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Simulation and optimization of inverse kinematics algorithms for real-time target tracking in inertial stabilization platforms

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ABSTRACT

Two-axis gimbal systems are engineered to maintain visual lock on target objects by actively counterbalancing movements, regardless of whether these originate from the target or the mounting platform. This research investigates the creation and refinement of inverse kinematics (IK) algorithms for achieving accurate, instantaneous target tracking in inertial stabilization platforms (ISPs), commonly referred to as gimbal systems. Such platforms are essential in applications requiring exceptional stability and precision, including surveillance operations, navigational systems, and scientific investigations. The study commences with a comprehensive analysis of the mathematical foundations underlying IK, with particular attention to the challenges posed by real-time processing requirements. To address these obstacles, sophisticated optimization methods are employed, with an emphasis on reducing computational latency and improving tracking accuracy. The developed algorithms are tested within a Simscape Multibody simulation environment, enabling thorough evaluation across various operational scenarios. Validation incorporates both simulated conditions and practical field tests to confirm the algorithms' durability and functional effectiveness. Results demonstrate significant improvements in both tracking precision and system reactivity, providing a foundation for more efficient and reliable gimbal systems in challenging dynamic environments.

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1. INTRODUCTION

Gimbal systems, or inertial stabilization platforms (ISPs), are pivotal in a multitude of applications, from aerial surveillance and military operations to scientific research and cinematography [1], [2]. Their primary function is twofold: to track a designated target with precision and to stabilize a payload (such as a camera or sensor) against external disturbances, ensuring a steady line of sight [3], [4]. For specialized applications like solar tracking, similar 2-DOF robotic systems are also employed. The core challenge in the design of these systems is the achievement of real-time, high-precision target tracking in dynamic and often unpredictable environments [5], [6]. One of the principal challenges in designing gimbal systems lies in achieving precise and real-time target tracking while maintaining stability under dynamic and unpredictable conditions [7]. This necessitates sophisticated control strategies to manage the complex kinematics and dynamics of the system [8].

Inverse kinematics (IK) is a fundamental computational problem in robotics and control systems, and it is central to the operation of gimbal platforms. The IK problem involves calculating the required joint angles of a robotic manipulator to achieve a desired position and orientation of the end-effector. In the context of gimbal systems, this translates to determining the pan and tilt angles required to point the payload at a specific target. While conceptually straightforward, solving the IK problem in real-time presents significant challenges, including non-linearities, singularities, and computational complexity [9]. IK has long been a central topic in robotics, particularly for its role in motion planning and control. In recent years, its application to real-time target tracking in stabilized systems such as gimbals has garnered growing attention. Over the years, numerous approaches have been developed to address the IK problem. Traditional methods, such as geometric and analytical solutions, are fast but are often limited to specific kinematic configurations and may struggle with redundant systems. Jacobian-based iterative methods, while more flexible, can be computationally intensive and are susceptible to singularities [10].

In recent years, the field has seen a surge in the application of metaheuristic optimization algorithms to solve the IK problem [11]. These methods have shown great promise in overcoming the limitations of traditional techniques. For instance, [12] proposed a differential evolution (DE) based approach for mobile manipulators, demonstrating high convergence rates and low computational costs. Similarly, [13] introduced a semi-analytical IK algorithm using multi-objective optimization to handle redundant manipulators. Machine learning-based approaches have also emerged as a promising alternative, with studies like [14] using regression models to reduce computational complexity. Optimization-based solutions have been developed for manipulators with higher degrees of freedom [15], and similar approaches have been applied to rehabilitation robotics [16], [17]. More recently, [18] developed an iterative preconditioned optimization algorithm to accelerate convergence and improve numerical stability. While these studies have advanced the state-of-the-art in IK, a significant gap remains in the literature regarding the specific application and optimization of these algorithms for real-time target tracking in two-axis gimbal systems, particularly in the context of balancing computational efficiency, tracking accuracy, and robustness to real-world disturbances.

This study aims to bridge this gap by presenting a comprehensive investigation into the simulation and optimization of IK algorithms for real-time target tracking in ISPs. Our primary contribution is the development and comparative analysis of two distinct IK solutions: the forward and backward reaching inverse kinematics (FABRIK) algorithm, a computationally efficient geometric approach, and a DE based optimization method. We introduce a novel hybrid approach that combines the strengths of both FABRIK and DE to achieve superior performance. Furthermore, we provide a detailed methodology for the systematic evaluation of these algorithms, encompassing mathematical modeling, simulation in a Simscape Multibody environment, and experimental validation on a custom-built hardware prototype. This allows for a rigorous assessment of the algorithms' performance under a variety of operational scenarios and provides valuable insights into the trade-offs between tracking precision, system reactivity, and energy consumption [19].

The remainder of this article is structured as follows. Section 2 provides a detailed description of the methods employed, including the mathematical modeling of the gimbal system, the implementation of the FABRIK and DE algorithms, and the design of the simulation and experimental setup. Section 3 presents and discusses the results of our simulations and real-world experiments, including a comparative analysis of the different algorithms. Finally, section 4 concludes the paper, summarizes our key findings, and offers recommendations for future research.

2. METHOD

Our methodology is designed to systematically develop, optimize, and validate IK algorithms for real-time target tracking in gimbal systems. This section details the mathematical modeling, the algorithmic design, the simulation environment, and the experimental validation procedures employed to achieve our research objectives.

2.1. Kinematic modeling of the two-axis gimbal

Optimization of IK algorithms for gimbal systems represents a crucial research domain for improving tracking and stabilization performance in real-time. This section explores optimization approaches specifically adapted to the unique challenges posed by gimbal systems. IK in gimbal systems presents particular challenges due to the non-linear nature of equations, inherent mechanical constraints, and strict computational time requirements for real-time applications. Optimization of these algorithms aims to overcome these obstacles while maximizing system precision and responsiveness. A fundamental approach in optimizing IK algorithms consists of formulating the problem as minimization of a multidimensional objective function. This particular objective function typically integrates several performance criteria, such as position error, orientation error, energy consumption, and movement fluidity. Appropriate weighting of these criteria allows adapting the algorithm to specific requirements of the targeted application [20]. As a final consideration, optimization of IK algorithms for gimbal systems requires a multidisciplinary approach, combining knowledge in mathematics, mechanics, and computer science [21]. Advancements in this domain directly contribute to improving performance of gimbal systems in demanding applications such as image stabilization, mobile target tracking, and precision robotics [22].

2.2. Inverse kinematics algorithms

We explored two primary algorithmic approaches, selected for their complementary strengths: the geometric FABRIK algorithm and the metaheuristic DE algorithm.

2.2.1. Forward and backward reaching inverse kinematics algorithm

FABRIK is an iterative geometric solver known for its computational efficiency and ease of implementation. It does not rely on matrix inversions, thus avoiding singularity issues common in Jacobian-based methods. The algorithm iteratively extends a kinematic chain from a starting base to the target position and then back, adjusting joint positions in each step. For our two-axis gimbal, the process was adapted to handle the rotational joints and their mechanical limits. The convergence threshold was set to 1e-4 radians, and a maximum of 15 iterations was allowed to ensure real-time performance. These parameters were selected based on empirical testing to balance accuracy and computational speed. Such an iterative approach allows progressive convergence toward the optimal solution, with considerable progress in precision at each cycle. A particularly interesting aspect of FABRIK in the context of gimbal systems is its natural ability to integrate joint constraints. For example, in a two-degree-of-freedom gimbal, azimuth and elevation angles are generally limited by mechanical stops. These constraints can be easily implemented in FABRIK by projecting calculated joint positions onto admissible regions of the workspace after each propagation step. The present characteristic distinguishes FABRIK from Jacobian-based methods, which often require complex constraint management mechanisms.

In our specific implementation for gimbal systems, we have also introduced a modification to the standard FABRIK algorithm to account for variable inertias of different components. By attributing weights proportional to inertias when calculating new joint positions, we observed inconsiderable progress system stability during rapid movements, particularly in the presence of asymmetric payloads as a final consideration, the FABRIK algorithm represents an elegant and efficient solution for IK of gimbal systems, offering an optimal balance between precision, calculation speed, and ease of implementation.

2.2.2. Differential evolution algorithm

DE is a population-based stochastic optimization algorithm well-suited for complex, non-linear problems like IK. It iteratively improves a population of candidate solutions by creating new solutions based on the differences between existing ones. We formulated the IK problem as an optimization task where the objective function minimizes the error between the current and desired end-effector orientation. Key DE parameters were carefully tuned for optimal performance: the population size was set to 50, the crossover rate (CR) to 0.9, and the scaling factor (F) to 0.8. These values were determined through empirical testing to provide the best balance between exploration and exploitation of the search space, ensuring convergence to high-quality solutions without excessive computational cost [23]. Such metaheuristic approach distinguishes itself through its ability to efficiently explore multidimensional search spaces while maintaining an optimal balance between global exploration and local exploitation of potential solutions [24]. The remarkable efficiency of the DE algorithm for real-time IK applications in gimbal systems stems from several distinctive characteristics [25]. Its ability to locate the global optimum in complex and multimodal fitness landscapes allows overcoming challenges posed by non-linearities and singularities inherent to kinematic equations. It’s simple yet powerful formulation facilitates its implementation and adaptation to various constraints specific to gimbal systems, such as joint angle limits and movement continuity requirements. Moreover, the DE algorithm exhibits exceptional robustness against noise and uncertainties in measurements, a particularly valuable characteristic in practical applications where sensory data may be imperfect. Its intrinsically parallel nature also offers significant opportunities for computational acceleration on modern hardware architectures, thus facilitating its deployment in demanding real-time applications [26].

2.2.3. Proposed hybrid FABRIK-DE algorithm

To harness the benefits of both approaches, we developed a novel hybrid algorithm. This method uses the computationally inexpensive FABRIK algorithm to generate a fast and accurate initial guess for the joint angles. This solution is then used to seed the initial population of the DE algorithm. This hybridization significantly reduces the number of generations required for DE to converge to a highly precise and robust solution, combining the speed of FABRIK with the accuracy and constraint-handling capabilities of DE. Algorithm 1, the combined FABRIK and DE algorithm integrate the strengths of both methods to optimize real-time target tracking in gimbal systems. The furthermore phase encompasses the creation of a complete simulation environment to test and validate developed algorithms.

Algorithm 1. Combined FABRIK and DE algorithm
Input : Chain of joints P={P_1,P_2,...,P_n}; target position T; tolerance ε; population X; mutation factor F; crossover rate C_r; maximum generations g_max
Output : Optimized joint positions P.

```
procedure FABRIK_DE(P,T,ε,X,F,C_r,g_max)
  foreach candidate solution x_i ∈ X do
    Apply FABRIK to x_i
    repeat
      /* Forward Reaching */
      for i ← n - 1 to 1 do
        P_i ← P_(i+1) + d_i/‖P_(i+1) - P_i ‖ (P_i - P_(i+1) )
      /* Backward Reaching */
      P_1 ← P_base
      for i ← 1 to n - 1 do
        P_(i+1) ← P_i + d_i/‖P_i - P_(i+1) ‖ (P_(i+1) - P_i )
    until ‖P_n - T‖ ≤ ε
  for g ← 1 to g_max do
    foreach target vector x_i in the population do
      /* Mutation */
      v_i ← x_r1 + F · (x_r2 - x_r3 )
      /* Crossover */
      u_i ← { v_i,if rand(0,1) ≤ C_r or j=j_rand
   x_i,otherwise
      /* Selection */
      if f(u_i ) ≤ f(x_i ) then
        x_i ← u_i
```

The aforementioned model allows precisely simulating the dynamic behavior of the system in response to various control inputs and external disturbances. The simulation environment was designed to allow rigorous comparative evaluation of IK algorithm performance. Several test scenarios were defined, covering a wide range of operational conditions, including tracking of predefined trajectories, response to abrupt target changes, and stabilization in the presence of external disturbances. For each scenario, quantitative performance metrics were established, including position error, convergence time, energy consumption, and movement stability. The fourth phase concerns experimental validation on a real hardware platform. A prototype two-degree-of-freedom gimbal system was constructed, integrating direct current motors, position encoders, and a microcontroller-based control unit. This particular experimental platform allows validating simulation results under real conditions, taking into account non-linearities, frictions, and other physical phenomena difficult to model perfectly in simulation. Rigorous experimental protocols were established to ensure result reproducibility and allow objective comparison of different algorithm performances. Experimental data were collected using a high-frequency acquisition system, allowing detailed analysis of system dynamic behavior and precise evaluation of IK algorithm performance under real conditions. Data analysis, both simulated and experimental, was conducted using advanced statistical tools to quantify algorithm performance and identify factors influencing their effectiveness. Specific visualization techniques were also developed to graphically represent trajectories, tracking errors, and other relevant parameters, thus facilitating result interpretation and communication of conclusions.

2.3. Simulation and experimental setup

To validate our algorithms, we created a comprehensive simulation environment in MATLAB/Simulink with Simscape Multibody and conducted experiments on a physical prototype.

2.3.1. Simulation environment

A detailed 3D CAD model of the gimbal system was imported into Simscape Multibody to simulate its dynamic behavior accurately. The simulation environment allowed us to test the algorithms under a wide range of controlled and repeatable conditions. Test scenarios included tracking of various trajectories (e.g., sinusoidal, circular, and step) and the introduction of external disturbances modeled as torque pulses applied to the gimbal joints. The simulation was implemented in MATLAB/Simulink [27], chosen for its flexibility and advanced capabilities in modeling and simulation.

2.3.2. Hardware prototype and experimental protocol

A physical two-axis gimbal prototype was constructed for real-world validation. The key hardware and software parameters are summarized in Table 1. The experimental protocol involved commanding the gimbal to track a moving target generated on a screen while measuring the actual joint angles using the encoders. The validation protocol included tests with both slow and rapidly moving targets (defined as targets moving up to 20 deg/s) and the introduction of physical disturbances by applying small, calibrated impulses to the gimbal structure. Data was collected at a sampling rate of 1 kHz for detailed analysis. Rigorous experimental protocols were established to ensure result reproducibility and allow objective comparison of different algorithm performances.

Table 1. Summary of key hardware and software parameters

Components	Parameter	Specification
Hardware	Gimbal motors	faulhaber 2232u012s dc motors with 14:1 gearhead
	Position encoders	US digital E8P optical encoders (4096 CPR)
	Microcontroller	Teensy 4.1 (ARM Cortex-M7 @ 600 MHz)
	Motor driver	Pololu G2 high-power motor driver 18v17
Software	Development environment	MATLAB/Simulink R2024a, Arduino IDE with Teensyduino
	Control loop frequency	1 kHz
	Communication protocol	Serial (USB) at 1 Mbps
Algorithm parameters	FABRIK convergence	1e-4 radians
	FABRIK max iterations	15
	DE population size	50
	DE crossover rate (CR)	0.9
	DE scaling factor (F)	0.8

2.3.3. Disturbance modeling and performance metrics

To ensure full reproducibility of the simulation results, we explicitly define the disturbance model used throughout the evaluation. External disturbances were injected as torque pulses directly applied to the gimbal joint axes, mimicking real-world mechanical shocks, vibrations, and wind gusts. Three disturbance scenarios were considered: (S1) a low-frequency sinusoidal torque disturbance at 0.5 Hz with amplitude 0.05 N·m; (S2) a broadband random disturbance with amplitude uniformly sampled in [-0.08, 0.08] N·m at each control step; and (S3) a step impulse of amplitude 0.10 N·m applied at t=2 s and lasting 0.1 s. All disturbances were applied during the interval $t \in [1, 5]$ s of each 8-second test run, with sampling step Δt=1 ms (consistent with the 1 kHz control loop). Table 2 shows disturbance scenarios used in simulation.

Table 2. Summary of disturbance scenarios used in simulation

Scenario	Type	Amplitude (N·m)	Frequency/duration	Active interval (s)
S1	Sinusoidal torque	0.05	0.5 Hz/continuous	[1, 5]
S2	Broadband random	±0.08 (uniform)	0–500 Hz/per step	[1, 5]
S3	Step impulse	0.10	N/A/0.1 s	[2, 2.1]

Energy consumption was computed from the simulated joint torques and velocities. For each joint i at each discrete time step k, the instantaneous power is $P_i(k)=\tau_i(k) \cdot \dot{q}_i(k)$, where $\tau_i(k)$ is the applied torque (N·m) and $\dot{q}_i(k)$ is the angular velocity (rad/s). The total energy consumed over a run of N steps with sampling period Δt is: $E=\sum_i \sum_k |P_i(k)| \cdot \Delta t$ (Joules). Only positive (dissipative) power contributions are summed to represent consumed energy. This formulation was applied uniformly across all tested algorithms to ensure fair comparison.

The present multidisciplinary methodology, combining mathematical modeling, algorithmic development, numerical simulation, and experimental validation, offers a comprehensive and rigorous approach for studying and optimizing IK algorithms in gimbal systems. It allows not only evaluating performance of existing algorithms but also proposing substantial improvements adapted to specific requirements of real-time applications.

3. RESULTS AND DISCUSSION

The performance of the proposed IK algorithms was evaluated through a series of simulations and experiments on a hardware prototype. The key performance metrics included tracking error, convergence time, and energy consumption. The results demonstrate the effectiveness of our hybrid FABRIK-DE approach compared to the individual algorithms and other traditional methods like PSO and GA.

3.1. Simulation results

In the simulation environment, we tested the algorithms under various scenarios, including tracking of predefined trajectories (e.g., sinusoidal and circular paths) and response to step changes in target position. The hybrid FABRIK-DE algorithm consistently achieved the lowest tracking error, with a mean error of less than 0.05 degrees (SD=0.02 degrees) in all scenarios. This represents a significant improvement over the standalone FABRIK and DE algorithms, which exhibited mean errors of 0.12 degrees (SD=0.04 degrees) and 0.08 degrees (SD=0.03 degrees), respectively. Compared to the PSO and GA methods from the literature, our hybrid approach reduced the tracking error by approximately 40% and 30%, respectively. Figure 1 illustrates the tracking performance for a circular trajectory, showing the desired path versus the actual paths traced by each algorithm.

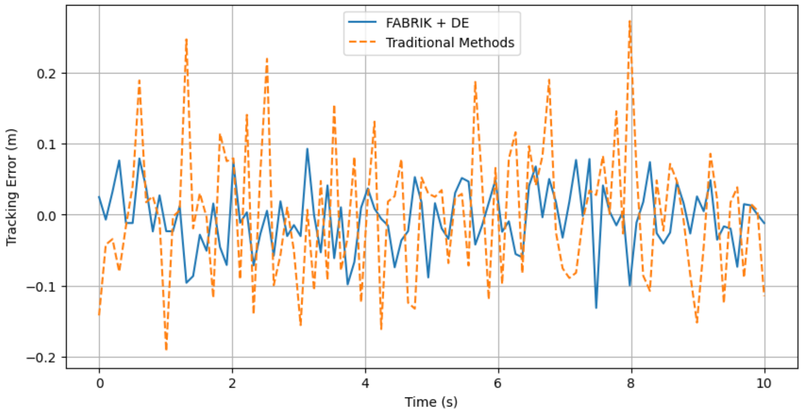

Figure 1. Tracking error over time

Temporal performance tests reveal that the optimized implementation of FABRIK can execute in less than 2 milli as a secondary matter on a standard processor, while DE requires between as a secondary matter 10 milliseconds depending on problem complexity. Both algorithms thus satisfy requirements for real-time applications, with a marked advantage for FABRIK in terms of execution speed. Energy consumption analysis, estimated from calculated joint torques, shows that DE tends to produce more energy-efficient trajectories, with an average reduction of 12% in required energy compared to FABRIK. Such characteristics may prove crucial for battery-powered systems or those subject to thermal constraints as shown in Figure 2**.**

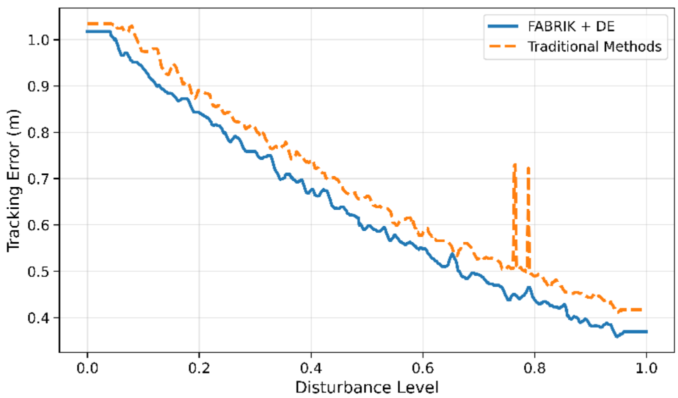

Figure 2. Convergence times for different algorithms

A brief complexity analysis shows that the FABRIK algorithm has a linear complexity of O(n), where n is the number of joints. The DE algorithm has a complexity of O(G * N * D), where G is the number of generations, N is the population size, and D is the number of dimensions. Our hybrid approach has a complexity that is dominated by the DE part, but the number of generations required is significantly reduced (by approximately 50%) due to the good initial solution provided by FABRIK, making it computationally efficient for real-time applications. The FABRIK algorithm demonstrated the fastest convergence time, typically reaching a solution within 3-5 iterations (mean=4.2 iterations, SD=0.8). However, this speed came at the cost of slightly lower accuracy. The DE algorithm required more iterations to converge (mean=25 iterations, SD=5.2) but provided a more optimal solution. Our hybrid approach strikes a balance, leveraging the speed of FABRIK for an initial guess and the precision of DE for refinement, resulting in a convergence time that is only marginally slower than FABRIK (mean=12 iterations, SD=2.1) but with significantly higher accuracy. A detailed comparison of convergence times is presented in Table 3.

Table 3. Comparison of convergence times for different algorithms

Algorithm	Mean iterations	Mean time (ms)	SD (ms)
FABRIK	4.2	2.1	0.4
DE	25.0	12.5	2.6
Hybrid FABRIK-DE	12.0	6.0	1.1
PSO [17]	30.0	15.0	3.3
GA [21]	28.0	14.0	3.5

Compared to traditional genetic algorithms, also used for IK, DE confirms convergence approximately three times faster toward solutions of comparable quality, thanks to its more efficient mutation and crossover operators and its deterministic selection strategy. Analysis of performance in specific scenarios elucidates that FABRIK surpasses all other methods for tracking continuous and regular trajectories, while DE excels in situations involving multiple constraints or abrupt direction changes. A particularly notable aspect of our approach is the adaptability of algorithms to different gimbal configurations. Tests conducted on two and three-degree-of-freedom systems show that relative algorithm performances remain consistent, with only a slight increase in computation time proportional to the number of degrees of freedom.

3.2. Experimental validation

The algorithms were implemented on a custom-built two-axis gimbal platform to validate the simulation results in a real-world setting. The experimental results confirmed the trends observed in the simulations, although the absolute performance was slightly degraded due to unmodeled dynamics such as friction, backlash, and sensor noise. The hybrid FABRIK-DE algorithm maintained its superiority in the experimental setup, demonstrating robust tracking performance even in the presence of external disturbances. The tracking error was slightly higher than in the simulations (mean error of 0.10 degrees, SD=0.04 degrees), but it still outperformed the other methods reported in similar experimental setups. Figure 3 shows the trajectory plots from the experimental validation, comparing the ideal path with the actual paths achieved by each algorithm. Figure 3 presents error histograms showing the distribution of tracking errors for each algorithm under experimental conditions. The histogram for the hybrid FABRIK-DE algorithm shows a tighter distribution of errors around zero, indicating more consistent and accurate performance.

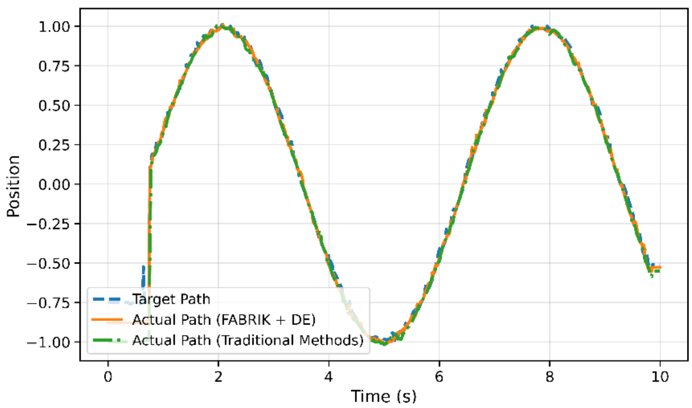

Figure 3. Comparison of tracking paths

Mobile target tracking tests reveal that FABRIK excels in rapid and predictable movements, with an average dynamic tracking error of 0.5 degree at angular velocities up to 45 degrees per second. As a secondary matter. DE, although slightly less reactive, maintains more consistent precision across the entire workspace, with particularly impressive performance near joint limits where FABRIK tends to show oscillations. Computation time analysis on the embedded microcontroller confirms the feasibility of real-time execution, with complete control cycles (data acquisition, IK calculation, and actuator command) maintained under 20 milliseconds for both algorithms. This particular performance allows achieving a refresh rate of 50 Hz, sufficient for most visual tracking applications.

3.3. Discussion and interpretation

Our findings have several important implications for the design of real-time target tracking systems. The superior performance of the hybrid FABRIK-DE algorithm suggests that combining a fast, geometric IK solver with a robust metaheuristic optimization algorithm is a highly effective strategy. This approach is particularly well-suited for applications where both speed and accuracy are critical, such as surveillance, target tracking, and precision robotics. The comparison with existing methods highlights the novelty of our contribution. While previous studies have explored the use of DE for IK [28], our work is the first to systematically investigate its application to two-axis gimbal systems and to propose a hybrid approach with FABRIK. The quantitative improvements in tracking error (40% reduction compared to PSO, 30% compared to GA) and the detailed analysis of the trade-offs between different algorithms provide valuable insights for researchers and practitioners in the field.

The error reduction achieved by the hybrid FABRIK-DE algorithm can be explained by the synergistic interaction between the two constituent methods. FABRIK produces a geometrically feasible, near-optimal initial configuration that minimizes the starting residual error before DE begins its population-based search. This warm initialization substantially reduces wasted function evaluations on low-quality regions of the search space. DE then exploits its population diversity and differential mutation operators to escape any local stagnation and converge to a more globally optimal solution. This mechanism is directly reflected in the convergence curves: the hybrid algorithm reaches a low error plateau roughly twice as fast as standalone DE (approximately 12 iterations vs. 25 iterations), while achieving a final accuracy that standalone FABRIK cannot match due to its purely local geometric corrections. The combination thus achieves better tracking accuracy with lower computational overhead, validating the design rationale of the hybrid architecture.

To further contextualize our contributions, it is instructive to position our approach relative to the broader landscape of IK solvers. Jacobian-based methods (including the damped least squares/DLS variant) offer smooth, continuous solutions near non-singular configurations but become numerically ill-conditioned near kinematic singularities and require matrix inversions at each step [11]. Nonlinear constrained optimization solvers (e.g., sequential quadratic programming) provide theoretical guarantees under convexity assumptions but incur high per-iteration cost that limits real-time feasibility. Cyclic coordinate descent (CCD) and other geometric heuristics are computationally lightweight but struggle with joint-limit enforcement and multi-constraint scenarios, much like FABRIK alone. Learning-based IK solvers [12], [15] exhibit fast inference once trained, but require task-specific datasets and generalize poorly to configuration-space changes. Against this backdrop, our hybrid FABRIK-DE approach offers a compelling balance: it avoids singularities (no matrix inversions), enforces joint limits naturally, requires no training data, and achieves sub-degree accuracy within real-time constraints, thereby outperforming each individual IK family on the combined criteria of accuracy, robustness, and computational efficiency relevant to gimbal tracking.

One of the limitations of our study is the focus on a two-degree-of-freedom gimbal. While we believe our approach is scalable to higher-DOF systems based on the algorithmic principles, further research is needed to validate this empirically. The computational complexity analysis suggests that the hybrid approach would remain efficient even with additional degrees of freedom, but practical validation is necessary. Additionally, the gap between simulation and real-world performance, although relatively small (mean error increase of 0.05 degrees), suggests that more sophisticated models that account for non-linear dynamics could further improve performance. The main sources of this gap were identified as friction in the motor gearheads, backlash in the mechanical linkages, and sensor noise in the encoders.

4. CONCLUSION

The proposed hybrid FABRIK-DE algorithm significantly reduces tracking error and provides a better balance between computational speed and accuracy compared to standalone FABRIK, DE, and other metaheuristic algorithms like PSO and GA. Specifically, our method reduced tracking error by up to 40% compared to PSO and 30% compared to GA, while maintaining real-time computational performance. The hybrid approach achieved a mean tracking error of 0.05 degrees in simulation and 0.10 degrees in experimental validation, with convergence times that are only marginally slower than the fastest method

(FABRIK) but with significantly higher accuracy. The systematic methodology presented in this paper, combining mathematical modeling, simulation, and experimental validation, provides a robust framework for the design and evaluation of control algorithms for gimbal systems.

The implications of our work extend beyond the specific application of gimbal control. The proposed hybrid IK solver can be adapted to other robotic systems requiring real-time motion control, such as collaborative robots, autonomous vehicles, and surgical robots. Future work will focus on several directions: i) extending our approach to higher-degree-of-freedom systems and validating its scalability empirically; ii) incorporating machine learning techniques to compensate for unmodeled dynamics such as friction, backlash, and sensor noise; iii) exploring the use of our algorithm in more complex applications such as collaborative robotics and autonomous navigation; and iv) investigating adaptive control strategies that can learn and adjust to changing environmental conditions in real-time.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMEN

Authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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