ADAPTIVE GATING IN GAUSSIAN BAYESIAN MULTI-TARGET TRACKING.

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ABSTRACT

Bayesian target tracking methods consist in filtering successive measurements coming from a detector. Linear and nonlinear Gaussian Bayesian filters are well adapted to estimate the successive *a posteriori* state distributions of a single moving target from a sequence of observations. However, when tracking several targets in a cluttered environment the previous techniques must be combined with dedicated procedures for validating and associating the measurements to their predictions. Gating validation techniques are used to increase reliability of the association technique by retaining only the measurements that could be originated from predicted measurements. In standard techniques, the only constrain imposed on the gate is to contain the correct measurement. However, as the shape of the validation gate is related to the covariance of the transition noise, it is of major importance to estimate it in a reliable manner. In this paper, we therefore review several methods to update the covariance of transition noise and we propose a new one that enables the validation gate to be adapted both to the smoothly evolving dynamic of a moving target and to an abruptly changing dynamic. All the methods are compared for performance on microscopy image sequences which typically contain objects that abruptly change their behaviors.

1. INTRODUCTION

Bayesian target tracking methods consist in filtering successive measurements coming from a detector. To estimate the successive *a posteriori* state distributions from a sequence of observations of a single moving target , methods like linear Gaussian Bayesian filter as Kalman Filter (KF)[1] and non-linear Gaussian Bayesian filter as Extended Kalman Filter (EKF) [2] or Interacting Multiple Model estimator (IMM) [3] are well suited. When tracking several targets in a cluttered environment, like in video microscopy sequences such as the one in Fig.1, the validation and association of measurement becomes an issue, however, and the previous techniques must be combined with dedicated procedures. Whether one uses probabilistic [4, 2, 5] or non-probabilistic [2, 5, 6] data association techniques, a validation gate is set around the predicted measurements to ensure that the association stage will pick up candidates only amongst the valid ones. In Probabilistic Data Association techniques the consistency of the validation gate is of major importance since it reduces the risk to take into account persistent clutter in the combined residual. In applications dealing with multi-target tracking in clutter, this validation gate is also essential to decide whether an object has been detected or not: in the situation when no measurement is found inside the validation gate, one is sure (with a given probability) that the object has disappeared or has escaped detection. In this paper, we address the problem of adaptively modifying the validation gate to adapt it to the evolving and abruptly changing dynamics of a moving target. In section 2, we recall the principle of Gaussian Bayesian filter. In section 3, we present several techniques to update the transition noise covariance and introduce our new method. Section 5 presents results on the comparison of these methods on the same experiment, and conclusions are drawn in the last section.

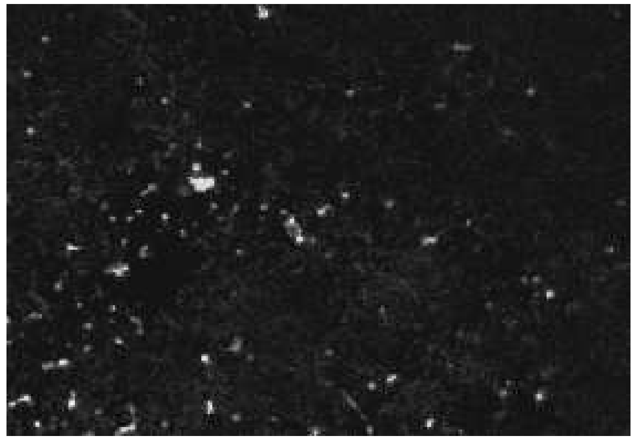

Fig. 1. Typical fluorescent spots in a video microscopy sequence.

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2. GAUSSIAN BAYESIAN ESTIMATION

The problem of tracking can be represented by a state-space approach [2, 7] where the evolution of each object is viewed as a sequence of hidden states $\{\mathbf{x}_t, t \in \mathbb{N}\}$. For non linear transition and observation models with additive Gaussian random noises, the system can be written as:

$$\mathbf{x}_t = f_t(\mathbf{x}_{t-1}) + \nu_t \quad (1)$$
$$\mathbf{z}_t = h_t(\mathbf{x}_t) + \mu_t \quad (2)$$

where ν_t and μ_t are zero mean uncorrelated gaussian random variables. This system is a general framework for KF, EKF and IMM. When f_t and h_t are linear it can be written:

$$\mathbf{x}_t = \mathbf{F}_t\mathbf{x}_{t-1} + \nu_t \quad (3)$$
$$\mathbf{z}_t = \mathbf{H}_t\mathbf{x}_t + \mu_t \quad (4)$$

The goal of Bayesian estimation is to obtain successively $p(\mathbf{x}_t|Z_t)$ (where $Z_t = \{z_1, .., z_t\}$). The Kalman filter enables to built $p(\mathbf{x}_t|Z_t)$ from $p(\mathbf{x}_{t-1}|Z_{t-1})$ in the following way:

$$p(\mathbf{x}_{t-1}|Z_{t-1}) = \mathcal{N}(\mathbf{x}_{t-1}; \mathbf{x}_{t-1|t-1}, \mathbf{P}_{t-1|t-1}) \quad (5)$$
$$p(\mathbf{x}_t|Z_{t-1}) = \mathcal{N}(\mathbf{x}_t; \mathbf{x}_{t|t-1}, \mathbf{P}_{t|t-1}) \quad (6)$$
$$p(\mathbf{x}_t|Z_t) = \mathcal{N}(\mathbf{x}_t; \mathbf{x}_{t|t}, \mathbf{P}_{t|t}) \quad (7)$$

where

$$\mathbf{x}_{t|t-1} = \mathbf{F}\mathbf{x}_{t-1|t-1} \quad (8)$$
$$\mathbf{P}_{t|t-1} = \mathbf{Q}_{t-1}\mathbf{F}_t\mathbf{P}_{t-1|t-1}\mathbf{F}_t^T \quad (9)$$
$$\mathbf{x}_{t|t} = \mathbf{x}_{t|t-1} + \mathbf{K}_t(\mathbf{z}_t - \mathbf{H}_t\mathbf{x}_{t|t-1}) \quad (10)$$
$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{K}_t\mathbf{H}_t\mathbf{P}_{t|t-1} \quad (11)$$

and

$$\mathbf{S}_t = \hat{\mathbf{H}}_t\mathbf{P}_{t|t-1}\mathbf{H}_t^T + \mathbf{R}_t \quad (12)$$
$$\mathbf{K}_t = \mathbf{P}_{t|t-1}\hat{\mathbf{H}}_t^T\mathbf{S}_t^{-1} \quad (13)$$

In the case when either f_t or h_t, or both, are non linear but yet derivable, they can be locally linearized and the resulting extended Kalman filter is applied as previously. If F_t or/and H_t switch between several predefined models with given probabilities, a bank of Kalman filters is used instead in an IMM estimator.

3. COVARIANCE UPDATE

After the prediction stage performed through equations (6),(8) and (9), the predicted measurement is given by $\hat{\mathbf{z}}_{t|t-1} = \mathbf{H}_t\hat{\mathbf{x}}_{t|t-1}$. For each filter, a validation gate around the predicted measurement is then defined as follows:

$$G_t = \{\mathbf{z}_t, [\mathbf{z}_t - \hat{\mathbf{z}}^i_{t|t-1}]^T[\mathbf{S}_t]^{-1}[\mathbf{z}_t - \hat{\mathbf{z}}^i_{t|t-1}] \leq g^2\}$$

where $\mathbf{S}_t$ is the innovation covariance and g is determined from a $\chi^2_{dim(z)}$ table as corresponding to a gating probability chosen to be > 0.95. In the following we show how to reduce this search area as much as possible, under the constraint that the valid candidate must be contained therein. This is done by estimating the covariance of the transition noise at each time step in order to update it. Let ν_t be a random process vector with zero mean and covariance matrix $\mathbf{Q}_t$. Then, an estimate of $\mathbf{Q}_t$ at each time step t when a realization $\tilde{\nu}_t$ of ν_t becomes available, can be computed by the following methods, for which we give the expression and the potential pitfalls:

1. If the model is well designed and the noise induced by the transition process is constant, we can choose:

   $$\hat{\mathbf{Q}}_t = \mathbf{Q}_0 \quad (14)$$

   i.e. the estimate is a constant. Not updating the covariance of the transition noise can however lead to problems if the input value is not correctly chosen. If it is too small, the target will probably get out of the validation gate. Conversely, if it is too large, the gate will probably contain lots of clutter and other targets, leading to possible association errors.

2. If we observe that the covariance of the transition noise evolves with time, we can compute the sample variance as being an estimate for $\mathbf{Q}_t$ at each time step t:

   $$\hat{\mathbf{Q}}_t = \frac{1}{t}\sum_{i=0}^{t}\tilde{\nu}_i\tilde{\nu}_i^T \quad (15)$$

3. Since the expression above may lead to computational bottle necks, we prefer its recursive equivalent which consists in computing recursively the sample variance at each t:

   $$\hat{\mathbf{Q}}_t = \frac{t-1}{t}\hat{\mathbf{Q}}_{t-1} + \frac{1}{t}\tilde{\nu}_t\tilde{\nu}_t^T \quad (16)$$

   In this case, it is clear that $\hat{\mathbf{Q}}_t$ converges to a constant value because the new comers are given less and less weight when t grows. This has the negative effect that sudden variations of the target behavior cannot be taken into account properly and therefore leading to loosing the track.

4. To try to tackle the previous problem, the weight $\frac{t-1}{t}$ can be replaced by a constant "memory" factor α, $0 < \alpha < 1$. Then, at each time t, the covariance estimate is obtained with :

   $$\hat{\mathbf{Q}}_t = \alpha\hat{\mathbf{Q}}_{t-1} + (1-\alpha)\tilde{\nu}_t\tilde{\nu}_t^T \quad (17)$$

This method has the advantage of controlling the confidence in a new evaluation of the error. However, as it reinforces the weight of last similar values, it has the negative effect to shrink the validation gate to small values and will produce the same effect as method 3 when $\tilde{\nu}_t$ is small during a significant amount of time.

5. It is clear that the methods above all fail in handling sudden changes in the object dynamics, in particular because they do not limit the shrinking of the validation gate. To improve on this, we propose to set a minimal value on the recursive estimate of the covariance $\mathbf{Q}_t$. This therefore leads to the following expression:

$$\hat{\mathbf{Q}}_t = \alpha\hat{\mathbf{Q}}_{t-1} + \beta\tilde{\nu}_t\tilde{\nu}_t^T + \gamma\mathbf{Q}_0, \tag{18}$$

with $\alpha+\beta+\gamma=1$, where α is the "memory" factor, γ determines the weight of the minimal gate and $\mathbf{Q}_0$ determines the shape of the gate.

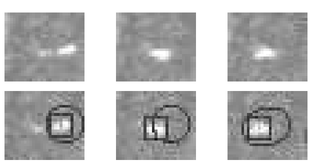
In the context of Gaussian Bayesian target tracking, we get successive values of $\tilde{\nu}_t$ by computing the error that is made between the state estimate $\hat{\mathbf{x}}_{t|t}$ and the predicted one, $\hat{\mathbf{x}}_{t|t-1}$:

$$\tilde{\nu}_t = \hat{\mathbf{x}}_{t|t} - \hat{\mathbf{x}}_{t|t-1} \tag{19}$$

This value can be obtained with a KF as described in previous section but also with an EKF or an IMM.

4. COMPARATIVE STUDY

We implemented the methods 1, 3, 4 and 5 above in our tracking algorithm, which uses Kalman Filter or IMM along with an association procedure to built the tracks [8, 6]. To compare the effectiveness of the methods in updating the transition noise covariance, we run the tracking algorithm on sequences such as shown in figure 2. For each track, at



26 27 28

Fig. 2. First row : cropped frames 26, 27 and 28 of a video microscopy sequence. Second row : the tracked spot moves suddenly to the opposite direction at frame 27 and keeps being in the validation gate on next frame thanks to the method 5.

each step, the following measures are computed:

- the Mahalanobis distance between predicted measurement and real associated measurement :

$$d_t = [\mathbf{z}_t - \hat{\mathbf{z}}^i_{t|t-1}]^T[\mathbf{S}_t]^{-1}[\mathbf{z}_t - \hat{\mathbf{z}}^i_{t|t-1}] \tag{20}$$

- the volume of the validation gate, i.e., except for a constant, the product of the eigenvalues of the residual covariance S_t. In our case, the validation gate is an hyper ellipsoid in four dimensions as each measure is constructed with the location x, y, the area a and the intensity i of each detected spot with method [9].

Figure 3 presents the evolution of these measures for the fluorescent spot of figure 2 computed with methods 1,3,4 and 5. This object is typical and represents well the behavior of all tested spots in that it changes dynamics very suddenly between two frames. It can be seen that only methods 1 and 5 succeed in keeping having the object inside of the validation gate, while methods 3 and 4 loose the object because the volume decreases too much to handle an unexpected event as the sudden change in direction of the object in frame 27, as shown by the error graph. Also, method 5 is able to adapt the validation volume to a shape related to the the error and to a size that is smaller than the one given by method 1. Figure 4 shows the influence of changing the parameters of method 5. In the example, the thick curve is a smoother version of the one in 3 where β has a smaller value. The thin curve presents a configuration where the "'memory' factor α is increased and the minimal gate is decreased, leading the validation volume to take more time to adapt itself to a smaller minimum.

5. CONCLUSION

We have presented several way to update the validation gate of a Bayesian Gaussian filter and proposed an improved method that enables the validation gate to be adapted both to the smoothly evolving dynamic of a moving target and to an abruptly changing dynamic. This method updates the covariance of transition noise using three components: a memory component that keeps track of the near past, an error component that takes into account the last error and a minimum size component that prevents the validation gate to collapse. The presented results of tracking fluorescent spots in video microscopy show that the proposed method outperforms methods that do not prevent the validation gate to drop at very low values, and which are therefore unable to keep tracking of an abrupt change in object dynamics.

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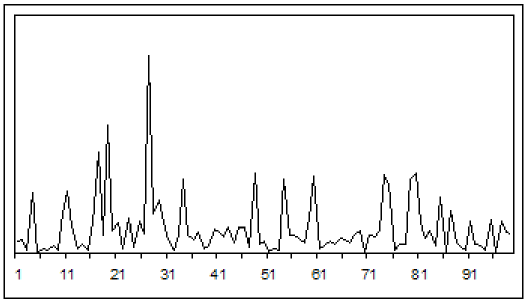

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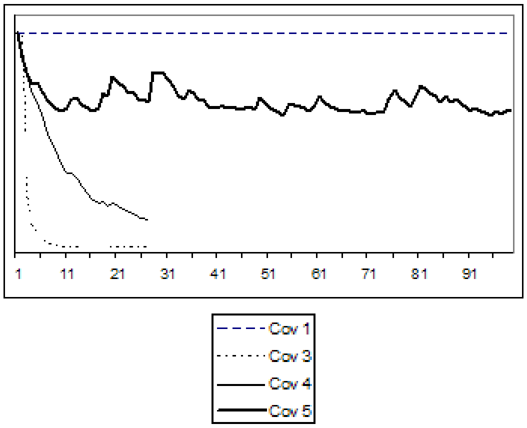

b

Fig. 3. a) error of measurement prediction b) volume of validation gate. When the object suddenly changes its direction at frame 27, the error is high and only the methods 1 and 5 are able to keep the object within the validation gate.

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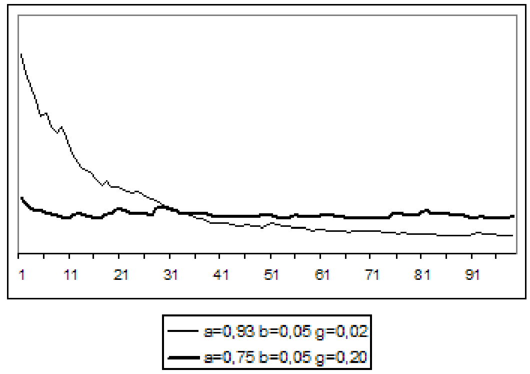

Fig. 4. Effect of the variation of parameters in method 5.

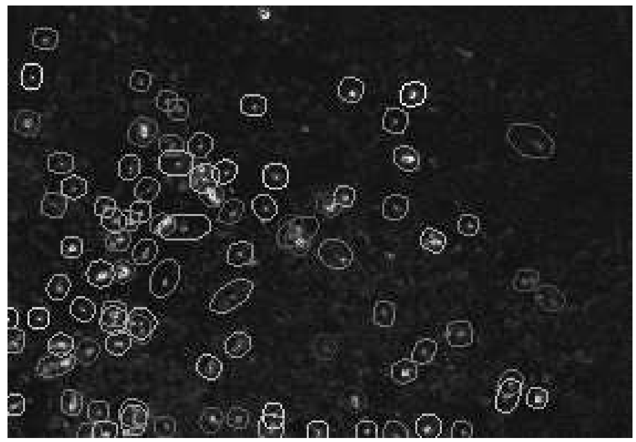

Fig. 5. An highest density of spot can be tracking with method 5.

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