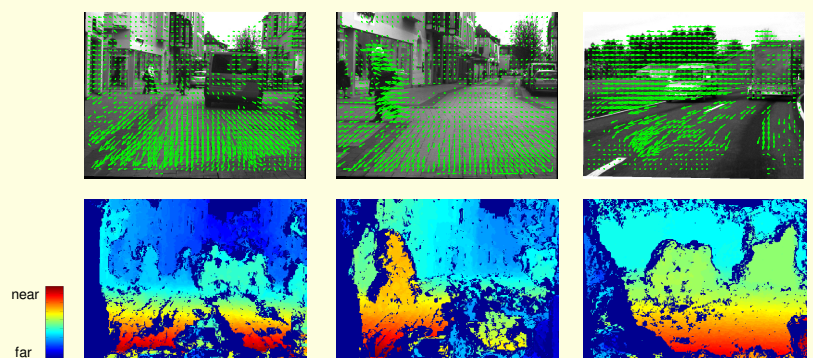
Horizontal disparity

Vertical disparity

Disparity and optic flow estimation

(real-world situation)

The images are acquired by moving stereo cameras, thus both ego-motion and independent motion of other objects in the scene are present.



near
far