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# DENOISING THE LARGE DISPLACEMENT OPTICAL FLOW USING TETROLET TRANSFORM FOR TRAFFIC SEQUENCE

**C.Jaiseeli, N.R.Raajan**

School of Electrical & Electronics Engineering, SASTRA University, Thanjavur-613401, Tamil Nadu, India.

Email: cjaiseeli@ece.sastra.edu

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**Abstract**

**Objectives**: With the recent developments in finding the three-dimensional structure of the scene from high speedy vehicles tracking, Optical flow field plays a significant role. Optical flow is utilized to ascertain the direction and speed of the motion of the objects from a video. The large displacement optical flow incurred by the various methods is unsuitable for practical applications due to the presence of noise. So we propose a new method for denoising the flow field by post applying different versions of Tetrolet Transform over the results obtained from two famed large displacement optical flow methods.

**Methods/Statistical Analysis:** Tetrolet Transform, a Haar based wavelet transform which decomposes the noises but preserves the edges that contains useful information. The multi resolution analysis can be done using Tetrolet Transform. The simulation of the Tetrolet Transform in terms of the metrics Peak Signal to Noise Ratio(PSNR) and Computation time was simulated in Matlab environment.

**Findings:** From the simulation results, the Tetrolet 16 rel edge, a version of modified Tetrolet surpass in excellence for the two flows which preserves the edges, so for denoising, the same can be used. The Tetrolet transform for denoising the large displacement optical flow is well suited for SIFT flow than Brox flow using many parameters.

**Application/Improvements:** This can be used in many applications like high speed tracking, stereo disparity, 3D reconstruction and diagnosing medical images.

**Keywords:** Tetrolet transform, optical flow, image warping, coefficients, edges, dense correspondence

**1. Introduction:** In Computer Vision, the primal problem is ascertaining optical flow, which can be defined as the pattern of seeming motion of objects caused by the proportional motion between perceiver and objects in the scene. A dense flow field appraisal of large displacement plays key role in most of the real time applications like long range tracking, motion segmentation, gesture recognition. Tetrolet transform, a Haar based wavelet transform which decomposes the noises in the image was applied to SIFT flow and regularized flow for getting better results free from noise.

## 2. Materials and Methods

### 2.1. Large displacement Optical flow

Optical flow is the ostensible motion of individual pixels on image plane. It influences the pattern of manifest motion of objects, surfaces, and edges in a visual scene caused by the proportional motion between an beholder (a camera or an eye) and the scene. The optical flow has been manipulated using differential, matching, energy-based and phase-based methods. For any two successive frames of the video, *I(x,y,t)* and *I(x,y,t+1)*,the apparent motion field $u(x,y)$ and $v(x,y)$ is calculated by assuming two constraints that are the rate of transfer of the image brightness and smoothness of the flow of images.

$$I_x \cdot u + I_y \cdot v + I_t = 0$$

To find large displacements, the two optical flow methods are the energy minimization of[1,2] model of coarse-to-fine image warping. These methods were override by spatio-temporal motion descriptor[3], difference-of-Gaussian[4], event-based motion interpretation[5], MRF deformation models[6]. Drawbacks in these methods are missing of smoothness assumption and lack of dense correspondence. SIFT flow[7] method overcomes these problems.

The energy for the flow is given as $E(x,y)$ ,

$$E(x,y) = \int (A_2(p+x,q+y) - A_1(p,q))^2 dpdq + \alpha \int (|\nabla x|^2 + |\nabla y|^2) dpdq$$

The energy minimization is given as,

$$E(r(p)) = \int \psi(|A_2(p+r(p)) - A_1(p)|^2) dp$$

$$+\gamma \int \psi(\nabla A_2(p+r(p)) - \nabla A_1(p)|^2) dp$$

$$+\beta \sum_{j=1}^{5} \int \rho_j(p) \psi((x(p)-x_j(p))^2 + (y(p)-y_j(p))^2) dp$$

$$+\alpha \int \psi(|\nabla x(p)|^2 + |\nabla y(p)|^2 + g(p)^2) dp$$

The variational method aggregated with the key point correspondences was described by[8] optical flow which applies to the regions that gives betterment for corners, finding affine patches and with this method all the displaced parts can be found.

**2.2. Tetrolet Transform**

The most estimal representation of the images is the demand in many practical applications. The Two-dimensional Discrete Wavelet Transform(DWT)[9] suits for horizontal and vertical directions only.In[10] introduced Tetrominoes shown in Figure 1, which became famous in the computer game [11]. Image features appearing other than horizontal and vertical directions can be estimated by using tetrominoes tilings in Tetrolet Transform[12] as shown in Figure 2. Four equal-sized squares forms Tetrominoes follows wedgelets[13]. The filter bank algorithm to split the low pass image into 4x4 blocks at every level so that the algorithm is very simple and fast. Due to the four equal sized squares, the[14] type wavelet named as 'tetrolets', basic for local orthonormal basis. For the image approximation, tetrolet coefficients can be applied.

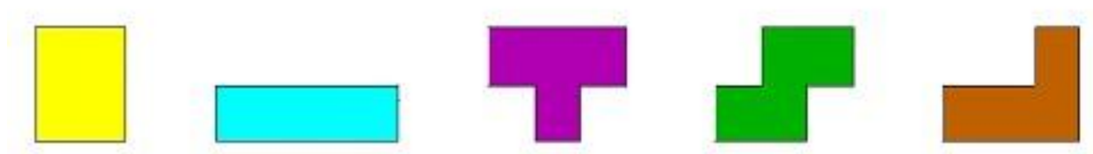

**Figure 1. Tetrominoes**

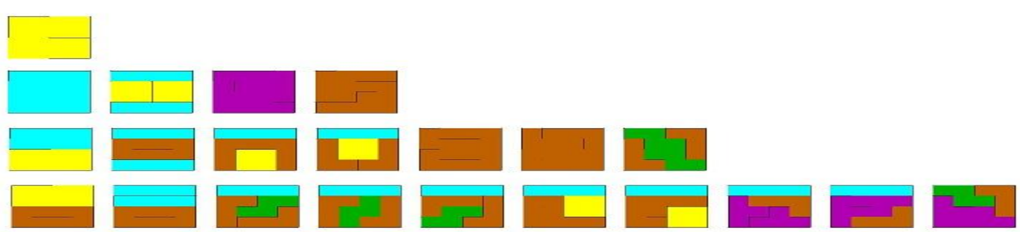

**Figure 2. 117 solutions from 22 fundamental forms tiling a 4 × 4 board.**

| |
|---|
| *Algorithm for Tetrolet Decomposition:* |
| *1.Image to be denoised of size 256x 256 as input* |
| *2.Split the image into 4x4 sub-blocks* |
| *3.Apply Tetrolet for individual blocks for 2x2 block, find the high pass and low coefficients* |
| *4.Save the high pass tetrolet coefficients only* |
| *5.Repeat the steps 2 to 5 to the image having low pass values* |
| *6.Decomposed image as a result* |

The algorithm can be explained as follows.

1. Get the image $p[i, j]$ and resize the image into 256x256.

2. Split the low pass image $p^{r-1}$ into $A_{i,j}$ sub-blocks of 4x4.

3. Tetrolet with maximum of 117 solutions with o as the tetrominoe covering for low pass coefficients were computed as,

$$p^{r,(o)} = (p^{r,(o)}[s])_{s=0}^{3} \; with \; p^{r,(o)}[s] = \sum_{(m,n)\in A_s^{(o)}} \in [0, M(m,n)] p^{r-1}[m,n],$$

high pass coefficients were computed as,

$$c_l^{r,(o)} = (c_l^{r,(o)}[s])_{s=0}^{3} \; withc_l^{r,(o)}[s] = \sum_{(m,n)\in A_z^{(o)}} \in [l, M(m,n)] p^{r-1}[m,n],$$

$M(m,n)$ is with smallest index value of 0 and largest index value of 3.

$o*$ is the covering with $l^1$ -norm is,

$$o* = \arg\ \min_c \sum_{l=1}^{3} \| p_l^{r,(c)} \| 1 = \arg\ \min_c \sum_{l=1}^{3} \sum_{s=0}^{3} | p_l^{r,(c)}[s] |$$

The decomposed coefficients can be computed for

$p[i, j]$

4. Save the high pass tetrolet coefficients only.

5. Repeat the steps 2 to 5 to the image having low pass values.

6. Decomposed image as a result.

**2.3. Denoising the Optical flow using Tetrolet Transform**

In this paper, we intend a method of post processing the results prevailed for large displacement optical flow using the two popular methods, Brox and SIFT flow with Tetrolet transform and different types of Modified Tetrolet transform for the purport of denoising. The work flow is shown in Figure 3.

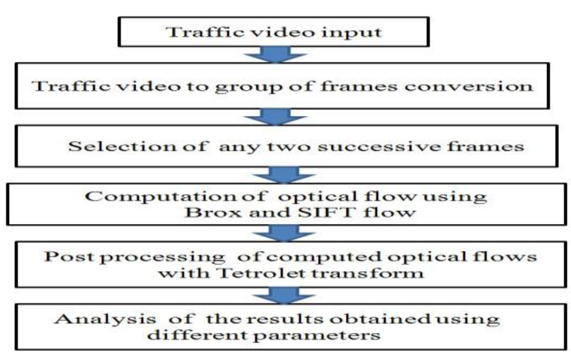


**Figure 3. Flow sheet for the proposed method.**

From the Traffic video input, the conversion of group of frames and computing optical flow for any two successive frames using Brox and SIFT flow methods. Then the Tetrolet subjected images were compared using different parameters like Peak Signal to Noise Ratio(PSNR), Computational Cost, Decompression time, Reconstruction time and Computation time.

**3. Results and Discussion**

From the traffic video input, the conversion of frames and selected two successive frames were shown in Figure 4. named as Car1 and Car2. Figure 5 shows the computed large displacement optical flow using Brox and SIFT flow in the MATLAB environment. The computed optical flow were compared using the parameters Maximum flow and Computation time as shown in Table 1.From the Table 1, depicts that SIFT flow can be computed faster than Brox, but in terms of flow density Brox gives better results having dense flow field.

**Figure 4. Successive frames from video input *Left:* car1 and *Right*: car 2.**

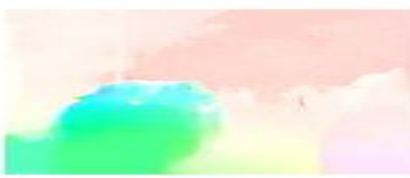

**Figure 5. Large displacement Optical flow using *Left:* Brox and *Right*: SIFT flow.**

**Table 1: Performance of the Optical flow results in terms of Maximum Flow and Computation time.**

| Parameters | Brox | SIFT flow |
|---|---|---|
| Maximum Flow | 6.8358 | 3.6056 |
| Computation time | 1.857900 s | 0.863155 s |

Tetrolet Transform preserves the edges[15] in both the flow fields. The reckoned optical flow images were converted into gray scale of 256x256 as shown in Figure 6 and subjected to Tetrolet and Modified Tetrolet Transform.

**Figure 6. RGB to gray conversion for the Optical flow results *Left:* Brox and *Right*: SIFT flow.**

The image has been reconstructed with 2047 coefficients for both the flow field and then reconstructed with 2048 coefficients as shown in Figure 7.

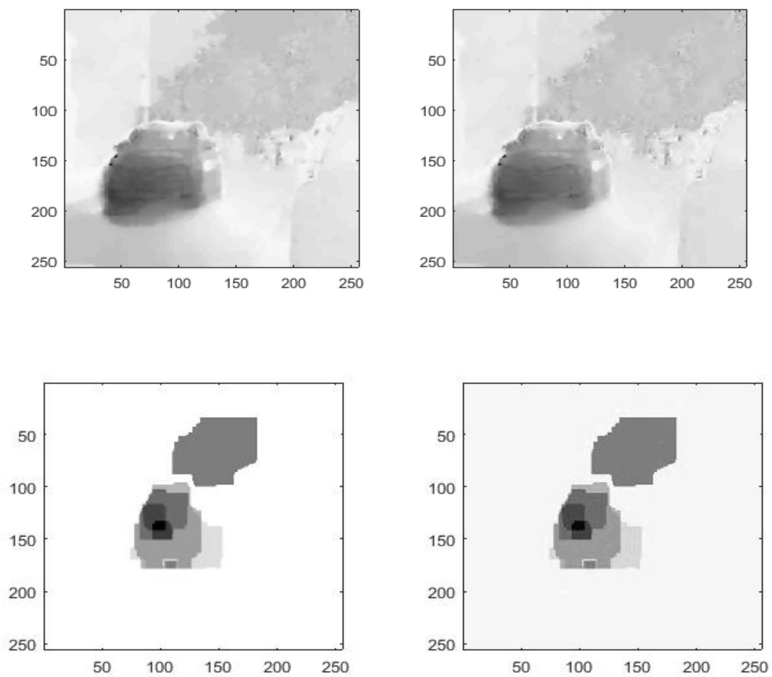

**Figure 7. Reconstruction of flow with *Left:* 2048 coefficients and *Right*: 2047 coefficients.**

The reconstructed images were compared in terms of PSNR(dB) for the purpose of denoising as shown in Table 2 which depicts that the SIFT flow has maximum PSNR(dB) for both the 2048 and 2047 coefficients compared to Brox.

**Table 2: Assessment of the reconstructed images in terms of PSNR(dB).**

| Method | Brox[6] | SIFT flow[13] |
|---|---|---|
| Tetrolet(2048 coefficients) | 45.63 | 55.43 |
| Biorth9-7(2047 coefficients) | 44.71 | 56.29 |

Different forms of Modified Tetrolet Transform like Tetrolet 16, Tetrolet rel, Tetrolet edge, Tetrolet 16 rel edges were applied for the two flow fields and the reconstructed images with 2048 coefficients were shown in Figure 8 and Figure 9.The performance were evaluated using the measures PSNR(dB), Reckoning time(Aggregate of Decompression and Reconstruction) and Computational Cost in Table 3.

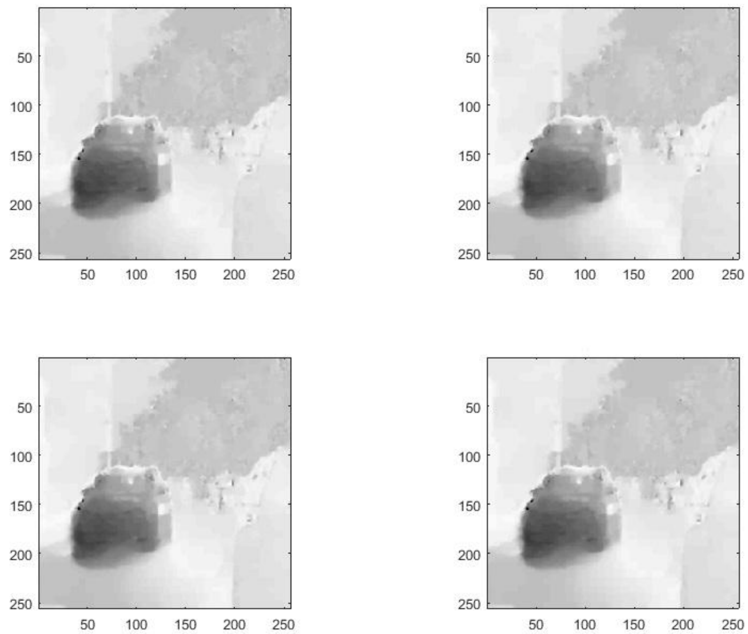

**Figure 8. Reconstruction of the image with 2048 coefficients using different methods for Brox Optical flow Top row: Tetrolet 16(*Left*) 2.Tetrolet rel(*Right*) Bottom row:1. Tetrolet edge(*Left*) 2. Tetrolet16 rel edges(*Right*).**

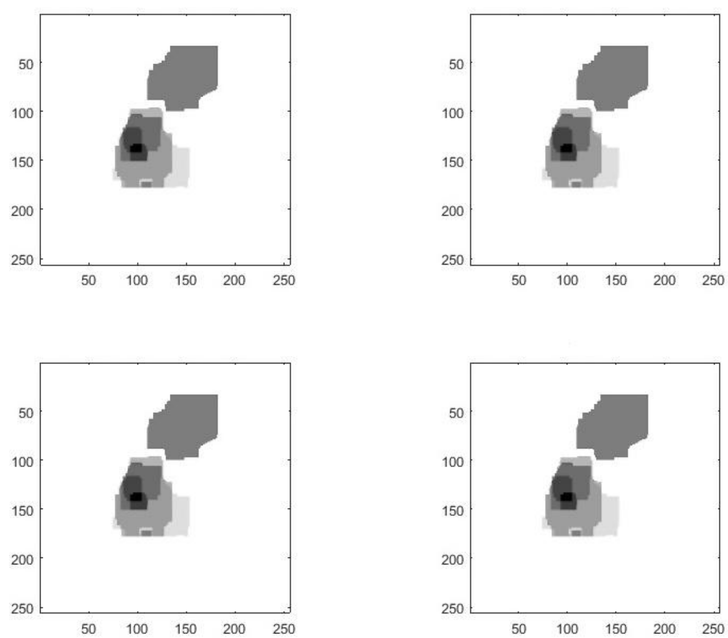

**Figure 9. Reconstruction of the image with 2048 coefficients using different methods for SIFT flow**

Top row: Tetrolet 16(*Left*) 2.Tetrolet rel(*Right*) Bottom row: 1. Tetrolet edge(*Left*) 2. Tetrolet16 rel edge(*Right*)

**Table 3:** Evaluation of different versions of Modified Tetrolet reconstructed images in terms of PSNR(dB), Reckoning time(s) and Computational Cost (bpp.).

| **Modified Tetrolet Transform** | **Brox** | | | **SIFT flow** | | |
|---|---|---|---|---|---|---|
| | **PSNR(dB)** | **Reckoning time (dec.+rec.) (s)** | **Computational Cost (bpp.)** | **PSNR(dB)** | **Reckoning time (dec.+rec.) (s)** | **Computational Cost (bpp.)** |
| **Tetrolet 16** | 45.2449 | 1.6088 | 0.98866 | 55.4344 | 1.5833 | 0.74851 |
| **Tetrolet rel** | 44.5484 | 1.7793 | 0.7588 | 55.4344 | 1.7936 | 0.73586 |
| **Tetrolet edge** | 45.0058 | 1.5549 | 0.83995 | 55.4344 | 1.6811 | 0.7479 |
| **Tetrolet 16 rel edge** | 44.4572 | 1.4813 | 0.72364 | 55.4151 | 1.4558 | 0.72947 |

The estimation shows that PSNR[dB] values for the purpose of denoising using all the methods were better for SIFT flow than Brox. In terms of Reckoning time, Tetrolet 16 rel edge performs faster than the remaining methods. According to Computational cost, Tetrolet 16 rel edge is better than others.

## 4. Conclusion

We conclude that the Tetrolet transform for denoising the large displacement optical flow is well suited for SIFT flow than Brox using many parameters. Tetrolet 16 rel edge, a version of modified Tetrolet surpass in excellence for the SIFT flow which preserves the edges, hence for denoising it can be used. The denoised large displacement optical flow can be applied to many computer vision applications like long range tracking , finding the motion of the body parts in sports(eg. Tennis) and disparity in stereo imaging.

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