# DIFFERENNTIAL TECHNIQUE FOR MOTION COMPUTATION USING COLOUR INFORMATION

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Abstract: Optical flow computation is an important and challenging problem in the motion analysis of images sequence. It is a difficult and computationally expensive task and is an ill-posed problem, which expresses itself as the aperture problem. However, optical flow vectors or motion can be estimated by differential techniques using regularization methods; in which additional constraints functions are introduced. In this work we propose to improve differential methods for optical flow estimation by including colour information as constraints functions in the optimization process using a simple matrix inversion. The proposed technique has shown encouraging results.

## 1 INTRODUCTION

The recent developments in computer vision, moving from static images analysis to video sequences, have focused the research on the understanding of motion analysis and representation. A fundamental problem in processing sequences is the computation of motion. Optical flow is a convenient and useful way for image motion representation and 3D interpretation. It often plays a key role in varieties of motion estimation techniques and has been used in many computer vision applications. Optical flow may be used to perform motion detection, autonomous navigation, scene segmentation, surveillance system (motion can be an important source for a surveillance system when objects of interest can be detected and tracked using the optical flow vector to define the future trajectories), motion compensation for encoding sequences and stereo disparity measurement (Barron 1994), (Beauchemin, 1995) and (Weickert, 2001). Thus an optical flow algorithm is specified by three elements (Barron, 1994):

* The spatiotemporal operators that are applied to the image sequence to extract features and improve the signal to noise ratio,

* How optical flow estimates are produced from a gradient search of the extracted feature space, and the form of regularization applied to the flow field considering confidence measures if they exist. Optical flow estimation and computation methods can be classified into three main categorie: differential approaches, block-matching approaches and frequential approaches (Baron, 1994).

Despite more than two decades of research, the proposed methods for optical flow estimation are relatively inaccurate and non-robust. Many methods for the estimation of optical flow have been proposed (Horn and Shunck (Horn, 1981); Lucas and Kanade (Lucas, 1981); Markandy and Flinchbaugh (Markandy, 1990); Fleet and Jepson (Baron, 1994) and (Beauchemin, 1995); Weber and Malik (Weber, 1995); Polina and Golland (Polina, 1995); Tsai et al. (Tsai, 1999); Ming et al. (Ming,2002); Zhang and Lu (Zhang, 2000); Bruno and Pellerin (Bruno, 2003); Barron and Klette (Barron, 2002), Arredondo and al. (Arredondo , 2004), Joachim Weickert and al. (Joachim, 2003), (Thomax, 2004) and (André, 2005) and Volker Willert and al (Volker, 2005) ) .

We present in this paper a differential approach using colour components as constraints functions for the optical flow computation. The rest of this paper is organized as follows: section 2 describes the main optical flow constraint equation. In section 3 we describe how to use colour in the process of optical

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flow estimation. In section 4, we present the method for the minimization of the function including the smoothing term based on colour information. Some experimental results are presented in section 5 and at the end, we address a conclusion.

## 2 OPTICAL FLOW CONSTRAINT EQUATION

Optical flow is the apparent motion of brightness patterns in the images sequence. It corresponds to the motion field, but not always.

Optical flow techniques are based on the idea that for most points in the image, neighbouring points have approximately the same brightness. Optical flow can be computed from a sequence by using the (Horn, 1981) assumption, known as the brightness constancy assumption, is represented by the following equation:

$$I_x u + I_y v + I_t = 0 \quad (1)$$

Where:

$I_x$, $I_y$ and $I_t$ are first partial derivatives of I respectively with respect to x, y and t and u and v are the optical flow components in the x and y directions.

Equation (1) is called optical flow constraint equation. It provides only the normal velocity component. So we are only able to measure the component of optical flow that is in the direction of the intensity gradient (aperture problem) and the system is undetermined. To overcome this problem, it is necessary to add additional constraints.

Another problem is that are assuming that δt is very small. The sampling error in the spatial domain also leads to errors in the computation of the $I_x$ and $I_y$.

## 3 USE COLOUR INFORMATION AS CONSTRAINT

The brightness assumption implies that the (R, G, B) components of each image remain unchanged during the motion undergone within a small temporal neighbourhood (Weber, 1995). Therefore, R, G and B images can be used in a similar way as the luminance function: they have to satisfy the optical flow constraint equation. Markandey and Flinchbaugh (Markandy, 1990) have proposed a multispectral approach for optical flow computation. Their two-sensors proposal is based on solving a system of two linear equations having both optical flow components as unknowns. The equations are deduced from the standard optical flow constraint (1). In their experiments, they use colour TV camera data and a combination of infrared and visible images. Finally, they use two channels to resolve the ill-posed problem (Barron, 2002).

Golland and Bruckstein (Polina, 1995) follow the same algebraic method. They compare a straightforward 3-channels approach using RGB data with two 2-channel methods, the first based on normalized RGB values and the second based on a special hue-saturation definition.

The standard optical flow constraint may be applied to each one of the RGB quantities, providing an over determined system of linear equations (Barron, 2002):

$$\begin{cases} R_x u + R_y v + R_t = 0 \\ G_x u + G_y v + G_t = 0 \\ B_x u + B_y v + B_t = 0 \end{cases} \quad (2)$$

Then the pseudo-inverse computation gives the following solution for the system:

$$V = (A^T.A)^{-1}.A^T.b \quad (3)$$

Where:

$$A = \begin{bmatrix} R_x & R_y \\ G_x & G_y \\ B_x & B_y \end{bmatrix},\ b = \begin{bmatrix} -R_t \\ -G_t \\ -B_t \end{bmatrix}\ and\ V = \begin{bmatrix} u \\ v \end{bmatrix} \quad (4)$$

This assumes that the matrix ($A^TA$) is non-singular.

By definition this matrix is singular if its columns or lines are linearly dependent, which means that the first order spatial derivatives of the colour components (R, G, B) are dependent. Since the sensitivity functions Dr(λ), Dg(λ) and Db(λ) of the light detectors are linearly independent, the first derivatives of the R, G, B functions will also be independent for images sequence with colour changing in two different directions. But if the colour is a uniform distribution, the (R, G, B) functions are linearly dependent or if the colours of the considered region change in one direction only, the gradient vectors of (R, G, B) are parallel so that the spatial derivatives are dependent and the matrix ($A^TA$) is singular. In addition to the estimates of the image flow components at a certain pixel of the image, we would like to get some measure of confidence in the result at this pixel, which would tell us to what extent we could trust our estimates. It is common to use the so-called condition number of the coefficient matrix of a system ($A^TA$) as a measure of confidence of this system (Polina, 1995). To improve this problem, the idea is the use of two independent functions for colour characterization so that their gradient directions are not parallel. If the quantities used here are denoted f and ff. The colour conservation assumption implies:

$$\begin{cases} f_x u + f_y v + f_t = 0 \\ ff_x u + ff_y v + ff_t = 0 \end{cases} \tag{5}$$

Here the solution is given by simple matrix inversion:

$$V = A^{-1}.b \tag{6}$$

The ideal case is obtained when the gradient directions of the two chosen functions are normal. One possible solution is the use of two different colour systems: the normalized RGB system, denoted rgb system and the HSV system (Barron, 2002), (Markandy, 1990) and (Polina, 1995).

It is clear that any pair of (r, g, b) forms a system of two independent functions. If we are taking the r and g components, the optical flow computation system to be solved is given by equation (6), where:

$$A = \begin{bmatrix} r_x & r_y \\ g_x & g_y \end{bmatrix},\ b = \begin{bmatrix} -r_t \\ -g_t \end{bmatrix}\ \text{ and } V = \begin{bmatrix} u \\ v \end{bmatrix} \tag{7}$$

Now we consider the HSV systems. H and S describe a vector in polar form, representing the angular and magnitude components respectively (Robert, 2003).

The HSV space is computed in the following way:

$$V = Max(R, G, B),$$

$$S = \frac{Max(R,G,B) - Min(R,G,B)}{Max(R,G,B)},$$

$$H = \begin{cases} \dfrac{G-B}{Max(R,G,B)-Min(R,G,B)} & If\ \ R=Max(R,G,B), \\ 2+\dfrac{B-R}{Max(R,G,B)-Min(R,G,B)} & If\ \ G=Max(R,G,B), \\ 4+\dfrac{R-G}{Max(R,G,B)-Min(R,G,B)} & If\ \ B=Max(R,G,B) \end{cases} \tag{8}$$

The solution is given by equation (6), where:

$$A = \begin{bmatrix} H_x & H_y \\ S_x & S_y \end{bmatrix},\ b = \begin{bmatrix} -H_t \\ -S_t \end{bmatrix}\ \text{ and } V = \begin{bmatrix} u \\ v \end{bmatrix} \tag{9}$$

## 4 PROPOSED METHOD

It was shown that a colour sequence could be straightforwardly considered as a set of three different sequences produced by three types of light sensors with different sensitivity functions in response to the same input sequence (Markandy, 1990) and (Polina, 1995). So we propose to use the same formulation as those proposed by Horn and Schunck for the luminance function and to apply it to the three colour components.

In the first stage we have to minimize a function error containing the three colour components for the considered colour space, each component satisfying the optical flow constraint equation without any smoothness term, for the RGB space we have:

The problem will be posed as finding *(u, v)* optical flow components minimising *F*. The solution was given by using equation (6); Where:

$$\underset{u,v}{\mathrm{Min}} \begin{cases} F = \left(R_x.u + R_y.v + R_t\right)^2 + \left(G_x.u + G_y.v + G_t\right)^2 \\ \qquad + \left(B_x.u + B_y.v + B_t\right)^2 \\ = \varepsilon_R^2 + \varepsilon_G^2 + \varepsilon_B^2 \end{cases} \tag{10}$$

The matrix A must be non-singular. The smallest eigenvalue of $A^T A$ or the condition number of $A^T A$ can be used to measure numerical stability, i.e. if the smallest eigenvalue is below a threshold or the condition number is above a threshold, then we set the optical flow vector to be undefined at this image location.

So, in the second stage we add a local (on a small region around each pixel) smoothness term on the magnitude of optical flow vector with a weight α. The motion of any object between two successive times ($t_0$ and $t_0+\partial t$ where $\partial t \to 0$) is supposed to be very small and it can be used as a small displacement in any direction. So equation (9) with the smoothness term will be:

$$\underset{u,v}{\mathrm{Min}} \begin{cases} F = \left(R_x.u + R_y.v + R_t\right)^2 + \left(G_x.u + G_y.v + G_t\right)^2 \\ \qquad + \left(B_x.u + B_y.v + B_t\right)^2 + \frac{1}{2}\alpha^2 \|V\|^2 \\ = \varepsilon_R^2 + \varepsilon_G^2 + \varepsilon_B^2 + \varepsilon_s^2 \end{cases} \tag{12}$$

Deriving F over u and v and solving the result system. The same solution is found when adding the smoothness term in the function F to minimize. Deriving This solution is obtained by equation (6), where :

We do not use iterative method to compute the

$$A = \begin{bmatrix} R_x^2 + G_x^2 + B_x^2 & R_x R_y + G_x G_y + B_x B_y \\ R_x R_y + G_x G_y + B_x B_y & R_y^2 + G_y^2 + B_y^2 \end{bmatrix}; \tag{11}$$

$$b = -\begin{bmatrix} R_x R_t + G_x G_t + B_x B_t \\ R_y R_t + G_y G_t + B_y B_t \end{bmatrix}.$$

$$A = \begin{bmatrix} R_x^2 + G_x^2 + B_x^2 + \alpha^2 & R_x R_y + G_x G_y + B_x B_y \\ R_x R_y + G_x G_y + B_x B_y & R_y^2 + G_y^2 + B_y^2 + \alpha^2 \end{bmatrix}; \tag{13}$$

$$b = -\begin{bmatrix} R_x R_t + G_x G_t + B_x B_t \\ R_y R_t + G_y G_t + B_y B_t \end{bmatrix}.$$

optical flow components here and the proposed method is only based on the function optimisation and matrix inversion.

## 5 EXPERIMENTAL RESULTS

This section examines the quantitative performances and the implementation of the proposed method.

### 5.1 Error Measurement

In order to quantify the accuracy of the estimated range flow, the following errors measures are used. Let the correct range flow be denoted as Vc and the estimated flow as Ve. The relative error in the velocity magnitude (Barron et al., 2004), (Baron and Klette, 2002), (Volker et al., 2005):

$$Er = \frac{\left\| V_c - V_e \right\|}{\left\| V_c \right\|}.100\ [\%] \qquad (14)$$

We use the directional error as a second error measure:

$$Ed = \arccos\left( \frac{Vc.Ve}{|Vc|.|Ve|} \right)[^\circ] \qquad (15)$$

This quantity gives the angle in 3D between the correct velocity vector and the estimated vector and thus describes how accurately the correct direction has been recovered. We address this table, to prove the efficiency of optical flow method for studied sequences and for a precise confidence measure (Barron, 2002), (Arredondo, 2004), (Joachim, 2003), (Thomax, 2004), (André, 2005) and (Volker, 2005).

### 5.2 Implementations and Results

In the implementation of all studied methods, the images of R, G and B, (r and g) and (H and S) are obtained from the brightness function of images sequence (R, G, B).

The first order derivatives of the sequence functions are computed by using the (1/12) (-1, 8, 0, -8, 1) kernel. We used a 5x5 neighbourhood, where each line was a copy of the estimation kernel mentioned above. For the computation of temporal derivatives, a 3x3x2 spatiotemporal neighbourhood was used.

In our case, we first computed the time taken by any studied method addressed in Table 2, using Matlab implementation on Toshiba PC Intel® pentium®, Microprocessor 1.70GHz and 1Go of RAM. We used the ball sequence with different sizes and Barron and Klette synthetic panning sequence in 2002.

The first synthetic sequence (figure 2), derived from the original sequence (figure 1), contains ball moving in the horizontal direction with 4 pixels/frame and in the vertical direction with 3 pixels/frames, with variable sizes. The second one is generated by Barron and Klette (figure 7) where the correct flow is known (Baron and Klette, 2002), (Volker et al., 2005).

Table 1: Time taken for computation by s CPU time.

| Method | 64x64 | 128x128 | 240X320 | Panning |
|---|---|---|---|---|
| Using rgb | 2.125 | 7.079 | 103.704 | 56.422 |
| Using HSV | 2.047 | 8.266 | 114.797 | 73.031 |
| Using Min RGB | 2.984 | 10.219 | 144.953 | 78.578 |
| Using Smooth. α | 3.062 | 10.625 | 146.719 | 83.781 |

In the second stage, we used the first synthetic colour ball sequence with 64x64 size (figure 2) to compare quantitatively the obtained results by each studied method (figures 5 to 8). The results are reported in table 2.

Table 2: Results Errors Comparison using synthetic colour ball sequence with 64x64 size.

| Proposed Method | | AME : Er±Std(Er) | AAE : Ed±Std(Ed) |
|---|---|---|---|
| Using rgb space | RGB | 5.50%±2.44% | 3.15°±1.39° |
| Using HSV space | RGB | 22.2%±25.45% | 11.6°±12.14 |
| Min. RGB space | RGB | 10.4%±11.41% | 5.83°±6.13° |
| Min.(smooth.: α) | RGB | 6.16%±4.11% | 3.52°±2.33° |

In the last stage, we used the synthetic panning sequence (figure 7) to compare quantitatively the obtained results (figures 8 to 15). In table 4, we added from the fourth line our results to the results presented in (Baron and Klette, 2002), (Volker et al., 2005).

Table 3: Comparison between the results (Figures: 10 to 16) using synthetic panning sequence.

| Method | | AME : Er±Std(Er) | AAE : Ed±Std(Ed) |
|---|---|---|---|
| Horn-Schunck | RGB | 17.44%±17.77% | 2.64°±4.08° |
| Goland-Bruckstein | RGB | 11.38%±17.36% | 5.04°±11.80° |
| Baron-Klette | RGB | 16.14%±17.57% | 0.16° |
| Using rgb space | RGB | 3.04%±0.72% | 1.74°±0.40° |
| Using HSV space | RGB | 9.66%±19.14% | 5.04°±8.63° |
| Min. RGB space | RGB | 6.06%±6.96% | 3.43°±3.79° |
| Min. RGB space with smoothing term | RGB | 3.52%±2.04% | 2.01°±1.16° |

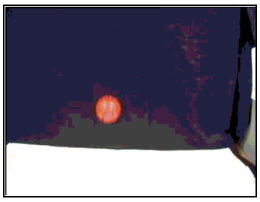
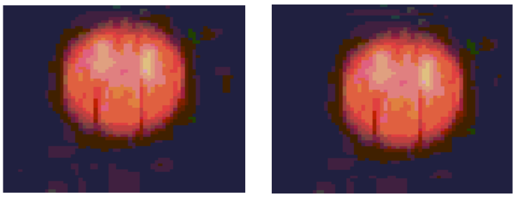


Figure 1: Original Image, of colour ball sequence with 240X320 size.



(a) (b)

Figure 2: (a) First image (b) Second image, of synthetic colour ball sequence size 64X64.

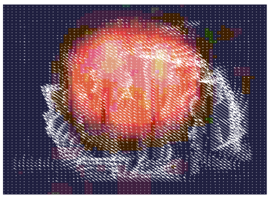


Figure 3: Proposed method using rgb space.

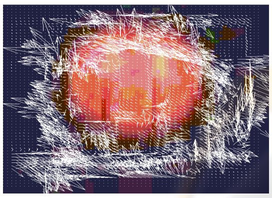


Figure 4: Proposed method using HSV space.

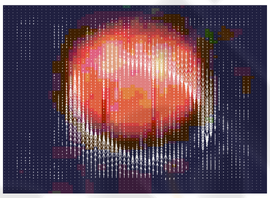


Figure 5: Proposed method using RGB space.

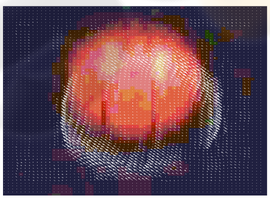


Figure 6: Proposed method using RGB space with smoothing term equal 3.

(a)

(b)

Figure 7: Images of Panning colour sequence (Real colour sequence).

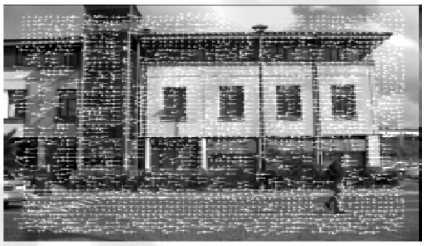


Figure 8: Horn-SchuncK flow for the Y component ($Y=0.299R+0.587G+0.114B$) with $\alpha=3$ and 100 iterations.

Figure 9: Golland-Bruckstein flow (RGB).

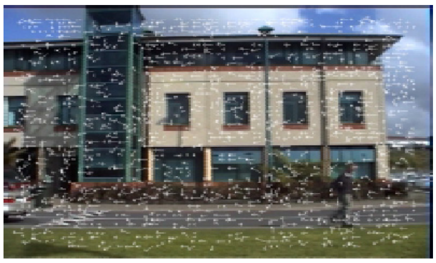


Figure 10: Baron-Klett flow (RGB).

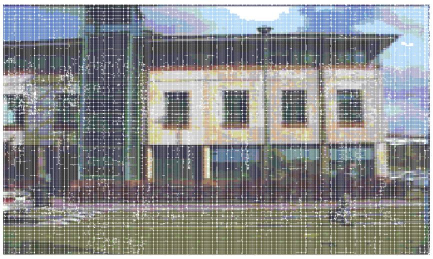


Figure 11: Proposed method using rgb space.

Figure 12: Proposed method using HSV space.

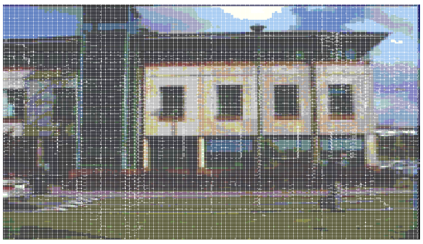


Figure 13: Proposed method using RGB space without smoothing term.

Figure 14: Proposed method using RGB space with smoothing term (α=100).

Figure 15: Proposed method using RGB space with smoothing term (α=3).

# 6 CONCLUSION

When we propose a new method, its drawbacks should also be discussed and compared with the other methods in the same environment. It has proved encouraging results.

Colour optical flow computed via the three colour components seems better than grey value optical flow. The proposed method using normalized rgb colour space gives good results followed by that using RGB space with smoothing term after that we found the proposed method using RGB space without smoothing term and finally that using the HSV space. In our case we used a 100% density of dense optical flow computation.

This proposed method requires the presence of significant gradients of the functions it is based on. If the gradient magnitude of these functions is small enough (≈0), any gradient based method would fail to give reliable results. This implies that all these methods should not be used when a scene contains objects with uniform colour.

The proposed method used the least squares techniques to minimize the combination of optical flow colour constraint equation using the matrix inversion to compute the dense flow optic. We have used the brightness constancy assumption, the colour information as constraint function and the same smoothness function as that proposed by Horn and Shunck.

We can extend the proposed smoothness function with other forms (as the combination of the local and global constraints) and we can use a bidirectional multigrid method for variational optical flow computation to resolve the real-time computation problem and the solving of the linear system of equations that results from the discretisation of the Euler-Lagrange equations.

We plan to investigate all these to find a robust and sufficiently method for optical flow computation for any given sequences in some specific applications.

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