Emerging Trends in Electrical, Electronics & Instrumentation Engineering: An international Journal (EEIEJ), Vol. 1, No. 2, May 2014

RIDGELETTRANSFORMFOR OPTICAL FLOWOF SEQUENCE VIDEO

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This method takes benefit of the Ridgelet transform property. This approach is fast and capable to estimate the OF with a low-complexity. However, the use of real wavelet in this approach suffers from two main problems. The lack of shift invariance and poor directionalselectivity.Ridgelet transform overcame these two troubles and still desired to provide special characteristics that wavelets cannot provide. The technique is suitable for video compression, and can be used for stereo vision, robotics and vision computer.

KEYWORDS

Ridgelettransform, Motion Estimation, Optical Flow

1. INTRODUCTION

A Great number of approaches for motion estimation have been proposed in the literature, including gradient-based, correlation-based, energy based, and phase based techniques [1].

The motion estimation is to determine the velocity field between two successive images. This phase can be extracted from this measure descriptive information of the sequence. This work described a method for calculating the optical flow of an image sequence based on Ridgelet transform. It consists in projecting the optic flow vectors on a basis of Ridgelet transform. This method opens the way for a quick and inexpensive computing optical flow.The use of waveletproduct two problems; the shift invariance and poor directional selectivity. The Ridgeletsolves these problems. The rest of the paper is organized as follows. In Section 2, we introduce the principle and the description of the proposed algorithm. Section 3 shows the experimental performance of optical flow estimation. Finally, Section 4 concludes our contribution and merits of this work.

2. OPTICAL FLOW ESTIMATION ALGORITHM

2.1. Geometric Wavelet

The interest of this transform is permit to concentrate the energy of a regular signal into a series of successively pieces which contain the coefficients as well as the wavelet transform.
At the latest, contrary to wavelet transform, this transform permit to take charge of the 2D linear breaking.

The discrete Ridgelet transform offered to take charge of passing through Fourier transform, it consist the Radon projection of an image and the approximation of this projection by the wavelet transform.

The coefficients connected with this projection are product by equations which it translate the discrete objects: lines or discrete level.

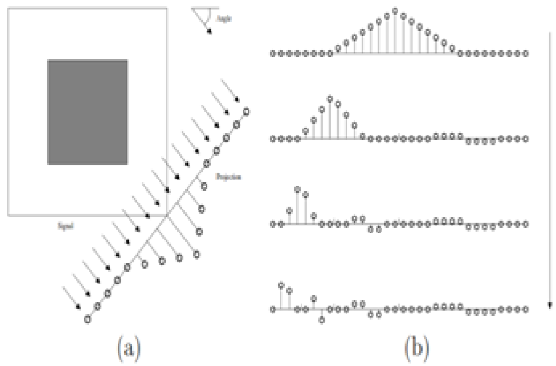

Figure (1): (a) Radon projection. (b) Approximationwith wavelet transforms**.**

2.2.Approch

The framework of the algorithm is illustrated in figure (2).Our work shows that Ridgelettransform seems more accurate in optical flow estimation. This technique is based on the assumption of the gradient constraint. This equation can be expressed as

$$I(x+\Delta x, y+\Delta y, t+\Delta t) = I(x,y,t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t + H.O.T$$

$$\frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t = 0$$

Or

$$\frac{\partial I}{\partial x}\frac{\Delta x}{\Delta x} + \frac{\partial I}{\partial y}\frac{\Delta y}{\Delta t} + \frac{\partial I}{\partial t}\frac{\Delta t}{\Delta t} = 0$$

Which result in:

$$\frac{\partial I}{\partial x}V_x + \frac{\partial I}{\partial y}V_y + \frac{\partial I}{\partial t} = 0$$

Thus:

$$I_x V_x + I_y V_y = -I_t$$

$$\nabla I^T.\vec{V} = -I_t$$

WhereV_x,V_y are the optical flow of $I(x,y,t)$ and$\frac{\partial I}{\partial x}$, $\frac{\partial I}{\partial y}$ and $\frac{\partial I}{\partial t}$or I_x,I_y and $I_t$are the derivatives spatial and temporal of the image.

Our method introduces an additional condition for estimating the optical flow because it is an equation in two unknowns and cannot be solved as such. To discover the optical flow another set of equations is needed, given by some additional constraint.

$$I_X \cdot f(X,Y)p = -I_t$$

$$f(X,Y) = \begin{bmatrix} & \cdots & & & \cdots & \\ x_i & y_i & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_i & y_i & 1 \\ & \cdots & & & \cdots & \end{bmatrix}^T,$$

Where

$$I_X = \begin{bmatrix} I_{x_1} & I_{y_1} & 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & I_{x_M} & I_{y_M} \end{bmatrix}$$

By applying the geometric wavelet transforms at the level *l*, we get the hierarchical gradient constraint functions (see figure 1).

$$A^l p = -I_t^l$$

The global equation of gradient constraint at all scale levels *L* is:

$$Ap = b$$
$$A = [A^0, A^1, \ldots, A^L] \;\; b = -(I_t^0, I_t^1, \ldots I_t^L)^T$$

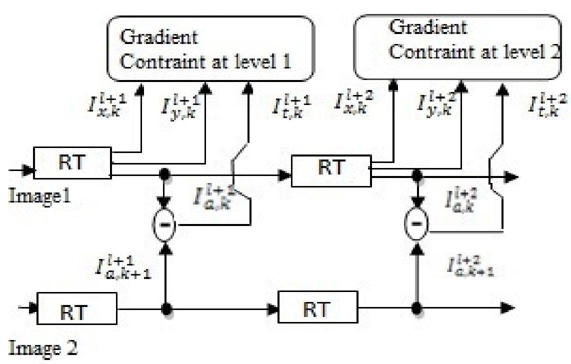

Figure (2): (a) Radon projection. (b) Approximation with wavelet transforms**.**

3 Experiment results:

In our experiments, we used three of sequences synthetic and four methods for comparison.

We evaluate the optical flow by using the angular error measurement between the correct velocity (u_c, v_c) and the estimate velocity (u_e, v_e) with 100% density, the average error and standard deviation were calculated.

Three images sequences were used to test our algorithm and compared with other optical flow technique:

$$\theta_{err} = arccos\left(\frac{u_e u_{c+} v_e v_c + 1}{\sqrt{u_e^2 + v_e^2 + 1}\sqrt{u_c^2 + v_c^2 + 1}}\right)$$

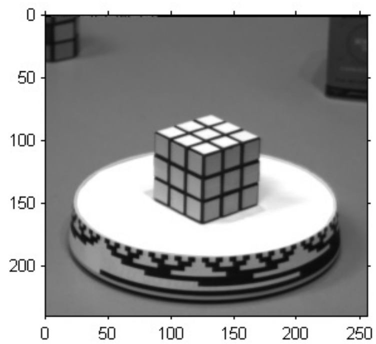

Figure 1.A. sequence cubic

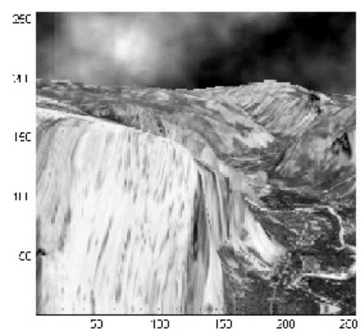

Figure 1.B. Optical Flow measuring by using real wavelet transform

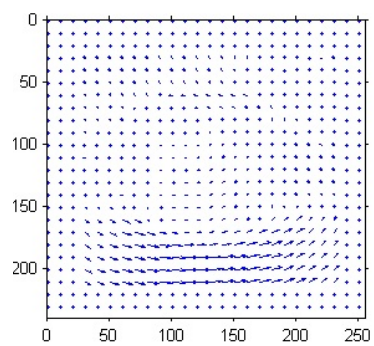

Figure 3.A. Sequence My sineC16

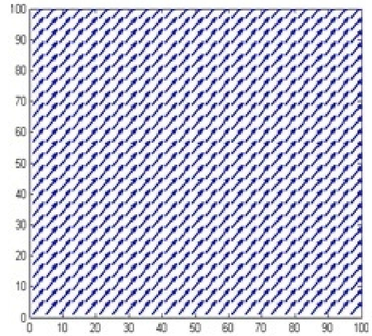

Figure 3.B. Optical Flow measuring by using real wavelet transforms

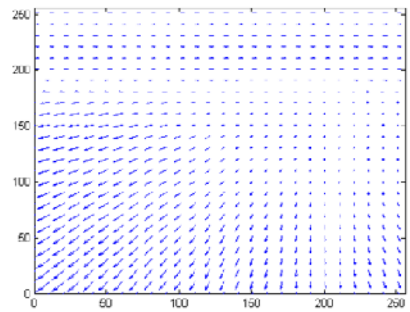

Figure 4.A. Sequence Yosemite

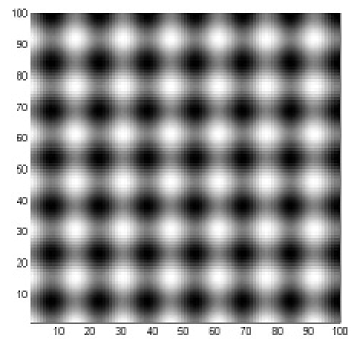

Figure 4.B. Optical Flow measuring by using real wavelet transforms

Table 1.Comparison of different methods of sequence “my sineC.16”.

Method	Images	Error	deviation	Density (%)
Motion estimation using Ridgelet	2	0.80°	0.70	100
Motion estimation using real wavelet	2	6.34°	7.56°	100
Horn et Schunk (original)	2	11.02°	13.72°	100
Horn et Schunk (modify)	7-13	4.55°	5.67°	100
Anandan	2	5.54°	9.96°	100
Singh	2	7.60°	9.78°	100

Table 2.Comparison of different methods of sequence “My sineC16”.

Method	Images	Error	deviation	Density (%)
Motion estimation using Ridgelet	2	0.99°	0.88	100
Motion estimation using real wavelet	2	7.98°	9.56°	100
Horn et Schunk (original)	2	14.02°	14.72°	100
Horn et Schunk (modify)	7-13	9.55°	9.67°	100
Anandan	2	9.64°	3.96°	100
Singh	2	12.60°	12.78°	100

Table 3.Comparison of different methods of sequence “Yosemite”.

Method	Images	Error	deviation	Density (%)
Motion estimation using Ridgelet	2	4.52°	4.65°	100
Motion estimation using real wavelet	2	9.43°	8.87°	100
Horn et Schunk (original)	2	32.43°	30.28°	100
Horn et Schunk (modify)	7-13	11.26°	10.59°	100
Anandan	2	15.84°	13.46°	100
Singh	2	13.16°	12.07°	100

4. Conclusion

This approach is essentially based on the projection of the constant intensity constraint on Ridglet transform. The experimental results show that Ridgelet transform technique is more accurate in the optical flow estimation. This technique is capable to estimate many kinds ofmovement because in comparison with wavelet transform possesses twokey properties for computer vision: shift invariance,which makes it possible to extract stable local featuresin an image; and good directional selectivity, making itpossible to measure image energy accurately in multiple directions. Testing on synthetic data sets has shown good performance compared par wavelet.

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