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Joint Tracking and Classification Based on Conditional Joint Decision and Estimation

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***Abstract*—In joint tracking and classification (JTC) problems, both decision and estimation are involved and they affect each other. Good solutions for JTC require solving the two problems jointly. A joint decision and estimation (JDE) framework based on a generalized Bayes risk was recently proposed for solving the problem of inter-dependent decision and estimation. In the JDE framework, a conditional JDE (CJDE) risk was proposed, and the corresponding optimal solution was obtained. Due to the development of modern sensor technology, multisensor data with different characteristics are available. In this paper, we solve a JTC problem using multisensor data by the CJDE method. First, a dynamic JTC problem based on kinematic and attribute measurements is formulated as a JDE problem. To solve this problem, we propose a multiple-model recursive CJDE (RCJDE) method, which is an extension of the original RCJDE to the multisensor scenario. For joint performance evaluation, we suggest two joint performance metrics (JPM) for the cases with known and unknown ground truth, respectively. Simulation results demonstrate the effectiveness of the proposed RCJDE method. They show that the multisensor data based RCJDE can outperform the traditional two-step strategies in JPM.**

I. INTRODUCTION

Target tracking is critical in many military and civilian fields. It has been studied extensively with abundant results [1]–[3], which usually estimate the target state (e.g., position, velocity, and acceleration). Target classification is also a critical problem, which aims to identify the target allegiance (friend, foe, and neutral), class label (bomber, fighter, commercial jet, ship, etc.), and so on [4]–[7]. In reality, there exists also the problem of joint tracking and classification (JTC), in which we want to know not only the target state but also the target class, and tracking and classification are usually inter-dependent. For example, tracking may affect classification by providing flight envelope information for different classes, while classification affects tracking via selecting appropriate class-dependent kinematic models. JTC has received increasing attention in recent years [8]–[17]. In essence, JTC is a typical joint decision and estimation (JDE) problem [18], and thus good solutions require solving the tracking and classification problems jointly.

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The traditional strategies for solving JDE problems can be classified into the following four categories [19]:

(a) Decision and estimation are handled separately: decision and estimation are considered as two separate problems without considering their inter-dependence [5], [8].

(b) Decision then estimation: first make the best decision disregarding estimation and then solve the estimation problem as if the decision were surely correct. Two serious disadvantages of this strategy are: it does not account for possible decision error in the subsequent estimation; decision is done disregarding the quality of the estimation that it would lead to [20], [21].

(c) Estimation then decision. This strategy considers that decision relies heavily on accurate estimation, and thus it does estimation first and then makes a decision based on the estimation [6], [7], [13]. The generalized likelihood ratio test (GLRT) and the marginalized likelihood ratio test (MLRT) follow this strategy if the goal is dual: hypothesis testing and particular estimation. However, this strategy does not work well if estimation depends significantly on decision [22].

(d) Decision and estimation are handled based on density estimation. This is beyond the scope of this paper, which is for point inference.

These solutions all have their drawbacks in solving JDE problems. In general, a joint approach would be more promising than separate decision and estimation as well as decision then estimation or estimation then decision. For the JDE problem, [18] proposed an integrated paradigm for JDE based on a new Bayes risk, which is a generalization of the traditional Bayes decision risk and estimation risk. This approach is inherently superior in joint performance to the conventional two-stage strategy or separate decision and estimation, especially for problems where decision and estimation are highly correlated. Reference [22] verifies the power of JDE through a static JTC example. For dynamic JDE problems, [19] proposed a recursive JDE (RJDE) method in the paradigm of [18]. In [23], we solved an extended object JTC problem in the JDE framework, and proposed a random-matrix-based multiple model RJDE method for extended objects. In [24], we applied the RJDE method to a multisensor data based JTC problem, which is formulated based on homogenous sensor data.

In the JDE framework of [18], we proposed a conditional JDE (CJDE) risk in [25], which is a Bayes JDE risk conditioned on data. To minimize the CJDE risk, the optimal solution was derived in [25]. CJDE inherits the theoretical superiority of JDE by fully utilizing the coupling between decision and estimation. For calculation, the CJDE method is simple and efficient, which makes it more practical.

Due to the development of modern sensor technology, more and more types of sensors are available, such as high resolution radar, electronic support measure (ESM), infrared imagers, identification of friend and foe (IFF), and electromagnetical imaging sensor. With more heterogeneous sensors, various data containing useful information for tracking and/or classification is available.

Although tracking and classification are fundamentally related, they are usually treated separately and solved by different techniques using various data. For example, many tracking algorithms are based on kinematic (e.g., radar and sonar) measurements, and target classification is usually handled using identity or attribute data from high resolution radar, acoustic, passive infrared, and seismic sensing modalities [6], [7], [14]. That is, either tracking or classification only utilizes partial measurements. With various data available, an integrated use of these data is promising to improve JTC performance [16].

JTC using multisensor data is a typical JDE problem and thus good solutions require solving the two problems jointly. The recently proposed CJDE is an integrated approach to solving JDE problems, and its superior performance and simple calculation make it preferable for practical JTC problems. When it is applied to solve real-world problems, however, it is often the case that great efforts are needed because the CJDE method proposed in [25] only provides a general solution for JDE problems. To apply it to JTC using multisensor data, intensive work is needed due to the characteristics of the heterogeneous data from multisensors.

In this paper, we extend the RCJDE method of [25] to a dynamic JTC problem using heterogenous sensor data, which is more practical. We first formulate JTC using radar data and ESM data as a JDE problem. These two representative measurements are continuous and discrete, respectively. To adapt the RCJDE method of [25] to this multisensor problem, significant modifications are needed mainly in the calculation of class probability and expected estimation cost. By fully considering the characteristics of the multisensor data, we propose a multiple model (MM) RCJDE method for this JTC problem.

To evaluate the estimation and decision performance jointly, we present two joint performance metrics (JPMs) for the cases with known and unknown ground truth, respectively. For unknown ground truth, a JPM based on the idea of mock data [22] is presented, which aims to measure the statistic distance between the original data and the mock data generated using the output of evaluated algorithms.

The novelties of this paper are as follows.

1) We formulate the multisensor data based JTC as a JDE problem, where radar and ESM data are used.

2) Considering the characteristics of the heterogeneous sensor data, we extend the original RCJDE method to the multisensor scenario by several modifications. The multiple model RCJDE method is then proposed for JTC using multisensor data.

3) For joint performance evaluation, we present two metrics which are suitable for this JTC problem.

This paper is organized as follows. Section II overviews the existing JDE and CJDE methods and techniques. Section III applies CJDE to the multisensor data based JTC problem. After formulating the problem based on radar and ESM measurements, the multiple model RCJDE algorithm is proposed. Two JPMs are also presented in this section. Section IV presents the simulation results. Section V concludes the paper.

II. Conditional Joint Decision and Estimation

A. Joint Decision and Estimation (JDE)

In the JDE framework, the following generalized Bayes risk [18] is minimized:

$$\bar{R} = \sum_{i,j}(\alpha_{ij}c_{ij} + \beta_{ij}E[C(x,\hat{x})|D^i,H^j])P\{D^i,H^j\} \quad (1)$$

where D^i stands for the ith decision, which is equivalent to the event $\{z \in \mathcal{D}^i\}$ ($\mathcal{D}^i$ is the decision region for D^i in the data space); c_{ij} is the cost of deciding on D^i while the true hypothesis is H^j; $P\{D^i,H^j\}$ is the joint probability of decision and hypothesis; $C(x,\hat{x})$ is the cost of estimating x by $\hat{x}$; $E[C(x,\hat{x})|D^i,H^j]$ is the expected cost conditioned on the fact that D^i is decided but H^j is true; and α_{ij} and β_{ij} are weight coefficients for decision and estimation, respectively, which provide additional flexibilities.

The optimal JDE is as follows [18]. For any given $E[C(x,\hat{x})|D^i,H^j]$, the optimal decision D is

$$D = D^i, \text{ if } C^i(z) \leqslant C^l(z), \forall l$$

where the *posterior cost* is given by

$$C^i(z) = \sum_{j=1}^{N}(\alpha_{ij}c_{ij} + \beta_{ij}E[C(x,\hat{x})|D^i,H^j])P\{H^j|z\} \quad (2)$$

and given any partition $\{\mathcal{D}^1,\cdots,\mathcal{D}^M\}$ of the data space, the optimal estimator for (13) with $C(x,\hat{x}) = \tilde{x}'\tilde{x}$ is the following *generalized posterior mean*:

$$\hat{x} = \sum_{i=1}^{M} 1(z;\mathcal{D}^i)\breve{x}^{(i)} \quad (3)$$

where $\tilde{x} = x - \hat{x}$, $1(z;\mathcal{D}^i) = \begin{cases} 1, & z \in \mathcal{D}^i \\ 0, & \text{else} \end{cases}$, and for $z \in \mathcal{D}^i$

$$\breve{x}^{(i)} = \sum_{j=1}^{N} \hat{x}^{(j)}\bar{P}_i\{H^j|z\},\ \hat{x}^{(j)} = E[x|z,H^j] \quad (4)$$

$$\bar{P}_i\{H^j|z\} = \frac{\beta_{ij}P\{H^j|z\}}{\sum_{k=1}^{N}\beta_{ik}P\{H^k|z\}}$$

and they are undefined if $z \notin \mathcal{D}^i$. Here $P\{H^j|z\}$ is the posterior probability of H^j.

A JDE algorithm with guaranteed global convergence is presented in [18]. This JDE approach explicitly accounts for the inter-dependence between decision and estimation, and it is theoretically superior to the existing method of separate decision and estimation or the two-stage methods.

B. Conditional JDE (CJDE)

In the above JDE framework, a conditional JDE (CJDE) risk was proposed [25], which is a generalization of the Bayes risk for decision and estimation conditioned on data.

The basic idea of CJDE is to minimize the CJDE risk:

$$R_C(z) = \sum_{i,j}(\alpha_{ij}c_{ij}+\beta_{ij}E[C(x,\hat{x})|D^i,H^j,z])P\{D^i,H^j|z\} \tag{5}$$

To minimize $R_C(z)$ (5), for any given estimation cost $E[C(x,\hat{x})|D^i,H^j,z]$, the optimal decision D is

$$D = D^i, \text{ if } C_C^i(z) \leqslant C_C^l(z), \forall l \tag{6}$$

where the posterior cost is

$$C_C^i(z) = \sum_j(\alpha_{ij}c_{ij}+\beta_{ij}E[C(x,\hat{x})|D^i,H^j,z])P\{H^j|z\} \tag{7}$$

And given any partition $\{\mathcal{D}^1,\cdots,\mathcal{D}^M\}$ of the data space, the optimal estimator with $C(x,\hat{x}) = \tilde{x}'\tilde{x}$ has a simple form, which is the same as (4). A proof of the optimal CJDE is given in [25].

Remark 1: To calculate the posterior CJDE cost $C_C^i(z)$, the key is to obtain $E[C(x,\hat{x})|D^i,H^j,z]$. With $C(x,\hat{x}) = \tilde{x}'\tilde{x}$, we have

$$\begin{aligned}
&\varepsilon^{ij}(z) \triangleq E[\tilde{x}'\tilde{x}|D^i,H^j,z] \\
&= \mathrm{mse}(\hat{x}^{(ij)}|D^i,H^j,z) + E[(\hat{x}^{(ij)}-\hat{x})'(\cdot)|D^i,H^j,z] \\
&= \mathrm{mse}(\hat{x}^{(j)}|H^j,z) + E[(\hat{x}^{(j)}-\breve{x}^{(i)})'(\cdot)|D^i,H^j,z], \forall z \in \mathcal{D}^i \\
&= \mathrm{mse}(\hat{x}^{(j)}|H^j,z) + (\hat{x}^{(j)}-\breve{x}^{(i)})'(\cdot), \forall z \in \mathcal{D}^i
\end{aligned} \tag{8}$$

where $\hat{x}$ is the CJDE estimate, $\mathrm{mse}(\hat{x}|A) = E[(x-\hat{x})'(x-\hat{x})|A]$ is the conditional (on A) scalar mean square error, and $(\cdot)$ denotes the same term right before it. For $z \in \mathcal{D}^i$, we have $\hat{x} = \breve{x}^{(i)}$, $\hat{x}^{(ij)} = E[x|D^i,H^j,z] = E[x|H^j,z] = \hat{x}^{(j)}$, and $\mathrm{mse}(\hat{x}^{(ij)}|D^i,H^j,z) = \mathrm{mse}(\hat{x}^{(j)}|H^j,z)$. Note that in the last equation above, the expectation disappear since $\hat{x}^{(j)}$ and $\breve{x}^{(i)}$ are both fixed given z and D^i.

In the JDE risk (1), for $C(x,\hat{x}) = \tilde{x}'\tilde{x}$,

$$\begin{aligned}
&\varepsilon^{ij} \triangleq E[C(x,\hat{x})|D^i,H^j] = \mathrm{mse}(\hat{x}|D^i,H^j) \\
&= E[(x-\hat{x}^{(ij)})'(\cdot)|D^i,H^j] + E[(\hat{x}^{(ij)}-\hat{x})'(\cdot)|D^i,H^j] \\
&= \mathrm{mse}(\hat{x}^{(ij)}|D^i,H^j) + E[(\hat{x}^{(j)}-\breve{x}^{(i)})'(\cdot)|D^i,H^j], \forall z \in \mathcal{D}^i
\end{aligned} \tag{9}$$

With the linear Gaussian assumption under H^j, $\mathrm{mse}(\hat{x}^{(j)}|H^j,z)$ with $z \in \mathcal{D}^i$ does not depend on the realization of z and is equal to $\mathrm{mse}(\hat{x}^{(ij)}|D^i,H^j)$, and the only difference between $\varepsilon^{ij}(z)$ of (8) and ε^{ij} of (9) lies in the calculation of the second term.

In $\varepsilon^{ij}(z)$ for CJDE, $(\hat{x}^{(j)}-\breve{x}^{(i)})'(\cdot)$ is based on the current observation z and can be obtained easily using z. In ε^{ij} for JDE, however, the expectation $E[(\hat{x}^{(j)}-\breve{x}^{(i)})'(\cdot)|D^i,H^j]$ is taken over the whole data space of the current observations, and thus integration is needed. This is the main difference in computation between CJDE and JDE.

Optimal CJDE algorithm

Because the optimal CJDE is the joint of (4) and (6), we have the following CJDE algorithm:

(1) E-step. Given z, compute the estimate $\breve{x}^{(i)}(z)$ for each i by (4).

(2) D-step. Compute $\varepsilon^{ij}(z)$ by (8) and $C_C^i(z)$ by (7). Then the optimal partition is $\mathcal{D} = \{\mathcal{D}^1,\cdots,\mathcal{D}^M\}$, where $\mathcal{D}^i = \{z\colon C_C^i(z) \leqslant C_C^l(z), \forall l\}$.

(3) Output. The optimal CJDE decision is D if $z \in \mathcal{D}^i$ from step 2, and the optimal CJDE estimator is $\hat{x} = \breve{x}^{(i)}(z)$ from step 1.

1) Analysis of CJDE

a) Compared with JDE, the main difference of CJDE results from the introduction of the data in the CJDE risk (5), which was discussed in detail in [25]. Considering the risk functions, the JDE risk $\bar{R}$ of (1) is averaged over the whole data space of the data z, but the CJDE risk $R_C(z)$ of (5) depends on a particular realization of z. If $(\breve{x}^{(i)}(z), D^i(z))$ minimizes the CJDE risk $R_C(z)$, then it is Bayes optimal for every z. A JDE result $(\breve{x}^{(i)}, D^i)$ is optimal only on the average for all possible data.

b) CJDE inherits the superiority of JDE by unifying decision and estimation into an integrated framework. For calculation, by conditioning on z, CJDE simplifies computation greatly compared with JDE. This makes CJDE more applicable in practice.

c) The CJDE algorithm differs from the JDE algorithm in [18] in implementation steps. In the CJDE algorithm, once the current data is available, the decision and estimation results can be obtained without decision-estimation iteration.

2) Recursive CJDE (RCJDE)

For dynamic systems, measurements are usually obtained sequentially. Although the CJDE algorithm is optimal theoretically, because of its batch form it may be computationally inefficient as data cumulate. A recursive CJDE (RCJDE) algorithm was developed for dynamic JDE problems in [25], which is a recursive implementation of CJDE.

At time k, the following RCJDE risk is minimized

$$\begin{aligned}
R_C(Z^k) = \sum_{i,j}(\alpha_{ij}c_{ij}+\beta_{ij}E[C(x_k,\hat{x}_k)|D_k^i,H^j,Z^k]) \\
\times P\{D_k^i,H^j|Z^k\}
\end{aligned} \tag{10}$$

where x_k is the true state at time k, $\hat{x}_k$ is its estimate, D_k^i stands for the ith decision at time k, and $Z^k = \{z_1,z_2,\cdots,z_k\}$. To minimize the RCJDE risk (10), the optimal RCJDE solution is given in (4) and (6) by substituting Z^k for z. More details about RCJDE can be found in [25].

In $R_C(Z^k)$, the expected estimation cost with $C(x_k,\hat{x}_k) =$

$\tilde{x}_k'\tilde{x}_k$ is

$$\varepsilon_k^{ij}(Z^k) \triangleq E[\tilde{x}_k'\tilde{x}_k|Z^k, D_k^i, H^j] \tag{11}$$
$$= \mathrm{mse}(\hat{x}_k^{(j)}|H^j, Z^k) + (\hat{x}_k^{(j)} - \check{x}_k^{(i)})'(\cdot),\ Z^k \in \mathcal{D}_k^i$$

where $\hat{x}_k^{(j)}$ is the state estimate under hypothesis H^j, and $\check{x}_k^{(i)}$ is the CJDE estimate under decision D^i. Under the linear Gaussian assumption, $\mathrm{mse}(\hat{x}_k^{(j)}|H^j, Z^k) = \mathrm{tr}(P_k^{(j)})$ does not depend on Z^k.

One cycle of RCJDE at time k.

1) Initialization: Obtain $\hat{x}_{k-1}^{(j)}$ and $P\{H^j|Z^{k-1}\}$.

2) Get the one-step prediction based on dynamics of x_k.

3) Update: With the current data z_k, update $\hat{x}_k^{(j)}$ and $P\{H^j|Z^k\}$. Compute $\check{x}_k^{(i)}$ for each i by (4).

4) Calculate $\varepsilon_k^{ij}(Z^k)$ by (11) to get the cost $C_C^i(Z^k)$. Then the CJDE decision is D_k^i if $C_C^i(Z^k) \leqslant C_C^l(Z^k), \forall l$.

5) Output the CJDE solution for time k: $D_k = D_k^i$ in step 4 and $\hat{x}_k = \check{x}_k^{(i)}$ in step 3.

Following the spirit of CJDE, the RCJDE solution minimizes the proposed RCJDE risk, which fits dynamic JDE problems well.

III. CJDE Based JTC Using Multisensor Data

As mentioned in Introduction, JTC using multisensor data is a typical JDE problem, and thus good solutions require joint tracking and classification. CJDE is promising for practical JTC problems due to its superiority in performance and simplicity in calculation. However, the original CJDE method can not be applied to multisensor data based JTC due to the characteristics of the heterogeneous sensor data.

In this paper, we aim to solve the multisensor data based JTC problem using the CJDE method. In the following, we present the problem formulation, the multiple model RCJDE algorithm, and the joint performance metrics suitable for this JTC problem.

A. Problem Formulation

Suppose that there is one target with multiple possible classes in the field of interest, and classes differ from each other in two aspects: dynamic behavior and feature attributes. Our goal is to estimate the target state and classify the target jointly, using mixed data from heterogeneous sensors.

The classes of targets are characterized by the dynamic behaviors and feature attributes. For dynamic behaviors, different target classes may differ in maneuverability, which is reflected in the dynamic model (change in position, velocity, acceleration etc.). For feature attributes, we consider a typical attribute measurement—electronic support measure (ESM). Different classes have different emitters on board, leading to different ESM characteristics, which contain emitter type information. Based on these feature attributes, we classify the target into one of s known classes $\{1, \cdots, s\}$.

Denote by x_k the state at time k and by c_i the target class, where c_i belongs to the set $\{1, \cdots, s\}$. The goal of the JTC is to estimate x_k and get c_i jointly using multisensor data (i.e., $H^i = c_i$). In this JDE problem, "decision" is to decide on the class label: D^i = "c_i" = "H^i". In the following, suppose the true target class is constant over time.

Usually, the joint target state-class pdmf (probability density-mass function) $p(x_k, H^i|Z^k)$ is a joint description of the true target state and class, where $Z^k = \{Z_c^k, Z_x^k\}$ with $Z_c^k = \{z_1^c, z_2^c, \cdots, z_k^c\}$ and $Z_x^k = \{z_1^x, z_2^x, \cdots, z_k^x\}$ being the measurement sequences from an attribute sensor and a kinematic sensor, respectively.

The joint measurement process of a kinematic sensor and an attribute sensor could be modeled by the following pdmf

$$p(z_k^x, z_k^c|x_k, f_k, H^i, Z^{k-1}) \tag{12}$$

where f_k is the target feature at k. For simplicity, assume that the two measurement processes (z_k^x and z_k^c) are conditionally independent: $p(z_k^x, z_k^c|x_k, f_k, H^i, Z^{k-1}) = p(z_k^x|x_k, f_k, H^i, Z^{k-1})p(z_k^c|x_k, f_k, H^i, Z^{k-1})$; the measurement process of a kinematic sensor can be represented by $p(z_k^x|x_k, m_k^i, f_k, H^i, Z^{k-1}) = p(z_k^x|x_k)$—that is, conditioned on the target state x_k, z_k^x is statistically independent of all other variables; and the attribute process $p(z_k^c|x_k, m_k^i, f_k, H^i, Z^{k-1}) = p(z_k^c|f_k)$—that is, conditioned on the target feature f_k, z_k^c is statistically independent of all the other variables. The above assumption also means that the kinematic measurement model does not depend on the target class or feature, and the attribute model does not depend on target kinematic state or motion.

B. Modeling

1) Dynamic model and kinematic measurement model: Assume each target class c_i has a set of r_i possible motion models. With the linear motion assumption, the jth motion model for class i is

$$x_k = F_{k-1}^{ij}x_{k-1} + G_{k-1}^{ij}u_{k-1}^{ij} + \Gamma_{k-1}^{ij}w_{k-1}^{ij},\ j = 1, \cdots, r_i \tag{13}$$

where u_k is the deterministic input, w_k is zero-mean white Gaussian noise with known covariance Q_k. F_k, G_k, and Γ_k are known matrices, and the superscript ij signifies quantities for the jth motion model of a class i target.

With the linear measurement assumption, the kinematic measurement is

$$z_k^x = H_k x_k + v_k \tag{14}$$

where H_k is the measurement matrix, and v_k is zero-mean white Gaussian noise with known covariance R_k.

2) Attribute model and ESM measurement model: ESM sensors are passive directional receivers which scans the frequency range of interest to intercept emitted electromagnetic signals from targets and identifies the likely source emitters. The signal processing that is carried out in ESM sensors is complicated and there are many sources of error in the emitter identification process [15]. In this paper, assume the detection probability is 1; that is, once the emitter is "on", it can be detected with probability 1. We only consider the following primary sources of error: (a) emitters may be on or off (usage); (b) detected emitters may be confused with other emitters.

a) Attribute model: Possible emitter types under consideration belong to the set $\Omega_E = \{E^1, E^2, \cdots, E^N\}$, where N is the total number of emitter types in the ESM sensors' emitter library. For simplicity, we consider the case with two emitters ($N = 2$) and each class has one and only one type of emitter on board. Class 1 has emitter E^1 and class 2 has emitter E^2, and therefore $\Omega_E = \{E^1, E^2\}$.

Emitter switching behavior is described by defining an emitter usage Markov chain for each emitter on a target. In this case we model emitter j as having a fixed usage Markov chain regardless of which target it is located on and independent of the other emitters. Let E_k^i denote the event that emitter i is "on" at time k, and $\bar{E}_k^i$ for "off". The transition probabilities matrix for emitter E^i is $\Phi^i = \begin{bmatrix} P(E_{k+1}^i|E_k^i) & P(\bar{E}_{k+1}^i|E_k^i) \\ P(E_{k+1}^i|\bar{E}_k^i) & P(\bar{E}_{k+1}^i|\bar{E}_k^i) \end{bmatrix}$.

Based on the above, a possible emitter feature at time k, denoted by f_k, belongs to the feature set $F = \{\bar{E}^1\bar{E}^2, E^1\bar{E}^2, \bar{E}^1E^2, E^1E^2\}$. Thus the feature probability vector consisting of the probabilities of all possible features is

$$\mu_k = [p_k^{(1)}\ p_k^{(2)}\ p_k^{(3)}\ p_k^{(4)}]^T \tag{15}$$

where $p_k^{(i)}$ ($i = 1, 2, 3, 4$) is the probability that the ith feature in F is true. The attribute model for a target in class i is

$$\mu_{k+1} = \Psi_i \mu_k \tag{16}$$

where Ψ_i is the $2^N \times 2^N$ overall feature transition probability matrix. For more details about Ψ_i, see [24].

b) ESM measurement model: To account for the errors which may be caused by the processing chain of the ESM receiver, we define an $m \times m$ measurement confusion matrix Π, where $m = 2^N - 1$ and Π has the (i, j)th entry

$$\pi_{ij} = P\{\text{declare } E^j|E^i \text{ is true}\},\ i, j = 0, 1, \cdots, m \tag{17}$$

The entry π_{ij} of the measurement confusion matrix Π is defined as the probability of declaring detecting the emitter E^j while the actual emitter is E^i. In this example, the ESM measurement z_k^c comes from the measurement space $\{\bar{E}^1\bar{E}^2, E^1\bar{E}^2, \bar{E}^1E^2\}$, which contains all possible emitter type combinations. Then z_k^c is a function of the feature f_k and the confusion matrix Π. More details can be found in [15].

C. RCJDE for JTC Using Multisensor Data

To use the ESM measurement, the original RCJDE [25] needs to be modified. By fully considering the characteristics of the ESM measurement, we propose the following multisensor data based RCJDE algorithm:

1. Assume $\hat{x}_{k-1}^{(j)}$, $P\{H^j|Z^{k-1}\}$, and u_{k-1}^j have been obtained. Here $\hat{x}_{k-1}^{(j)}$ is the MMSE estimate under H^j, $P\{H^j|Z^{k-1}\}$ is the posterior probability of H^j conditioned on both Z_c^{k-1} and Z_x^{k-1}, and u_{k-1}^j is the feature probability vector under hypothesis H^j, given by (15).

2. Update. Given z_k^x and z_k^c, update $\hat{x}_k$ and $P\{H^j|Z^k\}$ according to (4) and (18). The elements of u_k^j are also updated as in [15].

3. Calculate $\varepsilon_k^{ij}(Z^k) = \text{mse}(\hat{x}_k|Z^k, D_k^i, H^j)$ to get the cost $C_C^i(Z^k) = \sum_j(\alpha_{ij}c_{ij} + \beta_{ij}\varepsilon_k^{ij}(Z^k))P\{H^j|Z^k\}$ by (7). Then the optimal CJDE decision is D_k^i: $C_C^i(Z^k) \leqslant C_C^l(Z^k), \forall l$.

4. Output the CJDE solution for time k: $D_k = D_k^i$ and $\hat{x}_k = \check{x}_k^{(i)}$. Then let $k - 1 = k$ and go to step 1.

Remark 2: Compared with RCJDE using radar data only, the above multisensor data based RCJDE has two main differences: the posterior probability $P\{H^j|Z^k\}$ in step 2 and the expected estimation cost $\varepsilon_k^{ij}(Z^k)$ in step 3. In general, to use the attribute data, these two terms are calculated based on both the kinematic measurements Z_x^k and the ESM measurements Z_c^k.

Specifically, to calculate $P\{H^j|Z^k\}$, both radar and ESM measurements are used since they both carry target class information. Based on the assumption that different types of data are conditionally independent [17],

$$\begin{aligned} P\{H^i|Z^k\} &= P\{H^i|Z_x^k, Z_c^k\} \\ &= \frac{1}{c}p(z_k^x, z_k^c|H^i, Z^{k-1})P\{H^i|Z^{k-1}\} \\ &= \frac{1}{c}p(z_k^x|H^i, Z_x^{k-1})p(z_k^c|H^i, Z_c^{k-1})P\{H^i|Z^{k-1}\} \end{aligned} \tag{18}$$

where c is the normalization factor, Z^{k-1} contains both the kinematic measurement Z_x^{k-1} and the attribute measurement Z_c^{k-1}. $p(z_k^x|H^i, Z_x^{k-1})$ and $p(z_k^c|H^i, Z_c^{k-1})$ are likelihoods of H^i based on the kinematic and the ESM measurements, respectively. See [17] for more details.

For the expected estimation cost,

$$\begin{aligned} \varepsilon_k^{ij}(Z^k) &= \text{mse}(\hat{x}_k|Z_c^k, Z_x^k, D_k^i, H^i) \\ &= \text{mse}(\hat{x}_k^{(j)}|H^j, Z^k) + (\hat{x}_k^{(j)} - \check{x}_k^{(i)})'(\cdot), Z^k \in \mathcal{D}_k^i \end{aligned}$$

is calculated based on both the attribute measurement Z_c^k and the kinematic measurement Z_x^k. $\hat{x}_k^{(j)}$ and $\check{x}_k^{(i)}$ have the same meanings as in (11). With the linear Gaussian assumption, $\text{mse}(\hat{x}_k^{(j)}|H^j, Z^k) = \text{tr}(P_k^{(j)})$ does not depend on Z_c^k or Z_x^k.

Remark 3: Compared with RJDE based JTC using multisensor data [24], RCJDE has much simpler computation. In RJDE [19], the expected estimation error is

$$\begin{aligned} \varepsilon_k^{ij} &= \text{mse}(\hat{x}_k|Z^{k-1}, D_{k-1}^i, H^j) \\ &= \text{mse}(\hat{x}_k|Z^{k-1}, H^j) + \tilde{\varepsilon}_k^{ij} \end{aligned}$$

where $\tilde{\varepsilon}_k^{ij} = E[(\hat{x}_k^{(j)} - \check{x}_k^{(i)})^2|Z^{k-1}, D^i, H^j]$ is difficult to calculate and is usually approximated by the Monte Carlo (MC) method in RJDE. In JTC using multisensor data, both the kinematic and the attribute MC simulation data need to be generated, which aggravates the computation of RJDE. Note that this MC simulation consumes the most computation in the calculation of the RJDE algorithm. In view of this, the RCJDE method is preferable for JTC using multisensor data: not only is the coupling between tracking and classification utilized, but RCJDE has also much simpler computation compared with RJDE.

Remark 4: In the above steps, only the single model version is presented for simplicity, but the same approach works for the multiple-model cases without difficulty. A multiple model approach such as the IMM algorithm [1], [26] is a well-known candidate for improving overall tracking performance if the target may maneuver. The IMM algorithm can be integrated into our proposed RCJDE method easily, for example, using r_i models for the deterministic input u_k.

D. Joint Performance Evaluation Metrics

Traditionally, for performance evaluation of many practical JDE problems, decision performance and estimation performance are evaluated separately using their own metrics. For example, correct-decision rate is usually used for decision performance evaluation while mean square error is used to evaluate the estimation performance [27], [28]. This is seriously flawed since these measures do not consider the "joint" characteristics of decision and estimation, which is the cornerstone of JDE problems. As analyzed in [25], for JDE problems, decision and estimation performance should be evaluated jointly rather than separately. [22] proposed a joint performance measure (JPM) based on the statistical distance between the real data and the mock data generated by the JDE algorithm. Following this spirit and considering the characteristics of JTC using multisensor data, we present the following two JPMs for joint performance evaluation. These two metrics fit the cases with known and unknown ground truth, respectively.

(a) JPM1. For the case with known ground truth, we propose to use the mean predicted-state distance, defined as [25]

$$\lambda_k \triangleq \int d(x_k, \hat{x}_{k|k-1}) \mathrm{d}F(x_k, \hat{x}_{k|k-1}, H^j | \hat{x}_{k-1}, D_{k-1})$$

where $d(\cdot)$ is the distance between the true state x_k and the one-step predicted state $\hat{x}_{k|k-1}$ at time k. In λ_k, both the decision and estimation parts of the JDE results are contained in the one-step predicted state $\hat{x}_{k|k-1}$, so it is a joint performance metric.

(b) JPM2. For unknown ground truth, we suggest to use the metric proposed in [24]:

$$d^k = d_c^k(Z_k^c, \hat{Z}_k^c) + \gamma \cdot d_x^k(z_k^x, \hat{z}_k^x) \tag{19}$$

where $d_c^k(\cdot)$ and $d_x^k(\cdot)$ are the measures for the discrete data and the continuous data, respectively [24]. γ is a weight factor. Here, Z_k^c and $\hat{Z}_k^c$ are the real ESM data set and the mock ESM data set, respectively. z_k^x and $\hat{z}_k^x$ are the real radar data and the mock radar data at time k on the same simulation run, respectively.

For discrete data, we propose to use the Wasserstein distance [28] to measure the distance between the original data set Z_k^c and the mock data set $\hat{Z}_k^c$. Specifically in this JTC example, suppose Z_k^c and $\hat{Z}_k^c$ have the same size n, and each point in $Z_k^c = \{z_k^{c,i}\}_{i=1}^n$ may be matched by one and only one point in $\hat{Z}_k^c$. Let I be a permutation of data points in $\hat{Z}_k^c$, and under one specific permutation, we can get $\hat{Z}_k^c = \{\hat{z}_k^{c,(i)}\}_{i=1}^n$. All possible I's form a set $\mathcal{I}$. Then the Wasserstein distance between $\mathbf{z}_k^c$ and $\hat{\mathbf{z}}_k^c$ is [28] [24]:

$$d_c^k(Z_k^c, \hat{Z}_k^c) = \min_{I \in \mathcal{I}} \sum\nolimits_{i=1}^n d(z_k^{c,i}, \hat{z}_k^{c,(i)})$$

Considering the characteristics of ESM measurements, we recommend *Hamming distance* for $d(z_k^{c,i}, \hat{z}_k^{c,(i)})$ in this paper. For the continuous data, we propose to use the mean predicted-measurement distance [24]. For more details, see [24].

IV. Simulation and Discussion

In this section, we present a JTC example using the CJDE method with radar and ESM measurements. The compared methods are the traditional decision-then-estimation (DTE) and estimation-then-decision (ETD) in terms of Average Euclidean Error (AEE), the probability of correct classification (P_C), and the joint performance measure. We use AEE for estimation performance evaluation, because it is better than RMSE (root-mean-square error) as analyzed convincingly in [29].

A. Existing Methods

For JTC using multisensor data, traditional methods handle tracking and classification separately using their respective measurements. Specifically:

a) DTE. The optimal Bayes decision is made first based on posterior class probability $P\{H^i|Z^k\}$ using ESM and radar data

$$\frac{P\{H^1|Z^k\}}{P\{H^0|Z^k\}} \underset{D^0}{\overset{D^1}{\gtrless}} \frac{c_{10} - c_{00}}{c_{01} - c_{11}}$$

where c_{ij} is the cost of deciding on D^i while H^j is true. Then estimation is obtained using radar data only based on the decided class.

b) ETD. The best estimation of the target state is obtained by the autonomous multiple model (AMM) algorithm first, and then decision is made based on the ratio of current measurement likelihoods conditioned on the one-step predicted state $\hat{x}_{k|k-1}$ and H^j [19]. From the perspective of information utilization, estimation is based on radar data only while decision is based on both radar and ESM data. Note that ESM is important for classification and can be used for decision directly. Although ESM can help estimation (help build a more accurate kinematic model), it is difficult to be used for estimation directly without going through decision.

B. Simulation and Analysis

There is only one target with two possible classes c_1 and c_2. Classes differ from each other in the kinematic state and the ESM attributes. The dynamic model and measurement model are the same as in [24]. A target in class i ($i \in \{1, 2\}$) has its own model set M^i of possible control input u_k, given by

$$M^1 = \{0, g, -g\}, \ M^2 = \{2g, 2.5g, -2.5g, 3g, -3g\}$$

The initial state is $[x_0, \dot{x}_0] = [8000\mathrm{m}, 200\mathrm{m/s}]$. Each class has an equal initial probability, so are the models in M^i initially. The radar data follows the measurement model (14) with $H_k = [1, 0]$ and $v_k \sim \mathcal{N}(0, 50^2\mathrm{m}^2)$.

The usage process for each emitter and the ESM measurement process are the same as that in [24]. The probability of emitter "on" at the initial time is assumed to be 0.5. In this simulation, the joint performance metric (19) with $\gamma = 0.5$ is used. To save space, JPM1 (for the case with known ground truth) is omitted since its result is similar to JPM2. The parameters in RCJDE are chosen as: $c_{ij} = 1, c_{ii} = 0, \alpha_{ij} = 1$, and we add the constraints $\sum_i \beta_{ij} = 10^{-4}, \beta_{ii}/\beta_{ij} = 2$ for the comparison purpose. All results were obtained from 3000 MC runs. It is assumed that the target class is time invariant and is Bernoulli distributed with probability 0.5.

The comparison results are shown in Fig. 1. It can be seen that for position and velocity estimation, ETD performs worst, RCJDE best, and DTE is in the middle. ETD performs worst since only radar data is used for estimation, while DTE uses all information for estimation. DTE is inferior to RCJDE because DTE does estimation based on the decided class without considering possible decision errors. For estimation in RCJDE, all information is used and the effect of decision on estimation is also considered. So RCJDE outperforms the other methods in estimation performance. For decision performance, all methods are close to each other, and RCJDE is slightly worse than DTE and ETD methods.

For the joint performance, RCJDE outperforms DTE and ETD. This demonstrates that RCJDE can effectively utilize all the available data from multisensors and the coupling between decision and estimation.

Remark 5: This example verifies the superiority of CJDE in solving multisensor data based JTC problems in two aspects: a) CJDE can make full use of all the information contained in the heterogeneous senor data; b) CJDE can also take advantage of the coupling between decision and estimation, and can beat the traditional two-step strategies in joint performance.

V. Conclusions

In this paper, we have proposed a CJDE method for JTC using multisensor data. After formulating a representative JTC problem based on radar and ESM measurements, we solved it in the JDE framework. We adopt the CJDE method due to its theoretical superiority and simple calculational complexity.

Due to the introduction of the ESM measurement, the original CJDE method cannot be used directly. By fully considering the characteristics of the heterogeneous sensor data, we propose an applicable multiple-model RCJDE method for this JTC problem. The two main modifications lie in the calculation of the posterior probability and the expected estimation cost. Moreover, we present two JPMs for evaluating the joint performance of algorithms solving multisensor data based JTC problems. These two metrics can be used for the cases with known and unknown ground truth, respectively.

Simulation results show that the RCJDE method outperforms the traditional two-step strategies in JPM. This example verifies that RCJDE can fully utilize the information contained in all available data from heterogeneous sensors. Furthermore, it can take advantage of the inter-dependence between tracking and classification, which is critical for JDE problems.

In general, this paper sets an example for applying the CJDE method to real-world JTC problems. The superiority of CJDE for solving the JTC problem is demonstrated theoretically and also by simulation. In this paper, only a single target is considered. The problem of multiple targets with more available data is under further investigation.

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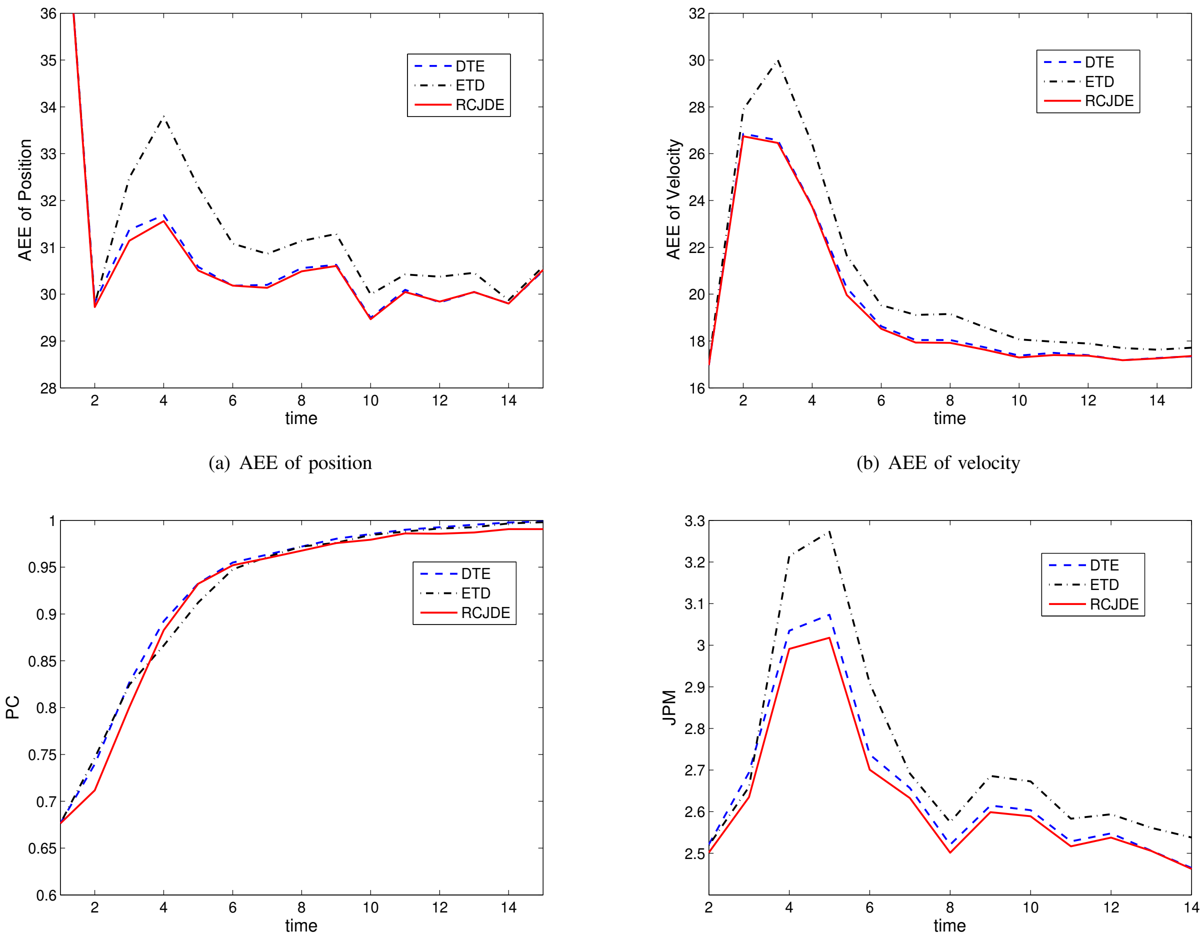

(a) AEE of position

(b) AEE of velocity

(c) probability of correct classification

(d) Joint performance measure

Fig. 1. RCJDE for JTC using multisensor data

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