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Optic flow estimation by support vector regression

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Abstract

In this paper, we describe an approach to estimate optic flow from an image sequence based on Support Vector Regression (SVR) machines with an adaptive ε-margin. This approach uses affine and constant models for velocity vectors. Synthetic and real image sequences are used in order to compare results of the SVR approach against other well-known optic flow estimation methods. Experimental results on real traffic sequences show that SVR approach is an appropriate solution for object tracking.

Keywords: Optic flow; Motion estimation; Support vector regression

1. Introduction

In the real world scene, we have the ability to detect and identify objects with different motions instantaneously. This is due to our perception system which has several levels of image processing. Thus, thanks to this faculty perception, we drive our car with much ease.

In automatic drive assistance domain, an incar camera is used to observe the environment scene and to estimate the car movements. Optic flow estimation method is usually used in order to compute the apparent motion in an image sequence. Indeed, optic flow method is sensitive to noise, large displacements, intensity discontinuities, etc. (Barnum et al., 2003). Moreover, it is considered as an ill-posed problem (aperture problem). Therefore, it is important to develop robust estimation algorithms to overcome these problems.

In computer vision literature, there are three families of optic flow estimation algorithms: frequency–domain motion, block-based motion and gradient-based motion (Barron et al., 1994). Since 1981, many robust estimators have been implemented to compute optic flow like: least squares (LS) (Lucas and Kanade, 1981), least trimmed squares (LTS) (Ye and Haralick, 2000), least median squares (LMS or LMedS) (Bab-Hadiashar and Suter, 1998), M-estimator (Black and Anandan, 1993), quick maximum density power estimator with a variable bandwidth (vbQMDPE) (Wang and Suter, 2003), etc.

Support Vector Machines (SVM) have been widely used in classification domain. In this paper, we propose to use its extension Support Vector Regression (SVR) machines to estimate optic flow in dynamic vision. Compared with classical local estimators, SVR possesses two advantages: a unique optimization solution and a large robustness against outliers (Vapnik, 1995, 1998).

The following section briefly describes optic flow principle. Section 3 presents the SVR approach for optic flow estimation purpose. In Section 4, we are going to evaluate the performance and show some results of the proposed approach using synthetic and real image sequences.

2. Optic flow principle

Optic flow is the apparent motion in an image sequence which is based on the hypothesis that the intensity is constant between two successive images. In fact, it gives the possibility to perceive the virtual motion of an object which is not necessary its real motion (Horn and Schunck, 1981).

The main assumption in this context is that a pixel (x, y) keeps its intensity along its trajectory, that is to say:

$$I(x, y, t) = I(x + \mathrm{d}x, y + \mathrm{d}y, t + \mathrm{d}t). \tag{1}$$

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The finite expansion of Eq. (1) to its first-order Taylor serie gives us:

$$I(x+\mathrm{d}x, y+\mathrm{d}y, t+\mathrm{d}t) \cong I(x,y,t) + I_x\mathrm{d}x + Iy\mathrm{d}y + I_t\mathrm{d}t, \tag{2}$$

where $Ix = \partial I/\partial x$, $I_y = \partial I/\partial y$ and $I_t = \partial I/\partial t$.

By replacing Eqs. (1) in (2), we obtain:

$$I_x\mathrm{d}x + I_y\mathrm{d}y + I_t\mathrm{d}t = 0$$

which can also be written as

$$I_x\frac{\mathrm{d}x}{\mathrm{d}t} + I_y\frac{\mathrm{d}y}{\mathrm{d}t} + I_t = 0. \tag{3}$$

Eq. (3) can be rewritten in the form of a scalar product:

$$(I_x\ I_y).\begin{pmatrix} \frac{\mathrm{d}x}{\mathrm{d}t} \\ \frac{\mathrm{d}y}{\mathrm{d}t} \end{pmatrix} + I_t = 0, \tag{4}$$

where $(\mathrm{d}x/\mathrm{d}t, \mathrm{d}y/\mathrm{d}t)^{\mathrm{T}}$ is the velocity vector which represents the motion of the pixel (x,y) and $(I_x, I_y)^{\mathrm{T}}$ represents the spatial intensity gradient vector.

Equation (4) is called the "optic flow constraint" (OFC) and its principle is illustrated in Fig. 1.

Usually, there are two velocity models: *Constant model and an Affine model*.

- Constant model:

$$\begin{pmatrix} \frac{\mathrm{d}x}{\mathrm{d}t} \\ \frac{\mathrm{d}y}{\mathrm{d}t} \end{pmatrix} = \begin{pmatrix} a \\ b \end{pmatrix}. \tag{5}$$

- Affine model:

$$\begin{pmatrix} \frac{\mathrm{d}x}{\mathrm{d}t} \\ \frac{\mathrm{d}y}{\mathrm{d}t} \end{pmatrix} = \begin{pmatrix} a_0 & a_1 & a_2 \\ b_0 & b_1 & b_2 \end{pmatrix}.\begin{pmatrix} x \\ y \\ 1 \end{pmatrix}. \tag{6}$$

In the following sections, the velocity affine model will be used.

Replacing Affine model of Eq. (6) in Eq. (4) gives us:

$$(I_x\ I_y).\begin{pmatrix} a_0.x + a_1.y + a_2 \\ b_0.x + b_1.y + b_2 \end{pmatrix} + I_t = 0 \tag{7}$$

which can be developed as:

$$a_0.x.I_x + a_1.y.I_x + a_2.I_x + b_0.x.I_y + b_1.y.I_y + b_2.I_y + I_t = 0. \tag{8}$$

Eq. (8) can be seen as scalar production as shown in Eq. (9):

$$(a_0\ a_1\ a_2\ b_0\ b_1\ b_2).\begin{pmatrix} x.I_x \\ y.I_x \\ I_x \\ x.I_y \\ y.I_y \\ I_y \end{pmatrix} + I_t = 0. \tag{9}$$

If we denote $\vec{X} = (x.I_x, y.I_x, I_x, x.I_y, y.I_y, I_y)^{\mathrm{T}}$ and $\vec{W} = (a_0, a_1, a_2, b_0, b_1, b_2)^{\mathrm{T}}$, Eq. (9) can be written in a vector form:

$$\vec{W}^{\mathrm{T}}.\vec{X} + I_t = 0, \tag{10}$$

where $\vec{W}$ is the vector of affine parameters which must be estimated by the SVR approach.

Since Eq. (9) contains derivative elements, it is necessary to smooth the image sequence before estimating them. The smoothing procedure is composed of two steps (Fig. 2): first, applying for each dimension a gaussian filter with $\sigma = 1.5$, and then computing the gradient intensity vector based on the smoothed image sequence. Intensity gradients I_x, I_y and I_t are obtained by a classical oriented filter (Barron et al., 1994), defined by

$$\hat{I}_t = \frac{1}{12} \times [-I_{t-2} + 8I_{t-1} - 8I_{t+1} + I_{t+2}],$$

$$\hat{I}_x = \frac{1}{12} \times [-I_{x-2} + 8I_{x-1} - 8I_{x+1} + I_{x+2}],$$

$$\hat{I}_y = \frac{1}{12} \times [-I_{y-2} + 8I_{y-1} - 8I_{y+1} + I_{y+2}].$$

The data set used for SVR estimation procedure of a given pixel (x,y) of the current image t is composed of N ($N = 25$) couples $(I_{t_i}, \vec{X}_i)$ where i is a pixel of the neighborhood window (5×5) centered on (x,y) at time t:

$$\vec{W}^{\mathrm{T}}.\vec{X}_i = -\hat{I}_{t_i},$$

$$r_i = \vec{W}^{\mathrm{T}}.\vec{X}_i + I_{t_i}, \tag{11}$$

where r_i is the residual value which is equal to $I_{t_i} - \hat{I}_{t_i}$.

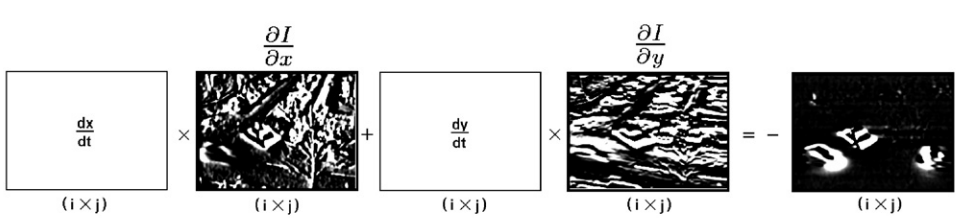

Fig. 1. Illustration of optic flow constraint applied on Hamburg's taxi example.