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# Compact Conditional Joint Decision and Estimation for Joint Tracking and Identification With Performance Evaluation

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**ABSTRACT** This paper presents a novel approach for the joint tracking and identification (JTI) problem. JTI involves interdependent tracking and identification, and thus solving them jointly is preferable. The recently proposed joint decision and estimation (JDE) framework provides a good solution for such problems involving coupled decision and estimation. To solve the JTI problem, this paper proposes a compact conditional JDE (CCJDE) method within the JDE framework. First, we propose a new CCJDE risk, which unifies the traditional decision and estimation risks in a concise form. Based on this, we present the optimal joint solution with analytical form. Second, inspired by the interacted parameters in CCJDE, we propose a new CCJDE scheme with time-varying parameters, which further utilizes the interdependence between decision and estimation. Third, we apply CCJDE to practical JTI problems. An applicable multiple model CCJDE algorithm is proposed for JTI. For performance evaluation, we propose a new joint performance metric (JPM), which unifies the tracking error and the identification error. Finally, two illustrative examples verify the superiority of the proposed CCJDE method. CCJDE outperforms the traditional two-step strategies in JPM. For multisensor data JTI, however, CCJDE can further utilize all information from heterogeneous sensor data. Besides, the effectiveness of the proposed JPM and the time-varying parameters in CCJDE are also demonstrated.

**INDEX TERMS** Joint tracking and identification, compact conditional joint decision and estimation, joint performance evaluation.

## I. INTRODUCTION

As two critical problems in battlefield surveillance systems, target tracking and target identification have been studied extensively [1]–[4]. The goal of tracking is to estimate the target state, i.e., position, velocity, etc., while the goal of identification is to identify which class the target belongs to [5]. In reality, there exists another important problem called joint tracking and identification (JTI). JTI involves both tracking and identification, and they are coupled: tracking helps identification since it can provide flight envelope information for different target types, while identification helps tracking by selecting appropriate identity-dependent kinematic models [6]. Especially in recent years, with the rapid development of the modern sensor technology, JTI has attracted more and more attention [7]–[17].

In essence, JTI is the so-called joint decision and estimation (JDE) problem, which has dual goals: decision and estimation, and they are coupled. Traditional methods for solving JDE problems contain the following [18], [19]: a) Estimation and decision are handled separately without considering their interdependence [20], [21]. b) Decision then estimation (D-then-E): the best decision is made first disregarding estimation and then estimation is done based on this decision as if it were correct [22], [23]. c) Estimation then decision (E-then-D): estimation is done first and then decision is made based on it [5], [7], [24]. d) Density-based decision and estimation [17], [25]. This is beyond the scope of this paper, which is for point inference. In general, the above methods all have their drawbacks in solving JDE problems [18].

For the JDE problem, Li [26] proposed a new integrated JDE paradigm. Its cornerstone is a novel generalized Bayes risk, which is a generalization of the Bayes decision and estimation risks. This JDE approach is inherently superior in joint performance to the traditional two-stage strategies (D-then-E and E-then-D) or separate decision and estimation. The power of this JDE framework was demonstrated in [6], [19], and [27]–[29] Based on JDE, we proposed a conditional JDE (CJDE) risk by introducing the on-line data [18]. CJDE is verified to be theoretical superior by accounting for the coupling between decision and estimation, and is also computational simple. It provides a general solution for practical JDE problems.

In CJDE, the decision risk and the estimation risk are unified through two parameters, which adjust the weights of decision and estimation, respectively. These design parameters provide enough flexibilities, and make CJDE more applicable for a large amount of JDE problems: decision and estimation are virtually equally important or one is primary and the other is secondary. When designing the parameters, we should give full consideration to their impact on the joint performance of decision and estimation. Specifically, we should first balance the respective contributions of the decision cost and the estimation cost to the total CJDE cost. Then, since decision and estimation are highly coupled, we should fully utilize their mutual-effect and make a good trade-off between them so that we can achieve a good joint performance finally.

Within the CJDE framework, and inspired by the above analysis, this paper proposes a compact CJDE (CCJDE) risk with only one design parameter. CCJDE unifies the traditional decision risk and estimation risk into one framework in the form of *product*. It inherits the theoretical advantages of CJDE by accounting for the interdependence between decision and estimation. CCJDE risk is simpler than the CJDE risk, and its computational complexity is also smaller. Based on the CCJDE risk, we focus on minimizing it. We present the optimal CCJDE solution containing decision and estimation results, which have analytical forms. Furthermore, by taking advantage of the parameter mutual-effects in the CCJDE risk, we propose a novel CCJDE scheme with time-varying parameters. By doing this, the interdependence between decision and estimation can be further utilized, and the joint performance is therefore improved. It is worthwhile mentioning that CCJDE is applicable for JDE problems in which decision and estimation are equally important.

This paper applies the proposed CCJDE to the practical JTI problems. After formulating the JTI problem, we propose an applicable multiple model CCJDE method to solve it. For performance evaluation, this paper proposes a new joint performance metric (JPM), which can evaluate the performance of tracking and identification jointly. This JPM converts the identification error and tracking cost into one unified metric. Two illustrative examples are presented to verify the superiority of the proposed CCJDE method. Simulation results show that CCJDE can take advantage of the coupling between tracking and identification, and finally beats the traditional two-step strategies in JPM. Also verified is the effectiveness of the proposed JPM. For the multisensor data JTI, besides the coupling between tracking and identification, CCJDE can further utilize all information contained in the heterogeneous sensor data. Besides, the effectiveness of the proposed CCJDE scheme with time-varying parameters is also demonstrated.

The main contributions of this paper are as follows:

1) This paper proposes a compact CJDE (CCJDE) risk, which integrates the traditional Bayes decision risk and estimation risk in a concise form. Based on this, we derive the optimal CCJDE solution.

2) We propose a CCJDE method with time-varying parameters, which provides additional flexibility, and what's more, the coupling between decision and estimation is further utilized.

3) This paper applies CCJDE to the practical JTI problem. An applicable multiple model CCJDE algorithm considering the characteristics of JTI is proposed.

4) For performance evaluation, this paper proposes a new joint performance metric, which unifies the identification error and the tracking error in an effective way.

5) Through two illustrative JTI examples, the superiority of the proposed CCJDE method is fully demonstrated. Also verified are the proposed JPM and the CCJDE scheme with time-varying parameters.

This paper is organized as follows. Section II overviews the existing Bayes joint decision and estimation. Section III proposes a new CCJDE risk, and also presents the corresponding CCJDE solution. Section IV proposes a CCJDE scheme with time-varying parameters. Section V applies the proposed CCJDE method to the JTI problem. An applicable multiple model CCJDE algorithm for JTI is proposed. Also presented is a new joint performance metric. Section VI presents the simulation results. Section VII concludes the paper.

## II. REVIEW OF BAYES JOINT DECISION AND ESTIMATION

For JDE problems, Li [26] proposed an integrated paradigm based on a new generalized Bayes risk:

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

where $x$ is the true target state and $\hat{x}$ is its estimate. $H^j$ is the $j$th hypothesis; $D^i$ is the $i$th decision; $C(x,\hat{x})$ is the cost of estimating $x$ by $\hat{x}$; $E[C(x,\hat{x})|D^i, H^j]$ is the expected estimation cost conditioned on the fact that $D^i$ is decided but $H^j$ is true; $\alpha_{ij}$ and $\beta_{ij}$ are the weight factors of decision and estimation, which provide additional flexibilities.

Essentially, $\bar{R}$ is a generalization of the traditional Bayes risk for decision and that for estimation. It fully considers the coupling between decision and estimation, and thus theoretically superior to the existing separate decision and estimation or the two-stage methods.

In the JDE framework, we also proposed a conditional JDE (CJDE) risk [18] by introducing the on-line data, as follows,

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

$R_C(z)$ inherits the theoretical superiority of JDE by converting the Bayes decision risk and estimation risk into one framework. For calculation, however, CJDE is much simpler than JDE due to the introduction of $z$.

## III. COMPACT CONDITIONAL JOINT DECISION AND ESTIMATION

### A. MOTIVATION

In the CJDE risk $R_C(z)$, the nonnegative $\alpha_{ij}$ and $\beta_{ij}$ work as relative weights to combine the individual decision and estimation costs. By properly selecting $\alpha_{ij}$ and $\beta_{ij}$, the JDE framework is suitable for all three classes of JDE problems [26]: a) decision is primary and estimation is secondary; b) estimation is primary and decision is secondary; c) decision and estimation are equally important.

As design parameters, $\alpha_{ij}$ and $\beta_{ij}$ are problem-dependent. For the third type of JDE problem mentioned above, i.e., decision and estimation are of equal importance, the parameters are expected to be simplified. On the premise of guaranteeing the joint performance, simplifying the parameters is promising. Therefore, within the framework of CJDE, this paper focuses on proposing a new and compact CJDE method. To achieve this goal, we need to take full consideration of the close relationship between $\alpha_{ij}$ and $\beta_{ij}$, meanwhile, take the final joint performance into account. Finally, the proposed joint risk is expected to integrate the decision and estimation costs in a concise and effective way.

### B. COMPACT CONDITIONAL JOINT DECISION AND ESTIMATION RISK

In view of the above, we propose the following compact conditional JDE (CCJDE) risk:

$$\bar{R}_C^c(z) = \sum_i^N \sum_j^N \gamma_{ij} E[C(x,\hat{x})|D^i, H^j, z] P\{D^i, H^j|z\} \quad (3)$$

where $\gamma_{ij}$ is the only parameter unifying the decision and the estimation costs. $N$ is the total number of target classes. Here, $x$, $\hat{x}$, $H^j$, and $D^i$ have the same meanings as in JDE (1). The expected estimation cost is denoted by

$$\varepsilon_{ij}(z) \triangleq E[C(x,\hat{x})|D^i, H^j, z] \quad (4)$$

Here are some properties of the CCJDE risk $\bar{R}_C^c(z)$.

a) Taking $\gamma_{ij}$ as decision cost and $\varepsilon_{ij}(z)$ as estimation cost, $\bar{R}_C^c(z)$ can be considered as the *product* of the decision cost and the estimation cost. This differs from the CJDE risk $R_C(z)$, which is a *summation* of decision and estimation costs.

b) $\bar{R}_C^c(z)$ inherits the virtues of CJDE by accounting for the interdependence between decision and estimation. Specifically, CCJDE converts the traditional decision cost and estimation cost into one unified framework, and thus they can be handled jointly to achieve a good joint performance.

c) For computational complexity, CCJDE is simpler than CJDE, making it more practical. Specifically, in the CJDE risk $R_C(z)$, both $\alpha_{ij}$ and $\beta_{ij}$ need to be designed: we should first balance the contributions of decision and estimation to $R_C(z)$ by adjusting $\alpha_{ij}c_{ij}$ and $\beta_{ij}\varepsilon_{ij}(z)$, and then further design $\beta_{ij}$ for different $(i, j)$s. In $\bar{R}_C^c(z)$, we only need to design appropriate $\gamma_{ij}$ to find a good trade-off between decision and estimation for the sake of a good joint performance.

d) The designing of $\gamma_{ij}$ is application-dependent, which is up to users to choose. The relative weight of decision and estimation can be captured by the ratio of $\gamma_{ii}/\gamma_{ij}$.

e) As analyzed in Motivation, CJDE is applicable to all three kinds of JDE problems: decision and estimation are equally important or one is primary while the other is secondary. For example, suppose decision is more important than estimation, we can choose $\alpha_{ij}c_{ij}$ larger than $\beta_{ij}\varepsilon_{ij}(z)$ in magnitude to emphasize more on decision. However, CCJDE can be applied only when decision and estimation are of equal importance. When it comes to this specific type of JDE problem, CCJDE is simple and effective.

### C. OPTIMAL CCJDE SOLUTION

To obtain the optimal CCJDE solution, we need to minimize the above CCJDE risk $\bar{R}_C^c(z)$.

#### 1) OPTIMAL DECISION

With any given estimation cost $\varepsilon_{ij}(z)$, to minimize $\bar{R}_C^c(z)$, the optimal decision $D$ is

$$D = D^i, \quad \text{if } C^i(z) \leqslant C^l(z), \ \forall l \quad (5)$$

in which the posterior decision cost

$$C^i(z) = \sum_{j=1}^N \gamma_{ij}\varepsilon_{ij}(z) P\{H^j|z\} \quad (6)$$

#### 2) OPTIMAL ESTIMATION

Given any decision $D^i$ and with the quadratic estimation cost $C(x,\hat{x}) = \tilde{x}'\tilde{x}$, the optimal estimator for $\bar{R}_C^c(z)$ is:

$$\check{x}^{(i)} = \sum_{j=1}^N \hat{x}^{(j)} \bar{P}_i\{H^j|z\} \quad (7)$$

where

$$\hat{x}^{(j)} = E[x|z, H^j] \quad (8)$$

is the state estimate conditioned on hypothesis $H^j$. $\bar{P}_i\{H^j|z\}$ is the generalized posterior probability, given by

$$\bar{P}_i\{H^j|z\} = \gamma_{ij} P\{H^j|z\} / \sum_l \gamma_{il} P\{H^l|z\}.$$

Note that in the above posterior CCJDE cost (6), the key is to obtain the expected estimation cost $\varepsilon_{ij}(z)$ defined in (4). Specifically, under the linear Gaussian assumption and for $z \in \mathcal{D}^i$ with $\mathcal{D}^i$ being the decision region for $D^i$, we have

$$\begin{aligned}\varepsilon_{ij}(z) &= E[\tilde{x}'\tilde{x}|D^i, H^j, z] \\ &= \text{mse}(\hat{x}^{(j)}|H^j, z) + (\hat{x}^{(j)} - \check{x}^{(i)})'(\cdot) \end{aligned} \quad (9)$$

where $\text{mse}(\hat{x}^{(j)}|H^j, z)$ is the estimation mse. $\hat{x}^{(j)}$ and $\check{x}^{(i)}$ are estimates under hypothesis $H^j$ and decision $D^i$, respectively. For more details, please refer to reference [18].

*Remark 1:* It can be seen that both the CCJDE decision and estimation have analytical forms, and they are interdependent: to get the CCJDE decision $D^i$, we need to calculate $\varepsilon_{ij}(z)$, in which the state estimates $\hat{x}^{(j)}$ and $\check{x}^{(i)}$ are required; to get the CCJDE estimation $\check{x}^{(i)}$, the weight factor $\bar{P}_i\{H^j|z\}(j = 1, \cdots, N)$ is needed, which relates to decision $D^i$.

## IV. CCJDE WITH TIME-VARYING PARAMETERS

In the CCJDE risk $\bar{R}^c_C(z)$, the parameter $\gamma_{ij}$ plays double roles: it adjusts both the contributions of decision and estimation to $\bar{R}^c_C(z)$. For decision, it is clear that we should choose $\gamma_{ij} > \gamma_{ii}(i \neq j)$ because with such $\gamma_{ij}$s, the incorrect decision is penalized more than the correct one, which benefits decision. For estimation, however, designing $\gamma_{ij}$ is much more complex [18]. Specifically, we should not choose $\gamma_{ij}$ excessively larger than $\gamma_{ii}$ because this deteriorates the estimation performance. In general, the estimation performance is closely related to the decision performance in JDE problems, and sometimes, their respective demands for $\gamma_{ij}$ even conflict [18].

Since the ultimate goal of JDE is to achieve a good joint performance (rather than separate decision or estimation), we should try to balance decision and estimation performances for the sake of better joint performance. Taking this into account and also considering the mutual effect between decision and estimation performances, we propose the following new CCJDE scheme with time-varying parameters.

### A. ANALYSIS

As analyzed in [18], on the average, if the decisions are often correct, i.e., the correct classification rate $P_C$ is high, we choose $\gamma_{ii} > \gamma_{ij}$. This benefits the estimation, and finally results in a better joint performance. On the other hand, if $P_C$ is low, we should better choose $\gamma_{ii} < \gamma_{ij}$, which can prevents the estimation performance from excessively poor.

In practice, at the beginning steps, as we know little about the true target identity, $P_C$ is usually low. With more data available, more information about the target identity is utilized, and $P_C$ goes up. Gradually, with the accumulation of data, $P_C$ becomes higher, and is finally close to some value not larger than 1. This inspires us to design a time-varying parameter, which accounts for the close relationship between decision and estimation, and finally leads to a better joint performance.

### B. TIME-VARYING-PARAMETER CCJDE

We propose a CCJDE scheme with time-varying parameters:

$$\bar{R}^{c,r}_C = \sum_{i,j} \gamma^k_{ij} E[C(x_k, \hat{x}_k)|D^i, H^j, z^k] P\{D^i, H^j|z^k\} \quad (10)$$

For comparison purpose, we have the constraints $\sum_i \gamma_{ij} = 1$, $\gamma_{ij} = \gamma_{ji}, \gamma_{ii} = \gamma_{jj}(i \neq j)$. Then we propose to use

$$\gamma^k_{ij} = \theta \gamma^{k-1}_{ij}, \quad \gamma^k_{ii} = 1 - \gamma^k_{ij} \quad (11)$$

where $\theta \in (0, 1]$ is a constant, which is application-dependent. In practice, we can choose different $\theta$s, as long as $\gamma^k_{ij}$ has a decreasing trend, e.g., we choose $\theta = 0.9$. Actually, $\bar{R}^{c,r}_C$ is a generalization of $\bar{R}^c_C$, and it reduces to $\bar{R}^c_C$ with $\theta = 1$.

To minimize $\bar{R}^{c,r}_C$, the optimal solution is the same as in CCJDE excepts that $\gamma_{ij}$ is replaced by $\gamma^k_{ij}$. In essence, through these time-varying parameters, not only the coupling between decision and estimation but also the time-varying characteristics of decision and estimation performances are fully utilized, which lead to a better joint performance.

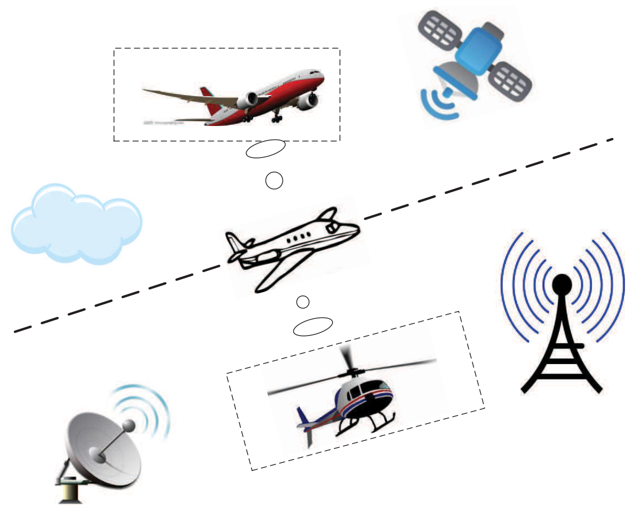

**FIGURE 1.** JTI using multisensor data.

## V. CCJDE BASED JOINT TRACKING AND IDENTIFICATION

### A. PROBLEM FORMULATION

There is only one target with multiple possible classes, in which different classes have different dynamics. As is illustrated in Fig.1. In this JTI problem, target tracking accurately estimate the target state (e.g., position, velocity, acceleration etc.), and target identification determines the type (a fighter or an airline). Our goal is to solve these two problems jointly using data transmitted from multiple sensors. Data are uncertain due to clutter, occlusion, maneuver, sensor resolution, etc.

In this problem, tracking and identification are coupled: information of the target identity can help build a more accurate target kinematic model, which benefits tracking;

**TABLE 1.** One cycle of imm estimator.

| | |
|---|---|
| 1. Model-conditioned re-initialization (for $i = 1, 2, \cdots, M$): | |
| Predicted mode probability: | $\mu_{k\mid k-1}^{(i)} \triangleq P\{m_k^{(i)} \mid Z^{k-1}\} = \sum_j \pi_{ji}\mu_{k-1}^{(j)}$ |
| Mixing weight: | $\mu_{k-1}^{j\mid i} \triangleq P\{m_{k-1}^{(j)} \mid m_k^{(i)}, Z^{k-1}\} = \pi_{ji}\mu_{k-1}^{(j)}/\mu_{k\mid k-1}^{(i)}$ |
| Mixing estimate: | $\bar{x}_{k-1\mid k-1}^{(i)} \triangleq E[x_{k-1} \mid m_k^{(i)}, Z^{k-1}] = \sum_j \hat{x}_{k-1\mid k-1}^{(j)}\mu_{k-1}^{j\mid i}$ |
| Mixing covariance: | $\bar{P}_{k-1\mid k-1}^{(i)} = \sum_j [P_{k-1\mid k-1}^{(j)} + (\bar{x}_{k-1\mid k-1}^{(i)} - \hat{x}_{k-1\mid k-1}^{(j)})(\bar{x}_{k-1\mid k-1}^{(i)} - \hat{x}_{k-1\mid k-1}^{(j)})]\mu_{k-1}^{j\mid i}$ |
| 2. Model-conditioned filtering (for $i = 1, 2, \cdots, M$): | |
| Predicted state: | $\hat{x}_{k\mid k-1}^{(i)} = F_{k-1}^{(i)}\bar{x}_{k-1\mid k-1}^{(i)} + G_{k-1}^{(i)}\bar{w}_{k-1}^{(i)}$ |
| Predicted covariance: | $P_{k\mid k-1}^{(i)} = F_{k-1}^{(i)}\bar{P}_{k-1\mid k-1}^{(i)}(F_{k-1}^{(i)})' + G_{k-1}^{(i)}Q_{k-1\mid k-1}^{(i)}(G_{k-1}^{(i)})'$ |
| Measurement residual | $\tilde{z}_k^{(i)} = z_k - H_k^{(i)}\hat{x}_{k\mid k-1}^{(i)} - \bar{v}_k^{(i)}$ |
| Residual covariance | $S_k^{(i)} = H_k^{(i)}P_{k\mid k-1}^{(i)}(H_k^{(i)})' + R_k^{(i)}$ |
| Filter gain | $K_k^{(i)} = P_{k\mid k-1}^{(i)}(H_k^{(i)})'(S_k^{(i)})^{-1}$ |
| Updated state | $\hat{x}_{k\mid k}^{(i)} = \hat{x}_{k\mid k-1}^{(i)} + K_k^{(i)}\tilde{z}_k^{(i)}$ |
| Updated covariance | $P_{k\mid k} = \sum_i [P_{k\mid k}^{(i)} + (\hat{x}_{k\mid k} - \hat{x}_{k\mid k}^{(i)})(\hat{x}_{k\mid k} - \hat{x}_{k\mid k}^{(i)})']\mu_k^{(i)}$ |
| 3. Model probability update (for $i = 1, 2, \cdots, M$): | |
| Model likelihood: | $L_k^{(i)} \triangleq p[\tilde{z}_k^{(i)} \mid m_k^{(i)}, Z^{k-1}] = \mathcal{N}(\tilde{z}_k^{(i)}; 0, S_k^{(i)})$ |
| Mode probability: | $\mu_k^{(i)} \triangleq \frac{\mu_k^{(i)}L_k^{(i)}}{\sum_j \mu_k^{(j)}L_k^{(j)}}$ |
| 4. Estimation fusion | |
| Overall estimate: | $\hat{x}_{k\mid k} = \sum_i \hat{x}_{k\mid k}^{(i)}\mu_k^{(i)}$ |
| Overall covariance: | $\mu_{k-1}^{j\mid i} \triangleq P\{m_{k-1}^{(j)} \mid m_k^{(i)}, Z^{k-1}\} = \pi_{ji}\mu_{k-1}^{(j)}/\mu_{k\mid k-1}^{(i)}$ |

information of the target motion behavior can help identify its class label. Thus, this is a JDE problem which requires a JDE solution.

Denote by $x_k$ the target state, $c_i$ the target class, and $z_k$ the kinematic measurement at time $k$. Our goal is to obtain

$$\{x_k, c_i\}$$

jointly using $z^k$, which denotes data up to time $k$. In this paper, decision and hypothesis are one-to-one correspondence: $H^j$ is the hypothesis of class $c_i$, and $D^i$ means $c_i$ is chosen.

With the linear motion and measurement assumptions, we have the following hybrid system:

$$x_k = F_{k-1}^{ij}x_{k-1} + G_{k-1}^{ij}u_{k-1}^{ij} + \Gamma_{k-1}^{ij}w_{k-1}^{ij} \quad (12)$$

$$z_k = C_k x_k + v_k \quad (13)$$

where $u_k$ is the deterministic input, $w_k$ and $v_k$ are zero-mean white Gaussian process and measurement noises, respectively. $F_k$, $G_k$, and $\Gamma_k$ are known matrices, and the superscript $ij$ denotes the $j$th model of class $i$. $C_k$ is the measurement matrix. For estimation, we adopt the well-known interacting multiple model (IMM) for better maneuver tracking performance. Table 1 shows one cycle of the IMM filter [30].

## B. MULTIPLE MODEL CCJDE APPROACH FOR JTI

*One Cycle of MM-CCJDE Algorithm at Time k:*

a) Initialization
Initialize the CCJDE algorithm by parameters $\hat{x}_{k-1}^{(j)}$ and $P\{H^j|z^{k-1}\}$. Here, $\hat{x}_{k-1}^{(j)}$ is the state estimate under $H^j$ and $P\{H^j|z^{k-1}\}$ is the probability of $H^j$.

b) Update step
With $z_k$ available, update $\hat{x}_k^{(j)}$ and $P\{H^j|z^k\}$.

c) Estimation step
For each decision candidate $D^i$, calculate the CCJDE estimate $\check{x}_k^{(i)}$ according to (7). Then, get the expected cost $\varepsilon_{ij}(z^k) = \text{mse}(\hat{x}_k|z^k, D_k^i, H^j)$ according to (9).

d) Decision step
Based on $\varepsilon_{ij}(z^k)$, obtain the posterior cost $C^i(z^k) = \sum_j \gamma_{ij}\varepsilon_{ij}(z^k)P\{H^j|z^k\}$ for each $i$. Then the optimal CCJDE decision is $D_k^i$: $C^i(z^k) \leqslant C^l(z^k), \forall l$.

e) Output
Output the CCJDE 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:* With this CCJDE algorithm, the optimal tracking and identification results can be obtained jointly without decision-estimation iteration. The proposed MM-CCJDE method can take advantage of the coupling between tracking and identification in JTI. Besides, MM-CCJDE has simple calculation, which makes it more practical.

## C. JOINT PERFORMANCE EVALUATION METRIC

Traditionally, decision performance and estimation performance are evaluated by correct-decision rate and root mean square error (RMSE), respectively [31], [32]. For JDE problems, however, they are incomprehensive and may even fail to compare different algorithms. It is pointed out in [27] that for JDE problems, decision and estimation performances should be evaluated jointly rather than separately. A joint performance measure (JPM) based on the idea of mock data was also proposed in [27]. In [6], we presented a JPM based on the one-step-predicted estimation error.

In essence, decision and estimation have different characteristics. The estimation error is usually a distance, and thus the average estimation error is always used for its performance evaluation. For decision, however, since the decision error is almost never a distance, a sum of decision errors is meaningless [26]. Therefore, the decision performance is usually evaluated by the proportion of the correct decisions to the total decisions, i.e., correct decision rate.

Considering the above differences between decision errors and estimation errors, we propose the following unified metric to evaluate the decision and estimation performances jointly:

$$\zeta = E_c(D_k, \hat{D}_k) + \lambda \cdot E_x(x_k, \hat{x}_k) \tag{14}$$

where $E_x(\cdot)$ and $E_c(\cdot)$ are errors of estimation and decision, respectively.

Specifically, $E_x(\cdot)$ and $E_c(\cdot)$ are defined as follows:

$$E_c(D_k, \hat{D}_k) = \begin{cases} 0, & \text{if } D_k = \hat{D}_k \\ 1, & \text{if } D_k \neq \hat{D}_k \end{cases}$$

and

$$E_x(x_k, \hat{x}_k) = (x_k - \hat{x}_k)' P^{-1}(\cdot)$$

where $P$ is a normalization factor, which converts the estimation MSE $(x_k - \hat{x}_k)'(\cdot)$ to [0,1]. $\lambda$ is a unit-free weight factor between decision and estimation. The bigger $\lambda$ is, the more emphasis we place on estimation. Generally, $\lambda$ is a design parameter, and its value depends on practical JDE problems.

*Remark 3:* The proposed metric (14) is a joint performance evaluation metric in the following sense: it reflects both the decision performance (through $E_c(\cdot)$) and the estimation performance (through $E_x(\cdot)$). In $\zeta$, both $E_c(D_k, \hat{D}_k)$ and $E_x(x_k, \hat{x}_k)$ are between 0 and 1, and they are unit free. Through the weighed sum, the decision error and the estimation error are unified in a reasonable and effective way.

## VI. SIMULATION AND DISCUSSION

In this section, we illustrate the proposed CCJDE method through two JTI examples. The compared methods are the traditional identification-then-tracking (ITT) and tracking-then-identification (TTI) in terms of root mean square error (RMSE), the probability of correct classification ($P_C$), and the joint performance metric (JPM). Specifically, in simulation 1, the constant turn (CT) motion model is adopted using radar data. In simulation 2, the constant acceleration (CA) motion model is adopted using multisensor data.

The compared methods are as follows:

a) In ITT, the optimal Bayes decision is made first according to the Bayes decision rule, which minimizes the Bayes decision risk. Then, the minimum mean square error (MMSE) estimation is done based on the decided class.

b) In TTI, the MMSE-based multiple model estimation is made first. Then, decision is made based on the ratio of current measurement likelihoods conditioned on $\hat{x}_{k|k-1}$ and $H^j$ [19].

### A. SIMULATION 1

Suppose there is only one target with two possible classes $c_1$ and $c_2$, which differ from each other in dynamics. Denote by $x_k = [x, \dot{x}, y, \dot{y}]$ the target state. The state evolves according to the constant-turn (CT) model:

$$x_{k+1} = F_{CT}(\omega) x_k + w_k$$

in which the transition matrix

$$F_{CT} = \begin{bmatrix} 1 & \sin\omega T/\omega & 0 & -(1-\cos\omega T)/\omega \\ 0 & \cos\omega T & 0 & -\sin\omega T \\ 0 & (1-\cos\omega T)/\omega & 1 & \sin\omega T/\omega \\ 0 & \sin\omega T & 0 & \cos\omega T \end{bmatrix}$$

and the covariance matrix of process noise is $Q = cov(w_k) =$

$$\begin{bmatrix} \frac{2(\omega T - \sin\omega T)}{\omega^3} & \frac{1-\cos\omega T}{\omega^2} & 0 & \frac{\omega T - \sin\omega T}{\omega^2} \\ \frac{1-\cos\omega T}{\omega^2} & T & -\frac{\omega T - \sin\omega T}{\omega^2} & 0 \\ 0 & -\frac{\omega T - \sin\omega T}{\omega^2} & \frac{2(\omega T - \sin\omega T)}{\omega^3} & \frac{1-\cos\omega T}{\omega^2} \\ \frac{\omega T - \sin\omega T}{\omega^2} & 0 & \frac{1-\cos\omega T}{\omega^2} & T \end{bmatrix}$$

The sampling time $T = 1$. A target in a class $i$ $(i \in \{1, 2\})$ has model set $M^i$ of possible turn rate $\omega$, given by

$$M^1 = \{5\pi/180, 3\pi/180, -3\pi/180\},$$
$$M^2 = \{-18\pi/180, 10\pi/180, -10\pi/180, 6\pi/180, -6\pi/180\}.$$

Each class has an equal initial probability, and so are the models in $M^i$ initially. The radar data follows the measurement model (13) with $C_k = [1, 0, 0, 0; 0, 0, 1, 0]$.

In the IMM method, the transition probability matrix for class 1 and class 2 are given by:

$$\text{TPM1} = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.15 & 0.85 & 0 \\ 0.15 & 0 & 0.85 \end{bmatrix}$$

$$\text{TPM2} = \begin{bmatrix} 0.9 & 0.025 & 0.025 & 0.025 & 0.025 \\ 0.15 & 0.85 & 0 & 0 & 0 \\ 0.15 & 0 & 0.85 & 0 & 0 \\ 0.15 & 0 & 0 & 0.85 & 0 \\ 0.15 & 0 & 0 & 0 & 0.85 \end{bmatrix}.$$

The simulation results are presented in Fig. 2. The JPM (14) with $\lambda = 1$ is used. $\gamma_{00} = \gamma_{11} = 1/3, \gamma_{01} = \gamma_{10} = 2/3$. All results were obtained from 5000 MC runs and the true target class is randomly generated from a binary distribution.

Fig. 2 shows that for the position and velocity estimation RMSE, TTI is the best, CCJDE is in the middle, and ITT is the worst. Here, TTI has the best estimation performance because estimation in TTI is the MMSE estimation, which is optimal in the MSE sense. For decision performance, ITT performs best because its decision is optimal in the sense of minimum error probability. For joint performance, however, CCJDE beats TTI and ITT. This verifies that CCJDE can make a good trade-off between decision and estimation. Although TTI and ITT have the optimal estimation performance and the optimal decision performance, respectively, CCJDE has the best joint performance, which we care most in a JDE problem.

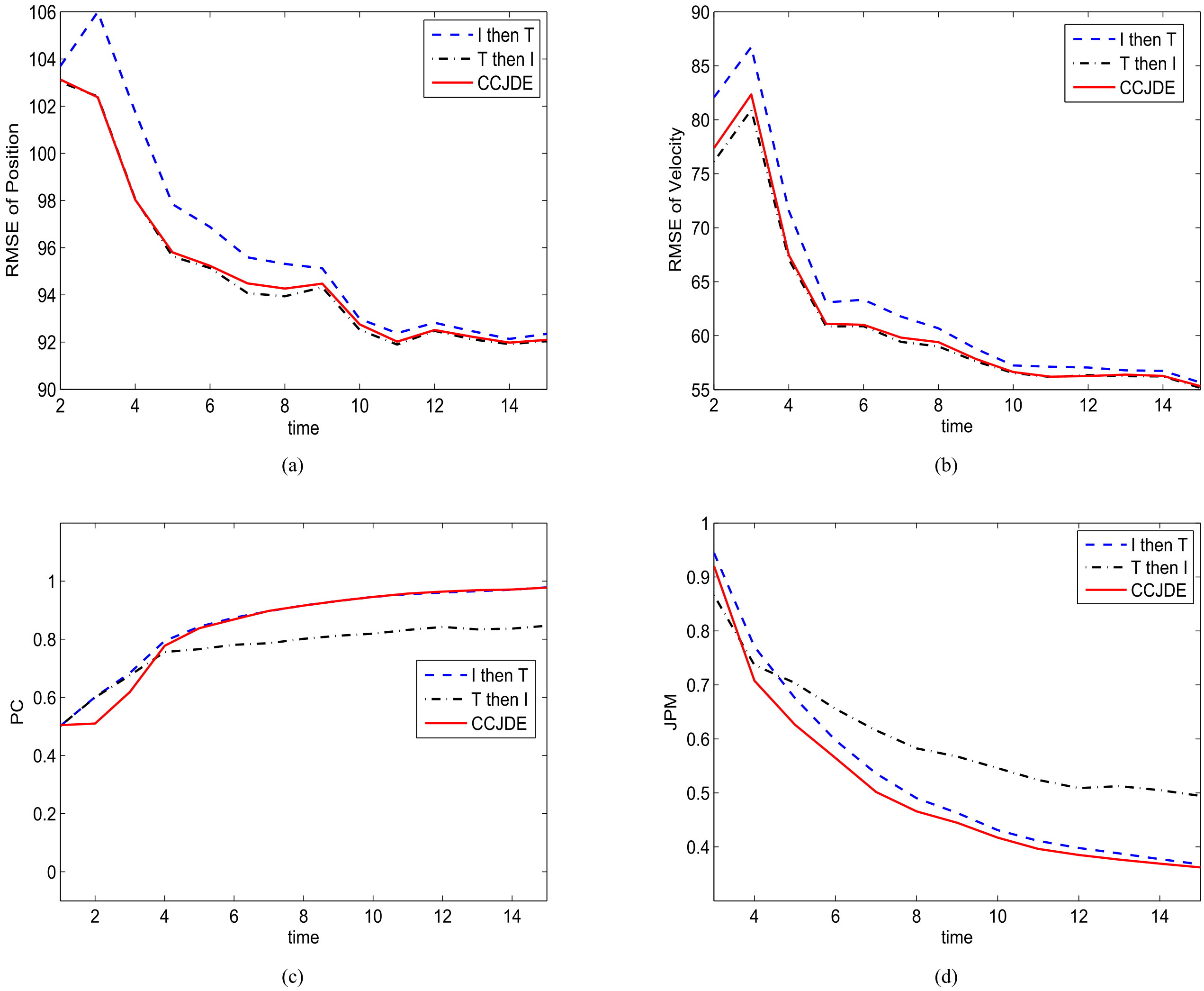


**FIGURE 2.** **CCJDE for JTI with constant turn model. (a) RMSE of position. (b) RMSE of velocity. (c) Probability of correct classification. (d) Joint performance measure.**

Besides, the effectiveness of the proposed JPM (14) is also verified. This JPM can effectively reflect the joint performance of decision and estimation.

### B. SIMULATION 2

In this simulation, we consider a typical JTI problem using multisensor data, same as in [6]. Classes differ from each other in two aspects: dynamic behavior and feature attributes [29]. Two types of measurements: radar and electronic system measure (ESM) are adopted, which are continuous and discrete data, respectively. Our goal is to estimate the target state and identify its class jointly using both radar and ESM data.

For dynamic evolution, with state $x_k = [x, \dot{x}]'$, the target state evolves according to the linear model (12) with

$$F = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}, \quad G = \begin{bmatrix} \frac{1}{2}T^2 \\ T \end{bmatrix}, \Gamma = \begin{bmatrix} \frac{1}{2}T^2 \\ T \end{bmatrix}.$$

The standard deviation of the process noise $w_k$ is 0.5. Different target classes have different control input $u_k$. Class 1 has model set $\{0, +g, -g\}$ for $u_k$ and class 2 has the model set $\{2g, 2.5g, -2.5g, 3g, -3g\}$. The initial probability of each class are equal, so are the models in each model set. The radar data follows the measurement model (13) with measurement matrix $C_k = [1, 0]$ and measurement noise $v_k \sim \mathcal{N}(0, 50^2\text{m}^2)$. The target attribute and ESM measurement models are the same as in [29], which are omitted here.

Denote by $z_x^k$ the kinematic measurements and $z_c^k$ the attribute measurements up to time $k$, respectively. The compared ITT and TTI methods are the same as in [29]. Specifically, in ITT, identification is made based on both $z_x^k$ and $z_c^k$. For TTI, the best estimation is made first using $z_x^k$ only since $z_c^k$ is difficult to be used for estimation directly without going through decision. Here, $\gamma_{00}^0 = \gamma_{11}^0 = 1/3$, $\gamma_{01}^0 = \gamma_{10}^0 = 2/3$. All results were obtained from 5000 MC runs and the true target class is randomly generated from a binary distribution.

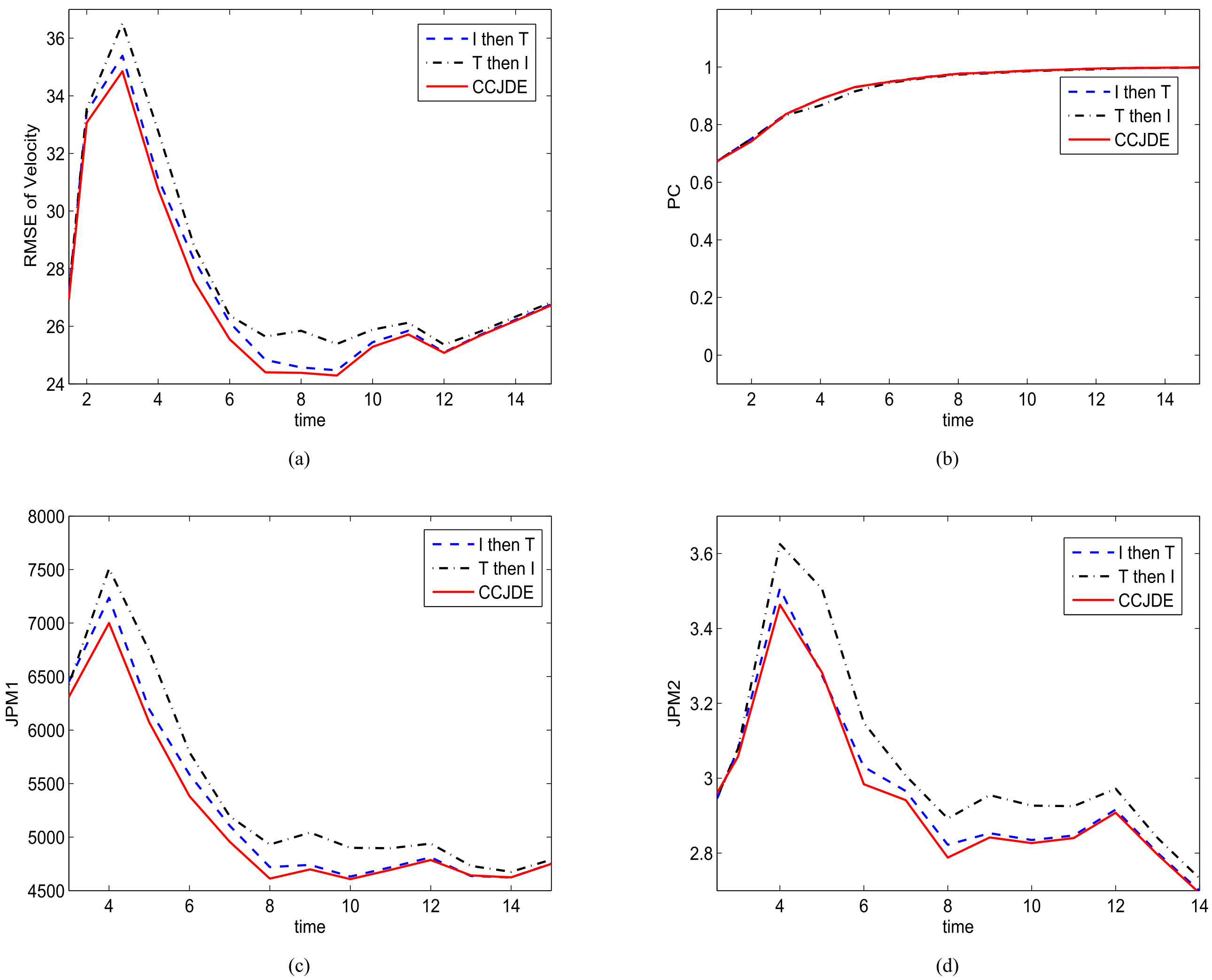


**FIGURE 3.** CCJDE for JTI with constant acceleration model using multisensor data. (a) RMSE of velocity. (b) Probability of correct classification. (c) Joint performance measure 1. (d) Joint performance measure 2.

For joint performance evaluation of multisensor data JTI, we consider two cases: the ground truth of the target identity and state are known and unknown, respectively. They will be given below in detail.

### 1) JOINT PERFORMANCE METRIC (JPM)

#### *a: JPM1*

For the case with known ground truth, we use the one-step-predicted error proposed in [28]:

$$\lambda_k = \frac{1}{M}\sum_{m=1}^{M}(x_k^m - \hat{x}_{k|k-1}^m)'(\cdot) \tag{15}$$

where $x_k^m$ is the ground truth and $\hat{x}_{k|k-1}^m$ is the one-step predicted state at $k$, respectively. $m$ denotes the $m$th run out of $M$ Monte Carlo runs.

#### *b: JPM2*

For the case with unknown ground truth, following the spirit of [27], we measure the distance between the original data set $z_k = \{z_k^x, z_k^c\}$ and the mock data set $\hat{z}_k = \{\hat{z}_k^x, \hat{z}_k^c\}$ generated by the algorithm [27], [32]. To achieve this goal, we propose to use the following unified metric as the JPM [6]:

$$d^k = d_c^k(z_k^c, \hat{z}_k^c) + \xi \cdot d_x^k(z_k^x, \hat{z}_k^x) \tag{16}$$

where $d_c^k(\cdot)$ and $d_x^k(\cdot)$ are the distances for discrete data and that for continuous data, respectively. $\xi$ is a weight factor.

Specifically, in order to obtain $d_c^k(z_k^c, \hat{z}_k^c)$, we measure the distance between two discrete data sets $z_k^c = \{z_k^{c,(i)}\}_{i=1}^{N_i}$ and $\hat{z}_k^c = \{\hat{z}_k^{c,(i)}\}_{i=1}^{N_i}$, where $i$ denotes the $i$th simulation and $N_i$ is the total MC runs. The Wasserstein distance [32] is adopted here due to its nice property and adaptability to our situation [6]. Based on the Wasserstein distance, the distance between $z_k^c$ and $\hat{z}_k^c$ is

$$d_c^k(z_k^c, \hat{z}_k^c) = \min_{I \in \mathcal{I}} \sum\nolimits_{i=1}^{n} d(z_k^{c,i}, \hat{z}_k^{c,(i)}) \tag{17}$$

where $I$ is a permutation of data points in $\hat{z}_k^c$, and $\mathcal{I}$ is the set of all possible such $I$'s. In this paper, we use the *Hamming distance* for $d(z_k^{c,i}, \hat{z}_k^{c,(i)})$ because it suites our problem [6].

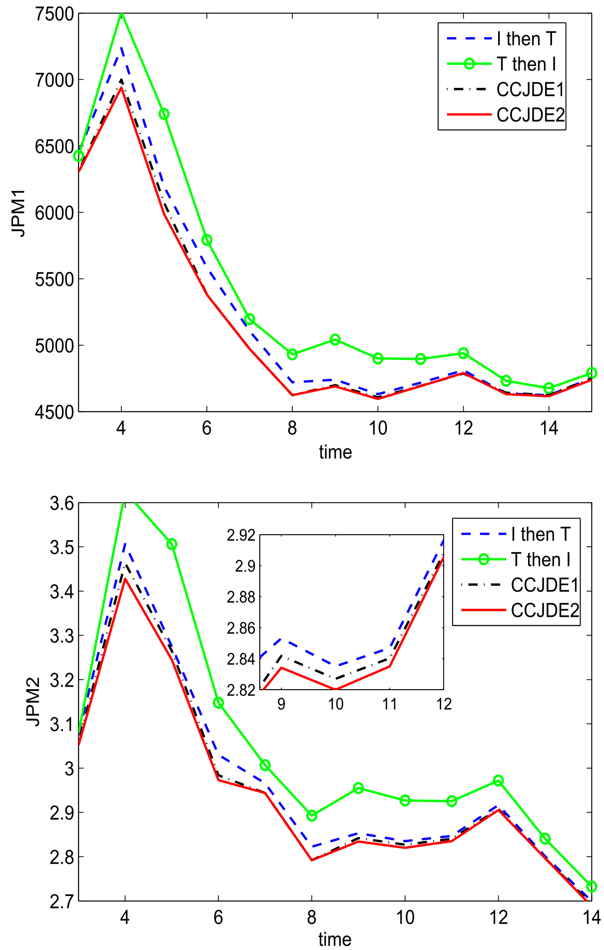


**FIGURE 4.** CCJDE with time-varying parameters.

To obtain $d_x^k(z_k^x, \hat{z}_k^x)$, we measure the distance between $z_k^{x,(i)}$ and $\hat{z}_k^{x,(i)}$, where the superscript $i$ denotes that they come from the same simulation run. We propose the following mean predicted-measurement distance:

$$d_x^k(z_k^x, \hat{z}_k^x) = \frac{1}{I} \sum_i^I \zeta_k^i \tag{18}$$

where $\zeta_k^i = \frac{1}{J} \sum_j^J (z_k^{x,(i)} - \hat{z}_{k,j}^{x,(i)})' R^{-1}(\cdot)$. Here, $z_k^{x,(i)}$ is the real kinematic measurement at time $k$ on the $i$th run out of $I$ runs. $\hat{z}_{k,j}^{x,(i)}$ is the $j$th one-step prediction of the measurement on the $i$th run out of $J$ runs.

### 2) SIMULATION RESULTS AND ANALYSIS

Simulation results are shown in Fig. 3 with JPM1 and JPM2 given in (15) and (16), respectively. Fig. 3 shows that for position estimation RMSE, TTI is worst, which mainly results from the incomplete use of information: TTI uses only radar data for estimation while ITT and CCJDE use all information (radar and ESM). ITT is worse than CCJDE due to the essential disadvantage of "decision then estimation". For estimation in CCJDE, all information is used and the effect of decision on estimation is also considered, and thus it performs best. For decision performance, the differences among all methods are not significant. When it comes to the joint performance, CCJDE beats TTI and ITT.

This simulation verifies that CCJDE can fully utilize the multisensor data information, and also take advantage of the coupling between decision and estimation. Finally, it outperforms the traditional two-step strategies in JPM.

*Remark 4:* In order to verify the effectiveness of the time-varying parameters, we further compare CCJDE algorithms with different parameters. The form $\gamma_{ij}^k = \theta \gamma_{ij}^{k-1}$ is adopted. In CCJDE1, $\theta = 1$; In CCJDE2, $\theta = 0.95$. Actually, CCJDE1 is used for comparison purpose. At the initial time, $\gamma_{00}^0 = \gamma_{11}^0 = 1/3$, $\gamma_{01}^0 = \gamma_{10}^0 = 2/3$. Fig. 4 shows the results. To save space, we only present the joint performances of all compared methods since other performances of CCJDE1 and CCJDE2 are close, and so they are omitted.

Fig. 4 verifies the effectiveness of the proposed CCJDE scheme with time-varying parameters. It can be seen that with appropriate choices of $\gamma_{ij}^k$, CCJDE2 is slightly better than CCJDE1 in JPM. This demonstrates that with time-varying parameters, the coupling between decision and estimation can be further utilized so that a better joint performance can be achieved.

## VII. CONCLUSION

This paper proposes a compact conditional JDE (CCJDE) method for the joint tracking and identification (JTI) problem. JTI is essentially a JDE problem, and better solutions require solving the tracking and identification problems jointly. The recently proposed JDE framework provides a good solution for such problems involving coupled decision and estimation.

Within the JDE framework, we propose a new CCJDE risk, which integrates the traditional decision and estimation risks through a simple form. CCJDE inherit the merits of JDE by utilizing the coupling between decision and estimation. Based on the CCJDE risk, we present the CCJDE solution containing decision and estimation. Besides, inspired by the parameter effects in CCJDE, this paper proposes a new CCJDE scheme with time-varying parameters. By doing this, the mutual effect between decision and estimation could be further utilized so that the joint performance can be improved.

This paper applies the proposed CCJDE method to practical JTI problems. After the problem formulation, we propose an applicable multiple model CCJDE method for the JTI problem. For performance evaluation, a new joint performance metric (JPM) is proposed, which unifies the tracking error and the identification error into one metric in an effective way.

Two illustrative JTI examples are presented for illustration. They show that CCJDE can take advantage of the coupling between tracking and identification, and finally beats the traditional two-step methods in JPM. For multisensor data JTI, besides this coupling, the information contained in heterogeneous sensor data is also utilized. Besides, the effectiveness of the proposed CCJDE scheme with time-varying parameters is also verified. In general, this paper focuses on the CCJDE method, and more complex practical JTI problems are still under further investigation.

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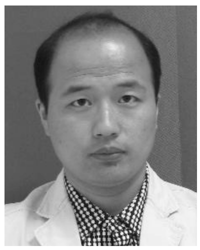

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