Enhancing the Optical Flow for a Smoother Identification of Real-Time Global Motion

Optical Flow

Optical flow is a pattern of apparent motion of image objects between two consecutive frames caused by an object or camera movement. It is a 2D vector array where each vector is a displacement vector showing the movement of points from the first frame to the second. This method is called differential since it is based on local Taylor series approximations of the image signal; that is, they use partial derivatives with respect to the spatial and temporal coordinates.

Diagram

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Assumptions that Optical Flow relies on

1. Brightness constancy: Optical flow relies on the assumption that the brightness of an object in an image sequence at pixel level remains the same over time, even in an object which moves across the frames. (Surface radiance remains fixed from one frame to the next)
2. Small motion: Optical flow assumes that the motion between two consecutive frames is very small. If the motion is too large, the optical flow algorithm may not be accurate.
3. Spatial coherence: Another assumption that optical flow relies on is the neighboring pixels having a similar motion. In other words, the motion of a pixel should be similar to the motion of the pixels around it.
4. Continuity over time: Optical flow assumes that the motion of an object is smooth over time. This means that the motion of an object should be continuous over time.
5. No occlusion: Optical flow assumes that there are no occlusions of tracking objects in the image sequence. If an object is partially or completely occluded, the algorithm may not accurately estimate its motion.
6. Constant lighting conditions: Another assumption that optical flow relies on is that image sequence remains constant over time. If there are changes in lighting, this can lead to errors in the optical flow estimation.

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| Paper | Research Work | Year |
| Distance Surface for Event-Based Optical Flow  (Mohammed Almatrafi, Raymond Baldwin, Kiyoharu Aizawa) | Proposed a novel optical flow method for neuromorphic cameras (event detection cameras that report the log-intensity changes exceeding a predefined threshold at each pixel).  In absence of the intensity value at each pixel location, this research introduced a notion of “distance surface”—the distance transform computed from the detected events—as a proxy for object texture. The distance surface is then used as an input to the intensity-based optical flow methods to recover the two-dimensional pixel motion.  ISSUE ADDRESSED: optical flow in the presence of fast motion and occlusions. | 2020 |
| Variational Optical Flow Computation in Real Time | Investigated the usefulness of bidirectional multigrid methods for variational optical flow computations. And also showed that the efficiency of this approach even allows for real-time performance. (Variational OF involves capturing the difference between the observed OF and Predicted OF)  The issue addressed: Noise-robust generalization of the Horn and Schunck technique, handled large displacements and complex motion patterns. | 2005 |
| A Database and Evaluation Methodology for Optical Flow | Proposed a new set of benchmarks and evaluation methods for the next generation of OF algorithms. To that end, they have contributed four types of data to test different aspects of OF algorithms:   1. sequences with non-rigid motion where the ground truth flow is determined by tracking fluorescent texture. 2. Realistic synthetic sequences 3. High frame-rate video used to study interpolation error. 4. Modified stereo sequences of static scenes. | 2010 |
| Optical Flow Estimation  (Javier S´anchez1 , Enric Meinhardt-Llopis2 , Gabriele Facciolo) | Implementation of the OF estimation method introduced by Zach, Pock, and Bischof in 2007. This method is based on the minimization of a function containing a data term using the L 1 norm and a regularization term using the total variation of the flow.  Issues addressed: Allowed discontinuities in the flow field while being more robust to noise than the classical Horn Schunk method. | 2013 |
| [Gradient based optical flow estimation.](http://www.cs.utoronto.ca/~jepson/csc420/notes/flowChapter05.pdf)  (David J.Fleet, Yair Weiss) | Mentioned practical issues that some image smoothing is generally useful prior to numerical differentiation (and can be incorporated into the derivative filters). From the first-order Taylor series approximation used to derive. By smoothing the signal, one hopes to reduce the amplitudes of higher-order terms in the image and to avoid some related problems with temporal aliasing.  Explained that Future research is needed to move beyond brightness constancy and smoothness. Detecting and tracking occlusion boundaries should greatly improve optical flow estimation. Similarly, prior knowledge concerning the expected form of brightness variations (e.g., given knowledge of scene geometry, lighting, or reflectance) can dramatically improve optical flow estimation. Brightness constancy is especially problematic over long image sequences where one must expect the appearance of image patches to change significantly. One promising area for future research is the joint estimation appearance and motion, with suitable dynamics for both quantities. | 2005 Sept |

Approach 01

Taylor Series approximation: When taking the optical flow equation by using the approximation of no intensity change, Taylor series approximation is used to remove the common terms. In this section, an investigation is intended to carry on the second-order and higher-order approximations of the Taylor Series.

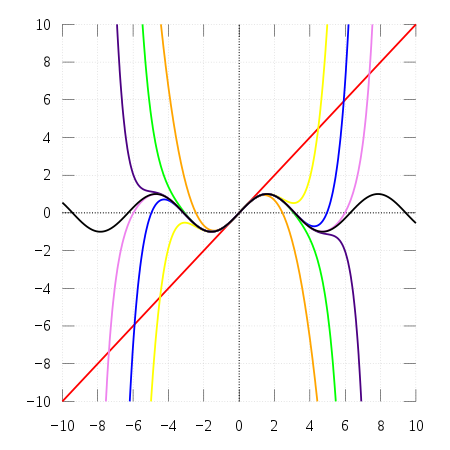
Approach 02

Investigation is intended to carry out on improving the quality of the image sequences through image processing techniques and then inputting them into the optical flow.

Let *I* denote a pixel in a given frame, which is essentially a function of the pixel coordinates & time.

By the Taylor series, any function *f(x)* can be approximated by,

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Now considering the Taylor series of a multivariable function,

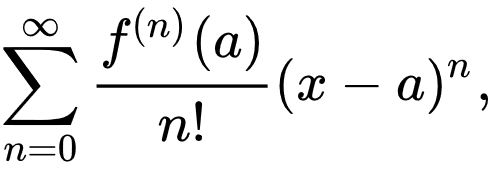
First, consider the linear approximation for *f(x)*

Where *D* is the Jacobian of *f*

This is the first-order Taylor polynomial. (Linear approximation)

Let us find a quadratic approximation for *f(x)* by adding quadratic terms to the linear approximation.

For the univariable function *f(x)* the quadratic term was



Therefore, we need to find the second derivative of the multivariate function *f(x)*

The first derivative of at *x = a* is the Jacobian of *f* at a.

For the second derivative, we take the partial derivatives of the function , which is denoted by the

This is also called the **Hessian Matrix** of *f* denoted by *Hf(x̅).*

Therefore *Hf(x) = DDf(x)*

Hence,

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Now, using the Hessian, the quadratic term can be written by,

Adding this to obtain second order polynomial,

The second order Taylor polynomial is a better approximation for *f* than first order Taylor polynomial.

Now considering the scenario,

Now for the Jacobian & Hessian

By applying back in above approximation,

0

Differentiate w.r.t. t;

Ix Iy It

So, from this we have finally derived our New Optical Flow equation.

In this we can determine Ix and Iy change in the pixel position.

Similarly, It is the gradient along time which we can calculate.

However, are unknown.

Hence B becomes an equation with 2 unknown variables,

We set

Hence B becomes,

We attempt to solve this by several methods, first we’ll focus on Lucas-Kanade method.

**Lucas-Kenade Method**

We have assumed that all neighboring pixels have the same motion.

In here, the neighborhood definition becomes ambiguous, which we define to be a 3 × 3 patch around the point in the case.

all 9 points in the patch have the same motion.

We determine Ix , Iy &,It for these pts

We are now left with 9 equations with 2 unknown variables, which are over determined.

Hence, we use the least square fit method we approximate the system of 9 equations

Consider the points in the selected path to be q1, q2, ……., q9

Then,

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Representing in a matrix,

A V b

We consider xt & yt are parameters to be learnt to determine the best fit line by the variables Ix(q) & Iy(q) by applying examples / data points q1 through q9

We use ordinary least square method for the purpose, where,

ATAv = ATb

v = (AT A)-1 ATb

Clarification: consider a matrix A as follows,

A = -> ATA =

ATA =

ATA =

When applied with the image pixels I def.

ATA =

ATA matrix is often called the structure tensor of the image at the center point p of the patch selected.,

Also

ATb =

Now using these we obtain, for our example

By using the solutions, we determine the complete solution to the problem.

i.e, we know of xt & yt that solves, hence solving the optical flow equations.

We obtain optical flows along the 2- dimensions of the image.