



Intent-informed state estimation for tracking guided targets

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ABSTRACT

This paper proposes a state estimation and prediction for tracking guided targets using intent information. A conditionally Markov process is used to describe the destination-oriented target motion, and the collision intent is incorporated through the zero-effort-miss guidance information. The expected arrival time necessary for the conditionally Markov model is determined through the collision geometry and destination motion. Finally, the Kalman filter technique is used to estimate and predict the target state. Numerical simulations demonstrate that the proposed approach can improve state estimation accuracy in both static and dynamic destination cases.

1. Introduction

Target tracking is essential in many applications, ranging from surveillance to autonomous navigation. A crucial aspect of target tracking is the development of an accurate state-space model that can capture the target behavior and enable the prediction of its future trajectory [1]. A stochastic process is commonly used to mathematically describe the target model; however, there is an inevitable mismatch with the actual target in the modeling process. This discrepancy may lead to inaccurate trajectory prediction state estimation errors. In general, the intents of most guided objects, such as autonomous vehicles, are pre-planned, and such objects are controlled by specific maneuvers. Consequently, it is challenging to capture their complex motion using simple kinematic models such as those based on constant velocity (CV), constant acceleration, and constant turning. State estimation based on these models may not yield the precise trajectory estimate required for effective target tracking.

The motion of objects can be more accurately predicted by incorporating the information of their intents into the target motion model. Many researchers have attempted to determine the intent expressed by objects of interest [2–7]. In general, the intent of the target can be expressed in terms of the destination or guidance mode [2,3]. The

destination represents *where* the target aims to go, and the guidance mode indicates *how* the object will behave in its quest for reaching the destination while satisfying the pre-designated flight plan. The guidance law determines the trajectory for a flight mode while satisfying a specific flight maneuver. The guided motion defines the shape and characteristics of the target trajectory. Owing to these characteristics, the destination and target movements are correlated with the future target position, and their contextual information can be used to capture the target behavior [8,9] and estimate trajectories [10–19].

For systematically accommodating the destination intent in target dynamic modeling, several researchers have attempted to establish destination-driven state-space models. For example, the Ornstein–Uhlenbeck (OU) process has been used to derive destination-driven target model. This stochastic process model includes a mean-diverting component such that the resultant state-space model tends to exponentially drift from the given initial states toward the mean values [20]. The spatial information of the destination is incorporated to build mathematical model, and several mean-reverting models can be extended to generalize the destination-driven model [21,12,18]. However, this approach requires stationary system matrices and their destination component. Moreover, because the state transition depends on the system

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parameters, they must be optimally selected to establish an effective surrogate model [21].

Alternatively, the conditionally Markov (CM) process can be used to describe the destination-directed target motion in a more generalized framework [22–26]. CM sequences consist of three components, i.e., the initial distribution, terminal distribution, and transition probability. Unlike the Markov process, the CM process requires the destination distribution with final time information a priori, and the state evolution is then evaluated as the state transition probability conditioned on the previous states and destination states. Furthermore, unlike the OU process model, the CM process model includes the effect of the temporal dependency of the endpoint on the current state. Specifically, the endpoint information encompasses temporal information in terms of the final time-to-arrival, and thus, the effects of the endpoint from the final time to the current state transition can be considered in the state-space model. Consequently, the CM process model can be applied when the temporal information is available a priori. Several researchers [23,25] have shown that the CM process contains the Markov process (MP), reciprocal process (RP) [27,23,28,29], and Markov bridge [13–15]. The destination-driven target motion modeled by CM sequences has been extended to state estimation [26], multiple waypoint tracking [25], and guided target tracking [30].

Despite considerable research, the existing CM-based approaches exhibit several limitations. First, only a few models simultaneously consider the guidance mode and destination in trajectory prediction. Rezaie and Rong Li [26] described the destination-aware motion using the CM process. However, the path was predicted under the assumption that the target moves with constant velocity to reach the destination. In this case, the target motion derived by the CV model may not accurately represent the guidance-specific motion, especially when the target aims to intercept an object. Second, target models based on the CM process have not yet been explored for moving destinations. Rezaie and Rong Li [30] proposed an approach to model a guided target that pursues a moving destination. The destination-driven model derived by the CM process was modified to simultaneously address the destination and target motions. This approach is effective when the target pursues a slowly moving destination. However, the modified CM process requires full information of terminal states, and the formulated sequence favors only tail-chase engagement.

Considering these aspects, this study aims to develop an intent-driven trajectory prediction approach against hostile targets. The intent information is assumed to be known in terms of destination and guidance. Motivated by the work of Rezaie and Rong Li [26], we formulate the target state-space model by the CM process. To reflect the guidance information, the guided target motion is derived by the predictive guidance law, which has been widely applied and noted to be compatible with other guidance schemes such as proportional navigation and optimal guidance laws [31–36]. Moving destinations are considered, and a predictive concept used in guidance schemes is used. A predicted intercept point (PIP) and the arrival time instance are specified. The guided target motion takes the PIP as the destination and uses the arrival time information to ensure that the derived target model can be interpreted to the CM process model. State estimation and trajectory prediction are realized using the Kalman filter theory.

The contributions of this study can be summarized as follows. First, a constructive approach reflecting the movement of the destination from the perspective of the CM process is established. The instantaneous collision geometry allows us to specify the terminal destination and arrival time. In contrast to the existing model [30], which follows an instant destination that is consistently moving, the proposed target model follows a predicted impact point as its stationary destination. Second, the proposed approach provides an intent-driven target model by accommodating guidance and destination intents for precision estimation. Unlike the CV-based model [30], the proposed model is derived using the guidance information in the form of a zero-effort-miss (ZEM)-based law, designed to arrive at the destination through a predictive concept. More

importantly, the guidance information based on the predicted geometry helps specify the expected arrival time, which is not known a priori. By incorporating the temporal information, the resulting target model complies with the CM process and exhibits better estimation performance than the CV-based models in the guided target tracking scenario. The performance improvements over the existing approach [30] are clearly demonstrated in trajectory prediction tasks with both head-on and tail-chase engagement scenarios.

The remaining paper is organized as follows. Section 2 presents the theoretical background as preliminary information. Section 3 describes the benchmark approaches for modeling the destination-directed trajectory (DDT) for target tracking. Section 4 describes the proposed state estimation filter, modeling of the ZEM-based guided target in the CM formulation, and trajectory prediction for moving destinations. Section 5 presents the simulation results. Section 6 presents the concluding remarks and highlights the scope for future work.

2. Preliminaries

2.1. CM process

We consider a stochastic process that incorporates the destination information in generating stochastic sequences. The following notation is used throughout the paper.

$$[\mathbf{x}_k]_i^j = \{\mathbf{x}_i, \mathbf{x}_{i+1}, \dots, \mathbf{x}_j\}, \quad [\mathbf{x}_k] = [\mathbf{x}_k]_0^N, \quad \mathbf{Z}_k = \{\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_k\},$$

where $\mathbf{x}_k \in \mathbb{R}^p$ represents the p -dimensional state variables, and $\mathbf{z}_k \in \mathbb{R}^q$ represents the q -dimensional observation output variables. Subscript k denotes the current time instance, and N denotes the final time instance. When the endpoint distributions are given, a proper stochastic process that describes the endpoint-directed motion must be established. In this study the CM process is used to describe the motion, which can be defined as follows:

Definition 1 (Definition of a CM sequence [27]). $[\mathbf{x}_k]$ is CM_c , $c \in [0, N]$, if $\forall i \in [0, N]$,

$$P(A, B | \mathbf{x}_i, \mathbf{x}_c) = P(A | \mathbf{x}_i, \mathbf{x}_c) P(B | \mathbf{x}_i, \mathbf{x}_c) \quad (1)$$

where $A \in \sigma([\mathbf{x}_i]_{i+1}^N \setminus \{\mathbf{x}_c\})$ and $B \in \sigma([\mathbf{x}_k]_0^{i-1} \setminus \{\mathbf{x}_c\})$; $\sigma(\cdot)$ on set X represents a collection Σ of subsets of X . Moreover, CM_c is termed CM_L when the endpoint $\mathbf{x}_c$ is selected to be $\mathbf{x}_N$.

By definition, the boundary $\mathbf{x}_c$ can be considered as either the initial point $\mathbf{x}_0$ or endpoint $\mathbf{x}_N$. In this study, we consider the CM process to be driven only by the endpoint $\mathbf{x}_N$. According to the definition for the CM_L sequences, the endpoint distribution $\mathbf{x}_N$ explicitly influences the evolution of the sequence $\mathbf{x}_k$ for $k \in [1, N-1]$. Using (1), the state transition probability under the CM_L sequences is

$$\begin{aligned} p(\mathbf{x}_k | [\mathbf{x}_i]_0^{k-1}, \mathbf{x}_N) &= \frac{p(\mathbf{x}_k, [\mathbf{x}_i]_0^{k-2} | \mathbf{x}_{k-1}, \mathbf{x}_N)}{p([\mathbf{x}_i]_0^{k-2} | \mathbf{x}_{k-1}, \mathbf{x}_N)} \\ &= \frac{p(\mathbf{x}_k | \mathbf{x}_{k-1}, \mathbf{x}_N) p([\mathbf{x}_i]_0^{k-2} | \mathbf{x}_{k-1}, \mathbf{x}_N)}{p([\mathbf{x}_i]_0^{k-2} | \mathbf{x}_{k-1}, \mathbf{x}_N)} = p(\mathbf{x}_k | \mathbf{x}_{k-1}, \mathbf{x}_N) \end{aligned} \quad (2)$$

The key difference between MP and CM pertains to the appearance of the $\mathbf{x}_N$ term in the state transition probability.

Using the state transition probability, the linear state-space model described by the CM process with zero mean nonsingular Gaussian (ZMNG) noise $\mathbf{w}_k$ can be obtained as follows.

Theorem 1. [24] A ZMNG $[\mathbf{x}_k]$ is CM_L iff it satisfies

$$\mathbf{x}_k = G_{k,k-1} \mathbf{x}_{k-1} + G_{k,N} \mathbf{x}_N + \mathbf{w}_k \quad (3)$$

and boundary condition

$$\mathbf{x}_N = \mathbf{w}_N, \quad \mathbf{x}_0 = G_{0,N} \mathbf{x}_N + \mathbf{w}_0 \quad (4)$$

where $\mathbf{w}_k \sim \mathcal{N}(0, G_k)$ and $(G_{k,k-1}, G_{k,N})$ represent state transition matrices.

Several researchers have investigated the properties of the CM process through a comparison with other stochastic processes, i.e., MP and RP [27,23,24]. The results highlighted an inclusive relation between these processes: $MP \subset RP \subset CM$, which indicates that the CM process is the most generalized among those processes [24]. Another advantage of using the CM process is that the influence of the terminal state on the current state evolution can be clarified.

2.2. Equations of motion

Consider the planar motion of a vehicle shown in Fig. 1. The vehicle moves from the initial position to the pre-specified goal point. The planar motion between two objects can be described in the discrete-time state-space form as

$$\begin{bmatrix} \mathbf{p}_k \\ \mathbf{v}_k \end{bmatrix} = \begin{bmatrix} I & \Delta t I \\ 0 & I \end{bmatrix} \begin{bmatrix} \mathbf{p}_{k-1} \\ \mathbf{v}_{k-1} \end{bmatrix} + \begin{bmatrix} 0 \\ \Delta t I \end{bmatrix} \mathbf{a}_k + \mathbf{w}_k \quad (5)$$

where $\mathbf{p}_k = [p_x, p_y]_k$ and $\mathbf{v}_k = [v_x, v_y]_k$ represent the position and velocity vectors, respectively. $\mathbf{a}_k = [a_x, a_y]_k$ is the acceleration, considered to be a control variable, and $\mathbf{w}_k$ is the process noise. The state variables $\mathbf{x}_k = [p_x, p_y, v_x, v_y]_k$ use the position and velocity vectors to describe the state transition model (3). The destination and guidance law are assumed to be provided as intents from intent inference [3,4]. Thus, the following conditions are established.

- (AS1) The target is assumed to move with awareness of its destination. The position of the destination is known in terms of the prior distribution, whereas the terminal time t_f and velocity $\mathbf{v}_f$ are unknown.
- (AS2) The target chases the destination with a specific guidance mode. The guidance command $\mathbf{a}_k$ uses the terminal position information in updating the current path to reach the desired destination.

The abovementioned conditions clarify the target tacking scenario considered in this study. Usually, the goal point of the target $\mathbf{p}_f$ is provided a priori through the destination information, and its arrival time and velocity at which the target arrives are rarely given. Considering this aspect, AS1 can sufficiently reflect the practical situation. AS2 defines the model information that affects the state transition probability. The resulting state-space model can belong to the CM process model. Note that the absence or inaccuracy of intent information can impede tracking performance. To address such cases, an intent inference procedure can be incorporated before intent-driven state estimation, which allows for the inference of the target's intent in cases where this information is missing or imprecise. For the measurement model, the position of the target is defined as [12,26]

$$\mathbf{z}_k = H \mathbf{x}_k + \mathbf{v}_k, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \quad \mathbf{v}_k \sim \mathcal{N}(0, V_k) \quad (6)$$

The objective of this study is to use the state/measurement models to estimate the target state.

3. Destination-directed guided trajectory modeling: benchmark approaches

This section describes two existing approaches for modeling the destination-directed target formulated by the CM process, which does not contain a guided mode in target motion. Section 3.1 describes the Markov-induced CM_L model [24], derived from the relationship between the MP and CM process, for a target chasing a stationary destination. Section 3.2 introduces a modified CM_L model [30] based on the Markov-induced CM_L model for a target chasing a moving destination.

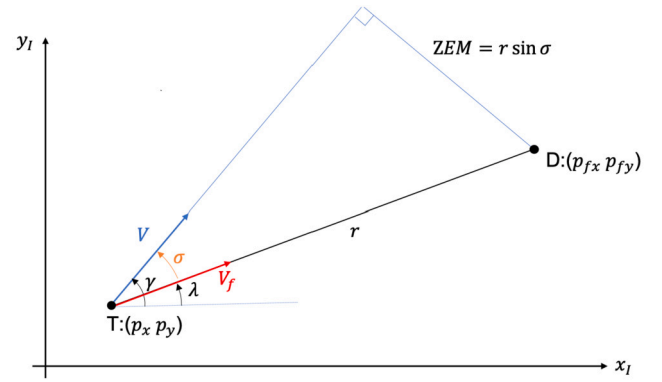


Fig. 1. Geometric representation.

3.1. Markov-induced CM_L model for stationary destination

For DDT modeling, the CM_L parameters (3) must be appropriately set. Unlike the conventional dynamic model based on the Markov assumption, the CM_L parameters cannot be directly determined in the dynamic equation form because they should be determined in relation to the conditional probability density function $p(\mathbf{x}_k | \mathbf{x}_{k-1}, \mathbf{x}_N)$. Rezaie and Rong Li [24] proposed a Markov-induced CM_L model to design parameters $(G_{k,k-1}, G_{k,N}, G_k)$ based on two assumptions: (i) The motion follows the nearly CV model driven by the MP, and (ii) the joint origin and destination density is known. According to (i), the nearly CV model takes the linear state-space form from the origin $\mathbf{x}_0 \sim \mathcal{N}(\mu_0, C_0)$ to $\mathbf{x}_N \sim \mathcal{N}(\mu_N, C_N)$ when the conditional transition is marginalized with $\mathbf{x}_N$ as

$$\mathbf{x}_k = M \mathbf{x}_{k-1} + \mathbf{w}_k^M \quad (7)$$

where $\mathbf{w}_k^M \sim \mathcal{N}(0, Q)$, and the state transition matrix F is defined as

$$M = \begin{bmatrix} I & \Delta t I \\ 0 & I \end{bmatrix}, \quad Q = q \begin{bmatrix} \frac{\Delta t^3}{3} I & \frac{\Delta t^2}{2} I \\ \frac{\Delta t^2}{2} I & \Delta t I \end{bmatrix} \quad (8)$$

where I is an identical 2×2 matrix, and 0 is the 2×2 zero matrix. The covariance matrix considering the cross-correlation between the origin and destination is $C = \begin{bmatrix} C_0 & C_{0,N} \\ C_{N,0} & C_N \end{bmatrix}$. Using Bayes's rule, the linear state-transition model (7) can be converted to the CM_L model, i.e., (3) as [24]

$$\begin{aligned} \mathbf{x}_k &= G_{k,k-1}^{CV} \mathbf{x}_{k-1} + G_{k,N}^{CV} \mathbf{x}_N + \mathbf{w}_k \\ \mathbf{x}_0 &= \mu_0 + G_{0,N} (\mathbf{x}_N - \mu_N) + \mathbf{w}_0 \end{aligned} \quad (9)$$

$$\mathbf{x}_N = \mu_N + \mathbf{w}_N$$

where the matrices are calculated to represent the evolution law (7) in terms of CM_L as

$$\begin{aligned} G_{k,k-1}^{CV} &= (I - G_{k,N} M^{N-k}) M, \quad G_{k,N}^{CV} = G_k (M^{N-k})' C_{N|k}^{-1} \\ G_k^{CV} &= (Q^{-1} + (M^{N-k})' C_{N|k}^{-1} M^{N-k})^{-1}, \\ C_{N|k} &= \sum_{n=k}^{N-1} F^{N-n-1} Q (M^{N-n-1})' \end{aligned} \quad (10)$$

After determining the parameters, the boundary covariance matrices $(G_0, G_{0,N}, G_N)$ can be selected from the initial distribution matrix C as

$$G_{0,N} = C_{0,N} C_N^{-1}, \quad G_N = C_N, \quad G_0 = C_0 - C_{0,N} C_N^{-1} C_{0,N}' \quad (11)$$

Note that every Markov sequence is CM_L , and $\mathbf{x}_k$ has the same evolution law but an arbitrary boundary condition. The CM_L model with the parameter-selection process is termed the Markov-induced CM_L model [24].

3.2. Markov-induced guided target model for moving destination

This section describes the benchmark approach for deriving a DDT model when the destination is moving [30]. If a target is chasing a moving object, the moving object can be considered the destination of the target. Let $\mathbf{d}_k = [p_x^d, p_y^d, v_x^d, v_y^d]$ represent the destination state variables. Assuming that the destination motion follows the MP, the state transition model of the destination can be expressed as

$$\begin{aligned}\mathbf{d}_k &= \mathbf{G}_{k,k-1}^d \mathbf{d}_{k-1} + \mathbf{w}_k^d \\ \mathbf{z}_k^d &= \mathbf{H} \mathbf{d}_k + \mathbf{v}_k^d\end{aligned}\quad (12)$$

where $[\mathbf{w}_k^d]$ represents white Gaussian noise with zero mean. For simplicity, we assume that the destination follows the CV model, i.e., $\mathbf{G}_{k,k-1}^d = \mathbf{M}$. The position vector is chosen as the observation for the destination, in accordance with the considered scenario.

Combining (9) with (12), Rezaie and Rong Li [30] derived a new state-space model for guided targets by modifying the *Markov-induced CM_L* model as

$$\mathbf{x}_k = \mathbf{G}_{k,k-1}^{CV,x} \mathbf{x}_{k-1} + \mathbf{G}_{k,k-1}^{CV,d} \mathbf{d}_{k-1} + \mathbf{w}_k \quad (13a)$$

$$\mathbf{d}_k = \mathbf{G}_{k,k-1}^d \mathbf{d}_{k-1} + \mathbf{w}_k^d \quad (13b)$$

$$\mathbf{x}_N = \mathbf{d}_N + \mathbf{w}_N \quad (13c)$$

Using this model, $\mathbf{x}_k$ is updated by assuming that $\mathbf{d}_{k-1}$ is stationary, i.e., a fixed destination, and $\mathbf{d}_k$ is updated by the Markov sequence. Notably, this approach has several drawbacks. The derived target dynamics requires full information of the terminal states. The unspecified terminal conditions $t_f, (v_{xf}, v_{yf})$ affect the estimation performance, similar to the stationary case. More importantly, the state estimation uses the destination information of the previous step, which cannot accurately reflect the motion especially when the destination motion is significant. In particular, the state equation accommodates the destination velocity components in $\mathbf{d}_{k-1}$, which inherently causes the state estimate to generate a tail-chase like trajectory of the target.

4. Proposed approach for guided trajectory prediction

This section describes the proposed approach for the state estimation of a guided target whose dynamics is driven by the guidance mode described in AS2. Section 4.1 describes the state transition modeling based on predictive guidance, which belongs to the category of *CM_L*. Section 4.2 describes the PIP calculation and determinations of terminal conditions considering the destination motion. Section 4.3 discusses the filtering and prediction of the target states using the estimation theory.

4.1. ZEM-based guided target model

The predictive guidance concept in terms of the ZEM is used to describe the guided target motion: The collision path is corrected based on the predicted collision geometry to ensure that the target pursues the PIP $\mathbf{p}_{PIP}$ to reach the destination at the predicted time of arrival $t_f = \Delta t N$. These guidance laws are introduced as they are consistent with AS1 and AS2 and compatible with the proportional navigation guidance (PNG) law with navigation gain K , which can describe the generic guided trajectories. Given that the final time instance N and final position $\mathbf{p}_{PIP}$ are known, the ZEM vector is defined as the expected dispersion from the destination when no corrective action is taken:

$$\mathbf{ZEM}_k = \mathbf{p}_{PIP} - \mathbf{p}_{k-1} - \mathbf{v}_{k-1} t_{go} \quad (14)$$

where the time-to-go t_{go} represents the time remaining until arrival at the destination and satisfies $t_{go} = t_f - t = \Delta t(N - k)$. The guidance command is then given by [31]

$$\mathbf{a}_k = \frac{K}{t_{go}^2} \mathbf{ZEM}_k = \frac{K}{t_{go}^2} (\mathbf{p}_{PIP} - \mathbf{p}_{k-1} - \mathbf{v}_{k-1} t_{go}) \quad (15)$$

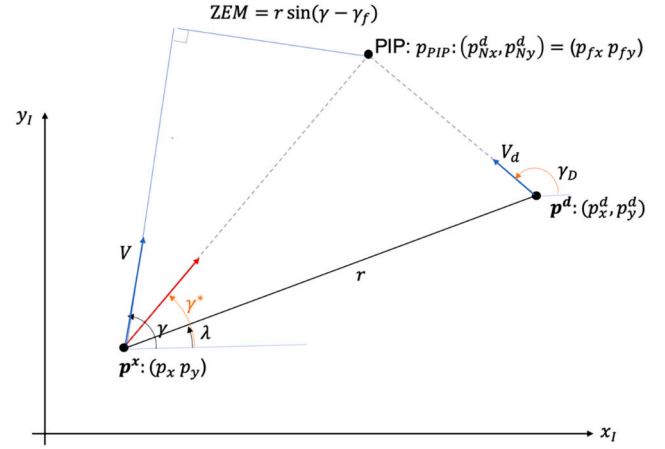


Fig. 2. Geometric definition of ZEM against moving destination.

where K denotes the guidance gain. When $K = 3$, the predictive guidance is equivalent to the ZEM guidance, which corrects a path in terms of the predictive error in an energy-optimal manner [33,37]. By substituting (15) into (5) along with $\mathbf{x}_N^{PIP} = [\mathbf{p}_{PIP}^T, \mathbf{v}_{PIP}^T]^T$, the guided-target model can be derived as

$$\begin{aligned}\begin{bmatrix} \mathbf{p}_k \\ \mathbf{v}_k \end{bmatrix} &= \begin{bmatrix} \frac{I}{K} & \frac{\Delta t I}{K} \\ -\frac{\Delta t I}{K} & I - \frac{\Delta t^2 I}{K} \end{bmatrix} \begin{bmatrix} \mathbf{p}_{k-1} \\ \mathbf{v}_{k-1} \end{bmatrix} \\ &+ \begin{bmatrix} 0 & 0 \\ \frac{\Delta t I}{K} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{p}_{PIP} \\ \mathbf{v}_{PIP} \end{bmatrix} + \mathbf{w}_k \\ &:= \mathbf{G}_{k,k-1}^{ZEM} \mathbf{x}_{k-1} + \mathbf{G}_{k,N}^{ZEM} \mathbf{x}_N^{PIP} + \mathbf{w}_k\end{aligned}\quad (16)$$

The zero entries in $\mathbf{G}_{N,k}$ indicate that the terminal velocity $\mathbf{v}_f$ is not necessarily specified for this model as it does not contribute to the state evolution. An initial guess can be arbitrarily selected for the unspecified $\mathbf{v}_f$ to convert the closed-loop system into the CM process model. In contrast, the terminal time t_f and N appearing in the state transition model must be properly specified to ensure that the state-space model corresponds to the CM process.

For a moving destination, the target motion is separate from the destination motion as the transition model does not directly depend on the destination states. The correlation between these two motions is considered by the reaching condition $\mathbf{p}_N = \mathbf{p}_N^d = \mathbf{p}_{PIP}$. The equations of motion can thus be rewritten as

- Target motion

$$\mathbf{x}_k = \mathbf{G}_{k,k-1}^{ZEM} \mathbf{x}_{k-1} + \mathbf{G}_{N,k}^{ZEM} \mathbf{x}_N^{PIP} + \mathbf{w}_k \quad (17a)$$

$$\mathbf{p}_N = \mathbf{p}_{PIP} + \tilde{\mathbf{w}}_N \quad (17b)$$

- Destination motion

$$\mathbf{d}_k = \mathbf{G}_{k,k-1}^d \mathbf{d}_{k-1} + \mathbf{w}_k^d \quad (18a)$$

$$\mathbf{p}_N^d = \mathbf{p}_{PIP} + \tilde{\mathbf{w}}_N \quad (18b)$$

Remark 1. This model has two key differences with the formal guided target model [30]: First, $\mathbf{d}_{k-1}$ appearing in (13a) is replaced by the PIP vector $\mathbf{x}_N^{PIP}$ as the goal point of the target. In effect, the proposed target model tends to approach the quasi-stationary point, i.e., the PIP point, instead of the consistently moving destination. Therefore, the state-space model (17) corresponds to the *CM* process, which ensures consistency with the theoretical foundation and justifies the extensibility of the proposed estimation for cases with stationary and moving destinations. Second, the proposed target model with $(\mathbf{G}_{k,k-1}^{ZEM}, \mathbf{G}_{N,k}^{ZEM})$ reflects the characteristics of the closed-loop dynamics guided by the predictive guidance schemes. The guided target model entails the col-

lision intent with the destination and can thus better reflect the target chasing moving objects in head-on and tail-chase geometries.

Remark 2. The terminal velocity is unspecified, according to AS1, and the ZEM-based guided target dynamics are derived in accordance. If the terminal velocity is known a priori, the guided target dynamics can be derived based on the generalized vector explicit (ZENEX) guidance [35], which expresses the closed-loop system in the zero-effort-velocity (ZEV) form. By introducing the ZEV variable $\mathbf{ZEV} = \mathbf{v}_f - \mathbf{v}(t)$ with the boundary condition $\mathbf{v}(t_f) = \mathbf{v}_f$, we obtain the optimal control command and corresponding closed-loop system as

$$\mathbf{a}_{cmd} = \frac{K_1}{t_{go}^2} \mathbf{ZEM} - \frac{K_2}{t_{go}} \mathbf{ZEV} \quad (19)$$

ZENEX guidance is equivalent to ZEM/ZEV guidance when (K_1, K_2) is chosen to be $(6, 2)$.

$$\begin{aligned} \begin{bmatrix} \mathbf{p}_{k+1} \\ \mathbf{v}_{k+1} \end{bmatrix} &= \begin{bmatrix} I & \Delta t I \\ -\frac{K_1}{\Delta t(N-k)^2} I & I - \frac{(K_1-K_2)}{N-k} I \end{bmatrix} \begin{bmatrix} \mathbf{p}_k \\ \mathbf{v}_k \end{bmatrix} \\ &+ \begin{bmatrix} 0 & 0 \\ \frac{K_1}{\Delta t(N-k)^2} I & -\frac{K_2}{N-k} I \end{bmatrix} \begin{bmatrix} \mathbf{p}_f \\ \mathbf{v}_f \end{bmatrix} + \mathbf{w}_k \\ &:= G_{k+1,k}^{ZENEX} \mathbf{x}_k + G_{N,k}^{ZENEX} \mathbf{x}_N^{PIP} + \mathbf{w}_k \end{aligned} \quad (20)$$

If not known, vector $\hat{\mathbf{v}}_f$ must be appropriately estimated. A potential approach is to recursively update the terminal values as the desired aiming direction shown in Fig. 1. The target directly pursues the destination with the desired velocity, which can be defined as

$$\hat{\mathbf{v}}_f = V [\cos \lambda, \sin \lambda] \quad (21)$$

4.2. PIP calculation

To consider the destination motion in target estimation, it is necessary to estimate the destination state. The intercept position can also be predicted in this stage as the interception occurs over the future destination trajectory. To calculate the terminal time index t_f and N , the PIP is estimated in destination motion. Specifically, $\mathbf{p}_{PIP}$ is obtained by assuming that the two objects are moving at constant speed in a non-maneuvering manner on the collision course. Using the confirmed PIP, the target estimation is realized considering the target motion (17). Consider the collision geometry used in the ZEM formulation shown in Fig. 2. V and V_D represent the current speeds of the target and destination, respectively. γ_D denotes the heading of the destination, defined by $\gamma_D = \tan^{-1}(v_y^d/v_x^d)$. γ^* is the desired heading to achieve the collision geometry. Using the sine formula and $r = \|\mathbf{p}_k^d - \mathbf{p}_k\| = \|H(\mathbf{d}_k - \mathbf{x}_k)\|$, the relation between the incident angles forming the collision geometry can be expressed as [31,38,39]:

$$\frac{V}{\sin(\gamma_D - \lambda)} = \frac{V_D}{\sin(\gamma^* - \lambda)} = \frac{\|H(\mathbf{d}_k - \mathbf{x}_k)\|}{\hat{t}_{go} \sin(\gamma_D - \gamma^*)} = C \quad (22)$$

By solving (22), the desired heading γ^* can be obtained as $\gamma^* = \lambda + \sin^{-1}\left(\frac{V_D}{C}\right)$. The time-to-go for arriving at the PIP, $\hat{t}_{go}$, and terminal time index estimates $\hat{N}$ can be explicitly obtained as

$$\hat{t}_{go} = \frac{\|H(\mathbf{d}_k - \mathbf{x}_k)\|}{C \sin(\gamma_D - \gamma^*)}, \quad \hat{N} = k + \text{round}\left(\frac{\hat{t}_{go}}{\Delta t}\right) \quad (23)$$

Once N is specified, $\mathbf{p}_{PIP}$ can be computed by propagating the moving destination from the current state to the predicted terminal incident N by assuming that the destination is moving at a constant velocity.

$$\mathbf{p}_{PIP} = H G_{k,N}^{cv} \mathbf{d}_k = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} \hat{t}_{go} I \\ I \end{bmatrix} \begin{bmatrix} \mathbf{p}_k^d \\ \mathbf{v}_k^d \end{bmatrix} = \mathbf{p}_k^d + \hat{t}_{go} \mathbf{v}_k^d \quad (24)$$

where $G_{k,N}^{cv}$ denotes the state transition matrix considering the constant speed motion. By augmenting a slack vector for the terminal velocity

$\mathbf{v}_f$, the PIP state vector $\mathbf{x}_{PIP} = [\mathbf{p}_{PIP}, \mathbf{v}_f]$ is obtained and used in the state estimation and prediction.

Remark 3 (ZEM-Based Guided Target for Stationary Destination. [30]). If the target is chasing a stationary destination, the PIP $\mathbf{p}_{PIP}$ is deduced to $\mathbf{p}_f$ known a priori. The time-to-go t_{go} and terminal time instance N can be calculated as

$$\hat{t}_{go} = \frac{\|\mathbf{p}_f - \mathbf{p}_k\|}{\|\mathbf{v}_k\|} \cos \sigma, \quad N = k + \text{round}\left(\frac{\|\mathbf{p}_f - \mathbf{p}_k\|}{\|\mathbf{v}_k\| \Delta t} \cos \sigma\right) \quad (25)$$

where σ is the lead angle defined by the deviation from the line-of-sight angle to the heading angle $\sigma = \gamma - \lambda$.

4.3. Filtering for state estimation and prediction

Kalman filtering is applied for a linear minimum mean square error estimator to yield the target state and destination estimates.

4.3.1. Target state estimation

After computing the PIP, the state estimator predicts the target trajectory from the current time k to the terminal instance N for the future destination. Let $\mathbf{s}_k = [\mathbf{x}_k, \mathbf{x}_{PIP}]$ be the augmented state variable. The state transition model can be expressed in the following Markov-like form:

$$\begin{aligned} \mathbf{s}_k &= G_{k,k-1}^s \mathbf{s}_{k-1} + \mathbf{w}_k^s \\ G_{k,k-1}^s &= \begin{bmatrix} G_{k,k-1}^x & G_{k,N}^{x,PIP} \\ \mathbf{0}_4 & I_4 \end{bmatrix}, \quad \text{cov}(\mathbf{e}_k^s) = G_k^s = \begin{bmatrix} G_k & \mathbf{0}_4 \\ \mathbf{0}_4 & \mathbf{0}_4 \end{bmatrix} \\ \mathbf{z}_k &= \bar{H}_k \mathbf{s}_k + \mathbf{v}_k \\ \bar{H}_k &= [I \quad \mathbf{0} \quad \mathbf{0} \quad \mathbf{0}], \quad \text{cov}(\mathbf{v}_k) = V_k \end{aligned} \quad (26)$$

where I_4 and $\mathbf{0}_4$ denote the 4×4 identity and zero matrices, respectively. As the state transition (26) is described in a linear form, the state predictive density $p(\mathbf{s}_k | \mathbf{Z}_{k-1}) = \mathcal{N}(\hat{\mathbf{s}}_{k|k-1}, \bar{P}_{k|k-1})$ and its a priori estimates are obtained as

$$\begin{aligned} \hat{\mathbf{s}}_{k|k-1} &= G_{k,k-1}^s \hat{\mathbf{s}}_{k-1|k-1}, \\ \bar{P}_{k|k-1} &= G_{k,k-1}^s \bar{P}_{k-1} (G_{k,k-1}^s)^T + G_k^s \end{aligned} \quad (27)$$

In the measurement update step, the observation predictive density follows the Gaussian distribution $p(\mathbf{z}_k | \mathbf{Z}_{k-1}) = \mathcal{N}(\hat{\mathbf{z}}_{k|k-1}, P_{k|k-1}^m)$, and its estimates are

$$\hat{\mathbf{z}}_{k|k-1} = H_k \hat{\mathbf{s}}_{k|k-1}, \quad P_{k|k-1}^m = \bar{H}_k \bar{P}_{k|k-1} H_k^T + V_k \quad (28)$$

The state posteriori and covariance matrix can be calculated as

$$\hat{\mathbf{s}}_{k|k} = \hat{\mathbf{s}}_{k|k-1} + K_k (\mathbf{z}_k - \hat{\mathbf{z}}_{k|k-1}), \quad \bar{P}_k = \bar{P}_{k|k-1} - K_k P_{k|k-1}^m (K_k)^T \quad (29)$$

where K_k and the covariance matrix are obtained as $K_k = \bar{P}_{k|k-1} \bar{H}_k^T (P_{k|k-1}^m)^{-1}$. Finally, the state estimates and its covariance matrix can be defined as

$$\hat{\mathbf{x}}_k = [I_4 \quad \mathbf{0}_4] \hat{\mathbf{s}}_k, \quad P_k = [I_4 \quad \mathbf{0}_4] \bar{P}_k [I_4 \quad \mathbf{0}_4]^T \quad (30)$$

In a similar manner, the state prediction and its covariance matrix for $k < t < N$ can be obtained as

$$\hat{\mathbf{s}}_{t|k} = G_{t|k}^s \hat{\mathbf{s}}_k \quad (31)$$

$$\bar{P}_{t|k} = G_{t|k}^s \bar{P}_k (G_{t|k}^s)^T + Q_{t|k} \quad (32)$$

where $G_{t|k}^s$ and $Q_{t|k}$ are calculated as

$$G_{t|k}^s = \prod_{i=k}^{t-1} G_{i+1,i}, \quad Q_{t|k} = \sum_{i=k}^{t-1} G_{t|i+1}^s G_i^s (G_{t|i+1}^s)^T \quad (33)$$

4.3.2. Destination state estimation

To estimate the destination state, the state-space model is governed by the MP. Using (18), the Kalman filter is applied to yield the destination estimates.

$$\hat{\mathbf{d}}_{k|k-1} = \mathbf{G}_{k,k-1}^d \hat{\mathbf{d}}_{k-1}, \quad \mathbf{P}_{k|k-1}^d = \mathbf{G}_{k,k-1}^d \mathbf{P}_{k-1}^d (\mathbf{G}_{k,k-1}^d)^T + \mathbf{G}_k^d \quad (34)$$

$$\hat{\mathbf{z}}_{k|k-1}^d = \mathbf{H} \hat{\mathbf{d}}_{k|k-1}, \quad \mathbf{P}_{k|k-1}^{md} = \mathbf{H} \mathbf{P}_{k|k-1}^d \mathbf{H}^T + \mathbf{V}_k^d \quad (35)$$

$$\hat{\mathbf{d}}_k = \hat{\mathbf{d}}_{k|k-1} + \mathbf{K}_k^d (\mathbf{z}_k^d - \hat{\mathbf{z}}_{k|k-1}^d), \quad \mathbf{P}_k^d = \mathbf{P}_{k|k-1}^d - \mathbf{K}_k^d \mathbf{P}_{k|k-1}^{md} (\mathbf{K}_k^d)^T, \quad (36)$$

$$\mathbf{K}_k^d = \mathbf{P}_{k|k-1}^d \mathbf{H}^T (\mathbf{P}_{k|k-1}^{md})^{-1}$$

where $\mathbf{G}_k^d$ and $\mathbf{V}_k^d$ represent the process and measurement noise covariance matrices, respectively.

5. Numerical simulation

Numerical simulations are performed to validate the proposed target estimation. We consider a planar engagement scenario, in which a target is expected to intercept stationary and moving destinations. The time step for the process update is set as $\Delta t = 0.05(20Hz)$. The initial conditions of the target are chosen as

$$\mathbf{V}_0 = 300\text{m/s}, \quad \gamma_0 = 30^\circ, \quad \mathbf{p}_0 = [0, 0], \quad \mathbf{p}_f = [7000, 0]$$

The PNG law is used to guide the target motion trajectory. The target kinematics are expressed as

$$\begin{aligned} \dot{r} &= -V_0 \cos(\gamma - \lambda) + V_d \cos(\gamma_d - \lambda) \\ \dot{\lambda} &= \frac{V_0}{r} \sin(\gamma - \lambda) + \frac{V_d}{r} \sin(\gamma_d - \lambda) \\ \dot{\gamma} &= \frac{a_{cmd}}{V_0}, \quad a_{cmd} = 3V_0 \dot{\lambda} \end{aligned} \quad (37)$$

To estimate the target, the intent-driven target dynamic model is used. The filter parameters including the initial covariance matrices are defined as

$$\mathbf{w}_k \sim \mathcal{N}(0, \mathbf{G}_k), \quad \mathbf{G}_k = \mathbf{G}_k^d = \begin{bmatrix} 0.0002 & 0 & 0.0050 & 0 \\ 0 & 0.0002 & 0 & 0.0050 \\ 0.0050 & 0 & 0.2000 & 0 \\ 0 & 0.0050 & 0 & 0.2000 \end{bmatrix} \quad (38)$$

$$\text{Cov}(\mathbf{x}_0) = \mathbf{C}_0 = \text{diag}\{10, 10, 100, 100\},$$

$$\text{Cov}(\mathbf{x}_f) = \mathbf{C}_f = \text{diag}\{10, 10, 100, 100\}, \quad (39)$$

$$\text{Cov}(\mathbf{x}_0, \mathbf{x}_f) = \mathbf{0}_4$$

For the measurement model, the position of the target is defined.

$$\mathbf{y}_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \mathbf{x}_k + \mathbf{v}_k, \quad \text{for } k \in [1, N_T], \quad \mathbf{V}_k = \mathbf{V}_k^d = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix} \quad (40)$$

Notably, the measurement update considerably affects the estimation accuracy [40]. The update rate depends on the target tracking scenario. A high update rate can be set using a high-performance sensor that uses all its resources to track a simple target. In contrast, a longer time interval may be required for the measurement updates if the tracking target is complex or there are multiple targets. To investigate the influence of the update rate on the estimation accuracy, the update rate is decreased from 10 Hz to 1 Hz. [41]

Hundred runs of Monte Carlo simulations are performed for each scenario. The average root-mean-square error (RMSE) and standard deviation (Std) are used to statistically evaluate the performance.

$$\text{AverageRMSE}_{pos} = \mu_{pos} = \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M \sqrt{e_x^2 + e_y^2} \quad (41)$$

$$\text{StdRMSE} = \sqrt{\frac{1}{NM-1} \sum_{i=1}^N \sum_{j=1}^M \left(\sqrt{e_x^2 + e_y^2} - \mu_{pos} \right)^2} \quad (42)$$

where $M = 100$ is the number of trials for Monte Carlo simulations. Moreover, $e_x = p_x - \hat{p}_x$ and $e_y = p_y - \hat{p}_y$ represent the position error from the actual target position.

5.1. Scenario 1: State estimation of a guided target chasing a stationary destination

The target guided by the PNG law pursues a stationary destination $\mathbf{p}_f$, and the proposed algorithm aims to track the target. For comparison, two target models are considered in the tracking simulation: the Markov model, which describes the constant velocity motion derived by the MP [42]; and the *Markov-induced CM_L* model in (9), which describes nearly constant velocity motion to reach the destination [26]. Because the *Markov-induced CM_L* model is required specify the final time instance N , we set three values in the simulation: true final time $t_f = 24\text{s}$ and two incorrect values of $\hat{t}_f = 30\text{s}, 20\text{s}$.

Fig. 3 shows the trajectories and estimate errors when the measurement sampling time is set as 0.2 s (5 Hz). The target moves to the destination with constant speed and reaches it at $t_f = 24\text{s}$. Among the considered models, the proposed model yields the smallest estimation error during the tracking period shown in Fig. 3-(b). The proposed method incorporates the guidance information in the target model and thus yields a more accurate estimate than the benchmark approaches that use the simple CV model. In addition, the time-to-go calculation in every state update step adequately corrects the final time parameter N , which helps enhance the accuracy of the proposed model. In comparison, the trajectory using the MP exhibits large deviations from the true target and irregular responses. The trajectory error increases when the target is maneuvering and decreases when the target exhibits linear motion. The model mismatch leads to increased errors in the coasting phase, and thus, repeated corrections are performed during the measurement update. The estimation performance of the *Markov-induced CM_L* model depends on the terminal time specified. When the final time instance is accurate, the estimation errors are decreased, and this model outperforms the Markov model, as shown in Fig. 3-(b). However, when the target model takes an incorrect value of the final time instance, the estimation accuracy drastically increases. When the terminal time is less than the actual time, i.e., $\hat{t}_f = 20 < 24\text{s}$, the estimator cannot update the state estimates after the time exceeds the specified terminal time. As shown in Fig. 3-(b), the estimation error considerably increases in this case. When the specified terminal time is larger than the true instance, the produced state estimates tend to approach the destination slower than the actual target. Thus, the estimation error is larger than that of the proposed algorithm. These results indicate that the temporal information is crucial for obtaining accurate state estimates using the CM process model. Table 1 summarizes the statistical results. The RMSE and Std increase for all methods as the measurement update becomes less frequent. This tendency is consistent with reported results [41]. The performance is severely degraded in the case of a low update rate, especially when the benchmark models are used. Nevertheless, the proposed method provides the highest estimation accuracy with the smallest RMSE and consistent performance.

5.2. Scenario 2: State estimation/prediction of a guided target chasing a moving destination

The guided target pursues a destination moving with constant velocity. For comparison, we consider three existing target models.

The Markov and *Markov-induced CM_L* models are considered, as in the previous stationary destination scenario. Note that the Markov-induced model does not consider the destination motion itself. To address this problem, the model is modified such that the target model takes the current destination position in every measurement update

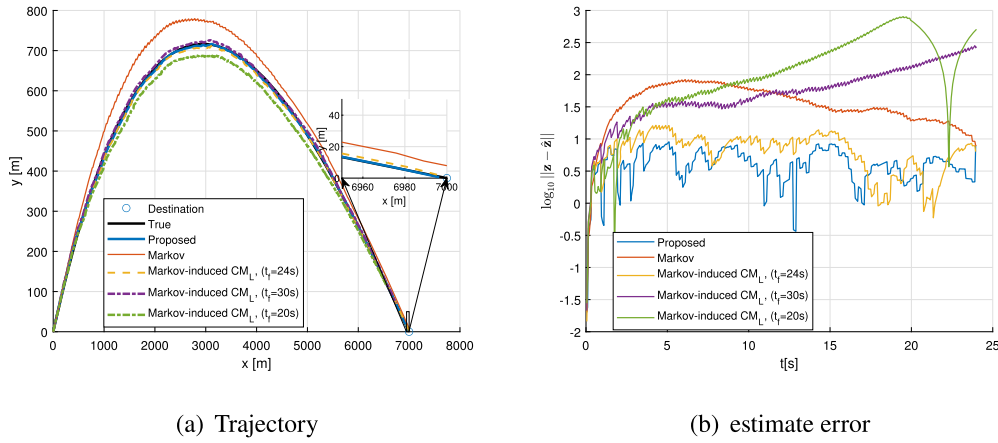


Fig. 3. Simulation results for Scenario 1: State estimation (Update: 5 Hz). The blue-solid line representing the proposed approach offers more accurate state estimation compared to the Markov model, depicted by the red-colored line. The tracking performance of the Markov-induced approach, indicated by the dashed line, is highly dependent on the selection of the terminal time t_f .

Table 1
Result: RMSE (Scenario 1).

	Proposed		Markov [42]		Markov-induced CM_L [26]					
	Mean	Std	Mean	Std	$t_f = 24$ s (true)		$t_f = 30$ s		$t_f = 20$ s	
					Mean	Std	Mean	Std	Mean	Std
10 Hz	3.997	2.592	20.157	9.543	6.224	3.240	56.962	48.084	172.18	188.88
5 Hz	4.362	2.078	40.853	22.923	7.404	3.915	74.432	63.04	198.83	215.75
2 Hz	6.904	4.321	109.46	68.599	10.954	6.328	104.410	85.178	245.08	261.19
1 Hz	8.137	5.366	249.75	137.00	13.161	7.896	132.72	108.73	282.33	289.99

Table 2
Comparative target models.

	Proposed	Markov [42]	Markov-induced CM_L [26]	Markov-induced guided target [30]
Target dynamics	ZEM guidance	CV	nearly CV	nearly CV
State-space model	(17)–(18)	(7)	(9)–(11)	(13)
Stochastic process	CM	Markov	CM	CM-like
Intent	Dynamic destination, guidance	-	Static destination	Dynamic destination

without considering the destination motion and corrects the goal point in the model. The third benchmark approach is the *Markov-induced* guided target model [30] designed for moving destinations. The simulation results for Scenario 1 indicate that when the specified final time approaches the actual value, accurate trajectory estimation is achieved in the CM process. Thus, we first perform the simulation for the proposed method. Next, we select $\hat{t}_f$ for the *Markov-induced* models as being close to the actual value. Two sub-scenarios are specified to evaluate the estimation performance. Other characteristics of the target models are summarized in Table 2.

5.2.1. Scenario 2-1: State estimation in head-on engagement

Fig. 4 shows the simulation results for the head-on scenario. The proposed approach outperforms the benchmark approaches in the tracking scenario. Compared with the *Markov-induced* CM_L model, the proposed target model accounts for guided behavior driven by the ZEM law. The guidance information effectively characterizes the collision motion by the true target and yields a more accurate state estimation. In comparison, the Markov and *Markov-induced* guided target [30] show considerable estimation errors, as shown in Fig. 4(a). In particular, the estimated trajectory using the guided target model is greatly distorted near the destination. The current destination in (13)-(a) confines the terminal velocity direction of the target to coincide with that of the current destination, owing to which, the *Markov-induced* guided target model exhibits limited dynamic representation. Table 3 summarizes the RMSEs pertaining to different measurement update rates. For the bench-

mark approaches, the statistical results deteriorate significantly as the update rate decreases. In contrast, the proposed target model provides reliable state estimations even with a low update rate.

5.3. Scenario 2-2: Trajectory prediction in tail-chase engagement

Trajectory prediction is performed for a scenario in which the target tracks the destination from behind. For the prediction, the measurement is updated up to $t < 20$, and the prediction is performed to produce $\hat{s}_{k|N_T}$ for $k > N_T$, where $N_T = 20/\Delta t = 400$ is the time step at which the prediction is initiated.

Fig. 5 shows the simulation results. The proposed target model outperforms the benchmark models in terms of the prediction accuracy. All benchmark methods exhibit significant tracking errors. The Markov model forecasts the trajectory based on the tangential velocity direction at the latest measurement update and thus deviated from the actual target. The *Markov-induced* CM_L model generates the predicted trajectory to the destination measured at $t = 20$ s, as the destination motion is not considered in the prediction. The *Markov-induced* guided target model generates the path such that the target reaches the actual destination. However, the path is aligned with the destination path. The target model instantaneously specifies the terminal velocity coinciding with the destination, causing the predicted trajectory to converge the target to the expected destination and move along as the destination is in motion. In contrast, the proposed model predicts the destination through (34)–(36) and also estimates the PIP. The trajectory shows that the tar-

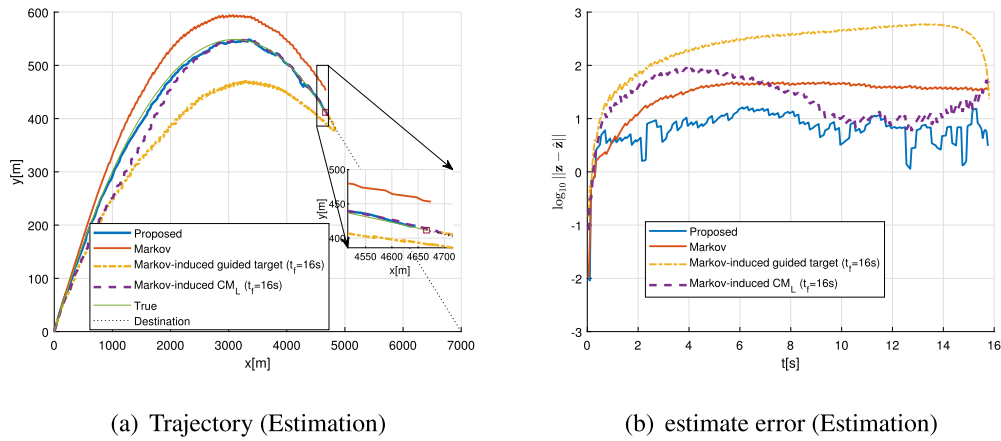


Fig. 4. Simulation result for Scenario 2-1: State estimation in head-on interception (Update: 5 Hz).

Table 3

Result: RMSE (Scenario 2-1).

Update Rate	Proposed		Markov [42]		Markov-induced guided target [30]		Markov-induced CM_L [26]	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
10 Hz	5.865	4.188	18.750	6.088	258.31	144.88	21.025	19.437
5 Hz	6.455	2.982	37.07	13.595	325.60	181.55	32.410	26.163
2 Hz	10.70	6.306	92.391	46.994	428.42	247.18	60.991	40.787
1 Hz	12.869	9.655	172.67	111.86	507.15	302.93	94.832	54.681

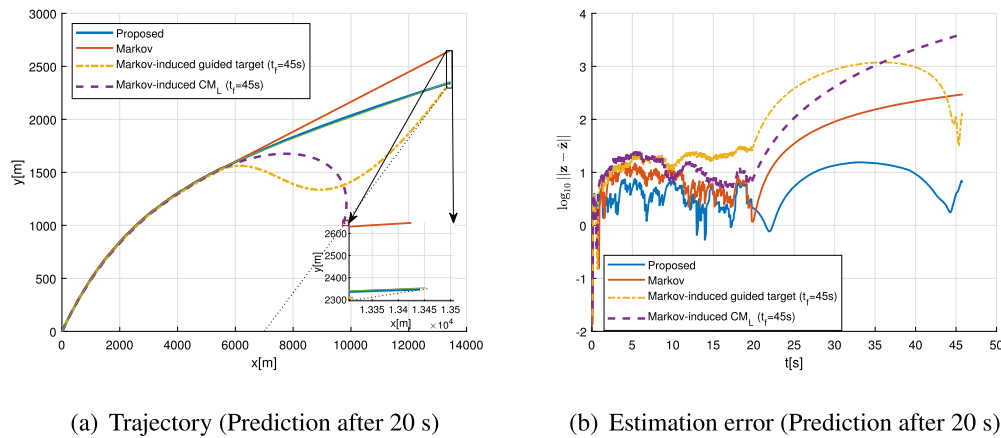


Fig. 5. Simulation result for Scenario 2-2: Trajectory prediction in tail-chase engagement (Update: 5 Hz).

get moves toward the PIP instead of the estimated current destination. The guidance information properly reflects the target model, thereby ensuring that the predicted path is consistent with the actual target path in the prediction period. This result indicates that the proposed estimation is superior to the benchmarks approaches in describing the target whose aim is to intercept moving objects in head-on and tail-chase engagements.

6. Conclusions

This paper proposes a novel method for estimating the trajectory of guided targets by using the intent information. The intent-driven target model is derived on the CM process. The ZEM-based guided target represents the hostile intent of colliding with the destination. The PIP is adequately considered in the guided target motion for the moving destination. Kalman filtering is introduced to yield the target state es-

timates and predicted trajectory. The predicted trajectory ensures that the target pursues the PIP instead of the current destination. The results of simulation studies demonstrate that the proposed approach outperforms the benchmarks in trajectory estimation and prediction. Intent inference and advanced target modeling, such as the use of a multiple-model approach, nonlinear filtering, and machine learning methods, can be integrated into the proposed approach to enhance and refine target estimation. The proposed intent-driven trajectory prediction model can facilitate air-traffic monitoring and target tracking systems for missile defense.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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