Tracking human motion using auxiliary particle filters and iterated likelihood weighting

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Abstract

Bayesian particle filters have become popular for tracking human motion in cluttered scenes. The most commonly used filters suffer from two drawbacks. First, the prior used for the filtering step is often poor due to relatively large, poorly modelled inter-frame motion. Second, the use of the prior as an importance function results in inefficient sampling of the posterior. The use of the auxiliary particle filter (APF) and the novel iterated likelihood weighting filter (ILW) are proposed here in order to help address these problems. Experimental results comparing the filters’ accuracy and consistency are presented for a scenario in which a person is tracked in an overhead view using an ellipse model. A likelihood model based on combined region (colour) and boundary (gradient) cues is motivated and used. The ILW filter is shown to outperform both Condensation and the APF on typical sequences from this scenario.

Keywords: Human tracking; Particle filters; Iterated likelihood weighting; Supportive environments; Head tracking

1. Introduction

Consider the task of tracking human motion in a scenario such as that shown in Fig. 1. Here a person’s head is tracked in a single overhead view using a method which will be described in Sections 5 and 6. The scene is extremely cluttered and the dynamic model will not always be reliable. In this sequence, for example, the person falls over, leading to relatively large and unpredictable inter-frame motion. In many applications it is important to track through poorly modelled motions in order to allow rare but salient events to be recognised.

Visual tracking is often formulated from a Bayesian perspective as a problem of estimating some degree of belief in the state $x_t$ of an object at time step $t$ given a sequence of observations $z_{1:t}$. Bayesian filtering recursively computes a posterior density that can be written using Bayes rule as:

$$ p(x_{t+1}|z_{1:t}) \propto p(z_{t+1}|x_{t+1})p(x_{t+1}) $$

Applying a Markov assumption, the prior density becomes the posterior density propagated from the previous time step using a transition density (dynamic model), $p(x_{t+1}|x_t)$:

$$ p(x_{t+1}) = \int p(x_{t+1}|x_t)p(x_t|z_t)\,dx_t $$

The posterior density cannot be computed analytically unless linear-Gaussian models are adopted (in which case the Kalman filter provides the solution). As is well-known, linear-Gaussian models are unsuitable for many visual tracking problems. Instead, simulation-based particle filters are often used to propagate what are often non-Gaussian, multimodal densities over time.

This paper explores the use of particle filtering for tracking human motion and suggests alternatives to the widely used Condensation algorithm that can improve both the accuracy and consistency of tracking. First, the auxiliary particle filter of Pitt and Shepherd [1] is used to more efficiently sample the posterior. Second, a new filter called iterated likelihood weighting (ILW) is described which, given an appropriate likelihood formulation, helps to ensure that
high likelihood regions of state space are sampled. This improves tracking in situations in which the prior is poor due to inadequately modelled motion.

The experiments reported here apply these filters to the problem of tracking the human head using ceiling-mounted, wide-angle cameras with vertically oriented optical axes in order to minimize occlusion by furniture. This scenario is motivated by a supportive home environment application which aims to help extend safe, independent living for older people [2]. The head shape is approximated as an ellipse in the image irrespective of pose. A well-behaved likelihood function is developed by combining contour (gradient) and region (colour) image evidence.

The remainder of this paper is structured as follows. Section 2 reviews some previous work on tracking using particle filters. Section 3 describes the frequently used Sampling Importance Resampling (Condensation) filter and discusses its limitations. The auxiliary particle filter (APF) is described in Section 4 and proposed as a potentially better tracking algorithm with more efficient sampling from the posterior. In Section 5, the iterated likelihood weighting (ILW) filter is introduced and motivated.

Fig. 1. Frames 1, 30, 50, 55, 60 and 75 of a sequence in which the head is tracked using iterated likelihood weighting. The person is tracked through a sudden fall. The white ellipse represents the most heavily weighted particle.
for human tracking. Sections 6 and 7 describe experiments used to compare these three filtering schemes and tracking results are presented. Conclusions are drawn in Section 8.

2. Related work

Particle filtering has become popular for visual tracking since it was suggested for contour tracking by Isard and Blake in the form of Condensation [3]. Condensation is essentially the Sampling Importance Resampling (SIR) filter of Gordon et al. [4], a specific sequential importance sampling (SIS) filter which uses the prior as the importance function. Isard and Blake later suggested using a secondary tracker to generate an importance function for sampling [5] but this still leaves open the problem of how to design the secondary tracker and how to specify its importance function if it is also an SIS filter. Tweed and Calway presented an extension to the Condensation algorithm for tracking arbitrary numbers of objects of the same type [6]. Here, we will restrict our attention to tracking a single object for simplicity. The behaviour of Condensation with finite particle sets was investigated by King and Forsyth [7]. They found that the state distribution of a Condensation-based tracker can collapse to a single peak, which has non-zero probability of being the wrong peak, within time linear in the number of samples. The main drawback of the Condensation algorithm is that a sample location is predicted purely based on the previous approximation of the state density and the dynamic model. This does not take into account the most recent observation.

Several authors have suggested alternative sampling schemes to improve the efficiency of the particle representation. An unscented Kalman filter to generate Gaussian importance densities for particle filter-based tracking was presented by Rui and Chen [8]. Li and Zhang found that using a Kalman filter to generate the importance density was more computationally efficient than the use of the unscented Kalman filter [9]. These methods can improve performance by steering sampling towards regions of high likelihood since they incorporate the most recent observation. However, they constrain the importance function to be Gaussian which may lead to inefficient sampling in the presence of multi-modal posterior distributions.

Choo and Fleet [10] used a hybrid Monte Carlo filter to sample the posterior for high-dimensional human tracking. Rather than weighting each particle by its likelihood, each particle produced a Markov chain to sample from the posterior using estimates of the gradient of the distribution. Deutscher et al. [11,12] proposed annealed and partitioned particle filtering for human tracking and also followed gradients to good hypotheses. Cham and Rehg used gradient information to search for multiple hypotheses [13] but without sampling fairly from the posterior. Torma and Szepesvai [14] combined local search with particle filtering for tracking. At each time step, the predictions were refined in a local search procedure that utilised the most recent observation.

Magee and Boyle [15] proposed taking a second set of samples from the current image based on a Condensation step (using a genetic-style combination operator).

Various other particle filtering schemes have been proposed outside the vision literature (see e.g. [16–18]). In particular, Pitt and Shepherd proposed an auxiliary variable method where the proposed distribution is a mixture that depends on both the past state and the most recent observation [1]. Arulampalam et al. [19] provide a useful tutorial.

In the context of visual tracking, the transition density, \( p(x_{t+1}|x_t) \), is a model of motion used to make predictions. Typically, a sample can be drawn from it by adding random process noise and then applying deterministic dynamics (drift). In other words, sampling from this density typically involves propagating samples \( x^s_t \) at time \( t \) forward to time \( t + 1 \) using a stochastic differential equation

\[
 x^s_{t+1} = Ax^s_t + v
 \]

where \( A \) defines the deterministic component and \( v \) is a stochastic component (see e.g. [3,20]). Stronger dynamic models are of course possible and can be learned from example data (see e.g. [21,22]). However, their use constrains the applicability of the resulting tracker to the particular type of motion modelled (e.g. walking). In order to obtain a flexible tracking system that can successfully track a very wide range of movements and in particular, rare and sudden movements, a very weak dynamic model can be adopted. In the experiments reported here, a zero-mean, additive Gaussian noise model is used i.e. \( v \sim \mathcal{N}(0, \Sigma) \) and \( A = I \). This simple transition density is in fact often used for human tracking (see e.g. [10,11]).

3. Sampling Importance Resampling

The now widely used Sampling Importance Resampling (SIR) [4] algorithm (otherwise known as Condensation [3]) approximates the posterior density \( p(x_t|z_t) \) at each time step \( t \) by a set of \( N \) particles \( \{x^n_t, w^n_t\}_{n=1}^N \) where each particle is a weighted random sample and \( \sum_{n=1}^N w^n_t = 1 \). The filtered posterior is then

\[
p(x_{t+1}|z_{t+1}) \propto p(z_{t+1}|x_{t+1}) \sum_{n=1}^N w^n_t p(x_{t+1}|x^n_t)
\]

where the prior is now a mixture with \( N \) components. The SIR filter involves (i) selecting the \( n \)th mixture component with probability \( w^n_t \), (ii) drawing a sample from it, and (iii) assigning the sample a weight proportional to its likelihood. Resampling is used to obtain samples with equal weights in order to facilitate sampling from the mixture in (4). The algorithm is given in Table 1 for completeness. The dynamic model is encapsulated by the transition density \( p(x_{t+1}|x^*_t) \).

The SIR filter is a particular kind of sequential importance sampling filter. In general, sequential importance sampling filters operate by drawing samples from an
importance density, \(q(x)\), and weighting them using weights computed according to Eq. (5) to give a particle representation of the posterior density.

\[
w^{n}_{t+1} \propto w^{n}_{1} p(z_{t+1}|x^{n}_{t+1})p(x^{n}_{t+1}|x^{n}_{t}) / q(x^{n}_{t+1}|x^{n}_{t}, z_{t+1})
\]

(5)

The SIR filter is an example of a sequential importance sampling filter in which the prior is used as the importance density. This is a convenient choice because an unbiased, asymptotically correct estimate of the posterior can be obtained by simply weighting the samples with their likelihood. The resulting algorithm is therefore intuitive and easily implemented. However, the prior is certainly not the optimal choice of importance function since it does not take into account the most recent observation, \(z_{t+1}\).

Sampling using SIR is particularly inefficient when the likelihood is in the tails of the prior or if the likelihood is narrow and peaked compared to the prior. Although SIR gives an asymptotically correct estimate of the posterior, its behaviour with finite sample sets is often not good [7]. In human tracking problems, the dynamic models used can often result in poor priors due to unexpected motion. In such cases, SIR will place many samples in the wrong regions of the state space. As a result, very large particle sets can be required in order to achieve acceptable performance.

4. Auxiliary particle filters

The auxiliary particle filter (APF) was proposed in the statistics literature by Pitt and Shephard [1] as a way of filtering with an importance density that depends on the most recent observation. It has recently been applied to robot localization [23] and target tracking in air traffic control [24]. This paper proposes its use for efficient human tracking. Auxiliary particle filtering is an extension of the SIR algorithm that approximates the filtered posterior of (4) as

\[
\hat{p}(x_{t+1}|z_{t+1}) \propto \sum_{n=1}^{N} w^{n}_{t} p(z_{t+1}|x^{n}_{t+1})p(x^{n}_{t+1}|x^{n}_{t})
\]

(6)

where \(p^{n}_{x_{t+1}}\) is some value likely to be generated by the dynamic model \(p(x_{t+1}|x^{n}_{t})\). The algorithm consists of sampling \(m = 1 \ldots N\) times from this mixture and then weighting the samples using

\[
w^{m}_{t+1} \propto p(z_{t+1}|x^{m}_{t+1}) / p(z_{t+1}|p^{m}_{x_{t+1}})
\]

(7)

where \(p^{m}_{x_{t+1}}\) is the value associated with the component \(p(x_{t+1}|x^{m}_{t})\) from which the \(m\)th sample was drawn. The algorithm is summarised in Table 2. Specifically, if the dynamic model is zero-mean Gaussian noise and \(p^{n}_{x_{t+1}}\) is taken to be the expected value of \(p(x_{t+1}|x^{n})\) then an APF is obtained by (i) choosing a component \(n\) with probability proportional to \(w^{n}_{t} p(z_{t+1}|x^{n}_{t})\), (ii) drawing a sample \(x^{n}_{t+1}\) from \(p(x_{t+1}|x^{n}_{t})\) and (iii) weighting the sample as:

\[
w^{n}_{t+1} \propto p(z_{t+1}|x^{n}_{t+1}) / p(z_{t+1}|x^{n}_{t})
\]

(8)

Auxiliary particle filtering generates particles from an importance density conditioned on the most recent observation and then samples the posterior using this importance density. When compared to the SIR filter, this requires an extra likelihood evaluation per particle. However, this can be more than offset in terms of computational efficiency since fewer particles are likely to be needed due to the more efficient sampling of the posterior.

5. Iterated likelihood weighting

Great care is usually taken to ensure that an unbiased estimate of the posterior is obtained when applying particle filtering to tracking problems. The importance sampling steps of (5), (7) and (8) are bias-correcting schemes used to obtain such an unbiased estimate. However, it is well known in statistical inference that approximation error

Table 1

<table>
<thead>
<tr>
<th>The Sampling Importance Resampling Algorithm</th>
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<tbody>
<tr>
<td>Draw samples (x^{n}<em>{t+1} \sim p(x</em>{t+1}</td>
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<tr>
<td>Assign weights (w^{n}<em>{t+1} = p(z</em>{t+1}</td>
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<tr>
<td>Normalise weights so that (\sum_{n=1}^{N} w^{n}_{t+1} = 1)</td>
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<tr>
<td>Resample with replacement to obtain samples (x^{n}<em>{t+1}) with equal weights (w^{n}</em>{t+1} = 1/N) (\forall n)</td>
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Table 2

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<tr>
<th>The auxiliary particle filter</th>
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<tr>
<td>For (n = 1 \ldots N)</td>
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<tr>
<td>Compute (p^{n}<em>{x</em>{t+1}})</td>
</tr>
<tr>
<td>Compute (w^{n}<em>{t+1} = w^{n}</em>{t} p(z_{t+1}</td>
</tr>
<tr>
<td>For each particle</td>
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<tr>
<td>Choose an index (n) with probability proportional to (w^{n}_{t+1})</td>
</tr>
<tr>
<td>Draw a sample (x^{n}<em>{t+1}) from (p(x</em>{t+1}</td>
</tr>
<tr>
<td>Assign weight (w^{n}<em>{t+1} = p(z</em>{t+1}</td>
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<tr>
<td>Normalise weights so that (\sum_{n=1}^{N} w^{n}_{t+1} = 1)</td>
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Table 3

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<tr>
<th>The iterated likelihood weighting filter</th>
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<tr>
<td>1. Draw (N) samples (x^{n}<em>{t+1} \sim p(x</em>{t+1}</td>
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<tr>
<td>2. Assign weights (w^{n}<em>{t+1} = p(z</em>{t+1}</td>
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<tr>
<td>3. Normalise weights so that (\sum_{n=1}^{N} w^{n}_{t+1} = 1)</td>
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<tr>
<td>4. Resample with replacement to obtain samples (x^{n}_{t+1}) with equal weights</td>
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<tr>
<td>5. Split the sample set at random into two sets of size (M = N/2) ({x^{n}<em>{t+1}}</em>{n=1}^{M}) and ({x^{n}<em>{t+1}}</em>{n=M+1}^{N})</td>
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<tr>
<td>6. For (k = 1 \ldots K)</td>
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<tr>
<td>Draw (M) samples (x^{n}<em>{t+1,k} \sim p(x</em>{t+1}</td>
</tr>
<tr>
<td>Assign weights (w^{n}<em>{t+1,k} \propto p(z</em>{t+1}</td>
</tr>
<tr>
<td>Normalise weights so that (\sum_{n=1}^{M} w^{n}_{t+1,k} = 1)</td>
</tr>
<tr>
<td>Resample with replacement to obtain (M) samples (x^{n}_{t+1,k}) with equal weights</td>
</tr>
<tr>
<td>7. For (m = 1 \ldots M)</td>
</tr>
<tr>
<td>(x^{m}<em>{t+1} = x^{m}</em>{t+1,1})</td>
</tr>
<tr>
<td>(x^{m}<em>{t+1} = x^{m}</em>{t+1,k})</td>
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Here, \(p(x_{t+1}|x^{n}_{t+1})\) is a transition density with expected value \(x^{n}_{t+1}\).
depends not only on the bias but on the variance (the so-called bias-variance dilemma). If the importance density is reasonably accurate, the correction step may in fact increase the approximation error for all but very large particle sets [25]. In other words, bias is reduced but at the cost of higher variance.

Furthermore, the prior density is often poor and noisy and it therefore makes little sense to attempt to obtain a computationally expensive, high accuracy approximation to the posterior. This is particularly true in many human tracking applications where inter-frame motion is often poorly modelled by the dynamic model (transition density).

A scheme is proposed here in which only a subset of the particles at each time step is sampled from the ‘posterior’. The remainder of the particles are used to increase sampling in regions of high likelihood via a simple iterative search using the most recent observation. This is useful when the prior (dynamic model) is poor. It can prevent tracking failure in the case of unexpected motion, for example. Rather than attempt to perform a potentially expensive and poorly constrained bias-correction step for

Fig. 2. Likelihoods for varying parameter values. Blue plot: gradient-based likelihood. Black plot: color-based likelihood. Red plot: combined likelihood (Eq. (9)). Plots are of likelihoods as the ellipse (a) translates and (b) changes scale away from the correct ellipse.
those particles used to search high-likelihood regions, they are weighted at each iteration based on their likelihood. The resulting algorithm is not an unbiased, Bayesian particle filter within the usual Markov framework. However, it can be thought of as SIR combined with an iterative application of SIR several times on the same observation. The algorithm is given in Table 3. After an initial iteration of SIR, the sample set is split uniformly at random into two sets of equal size. One of these sets is propagated to the next time step unaltered while the samples in the other set are subjected to further iterations of diffusion, likelihood weighting and resampling. This has the effect of migrating half of the particles to regions of high likelihood while the other half are sampled using the prior as the importance function. In a situation where the prior is good, its use as an importance function by half the particles will result in useful samples. However, if the prior is poor, the iterated particle set will still explore regions of high likelihood.

The variable $K$ is a free parameter of the algorithm whose value should depend on the extent to which the transition prior can become poor. The iterated likelihood steps seek to migrate samples from the prior towards high likelihood regions. Since the number of particles is usually relatively small, the tails of the prior will be poorly represented. If regions of high likelihood lie in the tails of the prior, particles need to migrate there by the diffusion/resampling process (step 6 in Table 3). The migration ‘step size’ for a particle depends on the variances in the transition density. If the system occasionally needs to track inter-frame motion of much greater magnitude than that suggested by the transition density, $K$ needs to be set appropriately high.

6. Likelihood model

In order to apply the above filtering schemes to the tracking problem, the state vector, $\mathbf{x}$, and the likelihood model, $p(\mathbf{z} | \mathbf{x})$, must be defined. A well designed likelihood model can significantly improve tracking performance [26]. The experiments reported here apply the filters to the problem of tracking the human head using a ceiling-mounted, wide-angle camera with vertically oriented optical axis. The head shape is reasonably well approximated as an ellipse in the image irrespective of pose. Previous authors have used an ellipse to track frontal-profile views of the head. For example, Rui and Chen [8] used a fixed ellipse and tracked its 2D translation using Canny edges to compute a likelihood. Nummiaro et al. [20] used an ellipse with fixed orientation and a likelihood based only on colour to track people. Birchfield [27] used an ellipse constrained to be vertically oriented and of a fixed

![Fig. 3. Frames from the sequence in Fig. 1 tracked using SIR. The tracker loses the object in frame 56 and is unable to recover.](image_url)
elongation leaving only three parameters to be estimated. However, orientation and elongation will vary with pose and position, particularly from an overhead view. Therefore, all five ellipse parameters are estimated here.

The likelihood model combines intensity gradient information along the head boundary with a colour model of the ellipse’s interior region. The region likelihood \( p(r|x^n) \) is obtained by computing a similarity measure between a 3D color histogram of the ellipse’s interior and a stored model color histogram. The boundary likelihood \( p(b|x^n) \) involves searching for maximum gradient magnitude points along short radial search line segments centered on the ellipse boundary. There are typically 30 such line segments, each 5 pixels long. The use of the short search lines allows the boundary to contribute when it is not exactly elliptical. Assuming conditional independence, the likelihood is obtained as

\[
p(z|x^n) = p(b|x^n)p(r|x^n)
\]  

(9)

Fig. 2 illustrates the characteristics of the likelihood of Eq. (9) and compares it to the use of boundary cues, \( p(b|x^n) \), and region cues, \( p(r|x^n) \), alone. The boundary cue alone

Fig. 4. Selected frames from a 400-frame sequence in which the occupant stands up, moves around the room, sits down on a chair, leans over and finally sits on the floor. The ILW filter successfully tracks the person’s head throughout.
results in a noisy likelihood with many local maxima. Translation of the ellipse does result in a smooth drop in the region cue likelihood. However, a decrease in scale does not result in a smooth decrease in this likelihood. The combined likelihood, on the other hand, gives a clear maximum in the correct location and varies in a well behaved manner as both translation and scale change.

7. Experiments

Results are reported here for scenes in which a person is tracked moving around a home environment using a wide-angle, ceiling-mounted camera. Whilst the articulated structure of the body will not always be readily apparent, it can reasonably be assumed that the head will nearly always be visible. The target application is a monitoring system to help extend independent living for older people in their own homes. The broader technical aims of such a system include the detection of important but relatively rare events such as falls and monitoring of patterns of activity and mobility. This technology could enable older people to live independently for longer with reduced healthcare costs and a more preventive approach [2]. Development of this application will clearly require extensive testing on the wide range of scene conditions that would arise in practice. Here, we give indicative results on some typical sequences of interest.

Likelihood computation is the main computational expense during tracking and the different filters require different numbers of likelihood evaluations per frame. In order to obtain a fair empirical comparison, the number of particles used with each filter was chosen so that the number of likelihood evaluations per frame was equal. Specifically, 2000 particles were used for SIR, 1000 particles for APF and 400 particles for ILW. The ILW filter performed iterated likelihood weighting 8 times on 200 of these particles making a total of 2000 likelihood evaluations per time-step. All filters were run with the same transition density (a Gaussian centered on the previous sample) and the same noise parameters.

Figs. 1, 3, 4 and 5 show typical runs of SIR and ILW on two sequences taken in different cluttered rooms. In each of these Figures, a red ellipse is used to indicate the mean estimated from the particle set and a white ellipse indicates the most heavily weighted particle for that frame. In Fig. 3 the SIR filter loses track when the person falls due to the sudden motion that is not adequately modelled by the transition density. However, Fig. 1 shows this entire sequence being successfully tracked using ILW. Similarly, Fig. 4 shows ILW successfully tracking a 400-frame sequence while the SIR filter was easily distracted by clutter (Fig. 5).

Fig. 5. Frames from the sequence of Fig. 4 showing the SIR tracker losing lock after frame 50. Tracking does not recover in this case.
Although the above runs were typical for these sequences, isolated runs of particle filters are not sufficient to evaluate performance as different runs on the same data can give very different results [7]. Fig. 6 compares multiple runs of all three filters on the same sequence with identical starting state. The SIR filter fails in the great majority of runs. In only 3 of the 20 runs did it provide a reasonable estimate in terms of the most heavily weighted particle. The mean did not provide good estimates of the state indicating that the distribution was clearly multimodal due to clutter. The APF gave reasonable estimates in 9 of the 20 runs. The ILW scheme gave good estimates in terms of both the mean and the most heavily weighted particle in all but one of the runs.

8. Discussion

The SIR (Condensation) filter was compared with the APF and the novel ILW filter in an overhead human tracking scenario. King and Forsyth [7] point out that

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Fig. 6. The mean ellipse (left) and the most highly weighted particle (right) at the end of each of twenty runs on a 55 frame sequence of (a) sampling importance resampling, (b) auxiliary particle filter, and (c) iterated likelihood weighting.
expectations computed using Condensation have high variance so that different runs of the tracker lead to very different answers. They also comment that “the tracker will appear to be following tight peaks in the posterior even in the absence of any meaningful measurement”. The experiments conducted here show that the variance can indeed be high while the approximation accuracy is often poor. The use of an auxiliary particle filter improved matters a little since it incorporates the most recent observation when estimating the importance density. However, the iterated likelihood weighting scheme proposed here yielded better accuracy and lower variance. In particular, it was able to successfully track motion that was poorly accounted for by the dynamic model.

The ILW filter does not attempt to compute a statistically unbiased representation of the posterior; rather it seeks an approximate density of use for efficient tracking. Approximation error depends not only on the bias but on the variance. Given unexpected motion, the Markov prior will inevitably be poor and expending extensive computational resources computing an accurate representation of the posterior in such cases is unwise. The approach taken by ILW is to divide computational resources between computing samples that are meaningful given a good prior and samples that are meaningful given a poor prior. The likelihood model was carefully formulated by combining region (colour) and contour (image gradient) cues. The nature of this likelihood meant that ILW’s random likelihood search was able to successfully sample regions of high likelihood even when the prior was poor. This, combined with samples from the posterior, yielded a tracker capable of dealing with unexpected motion and strong visual clutter.

Alternative strategies for searching regions of high likelihood and ways to control the allocation of computational resource between likelihood search and Bayesian sampling should be further explored. Future work will also concentrate on further developing the supportive home monitoring application.

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References
