Evaluation of three optical flow-based observation models for tracking

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Abstract

In this paper, we study the use of optical flow as a characteristic for tracking. We analyze the behavior of three flow-based observation models for particle filter algorithms, and compare the results with the ones obtained by a well-known, gradient based, observation model. In theory, optical flow could be used directly to displace an object model, but in practice flow estimation techniques lack the necessary accuracy. In view of the fact that probabilistic tracking algorithms enable imprecise or incomplete information to be handled naturally, these models have been used as a natural means of incorporating flow information into the tracking.

1. Introduction

Probabilistic models applied to tracking enable us to estimate the *a posteriori* probability distribution, $p(\mathbf{X}|\mathbf{Z})$, of the set of valid configurations for the object to be tracked, represented by a vector $\mathbf{X}$, from the set of measurements $\mathbf{Z}$ taken from the images of the sequence. The likelihood in the previous instant is combined with a dynamical model giving rise to the *a priori* distribution in the current instant, $p(\mathbf{X})$. The relation between these distributions is given by Bayes' Theorem:

$$p(\mathbf{X}|\mathbf{Z}) \propto p(\mathbf{X}) \cdot p(\mathbf{Z}|\mathbf{X})$$

In order to estimate $p(\mathbf{Z}|\mathbf{X})$, known as the *observation probability*, we will define several *observation models*, based on the optical flow of the sequence. We will also check their validity within a scheme of particle filter tracking, and compare their performance with the model proposed in [1].

2. Dynamical model

The tracking task involves localizing, in each frame of a sequence, the object associated to a state vector that characterizes evidence of the presence of a specific configuration of the model in question. Other authors have successfully used characteristics such as the gradient [1] or intensity distributions [10]. The model which represents the dynamical model of the object will provide an *a priori* distribution of all the possible configurations at the instant t_k , $p(\mathbf{X}(t_k))$, from the estimated distributions in previous instants of time. In this paper, a second-order dynamical model has been used in which the two previous states of the object model are considered. This is equivalent to taking a first-order dynamical model with a state vector for the instant t_k of the form [1]

$$\mathcal{X}_{t_k} = [\mathbf{X}_{t_{k-1}}, \mathbf{X}_{t_k}]^T$$

The integration of the *a priori* distribution $p(\mathbf{X})$ with the set $\mathbf{Z}$ of the evidences present in each image, in order to obtain the *a posteriori* distribution $p(\mathbf{X}|\mathbf{Z})$, is obtained with Bayes' Theorem. This fusion of information can be performed, if the distributions are Gaussian, by using Kalman's Filter [4]. However, in general, the distributions involved in the process are not Gaussian and multimodal [2]. Sampling methods for modelling this type of distribution [3] have shown themselves to be very useful, and *particle filter* algorithms [1, 10] based on sets of weighted random samples, enable their propagation to be performed effectively.

3. Observation models

3.1. Observation model based on intensity restrictions

This model, described more in detail in [7], uses a technique derived from the Lucas-Kanade algorithm[5], and takes advantage of knowledge about the position of the flow discontinuities predicted by the object model.

Let $\mathbf{x} = f(\mathbf{X}_{t_k}; \mathbf{m})$ (where $\mathbf{X}_{t_k}$ defines the specific configuration of the object model, and $\mathbf{m}$ is the parameter vector which associates each point within the model with a point on the image plane), a point belonging to the model outline at the instant t_k . Let S be a neighborhood of $\mathbf{x}$ subdivided in S_i and S_e (corresponding respectively to the parts of the neighborhood which remain towards the interior and exterior of the outline of the object), and $\mathbf{d}(\mathcal{X}_{t_k}, \mathbf{m})$ be calculated using the expression:

$$\mathbf{d}(\mathcal{X}_{t_k}, \mathbf{m}) = f(\mathbf{X}_{t_k}; \mathbf{m}) - f(\mathbf{X}_{t_{k-1}}; \mathbf{m}) \quad (1)$$

We then consider the optical flow constant in S_i and S_e respectively, and use the system of equations proposed in [5] to obtain $\mathbf{f}_{S_x} = (f_x, f_y)$, where S_x shall be S_i or S_e respectively. The temporal derivatives of the image are computed as

$$I_t(\mathbf{x}) = I^{(k)}(\mathbf{x} + \mathbf{d}(\mathcal{X}_{t_k}, \mathbf{m})) - I^{(k-1)}(\mathbf{x})$$

In this way, two different flow estimations are obtained, $\mathbf{f}_{S_i}(\mathcal{X}_{t_k}, \mathbf{m})$ and $\mathbf{f}_{S_e}(\mathcal{X}_{t_k}, \mathbf{m})$, corresponding to the inner and outer area of the neighborhood of $\mathbf{x}$, respectively.

The quadratic differences with the expected flow (which in this case equals zero) are equivalent to the squared norm of the estimated flow vectors:

$$\begin{aligned} Z_{S_i}(\mathcal{X}_{t_k}, \mathbf{m}) &= \|\mathbf{f}_{S_i}(\mathcal{X}_{t_k}, \mathbf{m})\|^2 \\ Z_{S_e}(\mathcal{X}_{t_k}, \mathbf{m}) &= \|\mathbf{f}_{S_e}(\mathcal{X}_{t_k}, \mathbf{m})\|^2 \end{aligned} \quad (2)$$

It should be noted that if the point $\mathbf{x}$ is really placed on an optical flow discontinuity, and the flow in S_i matches with $\mathbf{d}(\mathcal{X}_{t_k}, \mathbf{m})$, the value of Z_{S_i} must be close to zero and the value of Z_{S_e} must be considerably greater. Using the following expression, these values may be combined and a value of $Z(\mathcal{X}_{t_k}, \mathbf{m})$ may therefore be obtained:

$$Z(\mathcal{X}_{t_k}, \mathbf{m}) = \frac{Z_{S_e}(\mathcal{X}_{t_k}, \mathbf{m})}{Z_{S_e}(\mathcal{X}_{t_k}, \mathbf{m}) + Z_{S_i}(\mathcal{X}_{t_k}, \mathbf{m})} \quad (3)$$

The value of $Z(\mathcal{X}_{t_k}, \mathbf{m})$ satisfies the following properties:

- $0 \leq Z(\mathcal{X}_{t_k}, \mathbf{m}) \leq 1$
- If $Z_{S_e}(\mathcal{X}_{t_k}, \mathbf{m}) \gg Z_{S_i}(\mathcal{X}_{t_k}, \mathbf{m})$, then $Z(\mathcal{X}_{t_k}, \mathbf{m}) \rightarrow 1$, which indicates that the adjustment is much better in S_i than it is in S_e , and therefore the point must be placed exactly in a flow discontinuity, in which the inner area coincides with the displacement predicted by the model.
- If $Z_{S_e}(\mathcal{X}_{t_k}, \mathbf{m}) \ll Z_{S_i}(\mathcal{X}_{t_k}, \mathbf{m})$, then $Z(\mathcal{X}_{t_k}, \mathbf{m}) \rightarrow 0$. The adjustment is worse in the inner area than it is in the outer area, and therefore the estimated flow does not match the model's prediction.

- If $Z_{S_e}(\mathcal{X}_{t_k}, \mathbf{m}) = Z_{S_i}(\mathcal{X}_{t_k}, \mathbf{m})$, then the adjustment is the same in the inner area as it is in the outer area, and therefore the flow adequately matches the displacement predicted by the model, but it is impossible to guarantee that it is placed on a flow discontinuity. In this case, $Z(\mathcal{X}_{t_k}, \mathbf{m}) = 1/2$.

We will consider that the presence probability of the measurements obtained for the image, since they have been caused by the point of the outline corresponding to the vector $\mathbf{m}$ of the sample in question, defined by the vector $\mathcal{X}_{t_k}$, must be proportional to the function $Z(\mathcal{X}_{t_k}, \mathbf{m})$ computed previously,

$$p(\mathbf{Z}|\mathcal{X}_{t_k}, \mathbf{m}_i) \propto Z(\mathcal{X}_{t_k}, \mathbf{m}_i) \quad (4)$$

and that, given the independence between the different points of the outline,

$$p(\mathbf{Z}|\mathcal{X}_{t_k}) \propto \prod_i Z(\mathcal{X}_{t_k}, \mathbf{m}_i) \quad (5)$$

with $\mathbf{m}_i$ being the vector which identifies the i -nth point on the outline of the model.

3.2. Observation model based on similarity measures

If the model prediction about the object is good and the intensity maps corresponding to the neighborhood of each point are superimposed, the inner part of the model must fit better than the outer part [8]. We can therefore use similarity measurements to model the observation probability $p(\mathbf{Z}|\mathbf{X})$.

Let $\mathbf{x} = f(\mathbf{X}_{t_k}; \mathbf{m})$ be a point belonging to the model outline at the instant t_k , let S be a neighborhood of $\mathbf{x}$ subdivided in turn into S_i and S_e , let $\mathbf{d}(\mathcal{X}_{t_k}, \mathbf{m})$ be calculated from expression (1), and let $I^{(k-1)}$ and $I^{(k)}$ be images corresponding to the instants of time t_{k-1} and t_k . The quadratic errors are therefore computed in the following way:

$$\begin{aligned} Z_{S_i}(\mathbf{X}_{t_k}, \mathbf{m}) &= \sum_{S_i} W(\mathbf{x}) \left(I^{(k-1)}(\mathbf{x}) - I^{(k)}(\mathbf{x} - \mathbf{d}(\mathcal{X}_{t_k}, \mathbf{m})) \right)^2 \\ Z_{S_e}(\mathbf{X}_{t_k}, \mathbf{m}) &= \sum_{S_e} W(\mathbf{x}) \left(I^{(k-1)}(\mathbf{x}) - I^{(k)}(\mathbf{x} - \mathbf{d}(\mathcal{X}_{t_k}, \mathbf{m})) \right)^2 \end{aligned} \quad (6)$$

where $W(\mathbf{x})$ is a weighting function. Two non negative magnitudes are obtained, that may be combined using expression (3), in order to obtain a value of $Z(\mathcal{X}_{t_k}, \mathbf{m})$.

Figure 1. First frame of the two sequences used for the experiments.

3.3. Observation model based on optical flow

Let us suppose that an optical flow estimate $\mathbf{v}$ is available for the image I in the instant t_k . The following error function may be defined [6], with $S \subseteq I$ being an area inside the image:

$$Z_S(\mathbf{v}; \mathbf{d}) = \sum_{(x,y) \in S} W(x,y) \|\mathbf{v}(x,y) - \mathbf{d}(x,y)\|^2 \quad (7)$$

where $W(x,y)$ is a weight function and $\mathbf{d}(x,y)$ is derived from equation (1). This measurement will always be non-negative and will only be equal to zero when the flow vectors are perfectly adjusted to the displacement predicted by the model.

Being S a neighborhood of $f(\mathbf{X}_{t_{k-1}}; \mathbf{m})$, the measurement (7) would be:

$$Z_S(\mathcal{X}_{t_k}, \mathbf{m}) = \sum_{(x,y) \in S} W(x,y) \|\mathbf{v}(x,y) - \mathbf{d}(\mathcal{X}_{t_k}, \mathbf{m})\|^2 \quad (8)$$

We subdivide S in two areas as before, S_i and S_e , and therefore compute $Z_{S_i}(\mathcal{X}_{t_k}, \mathbf{m})$ and $Z_{S_e}(\mathcal{X}_{t_k}, \mathbf{m})$. Using expression (3), we compute $Z(\mathcal{X}_{t_k}, \mathbf{m}_i)$.

4. Experiments

We have used two image sequences, with a length of 10 seconds, at 25 frames per second, 320×240 pixels, and 8 bits per band and pixel. These sequences (figure 1) correspond to the movement of a hand over a background with and without clutter. Results can be downloaded from <http://wwwdi.ujaen.es/~mlucena/invest.html>.

In order to model the hand, we have used two spline-based contour models. For the first, 20 points/normals are selected, and 18 for the second. The second-order dynamical model for each sequence has been learnt using the multidimensional algorithm proposed in [1].

Model	Parameters
Blake	200 samples, $\sigma = 3$, First sequence: $\alpha = 0.025$ Second sequence: $\alpha = 0.055$
Intensity Restrict.	200 samples, 7x7 Neigh.
Similarity	200 samples, 5x5 Neigh.
Optical Flow	200 samples, Proesmans algorithm $W(x,y) = \nabla I(x,y) $

Table 1. Parameters used for the experiments.

Figure 2. Set of points selected from the first sequence.

We have used the CONDENSATION algorithm with the three proposed models and the contour-normals model (Blake) proposed in [1]. The parameters used for each model and sequence are depicted in table 1. In order to estimate the optical flow for using with the last observation model, we have used the algorithm proposed in [9]. The weighted average of the distribution obtained is used as the estimated position of the tracked object.

In order to measure the performance of the proposed models, we have proceeded as follows. Given the initial frame of each sequence, we have used the Harris operator to obtain a number of points, and manually selected five points placed on the contour of the object of interest (figure 2). We have then located the corresponding points for the entire sequence. When the tracking process is finished, we compute the mean euclidean distance between each point and the position estimated by the tracker for that point. The results obtained are in figure 3.

5. Discussion and conclusions

The observation model based on contour normals presents better results for the first sequence, but for the sec-

Figure 3. Results.

and loses the object in a significant number of frames. This is due to the presence of a significant number of edges outside the object, giving rise to a number of local maxima in the observation model.

The intensity restrictions based observation model performs slightly better for the second sequence than for the first. This is due to the absence of texture outside the object, that difficults the estimation of the optical flow. We can see that the model is distracted in the middle part of the sequence. This is caused by an ambiguity caused by the hand's shadow, making impossible to separate it from the hand attending only to the optical flow. This phenomenon also occurs, although in less degree, with the other two observation models.

The performance of the similarity-based observation model is very good for the two sequences. This demonstrates that the presence of clutter is not a problem for this model, in opposition to the results obtained with the Blake's model.

The optical-flow based observation model gives better results for the first sequence. At the beginning of the second sequence, there is mainly horizontal displacement of the object, and the absence of optical flow discontinuities in

the arm-hand joint causes some difficulties for the model in order to detect such movements. Nevertheless, the model doesn't loses completely the object.

The experiments presented here suggest that the optical flow is a valid characteristic in order to perform tracking tasks, and can give better results than gradient based models in presence of clutter. Of the three presented observation models, the one based on similarity measures gives the best results, although there are inherent limitations to those models, inherited from the optical flow estimation problem itself.

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