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Deterministic Sampling-based Switching Kalman Filtering for Vehicle Tracking

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ABSTRACT

Accurate tracking is a difficult task in most computer vision applications. Errors in target localization and tracking result not only from the general uncontrolled nature of the environment, but also from inaccurate modeling of the target motion. This work presents a novel solution for the robust estimation of target trajectories obtained from real-world scenes such as traffic intersections. The main contribution of this work is a deterministic sampling approach applied to the filtering step of the switching Kalman filter/smoother. The unscented transform is used to obtain a fixed set of samples of the state distribution in the filtering step. Results demonstrating the improved accuracy and robustness of the proposed method, namely, deterministic sampling or unscented transform-based switching Kalman filter (DS-SKS or UKS) and the standard switching Kalman filter/smoother (SKS) are presented.

KEYWORDS

Deterministic sampling, unscented transform, switching Kalman filtering, smoothing.

I. INTRODUCTION

Robust tracking in general outdoor scenes is an important problem in several Intelligent Transportation Systems (ITS) applications. Besides the complex nature of the scene due to sources such as clutter and sudden illumination changes, inappropriate models used for the target motion also contribute to inaccurate estimation. Assumed density filtering methods such as [1], [4] address the problem by using a small number of models to approximate the target motion. However, when applied to the estimation of non-linear models, the linearization and hypothesis pruning approximations result in poor tracking. For example, Fig. 1 shows an example of a lane changing vehicle and the estimation of a segment of its trajectory using a standard switching Kalman filter/smoother (SKS) in Fig. 2. As can be seen, while the straight moving portions of the target are estimated with good accuracy, the lane change is not. Such an approximation may not be acceptable particularly for an application such as data collection, traffic flow prediction or scene monitoring applications. The effect of errors and the inaccuracies in the premature hypothesis pruning in switching Kalman filters has been previously noted by [2] who used a mixture of Gaussian distributions to obtain robust performance from the switching Kalman filter. However, it is unclear how the samples are generated. Applying particle filtering based sampling methods will only

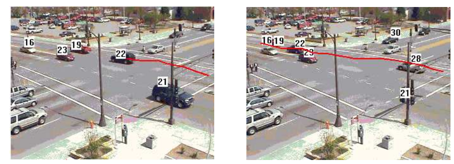


Fig. 1. An example of a lane changing sequence obtained from a video sequence.

make the tracking computationally intractable particularly when the number of targets is large. This work combines the unscented transform based sampling in the switching Kalman filter to address the problem of inaccurate estimation. The main contribution of this work is a computationally tractable, yet robust tracking solution for multiple target tracking in outdoor traffic intersections using a deterministic sampling-based switching Kalman filter (DS-SKF) or unscented transform-based switching Kalman filter/smoother (UKS). Fig. 2 shows the comparison of trajectory estimation using the proposed DS-SKS also referred as UKS in the paper and the standard switching Kalman filter/smoother (SKS).

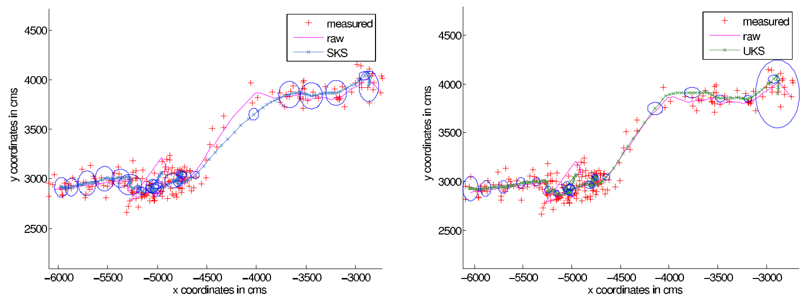
II. PROBLEM STATEMENT

A. Linearization Approximation

The standard method for estimating non-linear systems using the Kalman filter framework is the extended Kalman filter, where the system is locally approximated as a linear dynamic system. Thus, the extended Kalman filter makes use of the gradient of the first two moments, namely, the predicted mean and the covariance for function estimation. While this approximation works as long as the dynamics of the system are more or less smooth, inaccuracies arise in the presence of discontinuous or changing motions. The inaccuracy of the extended Kalman filter based approximation is discussed in [9].

B. Moment Matching Approximation

In a switching Kalman filter, the standard approach to make inference computationally tractable is through collapsing the belief states such that the number of belief states m in each step remains the same. This approximation however, affects the quality of the estimation particularly when applied to non-linear systems as well as the accuracy of smoothing. The state posterior $\hat{x}_t$ as a result of smoothing can be



(a) Tracking with Extended switching Kalman filter/smoother.

(b) Tracking with Deterministic particle switching Kalman filter/smoother.

Fig. 2. Comparison of tracking with extended switching Kalman filter/smoother (SKS) and the deterministic particle switching Kalman filter/smoother (DS-SKS or UKS). As shown, the lane change is more accurately captured by the proposed method in comparison to the standard extended switching Kalman filter/smoother. The ground truth measurements are indicated by the solid line while the '+' sign corresponds to the observed measurements. The results of the estimator are indicated by 'x-'. The ellipses along the trajectory correspond to the estimate of the uncertainty in the position estimate.

represented as,

$$p(\hat{x}_t, s_t | y_{1:T}) \propto \sum_{s_i} \int_{x_i} p(x_t | x_i, s_i, s_t, y_{1:t}) p(x_i, s_i, s_t, y_{1:T}) \quad (1)$$

where s is the set of hidden switch variables, $i = t+1$, and $y_{1:T}$ is the set of observations. The first term can be obtained from the forward step of the switching Kalman filter. The second term can be expanded, substituting i by $t+1$ as,

$$p(x_{t+1}, s_{t+1}, s_t, y_{1:T}) = p(x_{t+1} | s_t, s_{t+1}, y_{t:T}) p(s_t | s_{t+1}, y_{1:T}) \quad (2)$$

The last term $p(s_t | s_{t+1}, y_{1:T})$ is obtained through Bayes' rule as,

$$\begin{aligned} p(s_t | s_{t+1}, y_{1:T}) &= p(s_t | s_{t+1}, y_{1:t}) p(y_{t+1:T}) \\ &= \frac{p(s_t | y_{1:t}) p(s_{t+1} | s_t)}{\sum_{j=1}^{M} p(s_t^j | y_{1:t}) p(s_{t+1} | s_t^j)}. \end{aligned} \quad (3)$$

This approximation, based on the Markov assumption that all the information for a state x_t, s_t is contained in a previous state x_{t-1}, s_{t-1} is true only in the forward step and not necessarily for the backward or smoothing step. As such, the marginalization in Eqn. (3) is good only when $p(s_t^j | y_{1:t})$ correctly represents the entire distribution of x_t. Given that it is obtained from a collapsed mean of a Gaussian mixture, this approximation does not necessarily hold true, more so in the case of linearization approximation used for a non-linear system by the extended Kalman filter.

Hence, in order to deal with the above two mentioned problems, the posterior state and covariance are represented as a set of sampled points. Specifically, the collapsed state density of the switching Kalman filter is replaced by a set of samples obtained using the unscented transform, followed by the application of the standard switching smoother.

III. Related Work

Non-linear systems are estimated using the Kalman filter as locally linear systems. Common approaches for doing this approximation include, first- and second-order truncated Taylor series expansions such as the extended Kalman filters, the unscented Kalman filtering [9], [13], and Gaussian quadrature approximations such as [7]. Expectation propagation based methods [10] help address the problem of approximation due to moment matching in assumed density filters. The main limitation of this approach is that convergence is dependent on the starting solution. Barber [2] proposed several approaches including expectation propagation-based smoothing and mixture representation for improving the estimates of switching state space models.

Non-parametric estimators such as the sequential Monte Carlo or particle filters also address the problem of robust estimation of arbitrary non-linear functions [8], [5], [12]. The main disadvantage of particle filters and smoothers is the high computationally complexity and the poor scalability of estimation to the number of targets due to sample collapse. Higher accuracy can be achieved by using deterministic particle filters such as [3] with minimal computational requirements for low dimensional function estimation.

The proposed method differs from the above discussed methods in that a small number of samples is used to approximate the posterior of a mixture density. In this regard, this work resembles most closely to the mixture of Gaussians used for approximating the switching state space models as proposed by Barber [2]. However, since the samples are obtained from the unscented transform, a much smaller set of samples is required for the approximation as long as the noise model in the measurements is reasonably accurate.

A. Problem Domain

The application used in this work is the automatic data collection at traffic intersections. The input or the target trajectories for the data collection are obtained from computer vision-based tracking. The target trajectory measurements, consisting of the discrete target position and velocity in the image at each frame are obtained by combining cues such as motion segmented blobs and the target color distribution. The details of the tracking method are in our earlier work [11]. The individual cue measurements, namely position from motion segmented blobs and color are combined incrementally in the switching Kalman filter. The deterministic samples are generated from the state posterior obtained after the incorporation of the last available measurement in the given frame.

B. Outline

This paper is organized as follows: Section II presents the problem and the motivation for the proposed method while related research is discussed in Section III. Section IV presents details of the proposed deterministic sampling-based switching Kalman filter/smoother. The experimental results and their discussion are in Section V, and Section VI concludes the paper.

C. Notation

All column vectors such as state means are indicated by lower case letters such as x and matrices are indicated by upper case letters. A '$-$' in the superscript, x^- corresponds to a predicted estimate while a no sign corresponds to an updated state estimate. A '$+$' in the superscript, x^+ indicates the smoothed estimate. Measurements are indicated by z and the measurement noise or covariance by R. The state estimate, namely, the mean and the covariance are indicated by x and P. The subscript m used with the state estimates x_m, P_m corresponds to the state estimates for a filter model m. Model transitions are indicated as ${}^j s_k$ where the superscript corresponds to the model transitioned from and the subscript corresponds to the model transitioned to. Finally, the sampled distribution is represented as x^i where i corresponds to the i^{th} sample.

IV. Proposed Method: Deterministic Switching Kalman Filter

In this work, we address the inaccurate estimation in an extended switching Kalman filter through deterministic sampling of the state. The samples are obtained by applying the unscented transform to the individual model estimates. The unscented transform consists of computing a set of deterministic sigma vectors as,

$$\begin{aligned} X_0 &= \hat{x} \\ X_k &= \hat{x} \pm (\sqrt{(N+\lambda)\hat{P}_x})_k, \; k = 1, \ldots, 2N. \end{aligned} \tag{4}$$

$\hat{x}$ and $\hat{P}_x$ are the mean and the covariance of the random variable x. $X_0, \ldots, X_{2N}$ correspond to the sigma vectors, N is the number of sigma points or the number of dimensions

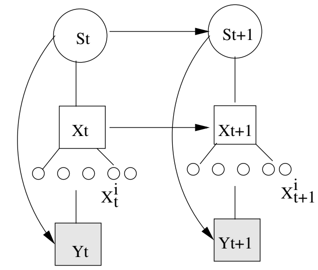


Fig. 3. Graphical representation of the deterministic sampling switching Kalman filter. The shaded nodes are observed and the clear nodes are hidden. The hidden state x_t, x_{t+1} consists of mixture of Gaussians for each filter model which are represented as a deterministic sample obtained from the unscented transform.

of the state, and λ is a constant scaling parameter computed as, $\lambda = \alpha^2(N+\kappa) - N$. α is a constant that determines the spread of the sigma points and κ is usually set to 0. The values of the scaling parameters are chosen assuming that the distribution is Gaussian as provided in the original paper [9].

A Graphical model of the filter is depicted in Fig. 3. As shown, the hidden variable or the state is represented as a mixture of Gaussians obtained from an unscented transform instead of the collapsed mean. To further improve the results of estimation, a standard Kalman smoother is applied in the backward step. Details of the forward and the backward algorithm are discussed in the following paragraphs.

Forward Algorithm: Deterministic Sampling-based Switching Kalman Filter The forward algorithm is depicted in Fig. 4. In the forward or the filtering step, the individual state densities of the mixture models are approximated using a set of deterministic sigma points obtained through the unscented transform Eqns. (4). Each one of these samples is then propagated through all the filter models as in a standard switching Kalman filter and recombined after the update step. The *aposteriori* x_t state estimate is computed in two steps. In the first step, the estimates resulting from the sigma points for each filter are recombined, followed by collapsing of the mean of the switching filters to obtain the collapsed mixture of state densities.

In essence, this representation of each state as a set of sigma particles resembles a particle filter approximation. However, the weights are deterministic and new samples are created from the posterior state estimate in each time step. Thus, there is no danger of sample degeneration or collapsing.

The filter models used by the individual filters consist of: (i) zeroth order or constant position, (ii) first order or constant velocity, and (iii) second order or constant acceleration filter to model the appropriate motion of vehicles in the scenes. The other filter parameters such as the system noise covariance and the static mode probabilities for the switching filters

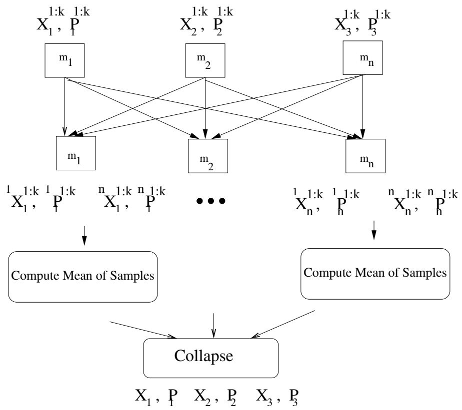


Fig. 4. Deterministic sampling-based switching Kalman filter. The steps involved in a single filtering iteration are illustrated. The state models indicated by m consist of n different models. The state estimate for each model is sampled using the unscented transform to produce k sigma points which are then propagated through the filters as in a standard switching Kalman filter and recombined after the collapse operation.

are design parameters that are estimated off-line from the observed data using an Expectation Maximization algorithm. Interested readers may find details of parameter estimation for state space models using expectation maximization in [6].

Backward Step: Switching Kalman Smoothing The backward recursion or smoothing consists of applying the standard switching Kalman smoother. The goal of these recursions is to refine the estimates obtained from the forward and backward recursion. This can be expressed as,

$$\begin{aligned} p(x_t^+, s_t^+ | y_{1:T}) &= \sum_{s_{t+1}^+} \int_{x_{t+1}^+} p(x_t, x_{t+1}^+, s_{t+1}^+, s_t, y_{1:T}) \\ &= \sum_{s_{t+1}^+} \int_{x_{t+1}^+} p(x_t, s_t | x_{t+1}^+, x_{t+1}^+, y_{1:t}) \\ & \quad p(x_{t+1}^+, s_{t+1}^+ | y_{1:T}). \end{aligned} \tag{5}$$

The '+' signs in the superscript indicate that the variables are smoothed posterior estimates, that is, $p(x_{t+1}|y_{1:T})$. Additional details on smoothing and the approximations to speed up smoothing were explained previously in II-B.

V. Experimental Results

A. Experimental Setup

The objective of the experiments was to evaluate the performance of the proposed deterministic sampling-based switching Kalman filter/smoother for robust estimation. The standard switching Kalman filter/smoother is used as a benchmark to assess the performance of the proposed method. Experiments were performed using trajectories obtained from a vision-based tracker using motion segmented blobs and color for target localization. Details of the tracking method are described in our previous work [11]. To evaluate the performance of the tracker under difficult conditions, additional

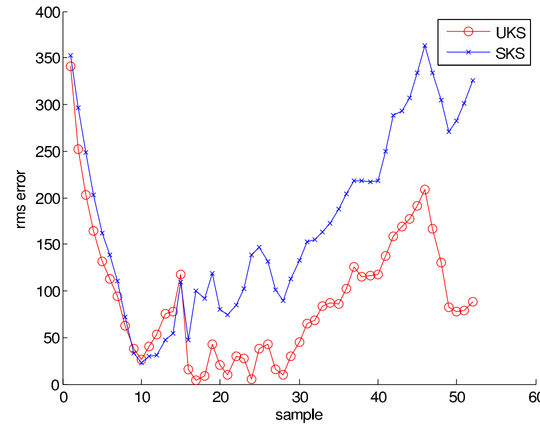


Fig. 5. Root mean square error in trajectory estimation for the DS-SKS or UKS and standard SKS. The ground truth was obtained manually from the image sequences.

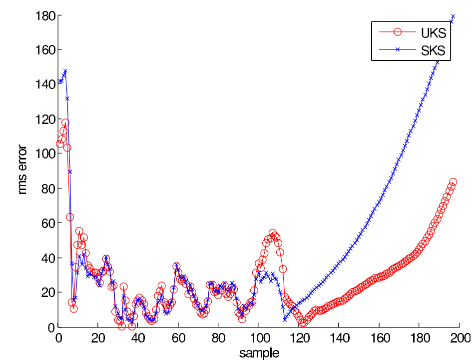


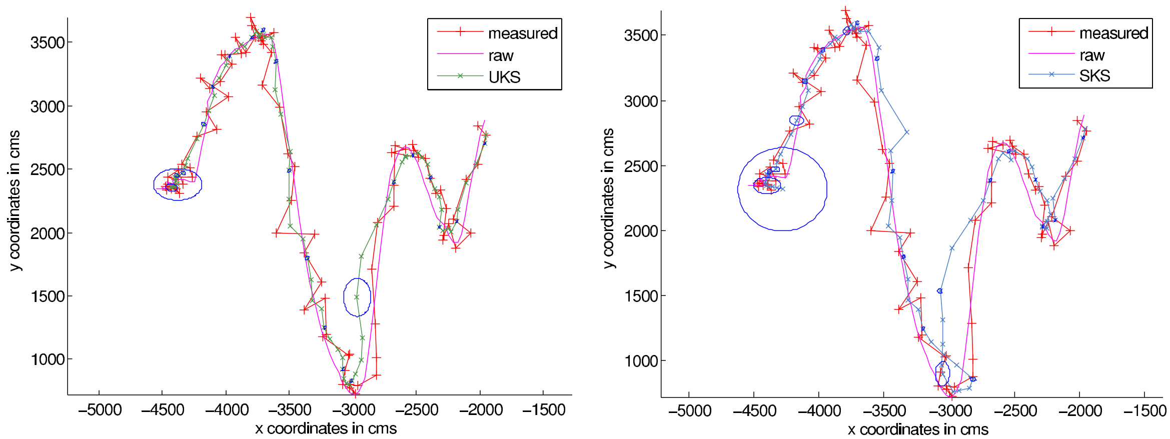
Fig. 6. Root mean square error in the trajectory estimates for the DS-SKS or UKS and standard SKS for the trajectory shown in Fig. 9.

Gaussian noise was injected into the sequences obtained from the vision-based measurements. [1]

B. Results

Fig. 7 shows the result of tracking a trajectory with lots of discontinuities using both the proposed deterministic sampling-based switching Kalman filter/smoother (DS-SKS) or UKS and a standard switching Kalman filter (SKS). As can be seen, the true trajectory indicated by the solid line is modeled more accurately using the sampling-based approach compared to the standard SKS. Fig. 5 shows the root mean square error in the estimates of a trajectory using both the DS-SKS and SKS. The corresponding image sequence is shown in Fig. 8. The ground truth was obtained manually from the image sequences. Fig. 6 shows the root mean square errors for a left turning vehicle undergoing occlusions as depicted in Fig. 9.

[1]Note that the additional Gaussian noise only makes the data worse than the actual real-world data in terms of signal to noise ratio.



(a) Deterministic sampling-based switching Kalman filter/smoother.

(b) Standard Switching Kalman filter/smoother.

Fig. 7. Example of tracking comparison for the DS-SKS or UKS and standard SKS. Ground truth measurements (raw) are indicated by the solid line, while the $+$ signs indicate the observed measurements. The results of the estimator are indicated by an $-x$ line. The ellipses correspond to the uncertainty in the current position estimate.

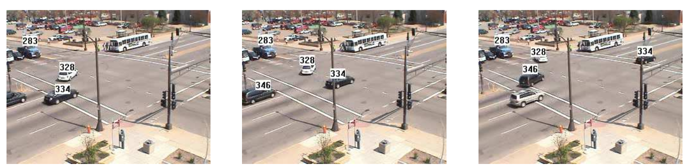


Fig. 8. Example tracking in an image sequence. The RMS errors using the two tracking methods are depicted in Fig. 5.

Fig. 9. Example tracking of a turning target. The RMS errors using the two tracking methods are depicted in Fig. 6.

C. Discussion of Results

As depicted in the results, even using a small set of deterministic samples obtained from the unscented transform helps obtain a much better approximation of the target trajectories compared to the switching Kalman smoother. However, one important issue with the robustness of the unscented switching Kalman smoother is the accuracy of measurement noise. Large inaccuracies in the measurement noise such as an underestimate can result in the tracker incorporating noisy measurements and vice versa for over-estimates. Because of sampling, and the integration used in the estimation, the inaccuracies are also projected further. Another issue resulting from using the unscented transform is the underestimate of the state covariance as observed earlier by [9]. Injecting covariances to the state estimates can improve the results of estimation, but this is still an issue that needs to be addressed in the future work.

Including trajectory smoothing to improve the accuracy of the trajectory estimation makes the approach off-line since batch smoothing requires that the entire sequence of observation be available. For an application such as data collection, this is not a concern. However, for other applications which require the data to be processed on-line, we plan to investigate a windowed version of smoothing.

VI. Conclusions

This work presented a solution to robust tracking and trajectory estimation in general outdoor scenes using a deterministic switching Kalman filter. As shown in the paper, the deterministic sampling helps to obtain a computationally tractable, albeit robust solution for trajectory estimation of noisy trajectories obtained from computer vision-based tracking.

VII. Acknowledgments

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