Optical flow using color information

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OPTICAL FLOW USING COLOR INFORMATION: PRELIMINARY RESULTS

Kelson R. T. Aires
Federal University of Rio
Grande do Norte
Natal RN Brazil

kelson@dca.ufrn.br

Andre M. Santana
Federal University of Rio
Grande do Norte
Natal RN Brazil

andremacedo@dca.ufrn.br

Adelardo A. D. Medeiros
Federal University of Rio
Grande do Norte
Natal RN Brazil

adelardo@dca.ufrn.br

ABSTRACT

Optical flow cannot be completely determined only from brightness information of images, without introducing some assumptions about the nature of movements in the scene. Color is an additional natural source of information that facilitates the solution of this problem. This work aims to illustrate the improvement in the optical flow estimation by using color information through experimental results.

Keywords

Computer Vision, Optical Flow, Colored Images

1. INTRODUCTION

Biological vision system executes, in real-time and using optical flow, tasks like obstacle and movement detection. Optical flow is related to the standard movement in the eye that specifies the direction of locomotion. Throughout the years, robotic researchers have used optical flow in different tasks: object detection and tracking [14], image dominant plane extraction [10], movement detection, robot navigation [13] and visual odometry [9].

Luminance information is widely used as the only low level data in Computational Vision applications, even with color information is available. Using color prevents loss of information due to isoluminance. On the other hand, a bigger amount of data must be processed.

A color image corresponds to a multi-channel image where each pixel is associated to more than one value that represents color information and brightness intensity. Color information can be used in optical flow estimation. In contrast to gray images case, the using of additional constraints is not necessary [6, 16, 12].

This article illustrates the improvement in optical flow estimation by using color information. In applications like robot navigation based on optical flow this improvement is important because robots need accurate and reliable information concerning the environment for safe navigation.

2. OPTICAL FLOW

In computer vision, optical flow is a velocity field associated with image changes. This effect generally appears due to the relative movement between object and camera or by moving the light sources that illuminates the scene [7, 8]. Most approaches to estimate optical flow are based on brightness changes between two scenes.

2.1 Brightness Optical Flow

Among the existing methods for Optical Flow estimation, gradient based techniques are distinguished. Such techniques are based on image brightness changes of each pixel with (x, y) coordinates. Considering that small displacements do not modifie brightness intensity of a image point, a *Constraint Optical Flow Equation* can be defined as

$$I_x u + I_y v + I_t = 0, \tag{1}$$

where u and v are the optical flow components in x and y directions for a displacement $\mathbf{d} = (dx, dy)$, I_x, I_y and I_t are the partial derivatives of the image brightness, $I(x, y)$, with regard to the horizontal (x) and vertical (y) coordinates, and time (t). The optical flow vector, defined by $\mathbf{v} = (u, v)$, is illustrated in Figure 1. Optical flow cannot be estimated only from Equation 1 (Aperture Problem). Thus, some additional constraint needs to be used to find a solution for the flow components, u and v.

2.1.1 Lucas and Kanade's Method

Lucas and Kanade [8] used a local constraint to solve the aperture problem. This method considers that small regions in the image corresponds to the same object and have similar
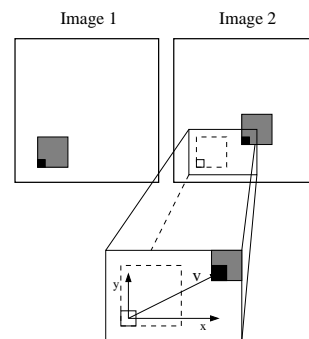

Figure 1: Optical flow vector.

movement. The image is divided in windows of size $N \times N$, each one with $p = N^2$ pixels. A local constraint of movement is used to form an overconstrained system with p equations and 2 variables, as in 2.

$$
\begin{aligned}
I_{x1}u + I_{y1}v + I_{t1} &= 0 \\
I_{x2}u + I_{y2}v + I_{t2} &= 0 \\
&\vdots \\
I_{xp}u + I_{yp}v + I_{tp} &= 0
\end{aligned}
\tag{2}
$$

System 2 can be solved by the Least Mean Square (LMS) method for estimating the optical flow vector. The estimated optical flow for each $N \times N$ window corresponds to the optical flow vector of all pixels in the related window, as shown in Figure 2.
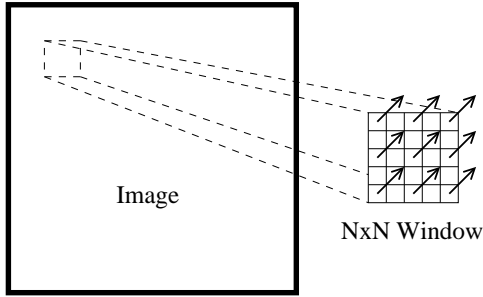

Figure 2: Optical flow vector corresponds to all window pixels.

2.1.2 Bouguet's Method:

Bouguet's method [2] uses hierarchical processing applied to Lucas and Kanade's method [8]. A justification for using of hierarchical processing is the necessity of better precision in measures of the obtained optical flow vectors. This method uses pyramidal representation of gray image frames. Bouguet algorithm consists of using down level estimations as initial guess of pyramidal top level. The estimation of pyramidal highest level is the estimated optical flow.

2.1.3 Eliete's Method:

Eliete's method [3] is a variation of Lucas and Kanade's method (Section 2.1.1). Eliete uses a bigger window for the brightness conservation model than the one considered by Lucas and Kanade. Only some pixels of each window are randomly chosen for the flow vector estimation. The overconstrained equation system is solved by the LMS method.

2.2 Color Optical Flow

Optical flow cannot be completely determined from a simple gray image sequence without introducing assumptions about movements in the image. Color image is an additional natural resource of information that can facilitate the problem resolution. Ohta [11] was the first one to consider a optical flow estimation method that does not use additional constraints about movements in the image. His method is based on multi-channel images (as color images) to obtain multiple constraints from a simple image pixel.

A multi-channel image consists of some associated images, making easy to obtain more information from a point of the scene [12]. The optical flow equation 1 can be applied to each image channel n. For color images with three channels (RGB, HSV, HSI, YUV) the system would result in 3

$$
\begin{aligned}
I_{1x}u + I_{1y}v + I_{1t} &= 0 \\
I_{2x}u + I_{2y}v + I_{2t} &= 0 \;. \\
I_{3x}u + I_{3y}v + I_{3t} &= 0
\end{aligned}
\tag{3}
$$

Another idea proposed by Golland [6] is the color conservation. Since that geometric component does not depend on light model, the color intensities can be represented by Equations 4,

$$
\begin{aligned}
R &= c(\varphi, \theta, \gamma)C_r \\
G &= c(\varphi, \theta, \gamma)C_g \\
B &= c(\varphi, \theta, \gamma)C_b
\end{aligned}
\tag{4}
$$

where $c(\varphi, \theta, \gamma)$ is the geometric component related to the angles of incidence (φ), observation (θ) and phase (γ), and the spectral component C_i is defined by Equation 5

$$
C_i = \int_{\Omega} \rho(\lambda)I(\lambda)D_i(\lambda)d\lambda, \quad i \in \{r, g, b\},
\tag{5}
$$

where $\rho(\lambda)$ represents the reflectivity function, $I(\lambda)$ is the incident light and $D_i(\lambda)$ represents the light sensor detection function. The reflection geometry can significantly change with the object movement (rotation, movement in camera direction, etc.). This way, the brightness intensity function will no more satisfy the conservation assumption. The new C_i functions given by Equation 5 remain constant under any type of movement. Therefore it is not influenced by the reflection geometry. Although it is impossible extracting the C_i information from the (R, G, B) values provided by a color image, the ratio of two components (R, G, B) corresponds to the ratio of two C_i components. Thus, some color models based on relations of R, G and B functions can be used: normalized RGB, HSV, HSI and YUV.

The System 3 provides a solution to optical flow vector without additional constraints concerning image movement. The disadvantage of this method consists of the necessity of calculating the color gradient present in the scene. On the other hand, Golland's method is more robust to variations caused by illumination effects. Barron et al [1] in their analysis showed that optical flow estimation is improved when color information is used.

3. PROPOSED METHOD

The absence of brightness gradients in some image points compromises optical flow estimation from gray images. To solve this problem, a method of flow vector estimation using color information is considered. This method is based on Lucas and Kanade's algorithm [8].

In our method, pixels are grouped in regions of similar movement. For optical flow estimation only some pixels of each group are used. In addition, the information of all image channels are used to obtain an overconstrained equation system. The optical flow vector for each group of pixels is obtained from this equation system.

Each image frame is divided into several observation windows of fixed size $N \times N$. For each $N \times N$ window, an optical flow vector that corresponds to all pixels of the window is estimated.

3.1 Optical Flow Estimation

We use some of the pixels to estimate the window optical flow, using an approch similar to the one used by Eliete [3]. Here, only some pixels are chosen too, but the pixel choice is equally distributed in window space, as shown in Figure 3.
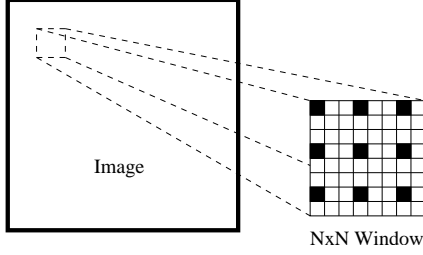

Figure 3: Black pixels are chosen for optical flow estimation.

The chosen pixels are used to optical flow estimation. The optical flow equation 1 is applied to each chosen pixel of all image channels. The System 6 is solved for each window.

$$I_{Ax1}u + I_{Ay1}v + I_{At1} = 0$$

$$\vdots$$

$$I_{Axn}u + I_{Ayn}v + I_{Atn} = 0$$
$$I_{Bx1}u + I_{By1}v + I_{Bt1} = 0$$

$$\vdots \qquad\qquad (6)$$

$$I_{Bxn}u + I_{Byn}v + I_{Btn} = 0$$
$$I_{Cx1}u + I_{Cy1}v + I_{Ct1} = 0$$

$$\vdots$$

$$I_{Cxn}u + I_{Cyn}v + I_{Ctn} = 0$$

In System 6, A, B and C represent the color channels. For example, I_{By1} represents the y partial derivative on pixel 1 of the B channel.

Spacial-temporal derivatives of System 6 can be estimated by the finite differences method [7] or any other numerical method to calculate partial derivates. In this paper, the finite differences method was chosen because of its simplicity and small processing time.

The System 6 has $3n$ equations and 2 variables and can be written in matricial form as 7

$$\mathbf{A} \cdot \mathbf{v} + \mathbf{b} = \mathbf{0}, \qquad (7)$$

where $\mathbf{v} = [u\ v]^T$ is the optical flow vector, $\mathbf{A}$ is the $3n \times 2$ spacial partial derivates (I_x and I_y) matrix and $\mathbf{b}$ is the $3n$ temporal derivates (I_t) vector. The System 7 can be solved by pseudo-inverse method, as

$$\mathbf{v} = (\mathbf{A}^T\mathbf{A})^{-1} \cdot (\mathbf{A}^T\mathbf{b}). \qquad (8)$$

In Equation 7, the $\mathbf{A}^T\mathbf{A}$ matrix must be non-singular. The condition number n of $\mathbf{A}^T\mathbf{A}$ is used to measure the numerical stability of the System 7. If n is above a certain threshold, $\mathbf{v}$ is not defined on that image location [1]. The condition number n of a matrix B is given by Equation 9.

$$n = \begin{cases} ||B|| \cdot ||B^{-1}||, & \text{if } B \text{ is non-singular} \\ \infty, & \text{if } B \text{ is singular} \end{cases} \qquad (9)$$

3.2 Optical Flow Filter

The following step consists on filtering the optical flow field. A filter based on the euclidian distance of optical flow vectors is used. A flow vector of a $N \times N$ window is only accepted as valid if it exists at least a neighbouring window (neighbourhood-8), where the square of the euclidian distance between the two flow vectors does not exceed 20% of the flow vector being analysed. Figure 4 illustrates the employed method. A similar method was used by Eliete [3].
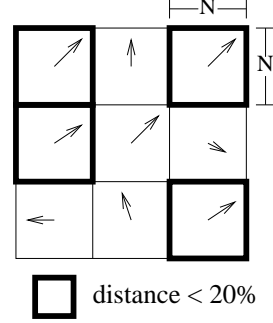

☐ distance < 20%

Figure 4: Portion of image with 9 $N \times N$ windows. The optical flow vector of central window is valid because there is among its neighbours at least one flow vector that satisfies the filter condition.

4. EXPERIMENTAL RESULTS

Some experiments were done to demonstrate the improvement on optical flow estimation by using color information. Figure 5 shows examples of 320×240 colored image frames used in the experiments.
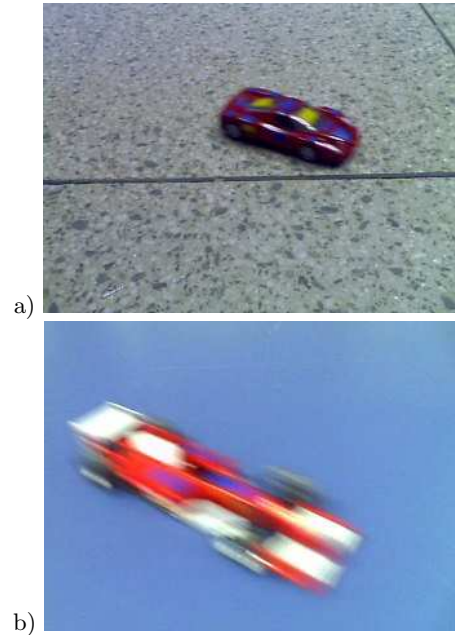

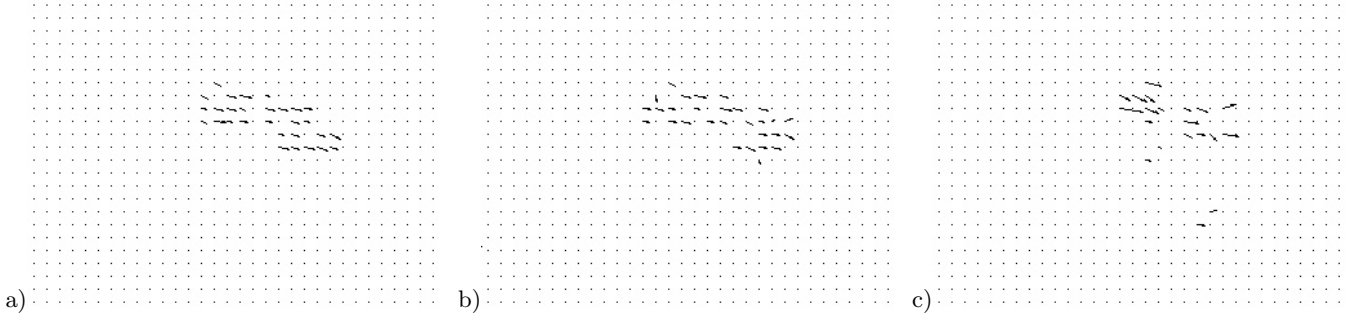**Figure 5: Example of colored frame used in tests.**

Figure 6: Optical flow obtained with the methods of Lucas and Kanade (a), Eliete (b) and Golland (c)

First, optical flow was estimated by using the proposed method and compared with optical flow estimated by the methods of Lucas and Kanade, Golland and Eliete. Invalid and null flow vectors are represented by dots in the estimated optical flow field, also called flow map. All tested methods have been applied to two consecutive frames of an image sequence.

Lucas and Kanade's method was tested with brightness conservation window of value $N = 10$. The obtained results, using only brightness information of two consecutive pictures like in Figure 5a, are shown in Figure 6a.

Eliete's method was tested with a window of size $N = 10$. Only 1/8 randomly chosen pixels of the window have been used in flow estimation. The obtained results for gray pictures like Figure 5a are shown in Figure 6b.

The Golland's method can calculate the optical flow on every image pixel. To exhibit a result that can be compared to the other ones, we only estimate the flow vector at each 10 lines and columns of the image. Golland's method was tested using the normalized RGB, HSV and YUV color models. The best result for color images like in Figure 5a was obtained with YUV color model. They are in Figure 6c.

The proposed method was tested using three color models: normalized RGB, HSV and YUV. YUV color model generated the best results. Only 1/9 pixels of the window are used in flow estimation. The result is shown in Figure 7.
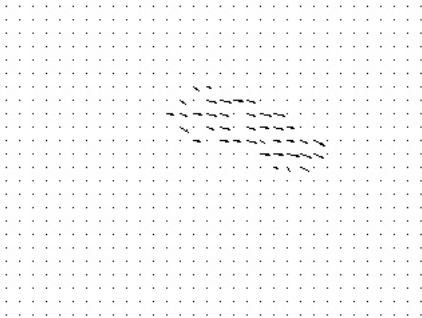

Figure 7: Optical flow map obtained with the proposed method using $N = 10$

A second test was performed. Only two channels of YUV color model were used to estimate the optical flow. The results are shown in Figure 8.

Finally, a comparative test between Bouguet's method and the proposed method was performed. Bouguet's method was implemented with 10×10 windows. The obtained re-
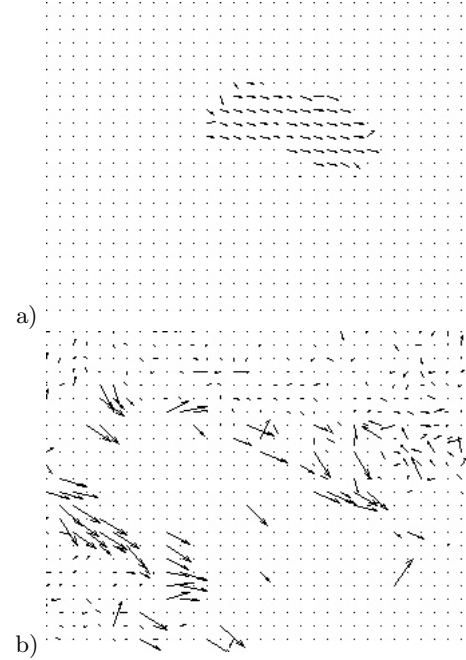

Figure 9: Optical flow with the Bouguet's method using frames like in Figure 5a (a) and Figure 5b (b).

sults with Bouguet's method using only brightness information of two consecutive frames like in Figure 5 are shown in Figure 9. The obtained result with the proposed method using frames like in Figure 5b is shown in Figure 10.
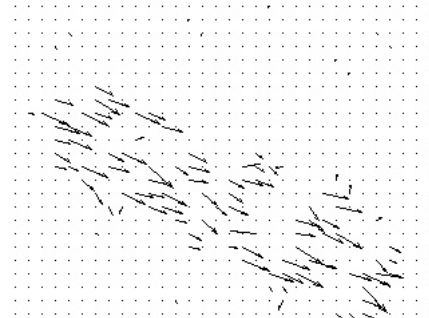

Figure 10: Optical flow obtained with the proposed method using frames like in Figure 5b.
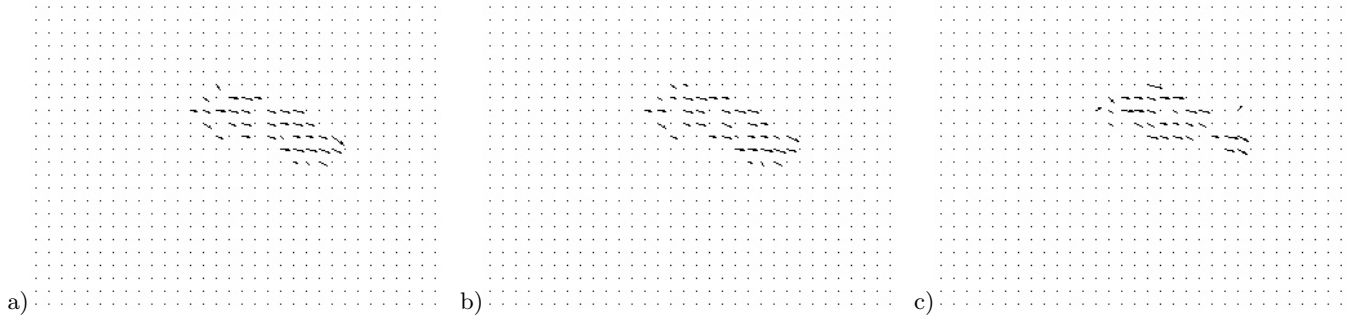
Figure 8: Optical flow map obtained using only YU (a), YV (b) and UV (c) channels.

5. CONCLUSION

A comparative analysis of the methods is based on the number of valid flow vectors considered after filtering. According to this criterion (Section 3.2), the use of color information can add up to 30% in the amount of valid estimated measures in comparison with methods that only use brightness information. The result in Figure 7 can be compared with the results in Figure 6 to illustrate this improvement.

Depending on the chosen color model, it is not necessary to use all channels of a tri-chromatic image. Tests have been made with the proposed method only using two color channels: YU, YV or UV. The results have shown differences of 5% maximum in the number of valid measures between the three options of choice. In comparison to the test with the three channels, the worst difference between the complet test and the tests with only two channels (YU, YV or UV) was only 7% of valid measures. Such results show that one of the channels can be excluded to reduce processing time. The results are shown in Figures 8a, 8b and 8c.

The random choice of pixels inside a $N \times N$ window, like in Eliete's method [3], can compromise the flow vector estimation. The tests have shown that a spatially uniform distribution of pixels improves the estimation.

Bouguet's method presented the best results with images without illumination changes (Figure 9a), but the optical flow estimation from images with variation of illumination is not good (Figure 9b). The proposed method is more robust to variations of illumination, as illustrated in Figure 10.

The choice of a method to estimate the gradient, mentioned in Section 3.1, directly influences the precision of the calculated flow vector. The results can be improved with a better investigation of such techniques. Some preliminary tests have been made with other techniques, as Sobel [5] and Simoncelli [15, 4] filters, and the results will be presented in future works.

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