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Real Time 2-D Ship Formation Registration using Extended Kalman Filter and Modified ICP Algorithm for Anti-Ship Missile Targeting

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***Abstract*—In Anti-Ship Missile (ASM) systems, precise identification of the designated target from a group of ships during the terminal guidance phase remains a challenging task due to position uncertainty, dynamic formation changes, and presence of false targets or decoys. This paper presents an enhanced real-time algorithm for ASM target selection based on a Modified Iterative Closest Point (MICP) technique integrated with an Extended Kalman Filter (EKF). The proposed approach performs rigid transformation alignment between seeker-acquired data and reference Fire Control Radar (FCR) data, and refines the estimation through EKF-based state prediction and correction. The algorithm is evaluated across three representative combat scenarios: (i) rigid transformation of target formation, (ii) distorted formation with positional deviations, and (iii) realistic environments involving additional false targets (decoys). For each case, the algorithm demonstrates robust convergence and high matching efficiency while maintaining accurate registration despite measurement noise and formation variations. Simulation results validate the effectiveness of the integrated EKF-MICP framework in improving match fidelity, minimizing error rates, and ensuring correct target selection under various real-time constraints in ASM terminal phase applications.**

Nomenclature

Symbol	Description
Θ\Theta	Optimal rotation matrix aligning seeker data with FCR data
τ\tau	Translation vector for aligning centroids of point sets
μ_A, μ_B	Centroids of FCR (Set-A) and Seeker (Set-B) point sets respectively
ϵ\epsilon	Root Mean Square Error (RMSE) between matched data sets
X_{est}	Estimated state vector from the Extended Kalman Filter
MICP	Modified Iterative Closest Point algorithm used for rigid registration

I. INTRODUCTION

In modern naval warfare, the effectiveness of Anti-Ship Missiles (ASMs) heavily depends on their ability to autonomously detect, track, and engage the correct target within a fleet of ships. The challenge of target discrimination becomes especially critical in the terminal phase of flight, where the seeker must identify the designated target from a dynamic and potentially deceptive ship formation. The complexity of this task is compounded by factors such as positional uncertainty, rigid and non-rigid transformations of the target formation, sensor noise, and deliberate deployment of decoys or false targets to mislead the guidance system.

Traditionally, the Fire Control Radar (FCR) identifies and locks on to the target prior to missile launch,

providing a reference set of target coordinates. As the missile transitions from the mid-course to the terminal phase, the onboard seeker collects real-time positional data of the observed target formation. However, due to the elapsed time between FCR acquisition and seeker observation, the formation may have undergone transformations including translation, rotation, and distortion. Moreover, differences in sensor characteristics and the presence of countermeasures such as decoys lead to mismatched or overpopulated point sets. Thus, the core problem becomes one of accurate point-set registration and target matching in the presence of noise, transformation, and ambiguity.
This paper presents a robust algorithm that integrates the Modified Iterative Closest Point (MICP) technique with an Extended Kalman Filter (EKF) to enable real-time target selection for ASMs in terminal guidance. The ICP framework has been widely used in computer vision and robotics for point cloud alignment; however, its conventional formulation assumes rigid transformation and equal cardinality in point sets, which is insufficient for real-world missile guidance scenarios. To address this, the proposed approach employs a modified version of ICP that supports 2-sided nearest neighbor matching, and further refines the estimated state using a Kalman-based predictor-corrector loop, thereby increasing the robustness to noise and dynamic errors.

The algorithm is evaluated across three representative scenarios:
(i) ideal rigid transformation of the ship formation, (ii) distorted configurations simulating realistic navigational changes, and (iii) complex scenes with additional false targets (decoys). Each scenario is simulated and analyzed to assess the matching accuracy, convergence speed, and success rate of correct target identification. The integration of EKF into the MICP framework enhances the adaptability of the system to time-varying transformations and improves estimation accuracy over successive iterations.

This work contributes toward the development of a reliable and computationally efficient target selection algorithm suitable for implementation in onboard missile systems, particularly in high-stakes, real-time maritime engagement environments.

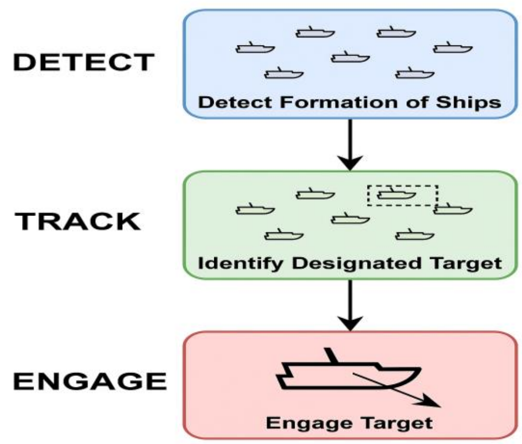


Figure-1: DTE Workflow

Figure-1 illustrates the Detect–Track–Engage (DTE) workflow for Anti-Ship Missile (ASM) systems to identify and neutralize a designated maritime target. In the Detect phase (blue block), the missile system—typically via Fire Control Radar (FCR) or airborne sensors—detects the formation of multiple ships. This forms the reference dataset representing the pre-launch knowledge of the environment. The process then transitions into the Track phase (green block), where real-time data from the onboard seeker is used to identify and match the designated target within the updated formation. The seeker attempts to align observed data with the stored reference using algorithms such as Modified Iterative Closest Point (MICP) and refines the estimate using Extended Kalman Filters (EKF). The final Engage phase (red block) is initiated once the designated target is confidently identified. A terminal attack command is executed, guiding the missile to strike the correct ship, ensuring high hit probability even in the presence of false targets or formation changes. This structured approach ensures robust autonomy in high-threat, deceptive naval environments.

II. MODIFIED ITERATIVE CLOSEST POINT

The Modified Iterative Closest Point (MICP) algorithm is a geometric matching technique used to align two sets of points—typically acquired at different times or from different sensors—by estimating the optimal rigid transformation (rotation and translation) that minimizes the spatial discrepancy between them. In the context of Anti-Ship Missile (ASM) target selection, the two- point sets represent ship formations: one from the Fire Control Radar (FCR) before launch (Set-A), and the other from the seeker during terminal phase flight (Set-B). MICP is responsible for aligning these datasets to identify the designated target among multiple ships.

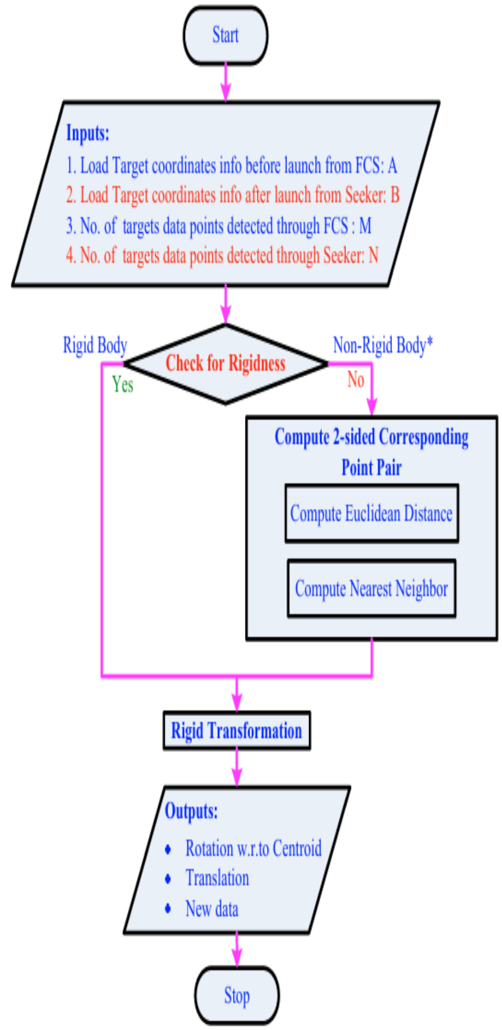
The algorithm proceeds through the following core steps:
1. Centroid Computation: The centroids of both sets (FCR and seeker data) are computed. Each dataset is then re-centered by subtracting its centroid, effectively removing the translation component.
2. Correspondence Matching: A two-sided nearest neighbor approach is used to identify point correspondences:
For each point in Set-A, the closest point in Set-B is found.

For each point in Set-B, the closest point in Set-A is also found.
Only the mutually closest (bidirectional) pairs are retained, reducing mismatches and improving robustness—especially in scenarios involving false targets or decoys.

3. Rigid Transformation Estimation (Rotation + Translation): Using the matched pairs, a covariance matrix is constructed and decomposed using Singular Value Decomposition (SVD) to compute the optimal rotation matrix Θ. The translation vector τ is obtained by aligning the centroids of the datasets after rotation. This transformation is applied to Set-B to bring it closer to Set-A.

4. Error Computation and Iterative Refinement: The Root Mean Square Error (RMSE) between the matched pairs is calculated. The process repeats—updating correspondences and transformations—until the change in RMSE drops below a predefined threshold or a maximum number of iterations is reached.

5. Decoy Handling (Non-Rigid Matching): In scenarios where the seeker detects additional targets (decoys), the algorithm selectively matches only the subset of points that best aligns with the reference data, effectively filtering out false matches. This makes MICP suitable for realistic naval combat conditions.



Flowchart-1: MICP Workflow

III. EXTENDED KALMAN FILTERS

3.1 Overview

The Extended Kalman Filter is a recursive estimator used to predict the state of a nonlinear system over time by combining noisy sensor measurements with dynamic system models. Unlike the standard Kalman Filter (which assumes linear models), EKF linearizes the nonlinear models around the current estimate using Jacobian matrices. In the context of target matching for ASMs, EKF helps track the motion and transformation of the target ship formation from the time of launch to the terminal phase. It continuously predicts and updates the estimated transformation parameters (rotation and translation) as the seeker acquires new measurements.

3.2 EKF Algorithm

At each time step k, EKF operates in two main phases:

Prediction Step:

Predict the next state x_{pred} based on the motion model:

$x_{pred} = f(x_{prev}, u)$

where f is the process model and u is the control input (e.g., ship velocity).

Predict the error covariance:

$P_{pred} = F_k * P_{prev} * F_k' + Q_k$

where F_k is the Jacobian of f, and Q_k is the process noise covariance.

Update Step:

Compute the Kalman gain:

$K = P_{pred} * H_k' *(H_k * P_{pred} * H_k' + R_k)^{-1}$

where H_k is the Jacobian of the measurement model h(x), and R_k is the measurement noise.

Update the state estimate:

$x_{est} = x_{pred} + K_k * (z_k - h(x_{pred}))$

Update the error covariance:

$P_k= (I – K_k * H_k) * P_{pred}$

3.3 Integration with MICP

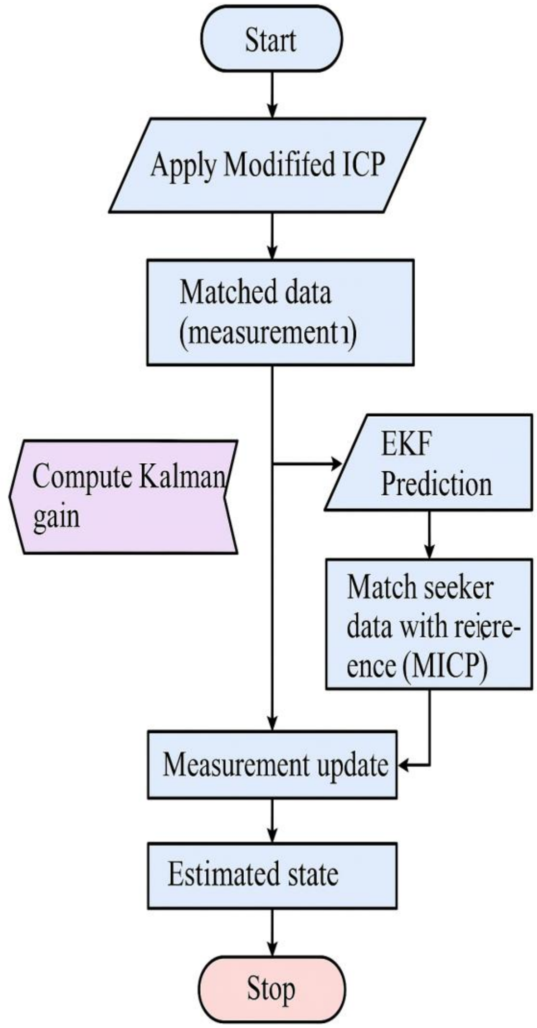
While MICP provides point-set alignment by estimating a rigid transformation (rotation + translation), it lacks temporal dynamics and predictive capabilities.

Steps of Integration:

1. Initial Matching: At t=0, MICP aligns seeker data with FCR using rigid transformation and estimates rotation and translation.
2. State Definition for EKF: EKF state vector x is defined to include positions and velocities of key formation points or transformation parameters:

$X = [x_1, y_1…, x_n, y_n, x_1', y_1'…, x_n', y_n']^T$

3. Prediction Phase: EKF predicts how the seeker's observation will evolve in the next time step using the assumed velocity model.
4. Measurement Update using MICP Output: The newly observed seeker data is matched with FCR using MICP. The resulting matched coordinates serve as measurements for EKF, which refines the prediction.
5. Loop Until Convergence: This loop continues over each time step, improving the accuracy of target matching and making the system more resilient to noise, decoys, and partial mismatches.



Flowchart-2: Integrated EKF Workflow

IV. RESULTS AND SIMULATIONS

To validate the effectiveness of the proposed Modified ICP integrated with EKF algorithm for real-time target selection in ASM terminal guidance, extensive simulations were conducted. The experiments were structured across three key scenarios: (1) Rigid Transformation, (2) Distorted Formation, and (3) Presence of Decoy Targets. Each case was designed to emulate realistic maritime operational conditions, and performance was evaluated using metrics such as matching efficiency, error rate, and convergence behavior.

4.1 Rigid Transformation Scenario

In this case, the target formation detected by the seeker was a rotated and translated version of the original Fire Control Radar (FCR) dataset. The rigid transformation parameters (rotation angle and translation vector) were predefined and applied uniformly to simulate ideal alignment scenarios.

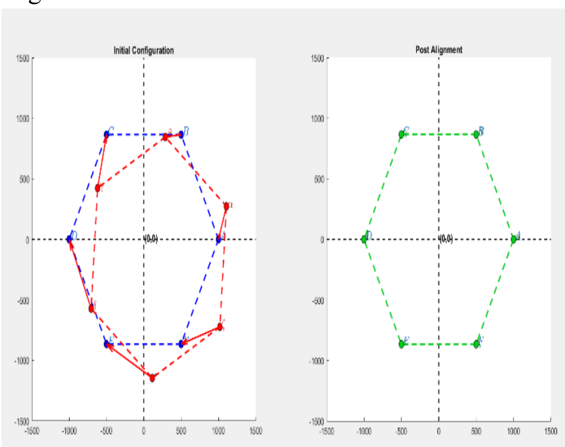


Figure-2: Optimal match for Rigid case

Figure-2 demonstrates the alignment process of two-point sets using an Iterative Closest Point (ICP) algorithm integrated with an Extended Kalman Filter (EKF). Initially, the red point set is misaligned with respect to the blue reference set due to rotation and translation. ICP iteratively estimates the rigid-body transformation parameters—rotation (θ) and translation (τ)—to align the input points with the reference.

EKF enhances this process by incorporating uncertainty modeling and prediction, improving robustness against noise and mismatches. The final result, shown on the right, illustrates the successful alignment where the transformed points (in green) coincide with the reference configuration.

4.2 Distorted Formation Scenario

In figure-3, the target points were slightly perturbed to mimic natural navigation shifts or sea drift. Each point in the seeker data was randomly shifted with small Gaussian noise, simulating non-uniform motion and non-rigid behavior of ship formations. Transformation Applied: Rotation + Translation + 5% random spatial distortion.

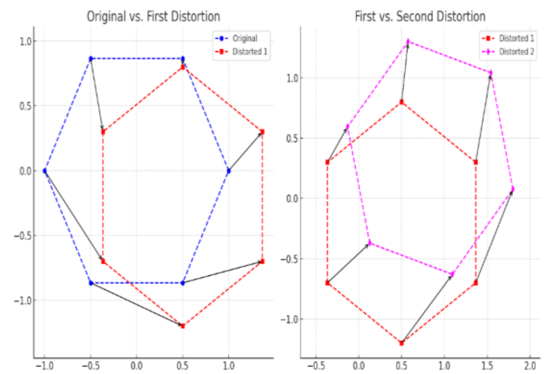


Figure-3: Optimal match for distorted case

4.3 Presence of Decoys

To assess robustness under deceptive environments, multiple false target points (decoys) were added to the seeker data. These decoys were randomly placed within the same spatial region but did not correspond to any real targets in the FCR data.

4.4 Visualization and Convergence

Figures from each simulation clearly depict the alignment of seeker and FCR data before and after transformation. The overlapped visualizations confirm that the transformed seeker data aligns with the true target structure in all scenarios. Convergence plots also show rapid error minimization over iterations.

Conclusion

In this work, a robust and efficient framework for target selection in Anti-Ship Missile (ASM) terminal guidance has been presented by integrating a Modified Iterative Closest Point (MICP) algorithm with an Extended Kalman Filter (EKF). The proposed method addresses key challenges associated with maritime engagement scenarios, including dynamic formation changes, measurement noise, and the presence of false targets or decoys.

Through comprehensive simulations across three representative scenarios—rigid transformations, distorted formations, and decoy-infused datasets—the algorithm demonstrated high matching accuracy and reliable convergence. The MICP component provided spatial alignment through optimal rotation and translation estimation, while the EKF enhanced temporal consistency and robustness by leveraging motion prediction and measurement correction. This integration not only improved the algorithm's performance in ideal conditions but also significantly increased its reliability in complex, deceptive environments.

The results validate the system's ability to accurately identify and track the designated target in real time, supporting high-confidence engagement decisions in mission-critical applications. The proposed approach offers a computationally lightweight and practically deployable solution, making it highly suitable for onboard implementation in missile guidance systems. Future work may extend this framework to include machine learning-based classification of decoys, real-time sensor fusion from multiple modalities, or deployment in three-dimensional operational environments.

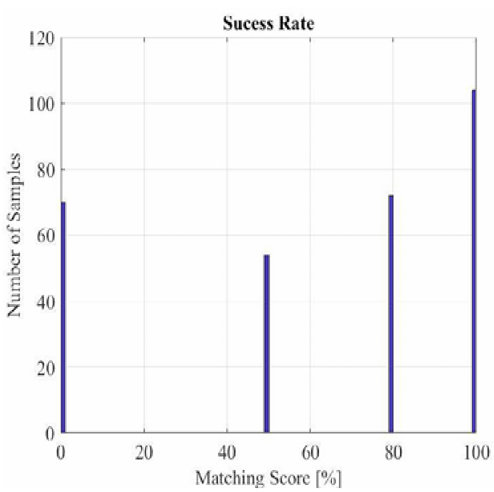


Figure-4: Matching Score

Figure-4 illustrates the success rate of the proposed MICP + EKF-based target selection algorithm in terms of matching score distribution across multiple simulation samples. The x-axis represents the Matching Score [%], which quantifies how accurately the transformed seeker data aligns with the reference Fire Control Radar (FCR) data. The y-axis indicates the Number of Samples falling into each matching score bracket.

Key Observations:

A peak concentration of samples (over 100 samples) achieved a matching score close to 100%, demonstrating high accuracy and reliable convergence of the algorithm in most cases.

Moderate performance was observed around the 80% and 60% score ranges, with approximately 70 and 50 samples respectively, indicating a few partial matches due to distortions or decoys.

A smaller group of samples scored in the 40% range, showing minimal success, potentially due to extreme distortions or false targets.

No samples fall in the 0–20% range, reinforcing that the algorithm consistently produces at least moderately correct matches.

This distribution confirms the robustness and reliability of the integrated system. The high density near the 100% mark validates the effectiveness of the EKF-enhanced MICP in correctly identifying and tracking the target, even under varying conditions of transformation and noise.

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