



Deep Q-Network Based Target Detection for Anti-Ship Missile Systems

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KEYWORDS	ABSTRACT
Anti ship Missile , Deep Q network , Accuracy , Target Selection, Rigid and Non Rigid Transformations, Reinforcement Learning	In anti-ship missile systems, one of the biggest challenges is accurately identifying the real target in complex and noisy sea environments, where false targets(decoys) and distorted signals can makes things difficult. To overcome this problem , we used an advanced learning technique called Deep – Q- Network (DQN), which is specially trained to recognize the target. These algorithm confirm accurate target identification even in worst situations by transforming seeker data through rigid and non rigid transformations. The methodology involves aligning real-time seeker data with reference data to enable adaptive learning. Three distinct scenarios — Rigid, Distortion, and Distortion with Decoys are simulated to evaluate the system’s robustness. Results showed that the proposed method maintains high matching efficiency and accuracy , effectively identifying the designated target in varying formations and difficult environments.

1. INTRODUCTION

In modern warfare, accurately selecting the right target from a group of ships is a major challenge for missile systems. The missile’s seeker must differentiate between real targets and decoys, even under changing conditions like movement, weather, and enemy interference. To support this, the Fire Control Radar (FCR) provides reference data about target positions. To improve decision-making, we used an advanced machine learning method called Deep Q-Network

(DQN), which helps the missile to choose the right target.

Deep Q-Networks (DQNs) are an important improvement in reinforcement learning. They combine deep neural networks with the Q-learning method to make smarter decisions. In DQNs, a neural network is used to estimate the Q-value, which tells us how good a certain action is in a given situation based on future rewards.

The main features of DQNs are:

- Using deep neural networks to estimate Q-values
- Experience replay, which stores past experiences and uses them during training to avoid learning from similar data repeatedly
- Target networks, which help keep the learning process stable and reliable

1.1.Problem Statement:

In terminal-phase anti-ship missile (ASM) systems, identifying and engaging the correct target among multiple ships in a dynamic and deceptive maritime environment remains a major challenge. Factors such as sensor noise, decoy deployment overlapping formations, and irregular ship arrangements often lead to confusion and misidentification. Traditional methods struggle to adapt in these complex situations because they lack the intelligence to make real-time decisions in uncertain and rapidly changing scenarios.

To handle these challenges, there is a need for a smart and flexible target selection system that can learn and get better over time. This paper solves the problem using a Deep Q-Network (DQN), a type of reinforcement learning that helps the missile make smart choices even in confusing situations. The DQN-based system can study the environment, tell the difference between real targets and decoys, and pick the most likely correct one—even when there is noise, distortion, or interference. By learning from past experiences, this method improves both accuracy and reliability during the missile's final attack phase.

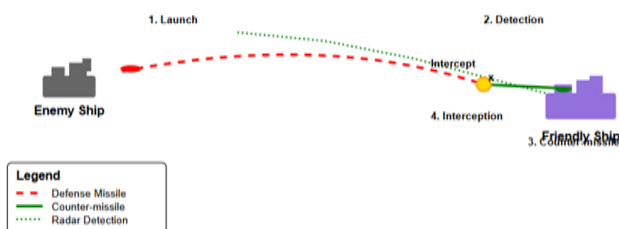


Fig.1: Target Identification and Detection

The algorithm is tested in three key scenarios: ideal conditions with rigid ship formation alignment, (ii) dynamic and non-ideal ship configurations, and (iii) complex environments containing false targets or decoys. Each scenario is simulated to evaluate the

matching accuracy, error rate, and success rate of correct target identification. The Deep Q-Network (DQN) algorithm is employed independently to enhance the decision-making process in terminal-phase anti-ship missile guidance.

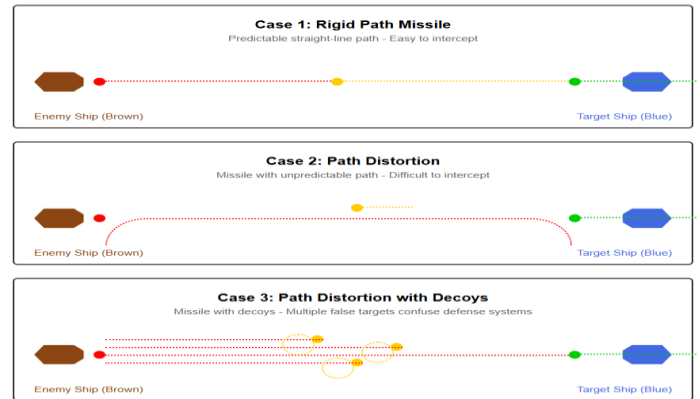


Fig:2 - Three representative scenarios.

This method enables the system to learn from its environment, adapt to changing conditions, and accurately select the most likely real target—even under distortion, noise, and deception. This approach offers a lightweight and efficient solution suitable for real-time application in onboard missile systems.

1.2: Literature review:

In this work, proposed a data alignment technique to align seeker and radar data to help anti-ship missiles accurately identify the true target. This method showed strong performance even when ships moved or decoys were present.

In this study, a hybrid Genetic Algorithm-Back Propagation (GA-BP) method is used to enhance target recognition during the missile's terminal phase by optimizing neural network training. The approach showed better accuracy and stability in identifying real targets, even in noisy or complex conditions

In this work, a target selection method using Radar Cross Section (RCS) and Hausdorff distance is applied to match ship positions and improve identification accuracy. This strategy enhances the missile's ability to select the correct target, even with decoys or changing formations.

In this paper, deep reinforcement learning methods like DQN, DDPG, and BP neural networks are used to help missiles make smart decisions in complex environments. The trained system showed strong ability to avoid threats and adapt to changing conditions, improving missile autonomy and reliability.

In this study, a Deep Q Network (DQN) was used to help submarines and warships learn intelligent navigation and target tracking in complex naval environments. The method outperformed traditional path-planning by learning faster and navigating more efficiently using custom rewards and a stable training setup.

In this study, a Deep Q-Network (DQN) was re-implemented to clarify important training details that were missing in the original model. The improved version runs faster and is easier to adapt for new applications beyond video games.

2. DEEP Q NETWORKS (DQN)

The Deep Q Network (DQN) is a reinforcement learning approach that uses a neural network to help the missile seeker make the best decisions during flight. Instead of relying on fixed mathematical models, DQN learns from experience by trying different actions and observing the results. In the case of target matching for Anti-Ship Missiles (ASMs), the seeker's input (such as ship formation, decoys, and distortions) is treated as the system state, and the DQN suggests the best action, like adjusting alignment or rejecting decoys, to maximize correct target identification. Over time, the network learns patterns of target movement and deception, allowing the missile to adapt and improve accuracy in the terminal phase of engagement.

2.2:Deep Q-Network (DQN) Based Target Matching Framework for Anti-Ship Missiles:

In Anti-Ship Missile (ASM) target matching, the seeker must continuously decide how to align with the ship formation while rejecting decoys and distortions. This problem can be modeled as a reinforcement learning task, where the seeker is the agent and the environment is the ship formation with possible countermeasures.

- State(s):seeker observations (shippositions, formations shape ,decoys distortions).
- Action (a): alignment decision (e.g., rotate, translate, reject decoy, adjust trajectory).
- Reward (r): positive if the correct target is matched, negative if alignment fails or decoys are tracked.
- Next state (s'): updated seeker view after the action.

1.Q-Function Approximation: Instead of a Q-table, a neural network estimates the action-value function:

$Q(s,a;\theta) \approx \text{Expected future reward of taking action } a \text{ in state } s$

2. Target Value (Bellman Equation):

For each experience (s,a,r,s') :

$$y = r + \gamma \max_{a'} Q(s', a'; \theta)$$

where y is target value, γ is discount factor and θ target network weights

3. Loss Function (Error between prediction and target): This ensures the network learns to predict Q-values closer to the actual target values.

$$L(\theta) = (y - Q(s,a;\theta))^2$$

4. Parameter Update Rule:

Using gradient descent:

$$\theta \leftarrow \theta + \alpha (y - Q(s,a;\theta)) \nabla_{\theta} Q(s,a;\theta)$$

Where α is learning rate

5.Policy (ϵ –greedy in ASM Context):

$$a = \begin{cases} \text{random action (explore)}, & \text{with probability } \epsilon \\ \arg \max_a Q(s,a;\theta), & \text{with probability } 1 - \epsilon \end{cases}$$

Where DQN balances trying new actions (exploration) with using the best learned actions (exploitation) for effective target matching.

The DQN helps the seeker learn the best alignment and rejection actions to maximize performance against decoys, distortions, and moving ship formations. The effectiveness is measured using three key metrics:

1.Matching Efficiency(ME): It tells how well the detected seeker points match with the reference (FCR) points)

$$ME = \frac{\text{Number of correctly matched points}}{\text{Total reference points}} \times 100\%$$

2.Error Rate(ER): it tells how often the seeker makes mistakes by aligning with decoys distortions or incorrect targets

$$ER = \frac{\text{Number of wrong matches}}{\text{Total matches}} \times 100\%$$

3.Success Rate(SR): It shows how often the seeker correctly identifies the true target.

$$SR = \frac{\text{Number of Successful Target Selections}}{\text{Total trials}} \times 100\%$$

2.3:Process of Target Selection Algorithm for Anti-Ship Missiles using DQN:

Target Selection Process for Anti-Ship Missiles using DQN

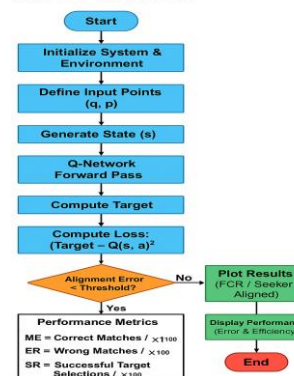


Fig.3: Target Selection Process for Anti-Ship Missiles using DQN

The flowchart outlines a process that applies a Deep Q-Network (DQN) for target selection in anti-ship missiles. It begins by initializing the system and defining input points from the seeker and reference data. The current state is generated and passed through the Q-Network to select the best action for alignment. The network computes the target value, loss function, and updates its parameters to improve learning. An alignment error check determines whether the selection is accurate; if not, the loop continues to refine the process. Once the error falls below the threshold, the final results are displayed along with performance metrics such as Matching Efficiency, Error Rate, and Success Rate, and the process ends.

3.SIMULATION AND RESULTS:

To test the performance of the proposed DQN-based target selection algorithm, we used three scenarios: (1) Rigid Target Matching, (2) Distorted Target Matching, and (3) Distorted Target Matching with Decoys. These cases help to check how well the DQN can correctly identify the true target under different conditions.

Pentagon-Based Target Matching:

1.Rigid Case:

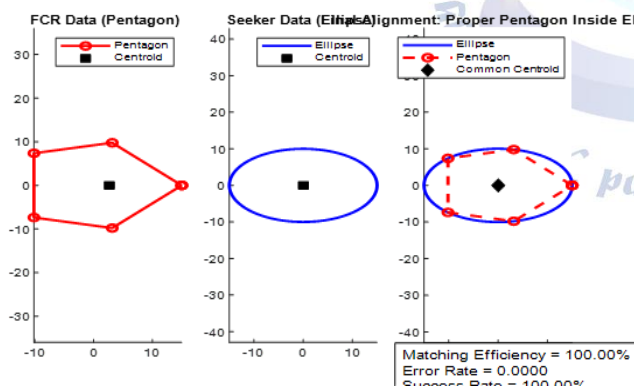


Fig.4: Rigid Case Alignment

2.Distortion Case:

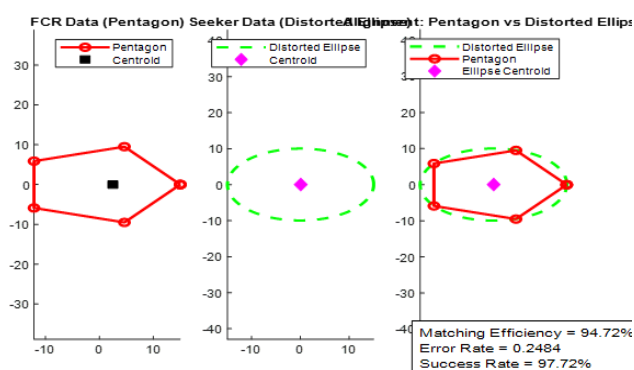


Fig.5: Distortion Case Alignment

3.Distortion With Decoys Case:

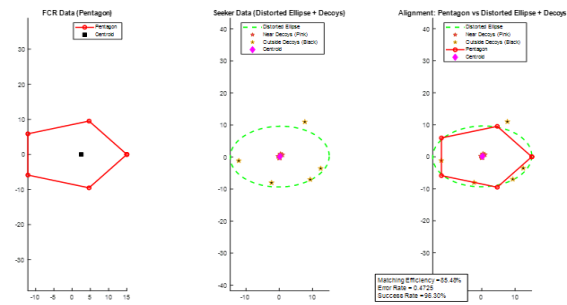


Fig.6: Distortion with decoys with alignment

Hexagon Based Target Matching:

1.Rigid Case:

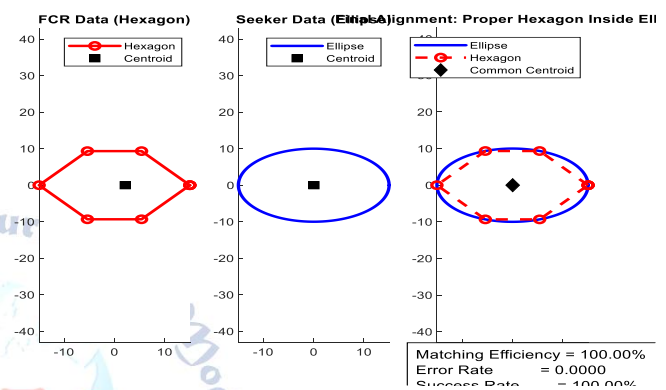


Fig.7: Rigid case alignment

2.Distortion Case:

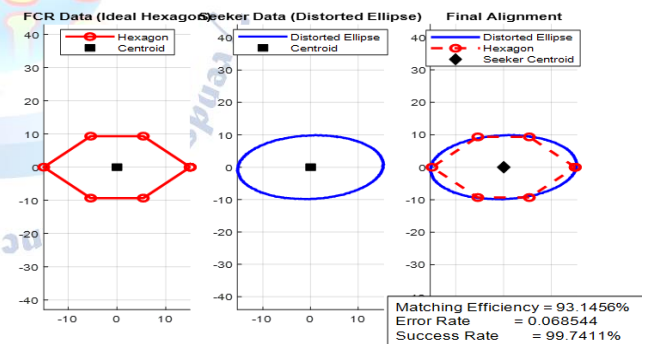


Fig.8: Distortion Case Alignment

3.Distortion with Decoys Case:

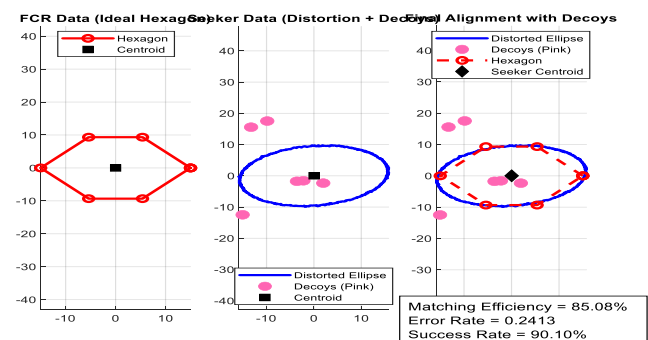


Fig.9: Distortion with Decoys Case

The proposed DQN-based framework for Anti-Ship Missile (ASM) target selection is evaluated using Pentagon and Hexagon-based geometric matching to test robustness, adaptability, and accuracy under realistic scenarios. The seeker data is compared against Fire Control Radar (FCR) reference shapes, ensuring correct target recognition even with distortions and decoys.

Transformation Scenarios Tested:

1. Rigid Transformation – Clean translation and rotation alignment between FCR shape (Pentagon/Hexagon) and seeker data.
2. Distortion – Seeker data undergoes mild deformation due to noise, irregular ship formation, or sensor jitter.
3. Distortion with Decoys – The most challenging case, where seeker data is distorted and false decoy points are added to mislead alignment.

Performance Insights:

1. Pentagon-based Matching:
 - Provides a simpler geometric reference with fewer vertices, making alignment faster and computationally efficient.
 - Useful for scenarios with low noise and mild distortions, but may be less resilient to heavy decoy interference.
2. Hexagon-based Matching:
 - Offers a more structured reference with six vertices, giving higher geometric precision and stability.
 - More effective under complex distortion and decoy-infused scenarios, ensuring better alignment and rejection of false targets.
3. DQN Integration:
 - The DQN intelligently selects the optimal transformation actions (alignment, rejection, or adjustment) to minimize mismatch.
 - Under pentagon and hexagon frameworks, DQN learns to filter decoys and improve success rate, even when seeker data is noisy or partially distorted.

1.Rigid Case Transformation: In this case The seeker data is a clean translation/rotation of the formation. With no deformation, the relative geometry is preserved and the correct target point is straightforward to confirm.

2.Distortion Case: The seeker points may shift due to dynamics or sensing effects, causing small mismatches.DQN corrects this by focusing on overall pattern consistency instead of single point errors.

3.Distortion with Decoys: In this case, distortions and false decoys appear near the center or edges to Confuse the seeker. DQN counters this by focusing On stable formation patterns to identify the true target.

Comparison of Pentagon and Hexagon Target Matching using DQN:

The table compares the performance of DQN-based target matching for Pentagon and Hexagon formations under three conditions: Rigid, Distortion, and Distortion with Decoys.

Shape	Condition	Matching Efficiency	Error Rate	Success Rate (SR)
Pentagon	Rigid	100.00	0.00	100%
	Distortion	94.72	0.24	97.72%
	Distortion + Decoys	85.48	0.47	96.30%
Hexagon	Rigid	100.00	0.00	100%
	Distortion	93.14	0.06	99.74%
	Distortion + Decoys	85.08	0.24	90.10%

Table.1:Performance Comparison of Pentagon and Hexagon Target Matching using

4.CONCLUSION

The proposed Deep Q-Network (DQN) based framework provides a robust and intelligent solution for target selection in the terminal phase of missile guidance systems. By continuously learning from seeker observations, DQN adapts to distortions, noise, and decoy interference, allowing it to distinguish true targets from false ones. The model performs effectively across a variety of formations, including both regular structures like pentagons and hexagons .Tested under different transformation scenarios—rigid alignment, distortion, and distortion with decoys—DQN demonstrates high success rates, strong matching efficiency, and significantly reduced false positives. Its ability to integrate past learning with real-time adaptability makes it a reliable and scalable solution for advanced guidance and tracking applications.

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Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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