On the Optimality of Motion-Based Particle Filtering

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***Abstract*— Particle filters have revolutionized object tracking in video sequences. The conventional particle filter, also called the CONDENSATION filter, uses the state transition distribution as the proposal distribution, from which the particles are drawn at each iteration. However, the transition distribution does not take into account the current observations, and thus many particles can be wasted in low likelihood regions. One of the most popular methods to improve the performance of particle filters relied on the motion-based proposal density. Although the motivation for motion-based particle filters could be explained on an intuitive level, up until now a mathematical rationale for the improved performance of motion-based particle filters has not been presented. In this letter, we investigate the performance of motion-based particle filters and provide an analytical justification of their superiority over the classical CONDENSATION filter. We rely on the characterization of the optimal proposal density, which minimizes the variance of the particles'weights. However, this density does not admit an analytical expression, making direct sampling from this optimal distribution impossible. We use the Kullback–Leibler (KL) divergence as a similarity measure between density functions and denote a particle filter as superior if the KL divergence between its proposal and the optimal proposal function is lower. We subsequently prove that under mild conditions on the estimated motion vector, the motion-based particle filter outperforms the CONDENSATION filter, in terms of the KL performance measure. Simulation results are presented to support the theoretical analysis.**

***Index Terms*— Adaptive block matching, Kullback–Leibler (KL) divergence, motion estimation, particle filtering, video tracking.**

I. Introduction

Recently, sequential Monte Carlo (SMC) filters [1] have become very popular for object tracking due to their flexibility and ease of implementation. These filters have been introduced to the tracking community in a paper by Isard and Blake [2]. SMC filters, also known as particle filters, are Bayesian filters, which use the importance sampling technique to estimate the distribution of nonlinear and non-Gaussian state-space models [1]. In the Bayesian framework, the tracking problem is formulated as the estimation of the posterior density of the target. In practice, the target's posterior is multimodal due to background clutter (hence non-Gaussian). Therefore, traditional density estimation techniques (e.g., Kalman filter) will not apply. In importance sampling, a proposal density, also called importance function, is used to easily generate samples. Each sample is then assigned a proper weight to make up the difference between the posterior and proposal density functions [1]. It can be shown that if the number of samples is sufficiently large, the sample approximation of the posterior density can be made arbitrarily accurate [1]. However, in practice, only a finite number of samples can be used. Moreover, when a good dynamic model (i.e., a model that accurately predicts the target's dynamics) is not available, or the state dimension of the tracked object is high, the number of required samples becomes even larger and particle filtering can be computationally prohibitive. The conventional approach is to sample from image regions having high probability mass values. In [3], we proposed the use of a motion estimation algorithm to estimate the target position at each frame and draw samples from the area around the estimated position. Several advantages emerge of this choice. First, the motion is estimated Online and hence no offline motion learning is needed. Second, the tracker is adaptive to all kinds of motion. Particulary, it can be viewed as a general case of the switching state-space model technique [4]. Third, we economize on the processing time by searching only the state space around the estimated position. Finally, unlike color- or shape-based proposal densities, a motion-based proposal is less sensitive to clutter. The incorporation of motion cues in particle filters have also been investigated in [5] and [6]. In [5], the authors proposed an adaptive state transition model by using an adaptive velocity model. In [6], an audiovisual tracking system is considered, where motion cues where incorporated in the likelihood model. The target's motion was estimated based on the absolute frame difference computed on successive pairs of images. Observe that in [5], [6] and [3], motion information was incorporated in the state dynamics distribution, the likelihood model, and the proposal distribution, respectively.

Many proposal distributions have been proposed in the literature so far [7], where each distribution has been experimentally shown to outperform the conventional particle filter (or CONDENSATION). However, no one up until now has tried to analyze analytically the performance of certain proposals over others. Zaritskii *et al.* [8] derived the optimal proposal density q_{opt}, which minimizes the variance of the particles' weights. However, this density does not admit an analytical expression in the general case, making direct sampling from it impossible. The challenge in particle filtering applications is, therefore, to design efficient proposal distributions that approximate the optimal density as closely as possible. Although we cannot practically sample from the optimal proposal, we propose to assess the performance of a given proposal density q by

Manuscript received April 14, 2007; revised December 30, 2007. Current version published July 22, 2009. This paper was recommended by Associate Editor I. Ahmad.

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Digital Object Identifier 10.1109/TCSVT.2009.2020477

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computing the Kullback–Leibler (KL) "distance" or similarity measure between q_{opt} and q.

The remainder of this letter is organized as follows. In Section II, we review the motion-based particle filter (MBPF) introduced in [3], [9]. In Section III, we formulate a general optimization problem, based on the KL divergence, to assess the performance of different proposal densities compared to the optimal proposal that minimizes the variance of the weights. We subsequently prove that under mild conditions on the estimated motion vector (namely that it should not be the output of a random process but the output of a "decent" motion estimation algorithm) the motion-based particle filter is superior to the CONDENSATION filter, in the KL divergence sense. In Section IV, we present some simulation results. Finally, concluding remarks are discussed in Section V.

II. Motion-Based Particle Filter

A. Bayesian Sequential Importance Sampling

In Bayesian sequential estimation, a Markovian discrete-time state-space model is assumed. Let X_k represent the target characteristics at discrete time k (position, velocity, shape, etc.). The state-space model is described by state transition and measurement equations

$$\begin{aligned} X_k &= f_k(X_{k-1}, \upsilon_k) \\ Z_k &= h_k(X_k, \omega_k) \end{aligned} \tag{1}$$

where $f_k : \mathbb{R}^{n_x} \to \mathbb{R}^{n_x}$ and $h_k : \mathbb{R}^{n_x} \to \mathbb{R}^{n_z}$ are possible nonlinear functions. The stochastic processes υ_k and ω_k represent the state and measurement noise processes. Denote all past observations up to time k by $Z_{1:k} = \{z_1, \ldots, z_k\}$. When the functions f_k and h_k are linear and the noise is Gaussian, Kalman filter [10] provides an analytical closed-form solution to the posterior density $p(X_k|Z_{1:k})$. However, for real-world applications, the clutter introduces multiple observations and a multimodel density is then necessary to fairly model the posterior density.

In particle filtering, the posterior distribution is approximated by a set of weighted samples (also called particles) denoted by $X^{(i)}$

$$p(X_k|Z_{1:k}) \approx \sum_{i=1}^{N} \pi_k^i \delta\left(X_k - X_k^{(i)}\right) \tag{2}$$

where $\pi_k^{(i)} = \omega_k^{(i)} / \sum_{j=1}^{N} \omega_k^{(j)}$ is the normalized weight, and $\omega_k^{(i)}$ is given by

$$\omega_k^{(n)} = \omega_{k-1}^{(n)} \frac{p\left(X_k^{(n)} \middle| X_{k-1}^{(n)}\right)}{q\left(X_k^{(n)} \middle| X_{k-1}^{(n)}, Z_k\right)} p\left(Z_k \middle| X_k^{(n)}\right). \tag{3}$$

Given a discrete approximation to the posterior distribution, one can then proceed to a filtered point estimate such as the mean of the state at time k

$$\hat{X}_k = \sum_{i=1}^{N} \pi_k^{(i)} X_k^{(i)}. \tag{4}$$

B. Motion-Based Importance Function

Unlike shape- and/or color-based importance functions [11], [12] we proposed in [3] a motion-based importance density. Any motion estimation technique can actually be used in our algorithm. In case of compressed videos, using standards like MPEG, motion vectors are readily available. In our simulations, we choose the adaptive block matching method (ABM) [13] because of its simplicity in implementation. For head tracking applications, we use a 4-D parametric ellipse to represent the state vector of the object

$$X = [x_c, y_c, b, \phi]^T \tag{5}$$

where (x_c, y_c) is the center of the ellipse, b is the minor axis of the ellipse, and ϕ is the orientation of the ellipse in radians. The ratio of the major to minor axis of the ellipse is kept constant, equal to its value computed in the first frame. For the experiments we conduct on head tracking, we found this assumption very reasonable and allows us to reduce the dimensionality of the state vector by 1. We use the least mean square (LMS) criterion to fit the ellipse to the mask output of the ABM. The motion vector $\widehat{\Delta X_k}$ that interests us is then given by the difference between the position of the center of the newly fitted ellipse $(x_c(k), y_c(k))$ and the position of the center of the previous mean estimate $(x_c(k-1), y_c(k-1))$, i.e.,

$$\widehat{\Delta X_k} = [x_c(k) - x_c(k-1), y_c(k) - y_c(k-1), 0, 0]. \tag{6}$$

The scaling and rotation parameters of each sample $X_k^{(n)}$(given by the 3rd and 4th coordinates) are randomly selected from a normal distribution with the mean scaling and rotation parameters of the previous sample $X_{k-1}^{(n)}$ and fixed variances, σ_s^2 and σ_r^2, respectively.

We then have the following sampling scheme:

$$X_k^{(n)} = X_{k-1}^{(n)} + \widehat{\Delta X_k} + \upsilon_k^{'(n)}, \quad n = 1, \ldots, N \tag{7}$$

where $\upsilon_k^{'(n)}$ is the diffusion noise of sample n at time k.

Let ΔX_k denote the true motion vector at time k. Then, we can write

$$\Delta X_k = \widehat{\Delta X_k} - \upsilon_k^{''} \tag{8}$$

where $\upsilon_k^{''}$ is the motion estimation error vector at time k. It is reasonable to assume that the motion error vector $\upsilon_k^{''}$ and the sampling noise $\upsilon_k^{'(n)}$ are uncorrelated for each sample n and at each time index k. Let $\upsilon_k^{(n)}$ be the cumulative noise of the diffusion and the error in the motion estimation, i.e., $\upsilon_k^{(n)} = \upsilon_k^{'(n)} + \upsilon_k^{''}$. Therefore, (7) becomes

$$X_k^{(n)} = X_{k-1}^{(n)} + \Delta X_k + \upsilon_k^{(n)}, \quad n = 1, \ldots, N. \tag{9}$$

The reason behind expressing the sampling scheme in terms of the true motion vector ΔX_k instead of the estimated motion vector $\widehat{\Delta X_k}$ will become evident in Section III when we compare the performance of the MBPF with the CONDENSATION filter. We assume that the vectors $\upsilon_k^{''}$ and $\upsilon_k^{'}$ are normally distributed with zero mean and fixed covariance matrices. Thus, the cumulative noise vector υ_k is also normally distributed with zero mean and covariance

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matrix Σ_G

$$v_k \sim N(0, \Sigma_G) \tag{10}$$

and

$$\Sigma_G = \begin{pmatrix} \sigma_x^2 & 0 & 0 & 0 \\ 0 & \sigma_y^2 & 0 & 0 \\ 0 & 0 & \sigma_s^2 & 0 \\ 0 & 0 & 0 & \sigma_r^2 \end{pmatrix} \tag{11}$$

where σ_x^2 and σ_y^2 are the variances of the motion in the $(x\text{–}y)$ direction. The motion-based importance density q_m is then the mixture of the translated and diffused samples around the target's estimated position, i.e.,

$$q_m(X_k|X_{k-1}, Z_k) \equiv \frac{1}{N}\sum_{n=1}^{N} \mathcal{N}_{X_k^{(n)}}\left(X_{k-1}^{(n)} + \Delta X_k, \Sigma_G\right) \tag{12}$$

where we make use of the following notation that will be used for the rest of this letter

$$\mathcal{N}_X(\mu, \Sigma) \equiv \frac{1}{2\pi|\Sigma|}\exp\left(-\frac{1}{2}(X-\mu)^T\Sigma^{-1}(X-\mu)\right). \tag{13}$$

In addition to the assessment of the importance function, we need to evaluate the likelihood $p(Z_k|X_k)$ and the state dynamics $p(X_k|X_{k-1})$ distributions [see (3)]. We calculate the particle likelihood based on color [12] and edge [2] cues. We choose a random walk model for the system dynamics, which reflects a poor prior knowledge of the target's dynamics in the video [5], [6].

III. Optimal Realizable Proposal Density

After synthesizing the proposed MBPF, we need to analyze its performance. The following basic question arises: What variables should we consider and what performance measure should we use? To study these questions, we consider the degeneracy problem of the importance sampling technique, where the variance of the particle's weights can only increase (stochastically) over time. That is, most of the weight will be concentrated on a single particle after a few iterations [1]. In practice, it is necessary to resample the particles to avoid degeneracy of the weights. Zaritskii *et al.* [8] introduced the optimal importance function, which minimizes the variance of the weights. It is given by

$$q_{\text{opt}} = p\left(X_k|X_{k-1}^{(i)}, Z_k\right). \tag{14}$$

However, this optimal density does not admit an analytical expression in the general case, making direct sampling from it impossible. Though we cannot practically sample from q_{opt}, we can assess the performance of a proposal density q by computing some kind of "distance" or similarity measure between q_{opt} and q. The KL divergence $I(q_{\text{opt}}, q)$ captures the "information" lost when a given proposal density q is used to approximate the optimal proposal density q_{opt}. It is defined as the multiple integral

$$I(q_{\text{opt}}, q) = \int_{\mathcal{S}} q_{\text{opt}}(x)\,\log\left(\frac{q_{\text{opt}}(x)}{q(x)}\right)dx \tag{15}$$

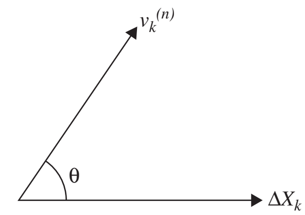

Fig. 1. Sufficient condition for the superiority of the motion-based proposal to the prior proposal, in terms of the KL divergence. The angle between the noise vector and the true motion vector does not exceed $\pi/2$ in absolute value.

where log denotes the natural logarithm and $\mathcal{S}$ is the region of integration. We want to minimize $I(q_{\text{opt}}, q)$ over a space of realizable densities indexed by $\mathbf{Q}$. The general optimization problem can be formulated as follows:

$$q^* = \min_{q\in\mathbf{Q}} I(q_{\text{opt}}, q) \tag{16}$$

where the space $\mathbf{Q}$ does not contain the optimal proposal density q_{opt}; i.e., the trivial solution $q^* = q_{\text{opt}}$ is precluded. In order to reduce the state space, we consider $\mathbf{Q}$ to be the set containing only two densities $\{q, q_c\}$, where q is any realizable density function and q_c is the proposal density in the CONDENSATION filter; i.e.,

$$q_c\left(X_k\,\middle|\,X_{k-1}^{(i)}\right) = p\left(X_k\,\middle|\,X_{k-1}^{(i)}\right).$$

In this letter, we will illustrate the approach proposed for characterization of the optimal realizable proposal density by focusing on MBPF. However, it is important to note that this approach could be extended easily to the comparison of the performance (in the KL divergence sense) of any pair of proposal density functions in particle filtering.

Assume the set $\mathcal{S}$ contains the region of support of the optimal density q_{opt}. Let Ω be the set of densities q satisfying the inequality $\int_{\mathcal{S}} \frac{q_{\text{opt}}q_c}{q} dX_k \leq 1$. The following proposition shows that the space Ω contains proposal densities, which are closer to the optimal density than the prior q_c.

Proposition 1: If $q \in \Omega$, then $I(q_{\text{opt}}, q) \leq I(q_{\text{opt}}, q_c)$.

Proof: Let q be a realizable density such that $q \in \Omega$. Then we have

$$\begin{aligned} & I(q_{\text{opt}}, q) - I(q_{\text{opt}}, q_c) \\ &= \int_{\mathcal{S}} q_{\text{opt}} \log\left(\frac{q_{\text{opt}}}{q}\right) dX_k - \int_{\mathcal{S}} q_{\text{opt}}\log\left(\frac{q_{\text{opt}}}{q_c}\right) dX_k \\ &= \int_{\mathcal{S}} q_{\text{opt}} log\left(\frac{q_c}{q}\right) dX_k \\ &\leq log\left(\int_{\mathcal{S}} \frac{q_{\text{opt}}q_c}{q}\, dX_k\right) && (17) \\ &\leq \int_{\mathcal{S}} \frac{q_{\text{opt}}q_c}{q}\, dX_k - 1 \leq 0 && (18) \end{aligned}$$

where (17) uses Jensen's inequality and (18) uses the inequality $\log(x) \leq x - 1$. ■

Observe that every density q satisfying $q \geq q_c$ belongs to the set Ω and therefore is closer to the optimal distribution than q_c. In the remainder of this section, we consider the former

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(a) Motion-based particle filter

(b) The CONDENSATION filter

Fig. 2. Tracking a jumping person.

to be a random walk with covariance matrix Σ_P, i.e.,

$$q_c = p(X_k|X_{k-1}) = \frac{1}{N}\sum_{n=1}^{N} p\left(X_k^{(n)}\middle|X_{k-1}^{(n)}\right) = \frac{1}{N}\sum_{n=1}^{N} \mathcal{N}_{X_k^{(n)}}\left(X_{k-1}^{(n)}, \Sigma_P\right). \tag{19}$$

In the following proposition, we show that, under mild conditions on the target's motions, $I(q_{\rm opt}, q_m) \le I(q_{\rm opt}, q_c)$.

Proposition 2: If $\Sigma_G = \Sigma_P = \Sigma$ and $\left[(1/2)\Delta X_k + v_k^{(n)}\right]^T \Sigma^{-1}\Delta X_k \ge 0$, for all $1 \le n \le N$, then $I(q_{\rm opt}, q_m) \le I(q_{\rm opt}, q_c)$.

Proof: We show that $q_m \ge q_c$. From (12), we have

$$q_m(X_k|X_{k-1}, Z_k)\frac{1}{N}\sum_{n=1}^{N}\frac{1}{2\pi|\Sigma|} \times \exp^{\left(-\frac{1}{2}\left(X_k^{(n)}-X_{k-1}^{(n)}-\Delta X_k\right)^T\Sigma^{-1}\left(X_k^{(n)}-X_{k-1}^{(n)}-\Delta X_k\right)\right)}$$
$$= \frac{1}{N}\sum_{n=1}^{N} p\left(X_k^{(n)}\middle|X_{k-1}^{(n)}\right)\exp^{\left(\left[\frac{1}{2}\Delta X_k + v_k^{(n)}\right]^T\Sigma^{-1}\Delta X_k\right)} \tag{20}$$
$$\ge \frac{1}{N}\sum_{n=1}^{N} p\left(X_k^{(n)}\middle|X_{k-1}^{(n)}\right) = p(X_k|X_{k-1}) = q_c \tag{21}$$

where the equality in (20) follows from (19) and the inequality in (21) follows from the assumption that $[(1/2)\Delta X_k + v_k^{(n)}]^T\ \Sigma^{-1}\Delta X_k \ge 0$, for all $1 \le n \le N$. ■

Corollary 1: If $\Sigma_G = \Sigma_P = \Sigma$ and $(v_k^{(n)})^T\Sigma^{-1}\Delta X_k \ge 0$, for all $1 \le n \le N$, then $I(q_{\rm opt}, q_m) \le I(q_{\rm opt}, q_c)$.

Proof: The proof follows immediately from Proposition 2 and since Σ^{-1} is a positive semidefinite matrix. ■

The condition in the corollary is equivalent to $(1/\sigma_x^2)v_{k_x}^{(n)}\delta x_k + (1/\sigma_y^2)v_{k_y}^{(n)}\delta y_k \ge 0$, where $(v_{k_x}^{(n)}, v_{k_y}^{(n)})$ and $(\delta x_k, \delta y_k)$ are the projections of the noise and the motion vectors along the first two coordinates, respectively. If $\sigma_x = \sigma_y$, we observe that a sufficient condition for the superiority of the motion-based proposal to the prior proposal, in terms of the KL divergence, is that the angle between the noise vector and the true motion vector does not exceed $\pi/2$ in absolute value. This sufficient condition is illustrated in Fig. 1.

Let us use $|x|$ and $sign(x)$ to denote the absolute value and sign of the scalar x, respectively. Moreover, we will use $[\mathbf{x}]_i$ to denote the ith component of the vector $\mathbf{x}$ and $[A]_{i,j}$ to represent the i, jth element of the matrix A.

Corollary 2: If $\Sigma_G = \Sigma_P = \Sigma$ and $|[\Delta X_k]_i| \ge 2|[v_k^{(n)}]_i|$, for $i = 1, 2$, and for every $1 \le n \le N$, then $I(q_{\rm opt}, q_m) \le I(q_{\rm opt}, q_c)$.

Proof: The proof follows immediately from Proposition 2 and since $sign([1/2\Delta X_k + v_k^{(n)}]_i) = sign([\Delta X_k]_i)$, for $i = 1, 2$, and for every $1 \le n \le N$, and the fact that the elements of Σ_G^{-1} are non-negative (i.e., $[\Sigma_G^{-1}]_{i,j} \ge 0$, for every i, j). ■

In this case, we observe that a sufficient condition for the superiority of the motion proposal to the prior proposal, in the KL divergence sense, is that the noise is small in comparison to the true motion of the tracked object. From Section II-B, recall that the sampling noise v_k is the sum of the motion estimation error and the diffusion noise. In particular, Corollary 2 states that if the motion estimation error is "small enough," then MBPF is superior to the CONDENSATION filter in the KL divergence sense. This result is somehow intuitive.

IV. Experimental Results

We address real-life tracking scenarios where the target undergoes fast motion in one video (Fig. 2) and erratic sudden motion in another (Fig. 3). We compare the tracking results of the MBPF with the CONDENSATION filter. In Fig. 2, the target is jumping. At least two equations are needed to describe its dynamics: the negative acceleration phase during the takeoff, and the positive acceleration phase during the landing. The model gets more complicated if we take into account the fact that the initial velocity varies from one jump to another. Fig. 2(a) displays the tracking output of the MBPF, which accurately captures the target's position. The prior density of the MBPF is a random walk process. The CONDENSATION filter's tracking result, with a random walk proposal density, was so poor and completely lost the target after few frames, that we chose not to display it here. Instead, we display the output of the CONDENSATION filter using a more sophisticated dynamic model given by the Langevin

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(a) Motion-based particle filter

(b) The CONDENSATION filter

Fig. 3. Tracking sudden and erratic movements

process [14]. Moreover, the parameters of the Langevin process were tuned offline to lead to the tracking results shown in Fig. 2(b). For real-time experiments, one cannot afford different offline procedures to properly adjust the parameters of the dynamic model. Despite a more sophisticated dynamic model, the CONDENSATION filter loses the target in most of the frames. On the other hand, despite a poor prior knowledge of the target dynamics (expressed by a random walk dynamic model), the MBPF accurately tracks the jumping target. The reason behind this is that the prior plays no role in locating the sample set since the particles are sampled from the motion-based proposal density and not from the prior density.

Fig. 3 shows a tracking scenario where the target undergoes erratic and sudden movements. The person in the video walks routinely, then suddenly bends down, and then stands up again as if he wanted to avoid someone's (or something's) sight. The CONDENSATION filter loses the target during the fast phase of bending and standing up again, whereas the MBPF accurately tracks the target during all phases.

V. Conclusion

Up until now, different choices of proposal densities, including motion-based proposal functions, were only shown to outperform the conventional CONDENSATION filter experimentally. In this letter, we provided an analytical justification of the superiority of MBPFs over the classical CONDENSATION filter. We used the KL measure to compare the similarity of different proposal functions to an optimal unrealizable proposal density, which minimizes the variance of the particle's weights. We proved that, if the motion estimation error is "small enough" compared to the true motion, then the motion-based particle filter outperforms the CONDENSATION filter, in the KL divergence sense. We then presented simulation results to support our analysis. The proposed framework could be used for the analytical comparison of the various proposal functions used in particle filtering.

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