Optical Flow

Optical flow allows for the estimation of depth information relative to the speed and direction of the linear velocity, and rotational velocity for each of the axes in 3D [8].

From: Indoor Navigation Strategies for Aerial Autonomous Systems, 2017

Related terms:

Sewers, Dataset, Histograms, Skin Friction, Motion Estimation, Motion Vector

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Advances in Computers

Pavan Turaga, ... Ashok Veeraraghavan, in Advances in Computers, 2010

4.1 Optical Flow

Optical flow is defined as the apparent motion of individual pixels on the image plane. It often serves as a good approximation of the true physical motion projected onto the image plane. Most methods that compute optical flow assume that the color/intensity of a pixel is invariant under the displacement from one video frame to the next. We refer the reader to Beauchemin and Barron [14] for a comprehensive survey and comparison of optical flow computation techniques. Optical flow provides a concise description of both the regions of the image undergoing motion and the velocity of motion. In practice, computation of optical flow is susceptible to noise and illumination changes. Applications include [15] which used optical flow to detect and track vehicles in an automated traffic surveillance application.

> Read full chapter

Video Surveillance

Joonsoo Lee, Al Bovik, in The Essential Guide to Video Processing, 2009

19.3.1.3 Optical Flow

Optical flow, or motion estimation, is a fundamental method of calculating the motion of image intensities, which may be ascribed to the motion of objects in the scene. Optical flow is an extremely fundamental concept that is utilized in one form or another in most video-processing algorithms. Chapter 3 of this *Guide* is devoted to this topic and so we will not explain it here. Optical-flow methods are based on computing estimates of the motion of the image intensities over time in a video. The flow fields can then be analyzed to produce segmentations into regions, which might be associated with moving objects. Methods for motion-based video segmentation are detailed in Chapter 6 of this *Guide.*

Optical-flow or motion-estimation algorithms can be used to detect and delineate independently moving objects, even in the presence of camera motion. Of course, optical-flow-based techniques are computationally complex, and hence require fast hardware and software solutions to implement. Since optical flow is fundamentally a differential quantity, estimation of it is highly susceptible to noise; ameliorating the noise sensitivity can imply increases in complexity. Therefore, smart camera-based video surveillance systems that use optical-flow calculations of some type must be equipped with substantial computational resources, for example, a dedicated DSP chip, FPGA, or other special-purpose acceleration device. Indeed, it is because such technologies are being introduced to smart camera technology (along with wireless-networking capabilities) that video surveillance systems having significant intelligent capability are being envisioned and realized.

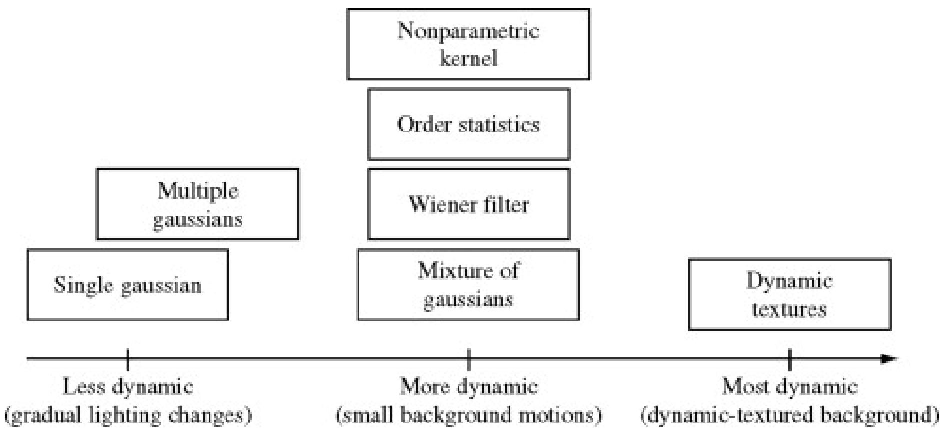

FIGURE 19.6. Summary of appropriate background models as a function of scene complexity.

Table 19.1 tabulates the tradeoffs of the various types of motion and change detection methods, broadly categorized as background modeling, temporal differencing, and optical flow as we have done in the preceding.

TABLE 19.1. Summary of motion/change detection tools.

	Background Modeling	Temporal Differencing	Optical Flow
Advantage	Works for relatively static backgrounds	Adaptable to dynamic backgrounds; easy to implement	Effective ondynamicbackgrounds
Disadvantage	Must select/decide among various statistical modeling assumptions	Does a poor job of entire moving objects; very noise sensitive	Computationally complex; highly noise-sensitive
Complexity	Moderate	Simple	Complex
Usage	Common	Moderate	Infrequent
Augments/augmented by	Statistical modeling and higher level post-processing	Connected component analysis	Special hardware

> Read full chapter

Novel Architectures for Streaming/Routing in Optical Networks

Vincent W.S. Chan, in Optical Fiber Telecommunications (Sixth Edition), 2013

19.10 Summary

OFS exploits the strengths of optics to serve large (sometimes called "elephant") transactions that can be a substantial fraction of the total traffic by providing end-to-end user all-optical access and will enable orders of magnitude in cost reductions and at the same time is energy efficient. This feature separates OFS from quasi-static circuit switching such as GMPLS where optical circuits are not scheduled per user sessions. The per-session scheduling substantially changes the dynamics of the control plane by speeding it up by orders of magnitude. The major hurdle of the architecture is the scalability in network management and control and session scheduling complexity. Thus, the shift toward OFS requires some architectural elements of the network, from the physical to the higher network layers, as well as network management and control, to be redesigned at the fundamental level. The architecture construct in this chapter shows how the physical architecture coupled with a matched media access control protocol can help slow down the control plane and still can operate the network at high efficiency which is critical for low cost and low power operations. The proposed architecture addresses this very important issue by using quasi-static WAN/MAN provisioning to slow down the wide/metro area network control planes by decoupling session-by-session scheduling of cross-flow traffic interior to the core network. The only fast per session process is the scheduling of transmission wavelength and time of transmission of the users, without necessitating any fast reconfigurations of optical switches. Thus, OFS only uses transmitter/receiver wavelength tuning and time of transmission for statistical multiplexing to achieve efficient use of resources, instead of using packet switching for multiplexing in the current IP architecture. With much higher data rates and more agile optical networks on the horizon, it is inevitable that the current network architecture including the control plane will have to be updated. Some simple changes to the network architecture can be implemented then to support OFS with significant cost benefits, especially to large transaction users.

While OFS is more efficient in the WAN, Figure 19.30, and in general for the future Internet architecture, for intra-data center and cloud interconnection, OBS may be more favorable in terms of delays if the fiber plant has enough bandwidths and the transceivers have broad enough tuning range to exploit them. In those cases the utilization of the wavelengths must be kept way below 1/2e. Finally, the future Internet will be very heterogeneous in transaction sizes. While OFS and OBS are suitable for large elephant files, electronic packet switching will, for the foreseeable future, be the transport of choice for small messages. Figure 19.31 attempts to roughly scope the ranges of the preferred transport mechanism for different transaction sizes. The boundaries are sensitive to technologies and architectures they allow.

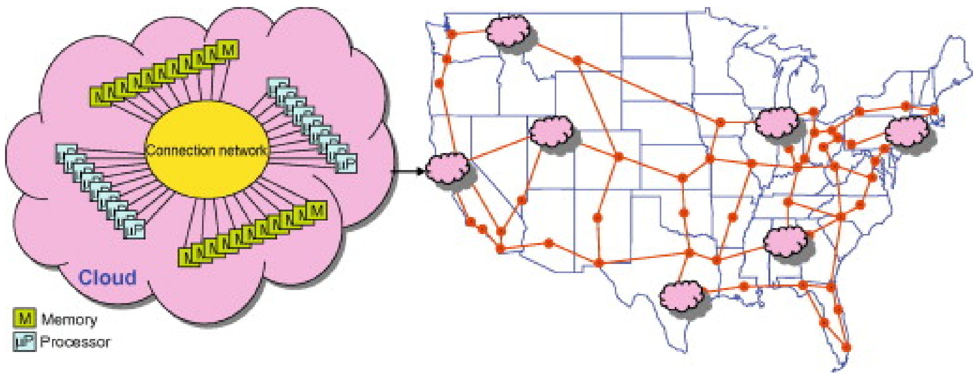

Figure 19.30. Cloud and data center applications of all-optical networks.

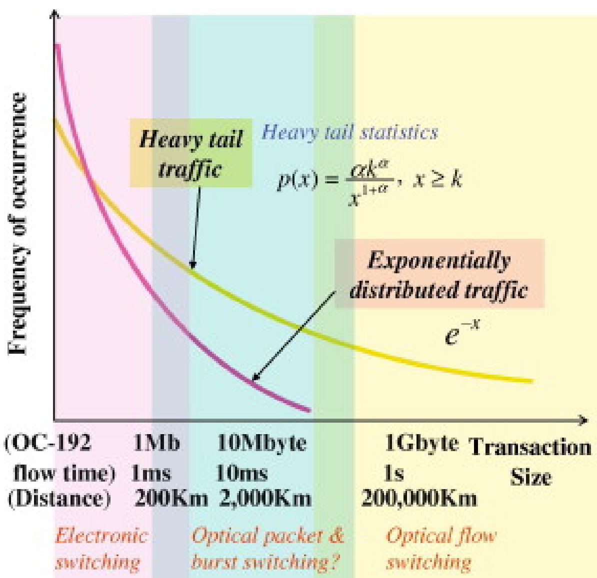

Figure 19.31. Ranges of the preferred transport mechanism for different transaction sizes.

> Read full chapter

Computer Vision for Human–Machine Interaction

Qiuhong Ke, ... Farid Boussaid, in Computer Vision for Assistive Healthcare, 2018

5.3.2.1 Extracting Optical Flow

Optical flow represents the motion of the scene context relative to an observer [26]. For a human gesture, a single frame with only a static scene can introduce ambiguity which makes the inference of the gesture class difficult. The motion of human bodies needs to be exploited for a good understanding of the gesture class. There are many methods of estimating the optical flow between two frames, including differential-based, region-based, energy-based, and phase-based methods [27]. The most widely used method is the differential method [28], which is based on the assumption of image brightness constancy. Given a video sequence, let the intensity of a voxel at position of the tth frame be . According to the brightness constancy assumption, the intensity of the voxel remains the same despite small changes of position and time period. More specifically,

(5.1)

where is the small change of the movement. can be expressed with a Taylor series expansion:

(5.2)

Therefore,

(5.3)

(5.4)

where , are two components of the optical flow of the voxel .

Once the optical flow is computed, it can be used to learn video-level representation for gesture recognition. Traditional methods used histograms of optical flow to represent the temporal information [29]. Using the histogram can result in the lose the structure of the data [30]. We represent optical flow as images that are then fed to a CNN to learn high-level temporal features for gesture recognition.

> Read full chapter

Data Fusion for UAV Localization

Pedro Castillo-García, ... Pedro García Gil, in Indoor Navigation Strategies for Aerial Autonomous Systems, 2017

Motion Parameters

Optical flow allows for the estimation of depth information relative to the speed and direction of the linear velocity, and rotational velocity for each of the axes in 3D [8]. Then optical flow is created by the translational and the rotational movements of a point in the camera reference frame. Considering that the camera imaging geometry can be modeled as a perspective projection [9], the point in the scene is projected onto in the image plane with

where is the focal length. The model equation for instantaneous or differential motion reads [8]:

(5.3)

where is the camera's linear velocity and is the rotational velocity. This equation relates the motion parameters of the point to the measurable optical flow vector. Notice from Eq. (5.3) that only translational flow depends on the linear velocity and that rotational components do not depend on the depth of the point.

In our practical implementation, to determinate the linear velocity of the aerial vehicle from the optical flow, we take into account that the camera shares the movements of the UAV, i.e., the camera is fixed on the UAV so that it has no degrees of freedom. Therefore, the camera's linear velocity is equivalent to the UAV's linear velocity. Moreover, we consider that the UAV's angular velocity is small enough so that the rotational components of the OF can be neglected. Nevertheless, several tests of the influence of the rotational component were carried out, and they are described in Sect. 5.5 of this chapter.

> Read full chapter

Academic Press Library in signal Processing

Béatrice Pesquet-Popescu, ... Frédéric Dufaux, in Academic Press Library in Signal Processing, 2014

5.02.3.3 Discussion

Optical flow approaches result in a dense motion vector field (one vector per pixel), which is qualitatively interesting for motion analysis applications. However, they also have several weaknesses:

- The derivation of the optical flow equation is based on a first-order Taylor series expansion. This only holds under the hypothesis that the motion between two frames is small.
- The equations are written for continuous-time and continuous-space variables and require to estimate the image gradient. For solving them, we need to discretize these variables. However, this sampling process introduces errors in the solution. In particular, gradient computation is sensitive to noise and is therefore subject to errors.
- The smoothness constraint (Horn-Schunck) or the local uniformity constraint (Lucas-Kanade) results in a poor accuracy along moving object boundaries.

In order to address the above shortcomings, numerous advances have been proposed resulting in improved performance.

Instead of the above formulation based on an L2 norm, the L1 norm is also a frequent choice [15], both for the optical flow equation and for the additional constraint (e.g., smoothness). Such cases are referred to as Total Variation (TV) methods.

A model to handle changes in illumination and blur is proposed in [16]. It also includes spatial weighting of the smoothness constraint. Anisotropic smoothness weighting is considered in [17]. The method also applies different weighting to color channels in the HSV color space.

A novel extended coarse-to-fine refinement framework is introduced in [18]. The reliance on the initial flow estimates propagated from a coarser level is reduced. Hence, motion details are better preserved at each scale. An adaptation of the objective function to handle outliers and a new optimization procedure are also proposed.

For a more detailed and in-depth tutorial on optical flow techniques, the reader is referred to [4]. An extensive performance comparison of several algorithms is given in [19]. More recently, a new set of benchmarks and evaluation methods for optical flow techniques have been introduced in [20]. A taxonomy of optical flow algorithms is also presented, along with a discussion of recent works. At the time of this writing, the method by Xu et al. [18] is one of the best performing techniques reported in the on-line optical flow evaluation database at http://vision.middlebury.edu/flow/.

From a video coding perspective, the fact that a dense motion field is obtained is not necessarily a positive point. Indeed, this field has to be encoded, which may result in a high bit rate overhead.

> Read full chapter

Digital Video Processing

John W. Woods, in Multidimensional Signal, Image, and Video Processing and Coding (Second Edition), 2012

Optical Flow Methods

Optical flow is a differential method that works by approximating the derivatives rather than the function error itself, as in block matching. It is a least-squares approximation to the *spatiotemporal constraint equation*,

(11.2–4)

which is derived by partial differentiation of the optical flow equation (11.2–1), rewritten as a function of real variables (x, y) with velocity parameters v_x and v_y,

Because of noise in the frame, (11.2–4) is then subjected to least squares approximation to give the optical flow velocity estimate. Specifically, we form the error criteria

to be minimized over local regions.

In practice, a smoothing term must be added to this error term to *regularize* the estimate, which otherwise would be much too rough—i.e., too much high-frequency energy in the estimate . In the Horn and Schunck method [13], a gradient smoothness term is introduced via a Lagrange multiplier as

which, for large values of the positive parameter , makes the velocity estimate change slowly as a function of the spatial variables x and y.

Integrating over the area of the image, we get the total error to be minimized as

We seek the minimizing velocity vector

The calculus of variations is then used to find the minimum of this integral in terms of the unknown functions $v_x(x, y, t)$ and $v_y(x, y, t)$ for each fixed frame t. The resulting equations are then approximated using first-order approximations for the various derivatives involved. Longer digital filters may provide improved estimates of these derivatives of the, assumed bandlimited, analog image frames [14]. An iterative solution is then obtained using Gauss-Seidel iterations.

While this estimate has been used extensively in computer vision, it is not often used in video compression because of its rather dense velocity estimate. However, optical flow estimates have been used extensively in video filtering, where the need to transmit the resulting motion vectors does not occur. There it can give a smooth and consistent performance, with few motion artifacts. A modern optical flow method is presented in Section 5.4 of Chapter 5 in *The Essential Guide to Video* [15]. The main problem with optical flow methods is that the smoothness of their motion does not allow discontinuities of motion across object boundaries in the scene.

> Read full chapter

A Neural Network Model for Optical Flow Computation

Hua Li, Jun Wang, in Neural Networks and Pattern Recognition, 1998

ABSTRACT

Optical flow computation in dynamic image processing can be formulated as a minimization problem by a variational approach. Because solving the problem is computationally intensive, we reformulate the problem in a way suitable for neural computing. In this paper, we propose a recurrent neural network model that may be implemented in hardware with many processing elements (neurons) operating asynchronously in parallel to achieve a possible real-time solution. We derive and prove the properties of the reformulation, as well as analyze the asymptotic stability and convergence rate of the proposed neural network. Experiments using both the test patterns and the real laboratory images are conducted.

> Read full chapter

Motion

E.R. Davies, in Computer and Machine Vision (Fourth Edition), 2012

19.11 Bibliographical and Historical Notes

Optical flow has been investigated by many workers over a good many years (see, e.g., Horn and Schunck, 1981; Heikkonen, 1995). A definitive account of the mathematics relating to FOE appeared in 1980 (Longuet-Higgins and Prazdny, 1980). In fact, foci of expansion can be obtained either from the optical flow field or directly (Jain, 1983). The results of Section 19.5 on time-to-adjacency analysis stem originally from the work of Longuet-Higgins and Prazdny (1980), which provides some deep insights into the whole problem of optical flow and the possibilities of using its shear components. Note that numerical solution of the velocity field problem is not trivial; typically, least-squares analysis is required to overcome the effects of measurement inaccuracies and noise, and to finally obtain the required position measurements and motion parameters (Maybank, 1986). Overall, resolving ambiguities of interpretation is one of the main problems and challenges of image sequence analysis (see Longuet-Higgins (1984) for an interesting analysis of ambiguity in the case of a moving plane).

Unfortunately, the substantial and important literature on motion, image sequence analysis, and optical flow, which impinges heavily on 3-D vision, could not be discussed in detail here for reasons of space. For seminal work on these topics, see, for example, Huang (1983), Jain (1983), Nagel (1983, 1986)Nagel (1983)Nagel (1986), and Hildreth (1984).

For early work on the use of Kalman filters for tracking, see Marslin et al. (1991). For the huge amount of more recent work on tracking and surveillance of moving objects, including the tracking of people and vehicles, see Chapters 22 and 23Chapter 22Chapter 23 (in fact, Chapter 23 is especially concerned with monitoring moving objects from within vehicles). For recent references on tracking, particle filters, and detection of moving objects, see the bibliographies in Chapters 22 and 23Chapter 22Chapter 23.

For further references on invariant features for wide baseline matching, see Chapter 6.

> Read full chapter

Motion

E.R. Davies, in Computer Vision (Fifth Edition), 2018

20.11 Bibliographical and Historical Notes

Optical flow has been investigated by many workers over a good many years: See, e.g., Horn and Schunck (1981) and Heikkonen (1995). A definitive account of the mathematics relating to FoE appeared in 1980 (Longuet-Higgins and Prazdny, 1980). In fact, foci of expansion can be obtained either from the optical flow field or directly (Jain, 1983). The results of Section 20.5 on time-to-adjacency analysis stem originally from the work of Longuet-Higgins and Prazdny (1980) which provides some deep insights into the whole problem of optical flow and the possibilities of using its shear components. Note that numerical solution of the velocity field problem is not trivial; typically, least-squares analysis is required to overcome the effects of measurement inaccuracies and noise, and to finally obtain the required position measurements and motion parameters (Maybank, 1986). Overall, resolving ambiguities of interpretation is one of the main problems and challenges of image sequence analysis [see Longuet-Higgins (1984) for an interesting analysis of ambiguity in the case of a moving plane].

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For early work on the use of Kalman filters for tracking, see Marslin et al. (1991). For the huge amount of more recent work on tracking and surveillance of moving objects, including the tracking of people and vehicles, see Chapters 22 and 23Chapter 22Chapter 23 (in fact, Chapter 23: In-Vehicle Vision Systems is especially concerned with monitoring moving objects from within vehicles). For recent references on tracking, particle filters, and detection of moving objects, see the bibliographies in Chapters 22 and 23Chapter 22Chapter 23.

For further references on invariant features for wide baseline matching, see Chapter 6, Corner, Interest Point, and Invariant Feature Detection.

> Read full chapter