Optical Flow Estimation on Omnidirectional Images: An Adapted Phase Based Method

Brahim Alibouch[1], Amina Radgui[1,2],
Mohammed Rziza[1], and Driss Aboutajdine[1]

[1] LRIT associated unit with CNRST (URAC29), Mohammed V-Agdal University, B.P 1014, Rabat, Morocco
alibouch_brahim@yahoo.fr, rziza@fsr.ac.ma, aboutaj@fsr.ac.ma
[2] INPT, Madinat AL Irfane, Rabat, Morocco
radgui@inpt.ac.ma

Abstract. Omnidirectional vision is one of emerging areas of research. Omnidirectional images offer a large field of view compared to conventional perspectives images. However, these images contain important distortions, and classical optical flow estimation are thus not appropriate. In this paper, we propose to estimate optical flow on omnidirectional images using a phase based method which proved its robustness and its accuracy on the perspective images. We will adapt different treatments that this method involve in order to take into account the nature of omnidirectional images.

Keywords: optical flow, omnidirectional vision, phase based methods, component velocity, Gabor filters.

1 Introduction

A fundamental problem in images processing is the computation of optical flow [1]. Optical flow is the distribution of apparent velocities of movement of brightness patterns in an image [2]. The information given by the optical flow can be used in many applications [3] such as object detection and tracking [4][5], robot navigation [6], video surveillance [7], ego-motion estimation [8]or visual odometry [9]. To estimate the optical flow there are several methods. A selection of those methods was tested and compared in [10] and grouped in four different classes: differential methods [11][12][2], phase-based methods [13][14], region-based methods [15] and energy based methods [16][17]. In optical flow estimation, Phase based methods are among techniques which proved their robustness and their accuracy [10]. Those techniques were introduced the first time by Fleet and Jepson [13]. Their method is based on the assumption that the level contours of constant phase provide a good approximation to the motion field [13].They propose to use spatiotemporal filters to decompose the image sequence according to scale and orientation [10], and then normal components of 2D velocity are calculated at each location in the different filters outputs. Finally, the full velocity is estimated by integrating all reliable normal components.

A. Elmoataz et al. (Eds.): ICISP 2012, LNCS 7340, pp. 468–475, 2012.

Based on this approach, Gautama et al [18] introduced a new technique based on spatial filters instead of spatiotemporal ones. They consider phase nonlinearity as a criterion of reliability instead instability [18].

In this paper, we will adapt this last approach to omnidirectional images. The remainder of the paper is as follows: in the next section we present the phase-based approach proposed by Gautama et al to estimate the optical flow when using perspective images. Then, in section 3, we describe how to adapt this approach to estimate optical flow on omnidirectional images. Section 4 shows experiment results. We present our conclusions in section 5.

2 Phase Based Method for Optical Flow Estimation

The phase-based technique proposed by Gautama et al [18] uses a set of 2D complex filters to extract spatial phase. Then, temporal phase gradient is estimated at every position in image sequence and a reliability measure is applied to determine valid component velocities. These component velocities are thereafter combined to generate the optical flow field.

2.1 Filters Setting

To extract the phase in [18] Gabor filters are used to proceed to the multichannel decomposition. Gabor filter's impulse response is given by :

$$G(\mathrm{x}) = \frac{1}{2\pi\sigma} e^{\frac{-|\mathrm{x}|^2}{\sigma^2}} e^{i2\pi f} \tag{1}$$

With $\mathrm{x} = (x, y)$ is the pixel position, $f = (f_x, f_y)$ are center frequencies which define filter orientation θ, and σ is the standard deviation of the elliptical Gaussian which defines scale parameter. Once an image $I(\mathrm{x})$ is filtered by such filter, the response is given by:

$$\begin{aligned} R(\mathrm{x}) &= I(\mathrm{x}) * G(\mathrm{x}) \\ &= \rho(\mathrm{x}) e^{i\phi(\mathrm{x})} \end{aligned} \tag{2}$$

$\rho(\mathrm{x})$ and $\phi(\mathrm{x})$ are respectively the amplitude and the phase component of the image convolved with the Gabor filter.

2.2 Optical Flow Estimation

Starting from the hypothesis that surfaces of constant phase provides a good approximation to the motion field [13], we can deduce the phase gradient constraint equation. Indeed, such surfaces satisfy:

$$\phi(\mathrm{x}, t) = c \tag{3}$$

Differentiating this equation with respect to t yields:

$$\nabla\phi.\mathrm{V} + \frac{\partial \phi}{\partial t} = 0 \tag{4}$$

Where $\nabla\phi$ is the spatial phase gradient, $\frac{\partial\phi}{\partial t}$ the temporal phase gradient and $\mathrm{V} = (v_x, v_y)$ is the velocity vector. As in the brightness constancy equation, the aperture problem appears also in the phase gradient constraint equation. In fact, we can estimate only the velocity component in the direction of the spatial phase gradient V_c. Equation (4) yields :

$$(\nabla\phi.\mathrm{V})\frac{\nabla\phi}{|\nabla\phi|} = -\frac{\partial\phi}{\partial t}\frac{\nabla\phi}{|\nabla\phi|} \tag{5}$$

Given that:

$$V_c = (V.\frac{\nabla\phi}{|\nabla\phi|})\frac{\nabla\phi}{|\nabla\phi|} \tag{6}$$

This gives:

$$V.\nabla\phi = \frac{V_c}{\nabla\phi}\left|\nabla\phi\right|^2 \tag{7}$$

Upon substituting equation (7), equation (5) become :

$$V_c = -\frac{\partial\phi}{\partial t}\frac{\nabla\phi}{|\nabla\phi|^2} \tag{8}$$

The spatial phase gradient $\nabla\phi = (\frac{\partial\phi}{\partial x}, \frac{\partial\phi}{\partial y})$ can be substituted with the local instantaneous frequency $(2\pi f_x, 2\pi f_y)$[19] :

$$V_c\left(x, y\right) = -\frac{\partial\phi}{\partial t}\frac{1}{2\pi\left({f^2}_x + {f_y}^2\right)}\left(f_x, f_y\right) \tag{9}$$

The temporal phase gradient $\frac{\partial\phi}{\partial t}$ is obtained from the temporal evolution of the phase by a accomplishing a linear regression in the least-squares sense [19][20] on the next equation:

$$\phi\left(\mathrm{x}, t\right) = c + \frac{\partial\phi}{\partial t}t \tag{10}$$

Note that the phase is unwrapped along the image sequence to deal with the phase periodicity. To determine the reliability of each component velocity, we calculate the mean squared error:

$$MSE = \frac{\sum_t\left(\Delta\phi\left(\mathrm{x}, t\right)\right)^2}{N} \tag{11}$$

Where N is the number of images and $\Delta\phi(\mathrm{x}, t) = (c + \frac{\partial\phi}{\partial t}(\mathrm{x}, t).t) - \phi(\mathrm{x}, t)$
Thereafter, valid component velocities are combined to estimate the full velocity:

$$V^*\left(\mathrm{x}\right) = \arg\min\sum\left(\|V_{c,i}(\mathrm{x})\| - V(\mathrm{x}, t)^T\frac{V_{c,i}(\mathrm{x})}{\|V_{c,i}(\mathrm{x})\|}\right)^2 \tag{12}$$

Where $V_{c,i}$ is the component velocity at pixel x corresponding to the i^{th} filter.

3 Optical Flow in Omnidirectional Images

Omnidirectional images offer a large field of view compared to conventional perspectives images, although they are distorted due to the non-linear projection of the scene points in the image [3]. Consequently calculating optical flow on such images in the same way as on perspectives images will lead to mistaken results. One of the most used techniques to avoid this problem is to project omnidirectional images on the sphere and using image processing in that new domain.

3.1 Projection on the Sphere

The equivalence between the catadioptric projection and the projection on the sphere has been proved by Geyer and Daniilidis [21]. In their work, they have presented a unifying theory for central panoramic systems. This equivalence is shown in Fig. 1.

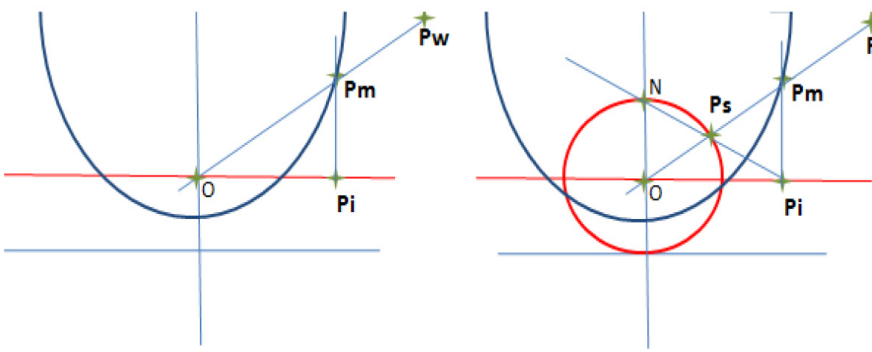

Fig. 1. Equivalence between the catadioptric projection and the two-step mapping via the sphere

The 3D point $P_w\left(X_w, Y_w, Z_w\right)$ is first projected in the mirror on a point $P_m\left(X_m, Y_m, Z_m\right)$, then reflected to the image plane on a point $P_i\left(x, y\right)$,such that it is parallel to the optical axis.
Let $P_s\left(X_s, Y_s, Z_s\right) = P_s\left(\theta, \varphi\right)$ be the equivalent point on the unit sphere. The Cartesian coordinates of this point are given by :

$$\begin{cases} X_s = \sin\theta\cos\varphi \\ Y_s = \sin\theta\sin\varphi \\ Z_s = \cos\theta \end{cases} \tag{13}$$

The stereographic projection of P_s on the image plane yields point $P_i\left(x, y\right)$ given by:

$$\begin{cases} x = \frac{X_s}{1-Z_s} \\ y = \frac{Y_s}{1-Z_s} \end{cases} \tag{14}$$

By combining Equations (12) and (13) we obtain the spherical coordinates of point P_i:

$$\begin{cases} x = \cot\frac{\theta}{2}\cos\varphi \\ y = \cot\frac{\theta}{2}\sin\varphi \end{cases} \tag{15}$$

3.2 Optical Flow on the Sphere

To adapt the phase based method to omnidirectional images, we need to reformulate the phase gradient constraint equation in the sphere. Let $\phi_s(\theta,\varphi)$ be the spherical phase in the unit sphere, and $\nabla\phi_s = \left(\frac{\partial\phi_s}{\partial\theta}, \frac{1}{\sin\theta}\frac{\partial\phi_s}{\partial\varphi}\right)$ the spatial phase gradient on the sphere, the phase gradient constraint given in equation (4) becomes :

$$\frac{1}{\sin\theta}\frac{\partial\phi_s}{\partial\varphi}V_\varphi + \frac{\partial\phi_s}{\partial\theta}V_\theta + \frac{\partial\phi_s}{\partial t} = 0 \tag{16}$$

Where $(V_\theta, V\varphi)$ are the components of the flow vector in the tangential coordinates system. As for perspective images this equation provides only normal velocity component:

$$V_c(\theta,\varphi) = -\frac{\partial\phi_s}{\partial t}\frac{\nabla\phi_s}{|\nabla\phi_s|^2} \tag{17}$$

4 Experiment and Results

To test our approach we use real sequences of omnidirectional images, and we compared it to the classical phase based method proposed by Gautama [18]. To extract phase we used a filterbank consisting of spherical Morlet wavelets [22], tuned at the same orientations as in Gautama method. The sequences are captured using a catadioptric camera embedded on a mobile robot as shown in Fig. 2.

The resolution of our images is 1280*960 pixel and the intrinsic parameters are: $\alpha_u = 243$, $\alpha_v = 236$ and $h = 0.86$.

We estimate the optical flow for two different motions kinds : a rotation of the camera around the Z-axis as shown in Fig. 3 , and object movement in the scene with a fixed camera as shown in Fig. 4. Since in the case of real images we do not have the ground truth, we will just present the 2D motion fields that illustrated the amelioration given by our adapted method.

In Fig. 3, the image on the bottom left represents the optical flow obtained by applying Gautama approach without adaptation on the omnidirectional sequence corresponding to rotation. Overall, the optical flow field is correct with some minor irregularities. The image on the bottom right represents the optical flow obtained by applying our adapted method. This optical flow field is much better and more regular than the first one.

Fig. 2. Top: omnidirectional sensor embedded on a mobile robot. Bottom: omnidirectional image.

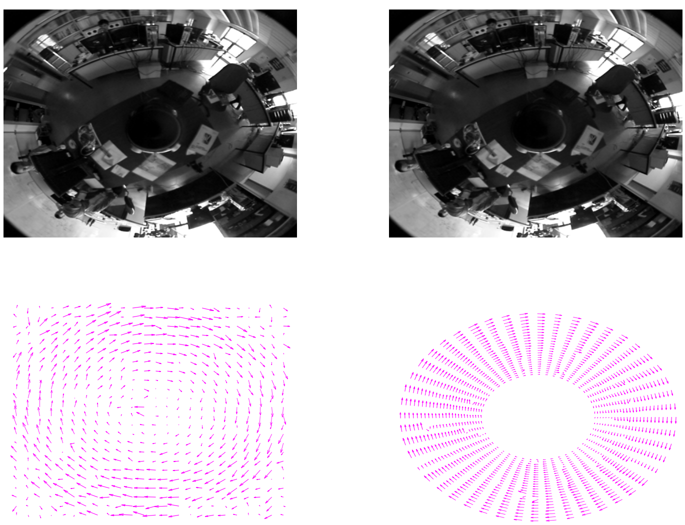

Fig. 3. Top: a sequence depicting a rotation. Bottom: optical flow obtained using classical Gautama method (Left) and using our approach (right).

Fig. 4 shows, on the bottom left, the optical flow obtained by applying Gautama approach without adaptation on the omnidirectional sequence corresponding to the object movement. This image shows an optical flow field who doesn't reflect the real motion on the sequence, and therefore a wrong one. On the other side the optical flow obtained by applying our adapted method is much closer to the real movement in the left of scene.

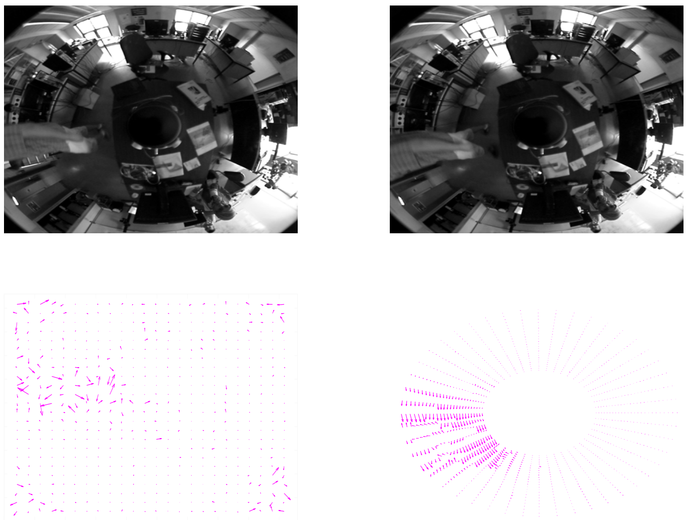

Fig. 4. Top: a sequence depicting an object movement. Bottom: optical flow obtained using classical Gautama method (Left) and using our approach (right).

5 Conclusion

Omnidirectional images are rich in information since they depict almost the whole scene. Unfortunately, they include severe distortions. That is why classical methods used to estimate the optical flow that work for perspectives images need to be adapted for omnidirectional ones. In this paper we have proposed an adaptation to a phase based method proposed by Gautama [18] which is one of the most robust optical flow methods. We applied our approach in real images and we compared it to the classical Gautama method. The comparison shows that our adapted Gautama method provides a correct local motion fields.

References

1. Beauchemin, S.S., Barron, J.L.: The Computation of Optical Flow. ACM Comput. Surv. 27, 433–467 (2003)
2. Horn, B., Schunck, B.: Determining optical flow. Artificial Intelligence 17, 185–203 (1981)

3. Radgui, A., Demonceaux, C., Mouaddib, E., Rziza, M., Aboutajdine, D.: Optical flow estimation from multichannel spherical image decomposition. Computer Vision and Image Understanding 115, 1263–1272 (2011)
4. Kim, J., Suga, Y.: An omnidirectional vision-based moving obstacle detection in mobile robot. International Journal of Control Automation and Systems 5, 663–673 (2007)
5. Yoshizaki, W., Mochizuki, Y., Ohnishi, N., Imiya, A.: Catadioptric omnidirectional images for visual navigation using optical flow. In: OMNIVIS 2008 (2008)
6. Winters, N., Gaspar, J., Lacey, G., Santos-Victor, J.: Omni-directional vision for robot navigation. In: IEEE Workshop on Omnidirectional Vision, pp. 21–28 (2000)
7. Wang, M.L., Huang, C.C., Lin, H.Y.: An intelligent surveillance system based on an omnidirectional vision sensor. In: IEEE Conference on Cybernetics and Intelligent Systems, pp. 1–6 (2006)
8. Gluckman, J., Nayar, S.: Ego-motion and omnidirectional cameras. In: IEEE International Conference on Computer Vision (ICCV), pp. 999–1005 (1998)
9. Bunschoten, R., Krose, B.: Visual odometry from an omnidirectional vision system. In: IEEE International Conference on Robotics and Automation (ICRA 2003), vol. 1, pp. 577–583 (2003)
10. Barron, J.L., Fleet, D.J., Beauchemin, S.: Performance of optical flow techniques. Int. J. Comput. Vis. 12, 43–77 (1994)
11. Kanade, T., Lucas, B.: An iterative image registration technique with an application to stereo vision. In: IJCAI 1981, pp. 674–679 (1981)
12. Nagel, H.H.: On a constraint equation for the estimation of displacement rates in image sequences. IEEE Transaction on Pattern Analysis and Machine Intelligence 11, 13–30 (1989)
13. Fleet, D.J., Jepson, A.D.: Computation of component image velocity from local phase information. Int. J. Comput. Vis. 5, 77–104 (1990)
14. Tsao, T., Chen, V.: A neural scheme for optical flow computation based on Gabor filters and generalized gradient method. Neurocomputing 6, 305–325 (1994)
15. Anandan, P.: A computational framework and an algorithm for the measurement of visual motion. International Journal of Computer Vision 2, 283–310 (1989)
16. Adelson, E., Bergen, J.: Spatiotemporal energy models for the perception of motion. Journal of Optical Society of America 2, 284–299 (1985)
17. Heeger, D.: Optical flow using spatiotemporal filters. International Journal of Computer Vision 1, 279–302 (1988)
18. Gautama, T., Van Hulle, M.M.: A phase-based approach to the estimation of the optical flow field using spatial filtering. IEEE Trans. Neural Networks 13, 1127–1136 (2002)
19. Pauwels, K., Van Hulle, M.M.: Optic Flow from Unstable Sequences containing Unconstrained Scenes through Local Velocity Constancy Maximization. In: BMVC, pp. 397–406 (2006)
20. Pauwels, K., Van Hulle, M.M.: Realtime phase-based optical flow on the GPU. In: Computer Vision and Pattern Recognition Workshops, pp. 1–8 (2008)
21. Geyer, C., Daniilidis, K.: Catadioptric projective geometry. Int. J. Comput. Vis. 43, 223–243 (2001)
22. Demanet, L., Vandergheynst, P.: Gabor wavelets on the sphere. In: SPIE Conference on Wavelets: Applications in Signal and Image Processing (2003)