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Design of a turret stabilization system using reinforcement learning with external disturbance compensation

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Abstract

Reinforcement Learning (RL), in particular, Proximal Policy Optimization (PPO), and Twin Delayed Deep Deterministic Policy Gradient (TD3), to stabilize a weapon turret system with a set of external disturbances was considered in this study. Compared to traditional control algorithms such as proportional-integral-derivative (PID) controllers, they have their limits in dynamic settings because of manual tuning and a lack of a durable response to disturbances. This research will compare RL-based controllers and PID in a simulated scenario in which the turret will experience disturbances related to recoil, vibrations, and angular oscillations. A kinematic model of the turret was designed, and Lagrangian mechanics were used to model the disturbances of the turret. The run was done in PyBullet alongside the evaluation of the performance via mean absolute error (MAE) and root mean square error (RMSE). These findings show that RL controllers, particularly PPO and TD3, performed better than the PID one in terms of faster stabilization, reduced errors, and compensation of disturbances. RL agents simulated independently to different patterns of disturbances in a noisy and dynamic environment, and performed better than conventional systems. The results prove that RL-based control systems can be used in real-world applications, especially where accuracy is necessary.

Keywords: Turret stabilization, Reinforcement learning, Disturbance compensation, Proximal policy optimization, Twin delayed deep deterministic policy

1. Introduction

In defense applications, turret-stabilization technology is especially critical on a movable platform, as the performance of defensive mechanisms depends on the accuracy of the control system. This need for precision has now become more pronounced with the rising threat of Unmanned Aerial Vehicles (UAVs), which are increasingly used in modern warfare. Among other shortcomings is the accurate detection and tracking of UAVs; defense systems rely on this ability, and any mistake in targeting accuracy can lead to severe consequences [1][2]. A weapon turret placed on a moving platform must be able to withstand various dynamic disturbances, including tremors, recoil forces, and sudden changes in the platform's motion. These disturbances are caused by the firing vibrations or by external stimuli such as wind or ground irregularities. Such effects can significantly degrade the efficiency of the turret's stabilization system. Consequently, maintaining the stability of the turret so that it could hold its target successfully in these moving conditions is a complicated engineering issue that needs advanced control strategies [3][4].

Managing external disturbances is one of the main challenges in stabilizing a weapon turret. These vibrations influence the motion of the platform and the accuracy of the turret, often resulting in faulty targeting [5]. As an example, the turret may shake during firing, thereby leading to misalignment of the targeting mechanism due to the recoil forces. Likewise, the unwanted motion of the turret caused by the vibrations of the platform or external vibrations, like explosions or the vicinity of the artillery, might cause unwanted motion of the turret. Because the intensity and frequency of these disturbances vary unpredictably, compensating for their effects in real time is particularly difficult [6]. In UAV-countermeasure operations, these external forces may result in the inability of target tracking or, even worse, cause the system to lose target lock, which implies reducing overall defensive effectiveness. Thus, a crucial task is the design of a turret stabilization system capable of operating under these disturbances and maintaining accurate targeting, thereby ensuring the success of any modern defense system [7].

Dynamically, the most common type of control system used to stabilize turrets on movable platforms is a Proportional-Integral-Derivative (PID) controller [8]. It is widely used in engineering applications due to its simplicity of use and effectiveness in the management of steady-state errors. However, PID controllers show several limitations [9]. The major drawback is the manual tuning of the controller parameters, which is time-consuming and may not always yield optimal performance under variable operating conditions [10][11]. During dynamic disturbances, the performance of the PID controller may deteriorate drastically, particularly when the disturbance magnitude or frequency changes; the PID controller might not respond well, hence the poor stabilization and incorrect targeting [12]. Furthermore, PID controllers are not suited to handle the non-linearities and interacting multi-variables in the system, i.e., the common-made non-system of turret stabilization systems. These drawbacks have motivated the exploration of alternative control strategies and mechanisms capable of maintaining robust performance under such challenging conditions [13][14].

To overcome the inadequacies of traditional control methods, RL, a branch of machine learning, has proven to be a viable solution. RL algorithms, unlike PID controllers, are not tuned manually [15]. Rather, they are trained on the best control policies through their environment, which informs them about the system's performance. This renders RL extremely appropriate whenever dealing with intricate, variable, and noisy upheavals that are challenging to determine and explicitly model. Among RL algorithms, Proximal Policy Optimization (PPO) and Twin Delayed Deep Deterministic Policy Gradient (TD3) have shown promising results when implemented in control applications [16][17]. Such algorithms can be especially well-suited to continuous action spaces, especially the challenge of managing a turret system. PPO is also described as having stability and efficiency, as it employs a trust region method that seeks to ensure the learning process does not make large, unstable updates [18][19][20]. TD3, instead, can be used to solve problems that are associated with unstable learning when Q-values get overestimated in reinforcement learning. TD3 applies such methods as target smoothing and delayed updates to stabilize the learning process [21]. Both PPO and TD3 have shown strong performance in various reinforcement learning tasks, such as robotics and complex control problems, due to their ability to generalize over noisy data and learn in dynamic conditions. The interest of RL-based control systems is that they can autonomously learn the optimum policies when there is no need for an explicit model-based control or manual tuning [22]. This aspect renders RL particularly appealing when contemplating the implementation of dramatic disturbances whose routes are either arbitrary or dynamic. Besides, RL methods like PPO or TD3 can learn highly non-linear (and thus unstable) control policies that can be readily updated on the fly in a non-stationary environment [23]. When applied to turret stabilization, RL-based control systems might be better than conventional PID controllers as they can autonomously learn to deal with disturbances and the variations in the system dynamics to maintain stability and accuracy [24].

Additionally, by learning from past experiences and continuously improving their control strategies, RL-based systems can respond more effectively to external interferences, thereby minimizing the need for human intervention. The primary objective of the above analysis is to explore the suitability of RL-based control systems to deal with the stabilization of a turret and to contrast it with conventional PID regulators [25]. To achieve this, simulation models of the turret system will be used, incorporating external disturbances such as recoil and platform vibrations. Specifically, the research will compare RL-based controllers, namely PPO and TD3, against a PID controller in terms of turret stability, accuracy, and adaptability under varying disturbance conditions. To this end, the environment will be simulated to closely resemble real operating conditions, including different levels of platform movement and external disturbances. RL agents will be trained in such an environment, and their performance will be measured according to response time, accuracy, and adaptability [26]. The study will also examine how RL algorithms can be tuned to enhance their applicability in handling real-world scenarios, where disturbances and systems are less predictable and more complex due to changes in dynamics [27].

This study contributes to the growing body of research on machine learning in control strategies by developing and comparing RL-based control systems with conventional ones. The results of the present work may pave the way for more complex and adjustable turret stabilization systems, which can be integrated onto contemporary defense platforms. Specifically, the results could indicate that RL-based control systems have the potential to provide a significantly improved situation in terms of robustness, adaptability, and disturbance rejection, ultimately resulting in more accurate and reliable targeting in dynamic environments [28]. Beyond turret applications, the study may have broader relevance for other fields where stability and regulation are crucial, such as robotics, aerospace, and autonomous vehicles [29]. With the continued development of RL, their future ability to deal with complex control issues in dynamic settings continues to stand out. It is therefore an active area where research and development work are exciting prospects.

2. Research method

This study uses a systematic approach to its methodology, which involves modeling the turret system, integrating disturbances, simulating the system in PyBullet, and applying control algorithms. These steps were carefully designed to achieve the study's purpose and to lay out a comparison between the RL-based control systems and conventional PID controllers.

2.1. Turret modelling

The initial part of the methodology will be forming a kinematic model of the turret system. The construction of the framework will be conducted based on the Denavit-Hartenberg (DH) procedure, which is a conventional approach to modeling a robot arm and other articulated bodies [29]. The turret system is viewed to have two degrees of freedom, namely the azimuth and the elevation. These will be the main movements necessary to adjust the weapon to point it at the target, and they will be modelled as rotational joints.

The standard DH parameters of d_i, 0_i, $a_{i,}$ and α_i are defined to model the turret [30][31]. These values are used to characterize the change that occurs between the successive coordinated frames within the system. The d_i parameter is the offset on the last z-axis, and θ_i is the angle around the last z-axis. The value of the a_i parameter defines the length of the common normal (distance between the z-axes), and α_i is the angle in the direction of the previous x-axis. Transformation matrices explaining the relations between various joints and links of the turret will be derived with the help of such parameters [32]. The DH method provides a systematic approach to modeling the turret's motion compactly and effectively, enabling accurate simulation and control [33]. In this regard, overall modelling is presented numerically in Table 1.

Table 1. Denavit-Hartenberg parameters for Turret model

Link i	Θi	Di	ai	αi
1	θ_1	d_1	a_1	α_1
2	θ_2	d_2	a_2	α_2
…	…	…	…	…

Note: θ, d, a, and 0 are standard Denavit-Hartenberg parameters of each joint and link in the system.

2.2. Disturbance modelling

The second step involves integrating external disturbances into the dynamic model of the turret. These disturbances include vertical vibrations, angular oscillations, and recoil impulses that may arise during turret operation. These disturbances are modeled using Lagrangian mechanics, which allows for the inclusion of energy-based terms such as kinetic and potential energy, as well as damping and frictional effects [34][35].

To account for the external forces acting on the turret, terms for friction and overload effects will be incorporated into the equations of motion. Frictional forces will be modeled as damping terms that resist motion, while overload effects will be represented by forces that arise when the turret exceeds its operational limits. These disturbances, when modeled appropriately, will simulate real-world conditions in which the turret system is subjected to unpredictable forces, such as vibrations from the platform or recoil from firing the weapon [36]. The inclusion of these disturbances is critical for evaluating the performance of the control algorithms under realistic conditions [37][38]. For the disturbance modeling (e.g., recoil, vibrations), equations for the Lagrangian mechanics that model the turret's response to external forces are given below:

The total Lagrangian L for the turret system is the difference between the kinetic energy T and potential energy V:

$$L = T - VL \qquad (1)$$

- Kinetic Energy (T):

$$T = 12mv^2 + 12I\omega^2T \qquad (2)$$

Where:

m is the mass, v is the linear velocity, I is the moment of inertia, and ω is the angular velocity.

- Potential Energy (V):

$$V=mghV = m\ g\ hV=mgh \qquad (3)$$

Where g is the gravitational constant and h is the height.

- External Forces:
  For modeling disturbances like recoil and vibration, we incorporate damping and frictional forces. For example, the frictional force F can be as:

$$F = c * x \qquad (4)$$

Where c is the damping constant & x is the velocity

2.3. Set up PyBullet environment

We shall create the simulation environment using PyBullet, a physics engine that enables the modeling of rigid-body dynamics. A virtual environment of the turret model will be established in PyBullet and is described in the URDF (Universal Robot Description Format) [39]. The properties of the robotic systems have a common way to be described: their geometry, kinematics, and dynamics, and they are under the URDF format.

Simulation parameters, such as the simulation facility (solver settings) and frequencies (time step), shall be fixed at 240 Hz to ensure high accuracy of the simulation dynamics [40]. Base vibrations and external forces will be applied to the simulation to introduce external disturbances, realistically simulating the real-world phenomena of platform motions and the recoil effects. Among the most critical variables that will be produced in the simulation are turret angles, tracking errors, and the control measures that were used by the algorithms. This data will be recorded and used to determine the work of the control systems.

2.4. Application of control algorithm

Stabilizing the turret by implementing control algorithms is at the center of this research. There will be two control systems deployed: one traditional PID controller and two RL-based agents based on PPO and TD3. The algorithms are explained below.

2.4.1. PID controller

A classical PID controller is applied to control the azimuth and elevation of the turret. There will be two independent controllers, one for each axis of freedom (azimuth, elevation). PID tuning will be performed in an empirical approach, with the tuning procedure focused on limiting the tracking errors and oscillations during the movement of the turret. The response of the system to different forms of disturbance will be used to fine-tune the controllers, and the result is to attain a stable and correct control. They use a PID controller to make a comparison of the performance of the RL-based control systems [41].

2.4.2. RL agents PPO / TD3

At the same time, two RL agents, PPO and TD3, will be trained to control the turret system. Those algorithms are trained with the help of Stable-Baselines3, which is a well-known library in the field of reinforcement learning. PPO and TD3 are both suitable for continuous action spaces; for example, to tilt the turret, one must set the angles until they stabilize [42].

The state space of the RL agents will be the normalization of errors and velocities corresponding to the difference between the actual position and desired position of the turret and the rate of change of the latter, respectively. Action space will be formed of the angle integers, where each integer will correspond to the slight commands the RL agents can instruct the turret to make about the azimuth and elevation [43].

The reward function will be developed in such a way that the minimization of tracking errors, as well as the ambition to lower the oscillations, will be encouraged. There will be a negative reward that will be applied to large errors and excessive oscillation, whereas the positive reward will be attributed to specific aiming and stability. Observing how agents use the simulation environment and adjust the turret's position to minimize error to optimal levels, one can understand how to maximize its cumulative, long-term reward [44].

The model architecture of the RL agents' neural network will adopt a multi-layer perceptron (MLP) with three layers, wherein each layer has 64 units [45]. This architecture has been selected due to trade-offs between computational efficiency and capabilities to learn complex control policies. The RL agents will be trained in the simulated environment, and their performance will be compared with the PID controller [46].

3. Results and discussion

The results of various simulations/ test scenarios for the control algorithm test are presented and discussed below.

3.1. Simulation conditions

To test the effectiveness of the control algorithms, several test scenarios were created to simulate various conditions related to targeting and disturbances. The angles at which the hits were aimed were two-fold (40° & 25°) and (90° & 60°). Such angles depict common points of the target that the turret is likely to target during its service application. The simulation was created in such a way that it would bring external disturbances that are likely to be experienced in real life. These perturbations involved sinusoidal vibration and recoil pulse, which were applied with an interval of 2, 4, 6, and 8 seconds. The parameters of the disturbances were well chosen to simulate the type of unpredictable disturbance that the turret would encounter during operation, like vibrations of the platform and recoil force developed during weapon firing. The functionalities of the control systems in the various disturbance conditions were also to be stress tested to test how they maintain stability and precision.

3.2. Graphical representation of results

The outputs of the PID controller, PPO agent, and TD3 agent were demonstrated graphically to illustrate the key dynamics of the system. Time-series plots were generated for the turret's angular positions, stabilization errors, and control signals for each algorithm. The angular dynamics plots show the turret's position over time under different disturbance conditions, reflecting the system's response to external perturbations. The stabilization errors were charted to graphically see how each controller was able to maintain the turret on its angle, with emphasis on deviations from the desired angles. Also, the control efforts of each algorithm were displayed as a result of the disturbance to demonstrate how the PID controller and the RL agents responded to a disturbance. Box plots were created showing the distributions of angular errors and allowed an easy comparison of the relative variability of the error of each controller, as shown in Figure 1.

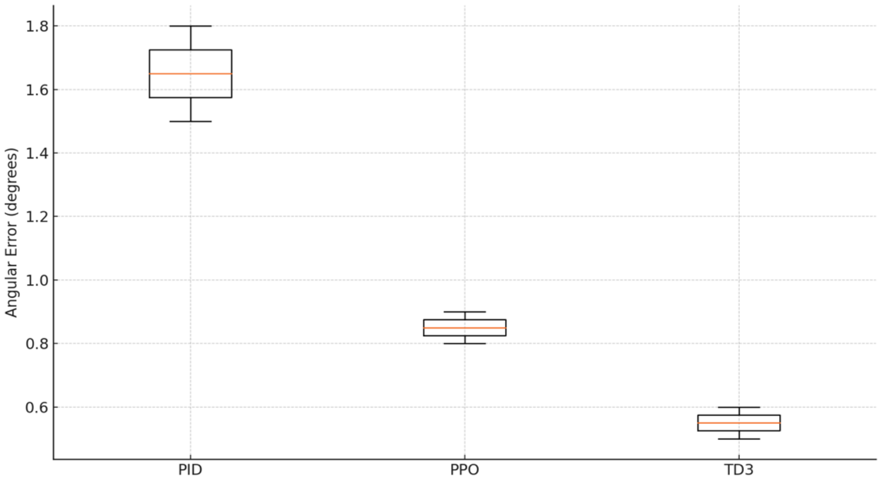

Figure 1. Box plot of angular errors

The plots also aided in determining the accuracy of some control algorithms that consistently outperformed the others during error minimizing and stabilizing the turret, as shown in Figure 2.

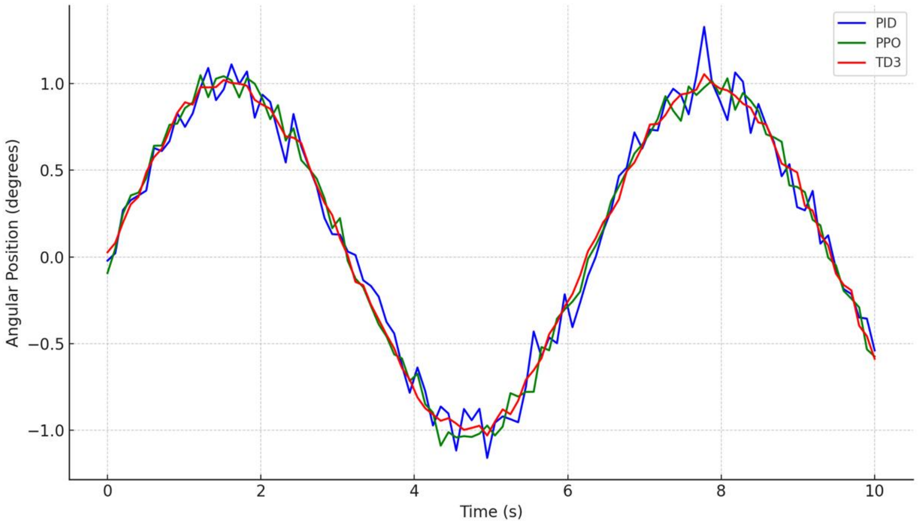

Figure 2. Angular dynamics comparison

The boxplots revealed that the error values were spread out; those with smaller interquartile ranges directed towards very uniform performance and error, as shown in Figure 3.

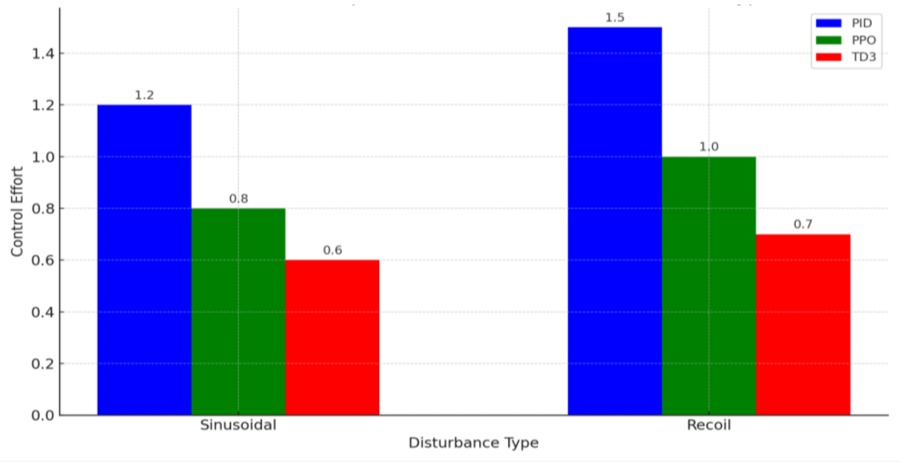

Figure 3. Control effort comparison

3.3. Performance metrics

To make a quantitative evaluation of the performance of the control algorithms, two significant quantities were computed, namely mean absolute error (MAE) and root mean square error (RMSE). The metrics have been adopted to measure the reliability and precision of all the controllers against the various test conditions. The MAE averages the absolute value of the errors without caring about their direction. In contrast, the RMSE puts more weight on large errors, causing it to be more sensitive to large deviations from the target. To compare the angular error results in each of the test scenarios, the MAE and the RMSE figures were determined for each control algorithm. The comparison of the performance of the PID controller with that of the RL-based controllers (PPO and TD3) was necessary to refer to how the algorithms minimized the error under various disturbance conditions [47]. The findings were reported with comparisons being drawn on which of the control algorithms recorded the lowest errors, both in MAE and RMSE. This examination was useful in highlighting the strengths and weaknesses of each controller in terms of stability and accuracy under dynamic conditions.

3.4. Findings discussed

The findings of the simulation offered informative answers to the work of the PID controller and the RL-based control algorithms. In general, the RL-based controllers, specifically PPO and TD3, had multiple benefits over the conventional PID controller, especially in instances that exhibited high disturbances. The agents operating under the RL algorithm could normally stabilize the turret faster than those working under the PID controller and shorten the response time to return to the target position after an obstacle. The results in the form of lower MAE and RMSE values of the RL agents were the indicators that those agents could more effectively track the target with minimum error, even in the adverse conditions of disturbance. Among the main strengths of the RL-based controllers was the fact that they managed to adjust to the changing disturbance pattern. Although the PID controller could only be tuned to mitigate many disturbances after extensive manual control, given the experience that the RL agents could acquire on their own by interacting with a specific environment, it could automatically learn to develop optimal control policies. It was noticeable in this flexibility when parameters of the disturbances were altered, with the RL agents swiftly altering control measures to reduce error.

The PID, however, had a hard time keeping accuracy when disturbances changed in frequency or magnitude, resulting in greater tracking errors and a reduction in the speed of stabilization. Based on the faster stabilization and reduced errors attained by the RL agents, it could be stated that reinforcement learning provides a futuristic way to achieve an efficient turret stabilization system, especially in dynamic and unpredictable worlds. The fact that RL algorithms can manipulate noisy action space, and with the learning aspect, leads to the fact that they are highly applicable in applications like weapon turret stabilization systems, where noise may change in real-time [48]. Additionally, the findings demonstrate that RL algorithms can outperform more conventional control techniques in complex, non-linear environments. When it comes to the comparison with the existing literature, the results of the present research can be compared with other studies regarding the use of reinforcement learning in control systems. RL-based controllers have been demonstrated to be better suited than traditional methods to tasks with dynamic disturbance as well as adaptation requirements in real-time. To illustrate, RL has been effectively applied in robot control, yielding better performance in activities such as balancing, path planning, and stabilization. This work is a continuation of the given findings as it utilizes RL in the particular issue of turret stabilization, and it further demonstrates the benefits of RL in the dynamic control tasks. The RL agents demonstrated good results; however, it is worth noting that in this case, the level of their performance was closely tied to the quality of the training process. The PPO and TD3 agents were very heavy in terms of both computation and training time on a computer to perform best. In the future, an attempt to optimize the training process and introduce another RL algorithm could be made, as well as continuing to refine the model so that it can learn a wider variety of disturbance cases.

3.5. Real-world implications

The employment of RL-based control methods in stabilizing turrets has great relevance for defense purposes. By developing better accuracy and speed in positioning the turrets, RL algorithms have the potential to make defense systems work more efficiently, especially against high-velocity threats like UAVs. Online adjustments to dynamically varying disturbance patterns will enable RL-based control systems to be more robust and productive under the conditions in systems where operational conditions may vary without warning or significantly faster than under test conditions.

Additionally, RL-based systems can be favorably integrated into an existing defense system, which is possible due to their flexibility. This differs from traditional control systems, which may require manual tuning depending on the platform or conditions. Still, RL systems can be trained on various platforms of operation and adapt to emerging threats without necessitating rigorous adjustments.

4. Conclusions

The findings of this study showed that RL controllers (PPO and TD3) outperform the conventional PID controller in stabilizing the turret system under dynamic disturbances. Controllers based on RL uniformly performed more accurately and more stably than the PID controller. In particular, the RL agents could meet the lower tracking errors, stabilization times, and robust compensation capacities against external disturbances, including recoil mayhem and sinusoidal vibrations. The findings indicated that the RL algorithms, because of their capacity to make adjustments and learn in real time, were far more able to absorb the changing patterns of disturbances and therefore continue to perform better in general. Conversely, the PID controller could not resist fluctuation in the magnitude and frequencies of disturbances, and it even necessitated manual adjustments depending on the situation. However, the RL agents proved to be intrinsically flexible and were able to continually improve their control policies, leading to better disturbance compensation and fewer errors in the end. The results indicate that RL-based control systems might give a stronger answer to turret stabilization, notably in unpredictable and dynamic situations that are experienced during defense applications.

This report has important practical implications, particularly for real-world defense systems. One key outcome is that the PID controller was successfully calibrated in a simulated environment and can serve as a benchmark for RL-based controllers. Such validation is essential to show the practical applicability of these control algorithms, since it can serve as a basis for further testing and implementation in a real turret application. The application of the RL algorithms in turret stabilization may become a revolution in the defense system design, because in such a way, a more precise and adaptive mechanism of control may be established. RL-based systems may theoretically help defense platforms respond to high-speed threats, such as UAVs, by making their targeting more accurate and less time-consuming to stabilize. Additionally, RL-based control systems may be more flexible and adaptive, enabling defense platforms to deliver their functionality in a broader range of conditions without the need for manual adjustments.

Despite the promising outcomes of the present work, there are several directions that future studies and advancements could take to improve the functioning of RL-based turret stabilization systems. The idea of incorporating visual tracking into the control system may be considered one of the potential paths for future work. Although this research focused on angular dynamics and disturbance compensation capabilities, a real-life turret system must also have the capability to track mobile targets. Through the implementation of computer vision and visual tracking algorithms, RL-based control constructs could be evolved not only to stabilize but also to dynamically change the aim of the turret in real time, depending on target position or movement. This would further enhance the system's efficiency, especially when tracking a mobile target, which is often the case in UAV tracking. Another exciting area of future research is the application of RL algorithms on hardware. Although the present project involved a simulated environment, it would be important to test the actual performance level of an RL-based control system in the real world. That would include porting the control algorithms to a hardware representation of the turret system, which could thus be tested against real-world conditions. The hardware tests would help provide insights into the RL controllers' limitations and strengths, particularly in terms of computational efficiency, sensor integration, and real-time flexibility. Lastly, an aspect of further research might be to look into the strategy of adaptive control through the use of RL. Adaptive control techniques enable modification of the control strategy to accommodate changes in system dynamics or working conditions. Combining adaptive control strategy and RL, the turret system may be even more receptive to unexpected disruptions or environmental variations to further enhance the stability and accuracy of the turret system.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

Authors contribution

Alexandr Dolya and Batyr Kolumbetov conducted the literature review and contributed to the development of the research methodology. Alizhan Tulembayev, Nessipova Saltanat, and Askar Buldeshov further developed the methodology and analyzed the collected data. Batyr Kolumbetov, Nessipova Saltanat, and Alexandr Dolya were responsible for the compilation of results, drafting, and writing of the manuscript. All authors discussed the findings, contributed to the improvement of the paper, and approved the final version of the manuscript for publication.

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