Diagonal Interacting Multiple Model H_∞ Filtering for Simultaneuos Sensor Localization and Target Tracking with NLOS Mitigation*

Xiaoyan Fu[2], Yuanyuan Shang[1], Hui Ding[2], and Xiuzhuang Zhou[1]

[1] Beijing Engineering Research Center of High Reliable Embedded System,
[2] Beijing Key Laboratory of Electronic System Reliability Technology,
College of Information Engineering, Capital Normal University, Beijing
fuxiaosg@163.com

Abstract. This paper is devoted to the problem of simultaneous localization and tracking (SLAT) in non-line-of-sight (NLOS) environments. By combining a target state and a sensor node location into an augmented vector, a discrete-time stochastic systems with Markov jump parameters is used to describe the switching of LOS/NLOS. A robust algorithm–diagonal interacting multiple model algorithm based on H_∞ filtering (DIMMH) is presented for simultaneous refinement of sensors' positions and target tracking when measurement noise is of unknown statistics. We use a measurement model from a real mine to handle all non-Gaussian uncertainties typical for mining environments, and analyze the performance of the classical interacting multiple model (IMM) algorithm, the DIMM algorithm and the cubature Kalman filter (CKF).

1 Introduction

Mine tunnels are extensive labyrinths with irregularly-shaped walls, in which a hundreds of employees are working on extraction of valuable ores and minerals. The miners work under hazardous environmental conditions caused by the high humidity and poor ventilation, the presence of flammable and toxic gases, corrosive water and dust, and the dangers of rock falls and mine collapses [1]-[3]. The knowledge of the last location of the miners is especially important in the aftermath of the accidents such as mine collapse or explosion, but can be also used for task optimization and traffic management. A GPS-based localization system provides the global position of a mobile vehicle or object in outdoor environment [4]. However, the GPS-based system has an inherent disadvantage because the GPS signal cannot be available in indoor scenarios [5]. A wireless sensor network (WSN) can be deployed across the mine to monitor the environmental conditions such as stability, humidity and toxic gas levels. The information obtained

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from the sensors can be used to control the ventilation system, and determine the unsafe areas and rescue paths. Beyond this ability, a WSN can be used to track the personnel, mobile equipment and vehicles [1].

However, the state-of-the-art algorithms [3],[6],[7] assume that the positions of the sensors are perfectly known, which is not necessarily true due to the imprecise placement and/or sensor drops caused by vibrations or wall collapses[1]. Though the miners can periodically verify if all the sensors' positions are correct, this approach is too costly and even infeasible in some areas due to the on-going mining activities. An effective option is to let the sensors estimate their individual positions while tracking a target in mine tunnels. In [9], the problem of target tracking by a network with unknown sensor positions has been addressed, which is also defined as simultaneous localization and tracking (SLAT). In [10], by assuming that sensors are randomly deployed, a sequential quasi-Monte Carlo-based filter has been developed to address the problem of SLAT. A distributed variational filter for SLAT has been proposed in [11], in which the energy consumption and bandwidth consumption are considered. Although much work has been done to SLAT, as shown in [9]-[11], almost all the proposed filters are derived based on the Sequence Monte Carlo (SMC) method, which are also known to be of high computational costs. Moreover, the received signal strength model is used to generate measurements in the aforementioned literature, whereas the non-line-of-sight (NLOS) effect is not considered.

In fact, there might be no direct path between a target and a sensor in a mine tunnels environment which are extensive labyrinths with irregularly-shaped walls. Furthermore, the propagating signal may travel excess path lengths of hundreds of meters due to reflection and diffraction. This error is referred to the NLOS error and may yield an estimation bias if not be addressed. To mitigate the NLOS error, many strategies have been proposed, a two state Markov process has been employed to describe the transition of the LOS/NLOS, and an interacting multiple-model (IMM) approach is used to derive the target-state estimate in [12]. Further improved results have been obtained in [13]-[15]. It is noted that combining the state estimations and corresponding covariance according to the scalar weights in the IMM algorithm. But in the problem of SLAT, the state augmented vector is the combining a target state and a sensor node location, The probability distribution of target state and sensor node location is difference, IMM algorithm can not distinguish the effects produced by different dimensions of the state. Moreover, simultaneuos sensor localization and target tracking in a mine tunnel, the measurement noise is of unknown statistics.

In this paper, H_∞ filtering are introduced into DIMM algorithm for SLAT in mine tunnels. We choose H_∞ filtering to deal with the state estimate problem in view of the following advantages of H_∞ estimate [16]: 1) H_∞ filtering provides a rigorous method for dealing with systems that have model uncertainty. 2) H_∞ filtering can be used to guarantee stability margins or minimize the worst

[1] Although not available in mines nowadays, we also envision that the uncertain sensors' positions can be an outcome of some (cooperative) sensor network localization algorithm[1],[8].

case estimate error. 3) H_∞ filtering may be more appropriate for systems whose models change unpredictably and when it is too complex or time consuming to model identification or gain scheduling.H_∞ filtering can deal with arbitrary signals with only a requirement of bounded noise, which replaces the Kalman filter method of modeling the noise as a random process. The results of H_∞ estimate are more robust than that in the signal models with uncertain parameters. In the DIMM algorithm, the diagonal matrices from the optimal multi-model fusion criterion are used as the weights of models. distinguish the effects produced by different dimensions of the state. The original edition of the DIMM algorithm can be found in our previous conference paper [17].

This paper is organized as follows. In section II, the problem of SLAT in NLOS environments is formulated as state estimate of discrete-time stochastic systems with Markov switching parameters, and IMM algorithm is reviewed and analyzed, which provides preliminaries for the following sections. In Section III, diagonal interacting multiple model algorithm based on H_∞ filtering (DIMMH) is presented. The conclusions are provided in Section IV.

2 Preliminaries

2.1 Markov Jump Systems Tracking Problem

Consider the following Markov jump system:

$$\mathbf{x}(k+1) = \mathcal{F}\mathbf{x}(k) + \mathcal{T}\nu(k) \tag{1}$$

$$\tau(k) = g_j(\mathbf{x})(k) + \omega_j(k) \tag{2}$$

where the state vector $\mathbf{x}(k)$ is an $n-$ dimensional vector, the observation process $\mathbf{z}(k)$ is an $m-$ dimensional vector, and the subscript $j \in \mathbb{S} = \{1, 2\}$ denotes the model. The matrix functions $\mathcal{F}(\cdot)$, $\mathcal{T}(\cdot)$ and $g_j(\cdot)$ are known. The model-dependent process noise is assumed to be a Gaussian random process with:

$$E[\nu(k)] = 0, \qquad E[\nu(k)\nu(k)^T] = Q_j \tag{3}$$

The measurement model switch between two types of the LOS and the NLOS situations. Then, we formulate the problem of mobile location estimation into the framework of nonlinear filtering for jump Markov systems with unknown statistics noise. Without loss of generality, exogenous inputs $D\mathbf{u}(k)$ can be considered in (1), but for notational convenience, here they are omitted.

- LOS case

$$\tau(k) = \frac{2\|x(k) - z(k)\|}{c} + \tau_{PT} + \omega^q(k) + \omega^m(k) \tag{4}$$

$$W^q_{t,n} \sim p_q(\omega_q) = Unif(\omega_q; 0, \frac{2D\sqrt{3}}{c}), W^m_{t,n} \sim p_m(\omega_m) = \mathcal{N}(\omega; 0, \sigma_w^2)$$

– NLOS case

$$\tau_{t,n} = \frac{2\|x_t - z_(k)\|}{c} + \tau_{PT} + \omega^q(k) + \omega^m(k) \quad (5)$$

$$\omega^q(k) \sim p_q(\omega_q){=}Unif(\omega_q; 0, \frac{2D\sqrt{3}}{c}), \omega^m(k) \sim p_m(\omega_m){=}\mathcal{B}(\omega; \mu_w, \alpha_w, \gamma_w)$$

where τ_{PT} is a known processing time on a target found by calibration, $c = 3 \cdot 10^8 m/s$ is the speed of light, $\omega^q(k)$ is quantization noise, and $\omega^m(k)$ is measurement noise. Note that the quantization noise is written outside the norm using an upper bound of the triangle inequality (i.e., $\| a + b \| \leq \| a \| + \| b \|$), which represents the worst case scenario. where σ_w is the standard deviation of the LOS component of the noise, and $B(\cdot)$ is a Weibull distribution with scale α_w, shape γ_w, and location parameters μ_w ($\alpha_w > 0$, $\gamma_w > 0$, $\omega > \mu_w$),

Let M_j^k denotes the flight model j at time k. The model dynamics are modeled as a finite Markov chain with known model-transitions probabilities from model i at time $k-1$ to model j at time k [18], [19].

$$\pi_{ij} \triangleq Prob\{M_j^k \mid M_i^{k-1}\} = \mathbf{P}\{M_j^k \mid M_i^{k-1}\} \quad (6)$$

$$0 \leq \pi_{ij} \leq 1, \qquad \sum_{j=1}^{s} \pi_{ij} = 1, \qquad i, j \in \mathbb{S} \quad (7)$$

The initial state distribution of the Markov chain is $\varphi = [\varphi_1, \cdots, \varphi_s]$, where

$$0 \leq \varphi_j \leq 1, \qquad \sum_{j=1}^{s} \varphi_j = 1, \qquad j \in \mathbb{S} \quad (8)$$

This Markov chain description of the target's models is used to model the unknown inputs.

It is also possible to use UWB and wideband received-signal strength (RSS) measurements using the models in [20], respectively. The noise in that case is a mixture of two Gaussians, corresponding to LOS and NLOS, respectively. However, RSS can only provide coarse distance estimates since it cannot exploit the very large bandwidth of the signal [1].

2.2 IMM Algorithm

IMM algorithm is the most prevalent for the state estimate of discrete-time stochastic systems with Markov switching parameters. The following steps are associated with IMM algorithm [21]:

Step 1. Calculate the mixed initial probability for the filter matched to model M_j^k ($j \in \mathbb{S}$)

Step 2. Calculate the mixed initial state and corresponding covariance for the filter matched to model M_j^k

Step 3. Kalman Filtering

Step 4. Combine the state estimates and corresponding covariances according to the updated weights

Remark 1. In IMM algorithm, updated weights of models are derived from the hybrid of *pdfs* and probability masses. It is known that any probability mass must be a value in the interval [0, 1], but any *pdf* has no such restriction, thus, the two kinds of values are at different levels. The resulting outcome μ_j^k is just an approximate probability. Moreover, when the measurement noise is of unknown statistics, IMM algorithm will produces more error. It is therefore necessary to propose a optimal filtering approach for the state estimate with uncertain noise.

3 Diagonal Interacting Multiple Model Algorithm Based On H_∞ Filtering

3.1 H_∞ Filtering

Consider the systems in (1-2) in the case where the process noise ν and the measurement noise ω_k are assumed to be energy bounded l_2 signals whose statistical properties are unknown.

Unlike the Kalman filter which aims to give the minimum mean-square estimate of the state vector $\mathbf{x}_k$, the optimal H_∞ filter tries to obtain the arbitrary linear combination of the state $\mathbf{x}_k$ using the measurements $\mathbf{Y}_k$ such that the effect of the worst disturbance on the estimate error is minimized, namely, $\mathbf{z}_k = L_k\mathbf{x}_k$ where L_k is a known matrix. Here, we are interested in state estimate, so L_k is taken as an identity matrix I. Let $\hat{\mathbf{x}}_{k|k}$ denotes the estimate of $\mathbf{x}_k$ given measurements $\mathbf{Y}_k$, and the estimate error is denoted as $\mathbf{e}_k = \hat{\mathbf{x}}_{k|k} - \mathbf{x}_k$

3.2 Cubature Kalman Filters

Consider the filtering problem of nonlinear dynamic system (1-2) with additive noise.

It is known that the Bayesian filter is rendered tractable when all conditional densities are assumed to be Gaussian. In this case, the Bayesian filter solution reduces to computing multi-dimensional integrals, whose integrands are all of the form $nonlinear function \times Gaussian$. The CKF exploits the properties of highly efficient numerical integration methods known as cubature rules for those multi-dimensional integrals [22]. Moreover, The CKF is numerically accurate and easily extendable to high-dimensional problems. In this paper, we extend the CKF and H_∞ filtering to form a cubature H_∞ filtering. The cubature H_∞ filtering is not only useful for multi-state estimation but it can also handle nonlinear and non-Gaussian systems.

3.3 DIMMH Algorithm

In this section, cubature H_∞ filtering is induced to receive the state estimate instead of the Kalman filter to obtain the optimal state estimates when the noise with unknown statistics. The following steps are associated with the DIMMH algorithm.

Step 1. Calculate the mixed initial diagonal-matrix-weight for the filter matched to model M_j^k $(j \in \mathbb{S})$:

$$
\begin{aligned}
B_{i|j}(k|k) &\triangleq \mathbf{P}\{M_i^{k-1}|M_j^k, Z^{k-1}\} \\
&= \frac{\pi_{ij} B_i^{k-1}}{\sum_{i=1}^{s} \pi_{ij} B_i^{k-1}} \\
&= \begin{pmatrix} \frac{\pi_{ij} b_{i1}}{\sum_{i=1}^{s} \pi_{ij} b_{i1}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{\pi_{ij} b_{in}}{\sum_{i=1}^{s} \pi_{ij} b_{in}} \end{pmatrix}
\end{aligned} \tag{9}
$$

where

$$
\begin{aligned}
B_i^{k-1} &= \mathrm{diag}(b_{i1}, b_{i2}, \cdots, b_{in}) \\
&\triangleq \mathbf{P}\{M_i^{k-1}|Z^{k-1}\}
\end{aligned} \tag{10}
$$

Step 2. Calculate the mixed initial state and corresponding covariance for the filter matched to model $M_j(k)$ $(j \in \mathbb{S})$:

$$
\hat{\mathbf{x}}_{0j}(k|k) = \sum_{i=1}^{s} B_{i|j}(k|k) \hat{\mathbf{x}}_i^{k-1} \tag{11}
$$

$$
\begin{aligned}
P_{0j}(k|k) = \sum_{i=1}^{s} B_{i|j}(k|k) \{ & P_i^{k-1} + [\hat{\mathbf{x}}_i^{k-1} - \hat{\mathbf{x}}_{0j}(k|k)] \\
& \times [\hat{\mathbf{x}}_i^{k-1} - \hat{\mathbf{x}}_{0j}(k|k)]^T \}
\end{aligned} \tag{12}
$$

Step 3. Cubature H_∞ filtering $(j \in \mathbb{S})$

$$
\hat{\mathbf{x}}_{k|k-1} = \frac{1}{2n} \sum_{i=1}^{2n} \chi_{i,k|k-1}^{*} \tag{13}
$$

$$
P_{k|k-1} = \frac{1}{2n} \sum_{i=1}^{2n} \chi_{i,k|k-1}^{*T} - \hat{\mathbf{x}}_{k|k-1} \hat{\mathbf{x}}_{k|k-1}^T + \mathcal{T} \tilde{Q} \mathcal{T}^T \tag{14}
$$

$$
\hat{\mathbf{x}}_j^k = \hat{\mathbf{x}}_{k|k-1} + K_k(\tau_k - \hat{\tau}_{k|k-1}) \tag{15}
$$

$$
P_j^k = P_{k|k-1} - K_k P_{\tau\tau,k|k-1} K_k^T - \gamma^{-}2 I_n \tag{16}
$$

$$
K_k = P_{x\tau,k|k-1} P_{\tau\tau,k|k-1}^{-1} \tag{17}
$$

where

$$\chi^*_{i,k|k-1} = \mathcal{F}\chi_{i,k-1|k-1} \tag{18}$$
$$\tau_{i,k|k-1} = g(\chi_{i,k|k-1}) \tag{19}$$
$$\chi_{i,k|k-1} = \sqrt{P_{k|k-1}}\xi_i + \hat{\mathbf{x}}_{k|k-1} \tag{20}$$
$$\hat{\tau}_{k|k-1} = \frac{1}{2n}\sum_{i=1}^{2n}\tau_{i,k|k-1} \tag{21}$$
$$P_{\tau\tau,k|k-1} = \frac{1}{2n}\sum_{i=1}^{2n}\tau_{i,k|k-1}\tau^T_{i,k|k-1} - \hat{\tau}_{k|k-1}\hat{\tau}^T_{k|k-1} \tag{22}$$
$$P_{x\tau,k|k-1} = \frac{1}{2n}\sum_{i=1}^{2n}\chi_{i,k|k-1}\tau^T_{i,k|k-1} - \hat{x}_{k|k-1}\hat{\tau}^T_{k|k-1} \tag{23}$$

Step 4. Combine of the state estimates and corresponding covariances according to the updated diagonal-matrix-weight:

$$\hat{\mathbf{x}}_D(k) = \sum_{j=1}^{s} B^k_j \hat{\mathbf{x}}^k_j \tag{24}$$

Updated diagonal-matrix-weight of model M^k_j is

$$B^k_j = \mathrm{diag}(b_{j1}, b_{j2}, \cdots, b_{jn}) \tag{25}$$

where

$$[b_{1i}, b_{2i}, \cdots, b_{si}] = \frac{\boldsymbol{e}^T(\mathcal{P}^i)^{-1}}{\boldsymbol{e}^T(\mathcal{P}^i)^{-1}\boldsymbol{e}} \tag{26}$$

with

$$\boldsymbol{e} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}_{s\times 1}, \quad \mathcal{P}^i = \begin{bmatrix} P^{(ii)}_1 & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & P^{(ii)}_s \end{bmatrix} \tag{27}$$

and $P^{(ii)}_j$ is the ith diagonal element of matrix P_j ($P_j = E[\tilde{\mathbf{x}}_j\tilde{\mathbf{x}}^T_j]$).

The error variance matrix of the optimal fusion estimate is

$$P_D(k) = \mathrm{diag}\,[P_{D1}, P_{D2}, \cdots, P_{Dn}] \tag{28}$$

where

$$P_{Di} = [\boldsymbol{e}^T(\mathcal{P}^i)^{-1}\boldsymbol{e}]^{-1} \tag{29}$$

Remark 2. For solving the problem of SLAT, the state of target and a sensor node location are combined into an augmented vector. The noise statistics is different between tracked target and sensor node. In DIMMH algorithm, the diagonal matrices from the optimal multi-model fusion criterion are used as the weights of models, which can be viewed as the joint probabilities of models. That is to say, the state vector is segmented into n scalars to carry on estimating, and every element of diagonal matrix can be interpreted as a probability mass of the model with dimension one. The new algorithm can not only avoid the mixture of likelihood function and probability mass and distinguish the effects produced by different dimensions of the state like DIMM algorithm but also deal with the noise with unknown statistics.

Remark 3. Another difference between the proposed algorithm and the celebrated IMM estimator lies on the fact that the H_∞ filtering and cubature rule are combined. The cubature rule is employed to deal with the nonlinear measurements in this work which is a derivative-free approximation scheme.

It is interesting to note that H_∞ filtering has the same observer structure as that of the Kalman filter, and $\tilde{Q}$ and $\tilde{R}$ play the same role as the variances of the process noise and the measurement noise when using the Kalman filtering [23]. Indeed, the H_∞ filter is equivalent to the Kalman filter in the Krein space and the H_∞ filter exists if and only if $P_k^{-1} > 0$ [24]. Specifically, the H_∞ filter is reduced to the Kalman filter when $\gamma \longrightarrow \infty$. Thus, the γ may be thought as a tuning parameter to control the tradeoff between H_∞ performance and minimum variance performance. The optimal H_∞ filter can also be interpreted in the frequency domain as an estimate that minimizes the peak error power whereas the Kalman filter aims to minimize the average error power or error covariance.

4 Conclusions and Future Work

In the paper, DIMMH algorithm is presented for maneuvering target tracking. It is principally similar to the popular IMM algorithm and DIMM algorithm proposed in our previous paper. The difference lies in the use of filtering. To obtain the optimal state estimates in the nonlinear switching system when the noise with unknown statistics, $H\infty$ filtering and cubature rule are combined instead of the Kalman filter. In future work, we will research on how to deal with arbitrary uncertain noise stretching beyond l_2 signal and demonstrate the computer simulations for indicate the superiority of proposed algorithms.

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