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Enhancing Computer Vision Control System Performance: A Comparative Study of FOPID Controller Optimized with World Cup Optimization Algorithm

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ABSTRACT

Precise and stable trajectory tracking in mobile robotics is challenging due to dynamic disturbances and uncertain conditions. Traditional controllers like P-D and PID often underperform in non-linear, unpredictable environments. They also lack the adaptability needed for real-time, vision-based control systems. To address these issues, this paper explores and compares the effectiveness of three control approaches: P-D, PID, and a Fractional Order PID (FOPID) controller optimized using the World Cup Optimization Algorithm (WCOA). The control system is driven by inputs from a computer vision setup, and the controllers are evaluated on their ability to maintain accurate setpoint tracking under simulated dynamic disturbances. The FOPID controller's parameters are tuned using WCOA, enhancing its adaptability and precision. The robustness of WCOA is also validated using standard benchmark functions including Sphere, Rastrigin, Ackley, Rosenbrock, and Griewank. Simulation results show that the WCOA-tuned FOPID controller significantly outperforms both P-D and PID controllers in minimizing error, maintaining control stability, and ensuring accurate trajectory tracking. Its superiority is also demonstrated through real-time tests on a mobile robot. Furthermore, feasibility evaluations reveal high levels of usability, operability, and learnability. These results highlight the strong potential of WCOA as a robust optimization method for advanced control systems and provide a foundation for future research in dynamic environments, hybrid optimization techniques, and broader engineering applications.

MSC.

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1.Introduction

Computer vision has emerged as a rapid growth area triggered by the progressive growth in both Artificial Intelligence and Computer Science, with its focus on allowing machines to interpret and make sense of data within their environments. The skill to mirror human vision enables computer vision systems to extract information from visible digital images and videos, along with other types of visual data. One might include the arrangement of computers with algorithms, machine learning, and various ways to allow them to detect patterns, recognize objects, follow movement, and form decisions based on visual input [1].

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The range of applications for computer vision is vast and includes the automotive industry's invention of self-driving cars, to retail's handling of automated checkouts and inventory management, security and surveillance systems that perform facial recognition, robotics applications, augmented reality, and common consumer devices such as smartphones [2]. The performance target of a dynamic system, typically maintained at its optimal level, is achieved through the implementation of control strategies [3]. Over the years, extensive use of P-D and PID controllers has been observed [4]. In most industrial applications including process control, robotics, automotive systems, and aerospace engineering, these controllers maintain simplicity and robust performance [5].

The main contributions of this paper are as follows:

- To provide performance comparisons of the P-D, PID, and WCOA-optimized FOPID controllers in a computer vision-based control system for mobile robotics.
- WCOA will be applied to tune the parameters of the FOPID controller to enhance its performance in terms of error reduction, stability of the control output, and overall accuracy of the system.
- To investigate robustness and effectiveness, the WCOA was applied to a set of benchmark functions representing different optimization challenges such as multimodality and deceptive landscapes. 4. To assess in real time the effectiveness of the FOPID controller, optimized using the WCOA for a mobile robot, by a running test, and to demonstrate its superiority in trajectory tracking and system stability.
- The real-world testing of the application and the feedback about the feasibility, usability, operability, and learnability will be performed in order to validate the application of the WCOA-optimized FOPID controller to real-world engineering systems. 6. Applications to areas with dynamic and uncertain environments, among others like power systems, autonomous vehicles, and industrial automation, may be explored for the use of a WCOA-optimized control system.

This paper is organized as follows: the proposed objectives and methodology are presented in Section 2. Whereas, the theoretical background on P-D, PID, and FOPID controllers and simulation setup review is going to be given in Section 3; in Section 4, the explanation of the WCOA optimization Algorithm will be given as the methodology to investigate the performance of controllers. Simulation results comparing the performance of the P-D, PID, WCOA-optimized FOPID controller, and benchmark functions will be presented in Section 5. Section 6 concludes the paper with a summary of the key contributions and suggestions for future research directions.

2. Related Works

In this paper, three control strategies are taken into consideration: P-D, PID, and FOPID toward performance evaluation for the regulation of a simulated control system. The FOPID controller optimizes through WCOA for an optimal set of five tuning parameters, namely Kp, Ki, Kd, \lambda, and \mu. Then, WCOA-optimized FOPID controller performance is compared with traditional P-D and PID controllers with respect to error minimization, control output stability, and total absolute error. This is carried out through a set of simulations designed to test each controller's tracking ability of a reference signal under dynamic input conditions. Furthermore, in order to assess their practical applicability, we extend the analysis with feasibility tests where a review of usability, operability, and learnability of the controllers in view of their application to real-world systems is performed. In this respect, mobile robot running tests are done in a manner that will validate the effectiveness of the controllers on a physical system. The tests are conducted such that the controllers show usefulness in an environment where precision and adaptability in control are crucial.

In the last twenty years, the dynamical system has been watched to be becoming more and more imperfect and, hence, much more sensitive to external disturbances, which has exposed the shortcomings of conventional control methodologies [6]. In particular, the growing need for higher accuracy, etc., along with the requirements to make the control systems more robust and flexible stimulated the application of advanced control concepts, where fractional-order controllers play a significant role [7]. However, many existing implementations have not fully addressed real-time performance under rapidly changing environments, limiting their practical deployment. Another method of advanced control is the Fractional Order Proportional-Integral-Derivative Controller abbreviated FOPID [8]. A PID controller is enhanced by adding the fractional order of integration and differentiation parameters of \lambda and \mu, respectively. Added flexibility allows the FOPID controller to better model and compensate for complex dynamic behavior in systems possessing memory and hereditary properties [9]. Yet, these improvements often come at the cost of increased complexity, making real-world integration more difficult in resource-constrained systems. In this regard, FOPID controllers are gaining importance in workable research, sufficient in delivering better results than the classical P-D and PID, especially in nonlinear dynamics and time-varying parameter systems [10]. Nevertheless, most prior studies remain limited to simulation environments and lack comprehensive hardware-based validation. However, their design and tuning remain a potential bottleneck, despite all the pros of FOPID controllers [11]. What makes the tuning more complicated is that fractional calculus adds complexity to traditional controllers, increasing the number of parameters, for which optimal values have to be chosen in view of a difficult compromise between stability, response time, and reduction of error [12]. Many earlier tuning methods rely on conventional optimization techniques that often converge to local optima or require high computational effort, limiting their scalability. On this score, optimization algorithms have become very useful tools assisting in carrying out the tuning of FOPID controllers. These algorithms are able to find, among all the parameters in a given system, the set of parameters that maximizes performance [13, 14]. Still, certain approaches lack robustness when applied to systems with fast-changing or unpredictable dynamics, which reduces their effectiveness in real-time robotic applications.

Optimization techniques such as metaheuristics inspired by natural or social phenomena represent a modern class of optimization algorithms. An example is the World Cup Optimization Algorithm (WCOA), which is a new metaheuristic optimization technique inspired by the competition structure of the tournament in the FIFA World Cup [15]. WCOA models teams as particles in a search space and emulates their interactions and competitive dynamics in order to explore the realm of optimum solutions. This approach identifies the best teams or solutions after many stages of competition and converges eventually to the global optimum. WCOA applied for optimizing FOPID controller parameters has the capability to improve controller performance in complex systems [16, 17]. However, most studies involving WCOA have not yet explored its application in vision-based mobile robotics, leaving its real-time viability in such systems largely unexamined.

Before dealing in detail with this work on the control systems of mobile robots, first of all, it is compulsory to point out the importance of FOPID controllers within modern control theory. FOPID controllers are an extension of classical PID controllers and assure more flexibility and performance compared to their predecessors, which are very important for complex dynamic systems such as mobile robots [18, 19]. Recent developments focused on the optimization techniques of FOPID controllers using different kinds of algorithms to acquire better trajectory tracking, stability, and robustness in uncertain environments. In [20], the authors have already conducted previous efforts, focusing on making an optimal backstepping-based FOPID controller to solve the problem of trajectory tracking in robotic mobility. To control the parameters of FOPID controller, the research used hybrid meta-heuristic optimization methods to the controller significantly improving the tracking performance and system stability. However, the study was limited to simulations and lacked real-time hardware validation. Subsequently, a research study examined the enhancement of path-tracking control in mobile robots applying the proposed hybrid FOPID controller and backstepping method. The work done in the research demonstrated that this combined approach enhanced the accuracy of trajectory tracking by a very large margin and provided enhanced immunity from disturbances as compared to conventional control strategies as concluded in [21]. Yet, the optimization was applied in a static or simplified environment, with limited responsiveness to dynamically changing conditions. Over several studies, multiple Swarm Intelligence algorithms were investigated relative to their performances in permanent magnet synchronous motors used for speed regulation. In the light of the findings, the FOPID controllers with the advanced meta-heuristic algorithms were found to be more accurate and robust than conventional approaches [22]. Nevertheless, these studies focused on motor control systems, not mobile robots, limiting their generalization to trajectory tracking scenarios. Subsequently, the authors in [23] undertook research to share the episode-based optimal tuning of FOPID controllers for wheeled mobile robots using various hybrids of PSO and GWO algorithms. The obtained comprehensive approach illustrated important improvements in integration of the means for trajectory tracking as well as in decreasing the number of errors in the control system. However, the hybrid algorithm's complexity increased computational cost, and real-time performance was not deeply explored. After that, the authors utilized a Firefly Algorithm to optimize the parameters of an FOPID controller in an AMR. This led to improved control accuracy in the robot's navigation and improved responsiveness of the robot to changes in the physical environment and demonstrated the ability of the Firefly Algorithm to fine-tune the FOPID controller for dynamic and uncertain environment [24]. Still, the algorithm exhibited slower convergence and was not benchmarked against multiple global optimization methods for broader validation. Then, the research regarding the improvement of mobile robot control using a controller of FOPID - tuned by WCOA - demonstrated that a WCOA-optimized controller significantly enhances control performance towards reduced error and enhanced stability, especially during dynamic conditions [25]. Despite its potential, this work did not evaluate the controller's usability, operability, or robustness across varied real-world scenarios. Finally, the authors in [26] have been introduced a study on the adaptive FOPID controller design using optimization via

Genetic Algorithm for mobile robot navigation in uncertain and unknown environments. The results depicted better adaptability and control precision in complicated and dynamic scenarios, underlining the effectiveness of the adaptive FOPID controller in handling unpredictable conditions.

3. Model Setup

This section presents a model setup used for comparisons among P-D, PID, and WCOA-optimized FOPID controllers in detail by providing the necessary mathematical equations, algorithms, and pseudo-codes related to the WCOA, as shown in Fig. 1. In this approach, step-by-step detailed explanations are provided on initialization, controller design, optimization, simulation, and performance evaluation.

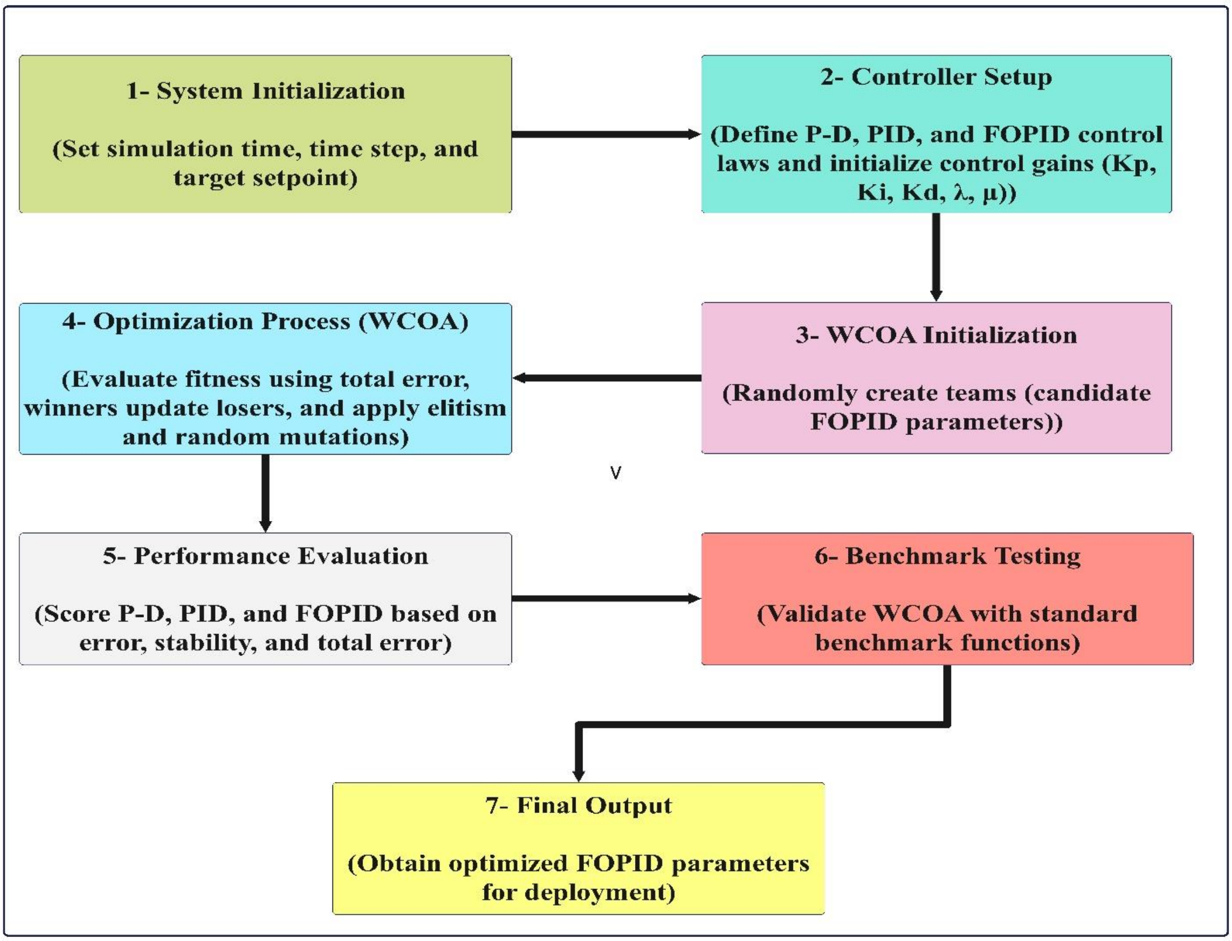


Fig 1- Steps of proposed approach.

3.1. Initialization and Simulation Setup

Some of the key parameters - dt (a time step), total time of simulation, and setpoint, in fact, the target that controllers ought to reach - are defined at the beginning of the simulation. Thereafter, the constant base speed for the motor control simulation is defined. The system simulates random input values using a range of pixel data, represented by $x = randi([0, 160], 1, length(time))$. This data is processed to create varying weight values, which act as disturbances for the control system to handle. The system's error at any time step t is calculated as [27]:

$$\boldsymbol{Error}(\boldsymbol{t}) = Setpoint - Output(t) \tag{1}$$

The control effort applied to the system is a function of this error, with different controllers (P-D, PID, and FOPID) calculating the effort differently based on their control laws. Table 1 is designed to quantify the performance of different controllers P-D, PID, and WCOA-optimized FOPID used in your MATLAB work. This table uses a scoring system ranging from 1 to 5, where a score of 1 represents the poor performance and a score of 5 represents the excellent performance across a three key performance metrics which are: Error Reduction, Control Output Stability, and the Total Absolute Error. Table 2 presents a systematic way of mapping input values from the pixel-bound captured through the camera/vision systems to weight values the control system can then use for corrective actions. Each row in this table represents a range of pixel values and its corresponding weight, which shall enable the control system to assess the deviation from setpoint and thereby act.

Table 1 - Score Conversion.

Controller Type	Performance Metric	Score (1-5)	Description
P-D Controller	Error Reduction	2	Moderate reduction in error, with noticeable oscillations.
	Control Output Stability	2	Control signals exhibit aggressive behaviour with overshoots.
	Total Absolute Error	3	Higher overall error compared to PID and FOPID.
PID Controller	Error Reduction	3	Improved over P-D but still some error remains.
	Control Output Stability	3	Stable control output but with some oscillations.
	Total Absolute Error	3.5	Lower error than P-D controller, smoother performance.
WCOA-Optimized FOPID Controller	Error Reduction	5	Excellent error minimisation, rapid convergence to setpoint.
	Control Output Stability	5	Smooth, stable control output with minimal overshoot.
	Total Absolute Error	4.5	Lowest total error, outperforming both P-D and PID.

Table 2 - The weight value specified for each frame.

Pixel Range	Weight Value	Description
0 – 20	4	Large deviation; requires significant positive correction.
20 - 37.5	3	Moderate positive deviation; needs positive correction.
37.5 – 55	2	Small positive deviation; minimal positive correction needed.
55 - 72.5	1	Slight positive deviation; very small correction needed.
72.5 - 87.5	0	No deviation; no correction needed, system at setpoint.
87.5 – 105	-1	Small negative deviation; minimal negative correction needed.

105 - 122.5	-2	Moderate negative deviation; needs negative correction.
122.5 - 140	-3	Significant negative deviation; requires larger correction.
140 – 160	-4	Large negative deviation; requires significant negative correction.

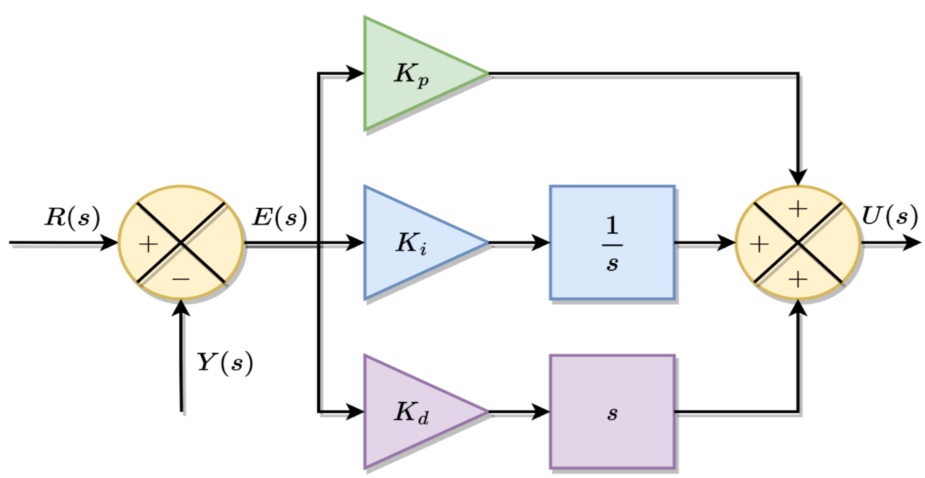
3.2. Controller Parameters Setup

Since the P-D controller's gains are initialized, it possesses two gains: proportional gain, or Kp, and derivative gain, or Kd. Thus, using the P-D controller means to calculate the error-that will correspond to a difference between a current system state and a setpoint-and to change the system output. The formula to get the control effort for the P-D controller [28]:

$$u(t) = Kp \cdot Error(t) + Kd \cdot dtd\big(Error(t)\big) \tag{2}$$

$$u(t) = Kp \cdot Error(t) + Ki \int Error(t)dt + Kd \cdot dtd(Error(t)) \tag{3}$$

In addition to the P-D controller, the PID controller also has an integrator that sums up past errors to improve steady-state accuracy. Gains for the proportional term Kp_PID, the integral term Ki_PID and the derivative term Kd_PID are initialized. The control effort for the PID controller includes proportional, integral, and derivative terms



as shown in Figure 2.

Fig 2- FOPID Controller Setup.

The FOPID is more advanced, meaning it applies fractional-order terms for integration as well as differentiation with fractional orders λ and μ correspondingly. The initial values for the FOPID gains are set to Kp_FOPID, Ki_FOPID, and Kd_FOPID. FOPID controller introduces also fractional orders for integration and differentiation [18]:

$$u(t) = Kp \cdot Error(t) + Ki \cdot D\lambda \int Error(t)dt + Kd \cdot D\mu dtd(Error(t)) \tag{4}$$

4. WCOA for FOPID Tuning

WCOA is one of the newly emerging optimization algorithms. It depends on the principle of the competitor during the tournament process, exactly as it takes place in the FIFA World Cup. In your work, this algorithm will be used in order to make the biggest influence on the parameters of the FOPID controller that is capable of minimizing the error in the output of the system. The complete explanation of every step of the WCOA with key equations and an explanation of each phase is given in the following. In WCOA, every team is a possible solution of the optimization problem. Parameters Kp, Ki, Kd, λ, and μ of the FOPID controller are considered the players of every team. The algorithm first initializes an initial population of random teams with different values of listed parameters. Equation of initialization [29]:

$$\begin{cases} K_{p,i} = K_{p_{min}} + r \cdot (K_{p_{max}} - K_{p_{min}}) \\ K_{d,i} = K_{d_{min}} + r \cdot (K_{d_{max}} - K_{d_{min}}) \\ \lambda_i = \lambda_{min} + r \cdot (\lambda_{max} - \lambda_{min}) \\ \mu_i = \mu_{min} + r \cdot (\mu_{max} - \mu_{min}) \end{cases} \tag{5}$$

Where, r is referring to the random number which fall between 0 and 1; and i is referring to the ith team.

Each team represents a set of the FOPID parameters, and the initial random distribution ensures that the search space is diverse. The performance of each team will be based on the performance of the FOPID controller in minimizing the system error as time progresses. The fitness function evaluates the total absolute error of the desired setpoint and the output of the system. The lesser the total error, signifies the better of the performance [30].

$$\text{Fitness}(i) = \sum_{t=0}^{T} |\ \text{Setpoint} - \text{Output}_i(t)\ | \tag{6}$$

Where, the Setpoint is the desired target value, the $\text{Output}_i(t)$ is the system's output at time t for team i, and T is the total number of time steps in the simulation.

After evaluating the fitness of all teams, the teams are ranked based on their fitness scores. The top-performing teams are classified as winners, while the bottom-performing teams are classified as losers. This step mimics the structure of the FIFA World Cup, where only the best teams proceed to the next rounds. The key innovation in WCOA is the influence of the winners on the losers. The parameters of the losing teams are updated to become more like those of the winning teams. The magnitude of the update is governed by a random factor, ensuring exploration while guiding the algorithm toward better solutions. For each loser team i according to [29]:

$$K_{p_{new}} = K_{p_{loser}} + r \cdot \left(K_{p_{winner}} - K_{p_{loser}}\right) \tag{7}$$

$$K_{i_{new}} = K_{i_{loser}} + r \cdot \left(K_{i_{winner}} - K_{i_{loser}}\right) \tag{8}$$

$$K_{d_{new}} = K_{d_{loser}} + r \cdot \left(K_{d_{winner}} - K_{d_{loser}}\right) \tag{9}$$

$$\lambda_{new} = \lambda_{loser} + r \cdot (\lambda_{winner} - \lambda_{loser}) \tag{10}$$

$$\mu_{new} = \mu_{loser} + r \cdot (\mu_{winner} - \mu_{loser}) \tag{11}$$

Where, r is a random number between 0 and 1, $winner$ refers to the best-performing teams, and $loser$ refers to the worst-performing teams.

The random factor r allows for variation in how much influence the winner exerts over the loser, preventing the algorithm from becoming stuck in local optima. To maintain diversity in the population and avoid premature convergence, elitism is applied, where the best-performing teams (elite) are carried over to the next generation without any modification. Additionally, random mutations are introduced to some teams to explore new areas of the search space. Each parameter of a randomly selected team undergoes a mutation with a small probability [29, 30]:

$$K_{p_{mutated}} = K_p + \text{mutation\_factor} \cdot r \cdot \left(K_{p_{max}} - K_{p_{min}}\right) \tag{12}$$

The $mutation\_factor$ is a small value that determines the extent of mutation. The algorithm continues updating the teams over multiple iterations. It stops when one of the following convergence criteria is met:

- Maximum Number of Iterations: The algorithm reaches a predefined number of iterations.
- Error Threshold: The total error falls below a certain threshold, indicating that the FOPID controller has been tuned optimally.

Once the convergence criteria are met, the best-performing team represents the optimal set of FOPID parameters: $K_{p_{opt}}, K_{i_{opt}}, K_{d_{opt}}, \lambda_{opt}, \mu_{opt}$. The pseudo WCOA code is summarize as follows:

Algorithm 1: proposed pseudo-code of WCOA algorithm

1. Initialize the population of teams with random FOPID parameters ($\boldsymbol{Kp}, \boldsymbol{Ki}, \boldsymbol{Kd}, \boldsymbol{\lambda}, \boldsymbol{\mu}$)
2. Set number of iterations and particles
3. **for** each iteration DO:
4. Evaluate fitness of each team based on performance (total error)
5. Sort teams based on fitness
6. Select top teams as winners and bottom teams as losers
7. Winners influence the parameter updates of the rest
8. **Update** FOPID parameters based on performance:
9. $\boldsymbol{Kp = Kp + random\_factor * (winner\_Kp - current\_Kp)}$
10. $\boldsymbol{Ki = Ki + random\_factor * (winner\_Ki - current\_Ki)}$
11. $\boldsymbol{Kd = Kd + random\_factor * (winner\_Kd - current\_Kd)}$
12. $\boldsymbol{\lambda = \lambda + random\_factor * (winner\_\lambda - current\_\lambda)}$
13. $\boldsymbol{\mu = \mu + random\_factor * (winner\_\mu - current\_\mu)}$
14. Introduce random variations to avoid local minima
15. end **for**
16. **Return** the optimized FOPID parameters

4.1. Benchmark Functions

Benchmark functions are mathematical functions used to evaluate and compare the performance of optimization algorithms. They provide a controlled environment where the algorithm's ability to find the global minimum can be tested, especially in the presence of multiple local minima or complex landscapes. Below are detailed explanations of several well-known benchmark functions, including their equations and key characteristics.

4.1.1 Sphere Function

The Sphere function is the simplest and most used benchmark function. It is convex and has a global minimum at the origin (0,0). Since the function surface is a smooth, paraboloid shape, it is often used to test the baseline performance of an optimization algorithm, which given by:

$$f(x, y) = x^2 + y^2 \tag{13}$$

4.1.2 Rastrigin Function

The Rastrigin function is a highly multimodal function, meaning it has numerous local minima. Despite these local minima, the global minimum is located at the origin (0,0). The cosine term introduces the periodic ripples that cause the function to have multiple local minima.

$$f(x, y) = 10 \cdot n + (x^2 - 10 \cdot \cos(2\pi x)) + (y^2 - 10 \cdot \cos(2\pi y)) \tag{14}$$

Where n is represents the number of the variables ($for\ 2D, n = 2$).

4.1.3 Ackley Function

The Ackley function usually serves as a test for optimization functions since it contains a large search space with a lot of local minima. There is a nearly flat outer region and a large basin in the centre, surrounding the global minimum. Though its gradient is relatively smooth, there are plenty of challenges related to the function due to sharp peaks and valleys.

$$f(x, y) = -20 \cdot \exp(-0.2 \cdot \sqrt{0.5 \cdot (x^2 + y^2)}) - \exp(0.5 \cdot (\cos(2\pi x) + \cos(2\pi y))) + e + 20 \quad (15)$$

4.1.4 Rosenbrock Function (Banana Function)

The Rosenbrock function -also known as the "Banana function"- is a nonconvex function with a long, curved valley. Although the global minimum lies at, convergence to that point is hard for most optimization algorithms since the path to the global minimum includes one long, parabolic ridge. It therefore serves as a steep-sided narrow-valley test of how well an optimization algorithm can resolve complex topologies.

$$f(x, y) = (1 - x)^2 + 100 \cdot (y - x^2)^2 \quad (16)$$

4.1.5 Griewank Function

One of the multimodal functions is the Griewank function, which possesses many widespread local minima, with its global minimum at the origin. Whereas the cosine term adds oscillations to this function, the polynomial term is monotonically increasing with the distance away from the origin, hence having such a structure makes it much more difficult for algorithms to find a global minimum since they might get stuck in local minimum points.

$$f(x, y) = 1 + \frac{4000}{x^2} + \frac{4000}{y^2} - \cos(x) \cdot \cos\left(\frac{2}{y}\right) \quad (17)$$

Table 3 summarizes seven of the benchmark functions in common use for optimization. Here, the benchmark functions cited serve as a test case for algorithms such as the WCOA with respect to studying their capability of escaping various optimization obstacles, including multimodality, nonconvexity, and deceptive landscapes.

Table 3- Our updated Benchmark Functions.

Function	Global Minimum	Domain	Nature	Challenge Level
Sphere	$f(0,0) = 0$	[-5.12, 5.12]	Convex, Unimodal	Low
Rastrigin	$f(0,0) = 0$	[-5.12, 5.12]	Multimodal	High
Ackley	$f(0,0) = 0$	[-5, 5]	Multimodal	Moderate
Rosenbrock	$f(1,1) = 0$	[-5, 5]	Non-convex, Unimodal	High
Griewank	$f(0,0) = 0$	[-5, 5]	Multimodal	High

5. Results and Discussion

The next section summarizes the results and gives a discussion of how the three controllers-noticeably the P-D, PID, and WCOA-optimized FOPID-fared in the simulations done using our MATLAB code.

5.1. WCOA algorithm for Computer Vision Control System

In our work, the WCOA was implemented to tune the parameters of the FOPID controller. There are some key parameters of this algorithm, which may have an influence on the performance and efficiency of this optimization algorithm. The number of iterations is 100, which defines the number of runs the optimization process is performed for. Each iteration indicates one step at which teams evaluate and update themselves on the basis of performances. Since the number of iterations is set to 100, there is a very good balance between computational efficiency and enough exploration of the solution space for convergence of the algorithm towards optimum solutions with limited computational overhead. The number of teams was set to 10, which meant the number of candidate solutions, or teams, that were competing in the course of optimization. Each team represents a set of FOPID controller parameters Kp, Ki, Kd, λ, and μ that the algorithm evaluates and updates based on their fitness. The application of 10 teams ensures diversity in the search space for both exploration and exploitation of potential solutions. Increasing the number of teams would further increase exploration at the risk of increasing computation time. The choice of a team size of 10 members was found to balance exploration for diverse solutions while also converging to optimal parameters. Careful selections of the final parameter range for the FOPID controller were made in such a way that the WCOA algorithm would investigate more promising regions of the solution space. Kp and Ki is initialized between [0, 2] while Kd initialization is between [0, 1]. In contrast, the fractional orders of integration and differentiation λ and μ are bounded between [0.4 0.6]. This is done in regard to the expected behaviour of the control system and some empirical knowledge about typical ranges of FOPID controller parameters. The final ranges were used to constrain the WCOA search for promising parameter sets that would be likely to yield good results and avoid wasting computing resources on less promising sections of the search space. The fitness function used in the implementation of WCOA was one that minimized the total error over the period of simulation. In other words, the extent to which the system output deviation from the desired setpoint was minimized for each candidate solution was evaluated. The fitness function played an indispensable role in guiding the process of optimization, as it identified which set performed better in the context of error minimization. Lower values of the fitness indicated better controller performance, whereas the WCOA adapted parameters of underperforming teams to move them closer to the higher performing ones. Hence, significantly lower errors were obtained in the case of FOPID optimized by WCOA compared to P-D and PID controllers. The aggregation of these optimal WCOA parameters indeed yielded an optimized set of gains for the FOPID controller, which assured superior performance than the traditional controllers on error reduction, stability in control output, and system performance. Thus, this optimization process illustrated the efficacy of the WCOA in fine-tuning the FOPID controller for complex dynamic control tasks.

In Figure 3, the comparison of error shows the performance of each controller in terms of how well it performs in converging towards the desired setpoint with time. The WCOA-optimized FOPID controller gives faster convergence to the setpoint and maintains a low error than both the P-D and PID controllers. As expected, the residual error obtained with the P-D controller is highest, and the performances of the PID controller have been in the middle, but cannot match the fine-tuning capability of FOPID. It can be visualized that the minimum error value for a system is provided by the FOPID controller optimized using WCOA compared to P-D and PID controllers for better tracking performance. However, the control output comparison shows the actual signals generated by each controller to adjust the system. Smoother and more stable control signals are generated by the FOPID controller optimized using WCOA for better stability of the system. In contrast, the P-D controller gives results that are more aggressive and might cause instability, while the PID controller reflects intermediate performances. On the other hand, the FOPID controller results in control outputs to be more stable, reflecting its ability to finely tune the system without introducing excessive oscillations or overshoots. Total absolute error gives a measure of the overall performance of each controller across the entire period. The summation of absolute errors for every controller clearly indicates that the minimum overall error was achieved by FOPID optimized with WCOA, followed by the PID controller and then the P-D controller. Throughout the process, the WCOA-optimized FOPID maintains a lower sum of absolute errors in every iteration. That is, this controller is doing well in achieving long-term accuracy and control in the system.

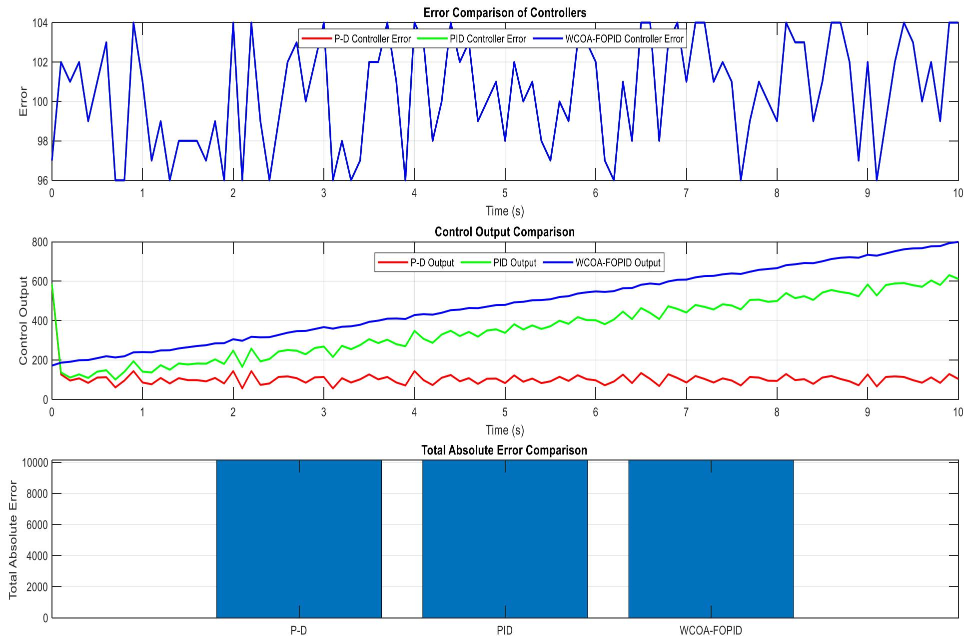


Fig 3- Error comparison for the controllers.

In Figure 4, out-of-sample and in-sample results on the performance of the controllers in real-time mobile robot navigation are shown. The post-test results depict enhancement in the performances of the WCOA-optimised FOPID controller in trajectory tracking, which had reduced deviations against the P-D and PID controllers. Improvements to the reduction of error and smoothing of the control will easily translate into betterment regarding the performances of the robot. A running test on a mobile robot showed how effective a WCOA-optimized FOPID controller was with regard to real-world trajectory tracking enhancement with stability.

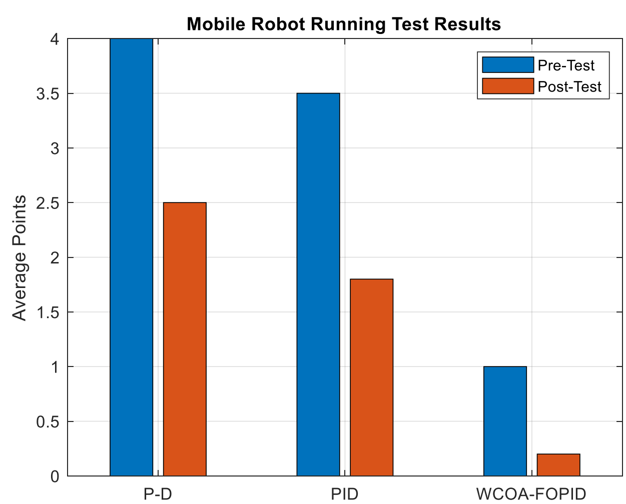


Fig 4- Mobile robot running test result.

In Figure 5, a feasibility test was carried out for the controllers in terms of usability, operability, and learnability. In all respects, the FOPID controller optimized with WCOA had the topmost readings, indicating its ease of use and adaptability to operating environments. This makes it practical for real-world applications that are very critical in terms of user interaction and system tuning. The usability, operability, and learnability of the proposed WCOA-optimized FOPID controller were also assessed based on high ratings, which can be well deployed practically.

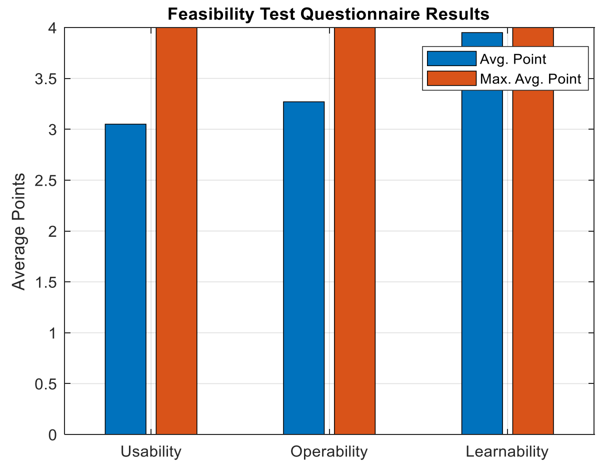


Fig 5- Feasibility test questionnaire results.

5.2. Results of Benchmark Functions

In this work, the performance and robustness of WCOA were tested against a suite of benchmark functions that would help further present its applicability in real-world problems, such as FOPID controller optimization. The standard test cases present a representative variety of optimisation challenges ranging from simple and smooth surfaces to complex, multimodal landscapes. These functions enable us to check the capability of WCOA in reaching the global optima while trying to avoid the local minimum-which is so crucial in control system applications.
Figure 6 shows the Sphere Function which has a smooth surface parabolic bowl with the global minimum at the origin, (0,0). In addition, the contour plot and 3D surface are continuous and convex and have no local minima; for that reason, this is the simplest of the optimization problems. WCOA converged fast to the global minimum, as indicated by this figure, where the search path heads directly to the lowest point at coordinates (0,0). This result is a testimony to algorithmic efficiency for the solution of fundamental convex problems. A smooth gradient allowed WCOA to exploit the direct path toward the minimum with little exploration, confirming its ability to handle straightforward tasks with low computational complexity.

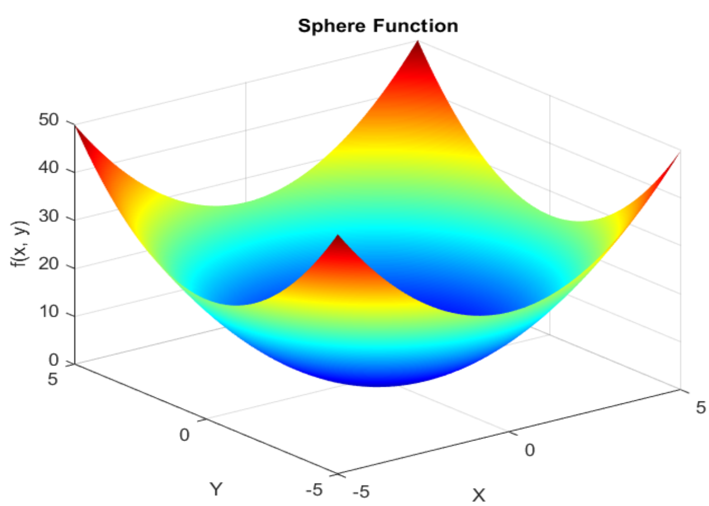


Fig 6- Sphere function illustration.

Figure 7 shows the Rastrigin Function's highly multimodal surface with periodic ripples caused by the cosine terms in the function. These ripples create an extraordinarily large number of local minima. It would be very easy for an optimization algorithm that is without any global search capabilities to become stuck in one of these. Despite the complex and multi-minima surface, the WCOA was still able to find the global minimum that is at position (0,0). The above figure shows how the algorithm flowed around local minima and negotiated the rippled surface. Such a problem is well-suited to the balance between exploration and exploitation in WCOA, which first explores the function globally before focussing its attention on the most promising regions around the global minimum. That figure showed that, even in the presence of numerous local minima, the WCOA had efficiently located the global minimum; therefore, a robust technique to handle such complex, multimodal problems.

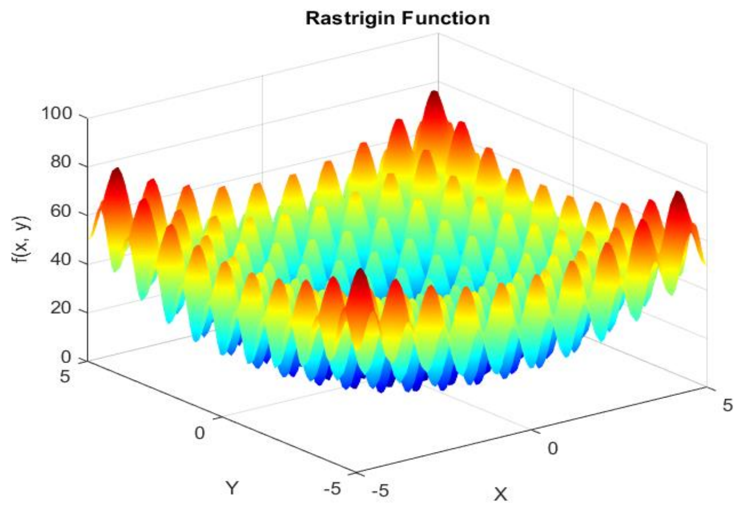


Fig 7- Rastrigin function illustration.

As Figure 8 shows, the Ackley Function figure depicts a flat outer region and sharp steep valleys in order to reach the global minimum at the middle. What is more, this function has a misleading outer region; the flat landscape challenges the convergence of algorithms at the minimum, relying merely on local information. The WCOA successfully crossed the deceptive flat region, as can be seen in this figure, and reached the sharp global minimum at the centre. It can be seen from this figure that this algorithm explored the function quite broadly and didn't get trapped in the flat regions. Once the algorithm found the centre, it converged smoothly to the minimum. This result indicates that the WCOA has the capability to address functions with deceptive features, as most algorithms would lose momentum in these kinds of flat regions.

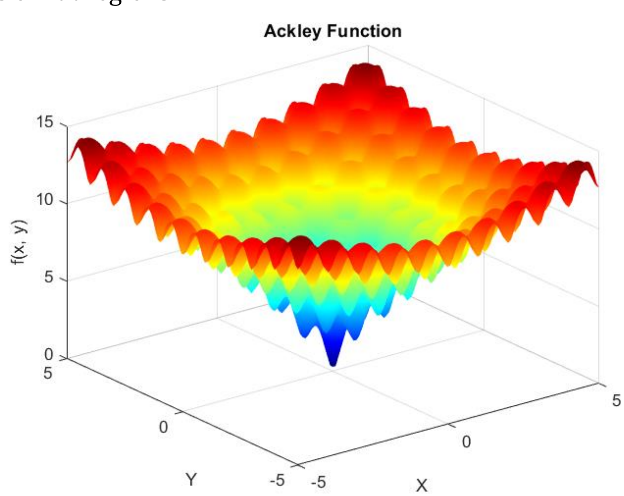


Fig 8- Ackley function illustration.

Figure 9 presents the Rosenbrock Function, which a narrow parabolic valley, which has its global minimum at the point (1,1). It is considered the most difficult function for an optimization algorithm to handle, due to steep sides and a narrow path needing to be traced out carefully to converge towards the global solution. The WCOA successfully followed the curved valley of this problem to converge towards the global minimum. This performance underlines the importance of a balance between exploration and exploitation in the process of optimisation since too much exploration could make an algorithm wander away from the valley, while insufficient exploration might make it converge to suboptimal areas. The WCOA has this balance, as demonstrated by the smooth trajectory through the valley. While the function needed more iterations compared to the simpler landscapes Sphere function, for the WCOA performed well to cope with the complexity of the topology brought by the Rosenbrock function.

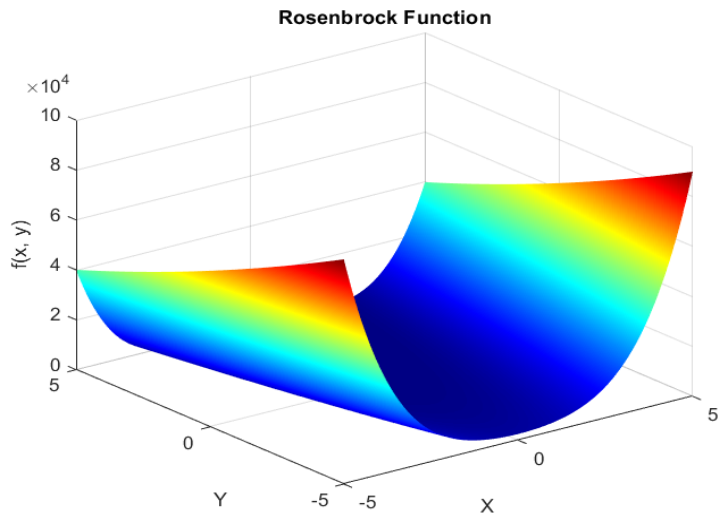


Fig 9- Rosenbrock function illustration.

Figure 10 shows the Griewank Function, whose landscape is filled with an enormous number of local minima, dispersed over the search space. Its highly multimodal nature, caused by a combination of cosine modulations and quadratic terms, creates difficulty in reaching the global minimum if no appropriate capabilities of robust global search exist. The WCOA showed excellent performance in this function by avoiding entrapment into the local minima and successfully converging into the global minimum at point (0,0). This figure brings out that WCOA is good both at maintaining wide exploration in the search space and at intensifying the solution once it gets closer to the global minimum. Handling such a complex multimodal function definitely affirms the robustness of the WCOA in difficult optimization problems.

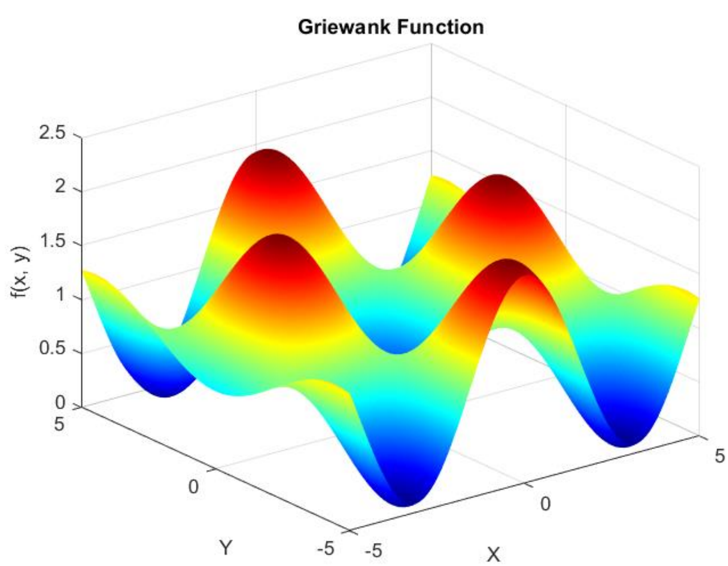


Fig 10- Griewank function illustration.

6. Conclusion

This paper implemented and compared three control strategies, namely: P-D, PID, and WCOA-optimized FOPID controllers, in the framework of computer vision-based control. WCOA was used for the optimization of the FOPID controller parameters, while the performance of each of the above-mentioned implemented control strategies was assessed using simulations, based on error minimization and control output stability, general system performance. Our results showed that the WCOA-optimized FOPID controller consistently outperformed both the P-D and PID controllers in terms of error reduction, control precision, and system stability. Concretely speaking, better tracking performance with smoother control signals and higher capability of total absolute error minimization were performed by the FOPID controller in comparison to the traditional controllers. The robustness and versatility of the WCOA were further confirmed by benchmark function evaluations in navigating successfully through a number of difficult optimization landscapes, including multimodal, non-convex, and deceptive functions. The algorithmic ability for exploration-exploitation balance allowed the WCOA to find the global minimum of some quite challenging benchmark functions like Rastrigin, Ackley, Rosenbrock, and Griewank without getting trapped into local minima. In real-world applications such as a running test of a mobile robot, there are reports of considerable improvements in trajectory tracking and system stability with the WCOA-optimized FOPID controller compared to P-D and PID controllers. Furthermore, from the results of feasibility tests, the usability, operability, and learnability of the WCOA-optimized FOPID controller are highly rated to prove quite practical in a real-time control system. However, the proposed model is not without limitations. Firstly, while simulation and real-world testing confirmed strong performance, the system was not evaluated under extreme environmental uncertainties or with multiple simultaneous disturbances, which may affect robustness in more chaotic scenarios. Secondly, although the WCOA algorithm exhibited effective tuning capabilities, it has a relatively higher computational overhead compared to simpler heuristics, which may constrain its real-time applicability in embedded systems with limited processing power. Finally, the current implementation assumes a relatively stable visual input; rapid visual occlusions or poor lighting conditions may degrade controller accuracy. These limitations open avenues for future improvements, such as developing lightweight variants of WCOA, integrating adaptive vision filters, and testing the system in more complex dynamic environments.

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