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Joint Target Tracking and Classification with Heterogeneous Sensors

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Introduction

For most conventional target tracking algorithms only the target kinematic measurements are used to evaluate the state estimates and covariance. These measurements include range, azimuth, elevation, and possibly Doppler-derived range rate from radar, sonar or other kinematic sensors. As a result of the effect of clutters, one track can be associated with several measurements which may have originated from the target of interest. In this situation data association [1], where the measurement-to-track associations are decided, is a critical phase in whole tracking process. The leading method to solve this problem is Probabilistic Data Association (PDA) which calculates the association probabilities for each validated measurement at the current time to the target of interest. Typically only kinematic measurements are used in PDA. In many situations the feature and attribute information about the target which come from attribute sensors like ESM is available. Conceptually speaking, It's clearly understood that these feature and attribute information can be used to the data association process to improve the tracking accuracy. Here a joint target tracking and classification algorithm (JTC) is proposed which jointly uses kinematic and feature measurements coming from heterogeneous sensors to improve the overall tracking performance.

In recent years some literatures have considered JTC from different perspectives. Reference [2] utilizes feature/attribute metrics to increase the accuracy and robustness of data association. In [3] a new multisensor fusion algorithm that integrates model-based target identification and multiple hypotheses tracking (MHT) was presented. The major contribution of this literature is to take into account target identification in Bayesian networks. Reference [4, 5] formulates a framework which allows joint state estimation for the continuous and discrete system with different types of measurement. In [6, 7] some attempts have been made to deducing target identity from kinematic measurements and using state constraints in improving target state estimates. But there exists no unified framework for treating the problems jointly. In [8] a general approach for multisensor data association that includes attribute information was presented. There the likelihood function which assigns the measurement to a track is defined using attribute measurement conditional probabilities. In [9] an algorithm for target tracking with classification-aided multiframe data association was proposed. Target class information is integrated into the data association process using the 2-D as well as multiframe assignment algorithm.

The approach proposed here integrates the target class information into the data association process of target tracking. First, we define a confusion matrix which specifies the uncertainty of target classification process. Second, the Bayesian classifier is used to output the class information given the attribute measurement sequence coming from feature sensor. Finally, the target tracking is done based on PDA with class information.

This paper is organized as follows. Second section gives the state and measurement models for our joint tracking and classification system. Third section presents the Bayesian classification method. In Fourth section the JTC algorithm is discussed based on the idea that the target class information can aid the data association process for improving the tracking accuracy. Simulation results and analysis are given in fifth Section and a summary of the work and conclusions are presented in last section.

System models

In the measurement process two kinds of sensors are used, a kinematic sensor and an attribute sensor. Target state vector is denoted as $\boldsymbol{x}_k$, the kinematic and attribute measurement sequences are represented by

$$\boldsymbol{z}_{1:k} = \{\boldsymbol{z}_{1:k}^x, \boldsymbol{z}_{1:k}^c\}, \tag{1}$$

where $\boldsymbol{z}_{1:k}^x = \{\boldsymbol{z}_1^x, \boldsymbol{z}_1^x, \cdots, \boldsymbol{z}_1^x\}$ and $\boldsymbol{z}_{1:k}^c = \{\boldsymbol{z}_1^c, \boldsymbol{z}_1^c, \cdots, \boldsymbol{z}_1^c\}$ respectively.

With the linear measurement assumption the measurement equation of a kinematic sensor can be represented by

$$\boldsymbol{z}_k^x = \boldsymbol{H}_k \boldsymbol{x}_k + \boldsymbol{w}_k, \tag{2}$$

where $\boldsymbol{H}_k$ is the measurement matrix, $\boldsymbol{w}_k$ is assumed to be zero-mean white Gaussian noise with known variance $\boldsymbol{R}_k$. The measurement process of an attribute sensor can be represented by

$$p(\boldsymbol{z}_k^c \mid \boldsymbol{x}_k, f_k, c_i) = p(\boldsymbol{z}_k^c \mid f_k), \tag{3}$$

where $\boldsymbol{z}_k^c$ is statistically independent of all other variables except target feature f_k.

The target motion in the Cartesian coordinate system is modeled by

$$\boldsymbol{x}_k = \boldsymbol{F}_k \boldsymbol{x}_k + \boldsymbol{G}_k \boldsymbol{u}_k + \boldsymbol{v}_k, \tag{4}$$

where $\boldsymbol{F}_k$ is the state transition matrix, $\boldsymbol{G}_k$ is the control matrix, $\boldsymbol{u}_k$ is maneuvering input, $\boldsymbol{v}_k$ is the process noise with Gaussian assumption of zero-mean, variance $\boldsymbol{Q}_k$.

Bayesian target classification

There are *s* classes of known targets. The output set of Classifier here is assumed to be the same as the set of target classes. The class of target is denoted by *c* and the probability that target belongs to class *i* is represented by $\Pr\{c=i\}$. The target classification problem consists of finding the posterior probability $\Pr\{c=i \mid \boldsymbol{z}_{1:k}^c\}$ given the attribute measurements sequence $\boldsymbol{z}_{1:k}^c$. To account for the output uncertainty of the classifier the confusion matrix $\boldsymbol{C}$ below need to be defined

$$\boldsymbol{C} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1j} \\ c_{21} & c_{22} & \cdots & c_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ c_{i1} & c_{i2} & \cdots & c_{ij} \end{bmatrix}, \tag{5}$$

where c_{ij} is the likelihood of the true class being *i* when the classifier output is *j*. That is

$$c_{ij} = \Pr\{\boldsymbol{z}_k^c = j \mid c = i\}. \tag{6}$$

Note that the row sums of the confusion matrix are unity. The evaluation of c_{ij} depends on the probabilistic relationship between the attribute sensor measurements and the target classes. For ESM measurements the emitter sequence can be used for target classification. According to the Bayesian formula, the posterior probability of a target class is given by

$$\begin{aligned} &\Pr\{c=i \mid \mathbf{z}_{1:k}^c\} \\ &= \Pr\{c=i \mid \mathbf{z}_{1:k-1}^c, \mathbf{z}_k^c\} = \\ &= \frac{\Pr\{\mathbf{z}_k^c \mid c=i, \mathbf{z}_{1:k-1}^c\}\Pr\{c=i \mid \mathbf{z}_{1:k-1}^c\}}{\sum_{j=1}^{s}\Pr\{\mathbf{z}_k^c \mid c=j, \mathbf{z}_{1:k-1}^c\}\Pr\{c=j \mid \mathbf{z}_{1:k-1}^c\}} = \\ &= \frac{c_{ij}\Pr\{c=i \mid \mathbf{z}_{1:k-1}^c\}}{\sum_{j=1}^{s} c_{ij}\Pr\{c=j \mid \mathbf{z}_{1:k-1}^c\}}, \end{aligned} \tag{7}$$

where $\Pr\{c=i, z_{1:k-1}^c\}$ is the prior probability of class (prior to the observation under consideration).

Joint target tracking and classification

It is assumed that there are m_k measurements at time *k*. According to PDA algorithm in [1] the updated state at time *k* can be written as

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{W}_k \boldsymbol{\upsilon}_k, \tag{8}$$

where $\boldsymbol{W}_k$ is the gain and

$$\boldsymbol{\upsilon}_k = \sum_{i=1}^{m_k} \beta_k^i \boldsymbol{\upsilon}_k^i \tag{9}$$

is the combined innovation. β_k^i is the association probability for $\boldsymbol{z}_k^i$ to the true target obtained from the PDA procedure.

The covariance associated with the updated state is

$$\boldsymbol{P}_{k|k} = \beta_k^0 \boldsymbol{P}_{k|k-1} + [1-\beta_k^0]\boldsymbol{P}_{k|k}^c + \breve{\boldsymbol{P}}_k, \tag{10}$$

where the covariance of the state updated with the correct measurement is

$$\boldsymbol{P}_{k|k}^c = \boldsymbol{P}_{k|k-1} - \boldsymbol{W}_k \boldsymbol{S}_k \boldsymbol{W}_k^T \tag{11}$$

and the spread of the innovation term is

$$\breve{\boldsymbol{P}}_k = \boldsymbol{W}_k \left[\sum_{i=1}^{m_k} \beta_k^i \boldsymbol{\upsilon}_k^i (\boldsymbol{\upsilon}_k^i)^T - \boldsymbol{\upsilon}_k^i (\boldsymbol{\upsilon}_k^i)^T\right] \boldsymbol{W}_k^T. \tag{12}$$

In view of the independence of the kinematic and attribute measurements, the combined association probability $\breve{\beta}_k^i$ for $\boldsymbol{z}_k^i$ is sum of the products of β_k^i in (9) and μ_k^{ij}, i.e.,

$$\breve{\beta}_k^i = \frac{1}{\delta}\sum_{j=1}^{s} \beta_k^i \mu_k^{ij}, \tag{13}$$

where $\mu_k^{ij} = \Pr\{c=i \mid \boldsymbol{z}_{i:k}^c\}$ in (7), δ is a normalizing constant.

Substituting $\breve{\beta}_k^i$ for β_k^i in (9) and (12), we get a new PDA algorithm where the target class information is integrated into the data association process. Target class estimates for the classifier only results from the attribute measurements. The joint uses of two type of sensor information only occur in tracker.

Simulation and result analysis

In the simulation scenario three target classes are considered: class 1, 2 and 3. The confusion matrix for classifier is given by

$$\boldsymbol{C} = \begin{bmatrix} 0.98 & 0.01 & 0.01 \\ 0.01 & 0.98 & 0.01 \\ 0.01 & 0.01 & 0.98 \end{bmatrix}. \tag{14}$$

The initial target class probabilities are assumed to be equal. The detection probability and the false alarm probability for kinematic sensor are 0.9 and 0.01. The standard deviation of process noise $\boldsymbol{v}_k$ is set as 1, sampling time is 1s. The target moves with speed 50m/s over a period of 100s. The maneuver is occurring at the sampling time instant 20 and 60 with a nearly coordinated turn model as shown in Fig. 1.

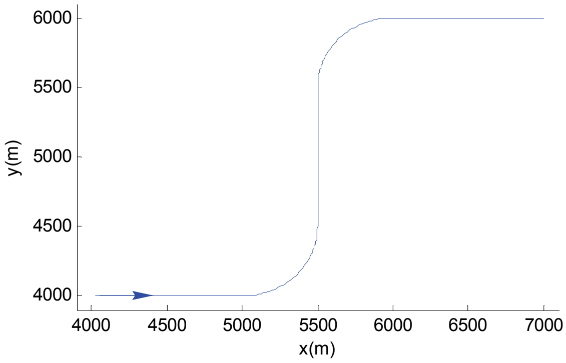

Fig. 1. Target true trajectory

This scenario represents a ground target tracking problem where the two heterogeneous sensors are used for detecting target: radar and ESM. The kinematic measurement sequence from radar and the attribute measurement sequence from ESM are assumed to have been associated with bearings. The initial target state are assumed to be

$$\boldsymbol{x}_0 = [4000m, 50m/s, 4000m, 0m/s]. \tag{15}$$

The radar position measurement at time k is given by

$$\boldsymbol{z}_k^x = [1 \;\; 0 \;\; 1 \;\; 0][\boldsymbol{x}_k \;\; \dot{\boldsymbol{x}}_k \;\; \boldsymbol{y}_k \;\; \dot{\boldsymbol{y}}_k]^T + \boldsymbol{w}_k. \tag{16}$$

where the standard deviation for measurement noise $\boldsymbol{w}_k$ is set to 50m. The IMM filter is chosen for maneuvering target tracking problem in this scenario. It consists two models, namely, a nearly constant velocity model and a nearly coordinated turn model. The initial model probabilities are assumed to be equal. The Markov chain matrix for this IMM tracker is

$$\boldsymbol{P} = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}. \tag{17}$$

Three kinds of algorithms for tracking the target in the simulation scenario are implemented to quantify the benefits of using class information. Algorithm 1 uses the probabilistic data association filter described in [1]; Algorithm 2 uses the IMMPDA filter in [10]; Algorithm 3 uses the JTC filter proposed in this paper. The position estimation RMS and velocity estimation RMS are shown in Fig. 2-Fig. 5 respectively.

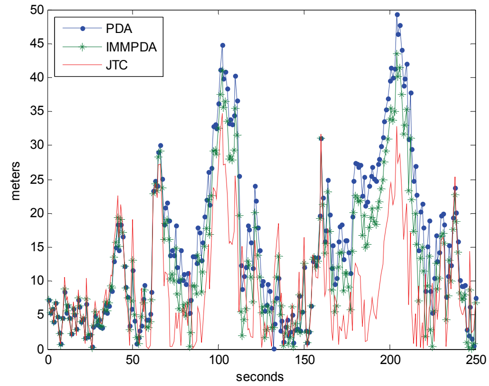

Fig. 2. RMS position error in X

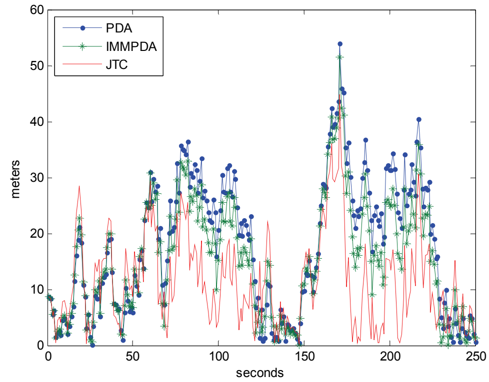

Fig. 3. RMS position error in Y

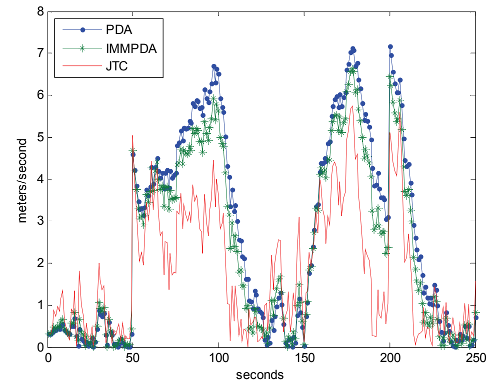

Fig. 4. RMS velocity error in X

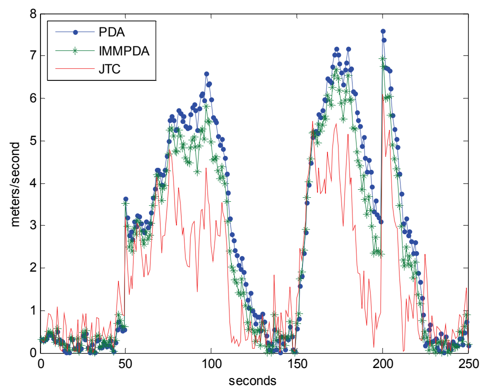

Fig. 5. RMS velocity error in Y

It can be seen that the position RMS obtained from one Monte-Carlo run has about 10% improvement and the velocity estimation RMS is about 15%. During the target maneuvers the performance improvement is very significant with the proposed algorithm. In traditional tracking algorithms the date association uncertainty increases during maneuvers but the kinematic information is not enough to resolve the ambiguities. This problem gets worse when the dense clutter is considered. By contraries, class information in the attribute measurement is not going to be affected by target maneuvers. From the simulation results we can explicitly see that the target class information decreases the uncertainty in data association process.

Conclusions

The joint target tracking and classification approach has been presented in this paper. The kinematic and attribute information coming from heterogeneous sensors are considered simultaneously in target tracking system. By applying Bayes' rule to the target attribute measurements the target class information is derived. Target class outputs of Bayesian classifier are integrated into data association process via the posterior probabilities. The simulation results with and without the use of the class information in target tracking suggest that the proposed JTC algorithm provide a more accurate solution to the target tracking problem using heterogeneous sensors.

Acknowledgements

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Target classification and target tracking are conventionally treated as two separate problems. The target tracking is usually performed using data from kinematic sensors like radar while target classification is performed using data from attribute/feature sensors like ESM. There are few consideration of the link between the target state and the target class. However, the methods of integrating target tracking and classification into a single framework does make sense. In this paper we present a joint target tracking and classification(JTC) approach. The approach presented here integrates the target class information into the data association process of target tracking. The target classification information results from the Bayesian classifier based on the confusion matrix which accounts for the uncertainty of target classification process. Performance comparisons with and without the use of the class information in target tracking are illustrated. The simulation results suggest that the proposed JTC algorithm provide a more accurate solution to the target tracking problem using heterogeneous sensors. Ill. 5, bibl. 10 (in English; abstracts in English and Lithuanian).

Hongwei Quan, Anke Xue, Dongliang Peng. Jungtinis taikinio sekimas ir klasifikavimas heterogeniniais jutikliais // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2012. – Nr. 4(120). – P. 61–64.

Taikinių klasifikavimas ir sekimas tradiciškai traktuojami kaip dvi atskiros problemos. Taikiniams sekti paprastai naudojami iš kinematinių jutiklių gaunami duomenys, o taikiniams klasifikuoti – duomenys iš atributų/ypatybių jutiklių. Apie taikinio būsenos ir taikinio klasės tarpusavio sąsają yra įvairių nuomonių. Tačiau taikinio sekimo ir klasifikavimo metodų integravimas į vieną struktūrą turi prasmės. Pristatomas jungtinis taikinio sekimo ir klasifikavimo požiūris, kuris integruoja taikinio klasės informaciją į taikinio sekimo duomenų asocijavimo procesą. Taikinio sekimo našumo palyginimas naudojant klasės informaciją ir jos nenaudojant. Modeliavimo rezultatai rodo, kad, naudojant pasiūlytą algoritmą, taikinio sekimo heterogeniniais jutikliais problema sprendžiama tiksliau. Il. 5, bibl. 10 (anglų kalba; santraukos anglų ir lietuvių k.).