

Application and Research of Quantum Optimisation Control Algorithms in Adaptive Optics Systems

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Abstract: Adaptive optics plays a crucial role in improving the stability and correcting aberrations of optical systems, whose performance largely depends on the optimization capability and convergence characteristics of control algorithms. Traditional control algorithms, such as genetic algorithm (GA), simulated annealing (SA), and stochastic parallel gradient descent (SPGD), have been widely applied; however, they exhibit certain limitations in global optimization ability, convergence speed, and noise immunity. In recent years, quantum optimization algorithms have attracted extensive attention owing to their potential advantages in global search and acceleration. Focusing on the application scenario of using adaptive optics to enhance fiber coupling efficiency, this paper investigates the feasibility of quantum optimization control algorithms. Taking quantum particle swarm optimization (QPSO) as a representative, a systematic comparison is conducted with traditional methods including GA, SA, and SPGD. The results demonstrate that under typical disturbance conditions, quantum optimization methods show significant advantages in improving fiber coupling efficiency, reducing the search time for optimal solutions, and enhancing system stability. This study indicates that adaptive optics control methods based on quantum optimization can provide a novel technical approach for stable and efficient coupling of optical links, and possess important application potential in the construction of quantum networks with ion traps as nodes.

Keywords: Quantum Network; Fiber Coupling; Adaptive Optics; Optimization Algorithm; QPSO.

1. Introduction

Through wide-area distributed quantum entanglement distribution, quantum networks can realize quantum secure communication, distributed quantum computing and high-precision quantum metrology functions that are unattainable by classical information systems, and have become a strategic highland in the global quantum information science and technology field. The decoherence effect induced by environmental disturbances and link transmission loss will directly lead to a sharp drop in the success rate of quantum entanglement distribution. Therefore, low-loss and highly stable quantum state transmission is a core prerequisite that must be broken through to construct scalable and practical quantum networks [1]. As a common core link running through quantum network transceiving terminals, space-ground fusion nodes, quantum relay units and optical switching modules, space-to-single-mode fiber coupling is an effective way to realize high-efficiency conversion of quantum signals between free-space functional optical paths and fiber transmission channels; stable and efficient fiber coupling control can suppress channel insertion loss, random phase jitter and mode mismatch noise to the maximum extent from the source, significantly block the decoherence of quantum states caused by environmental interference, and directly ensure the purity of quantum entanglement distribution, which is the key physical foundation for realizing long-distance, low-bit-error quantum state transmission and reliable full-link networking [2]. In recent years, with the accelerated deployment of the integration of space-ground integrated quantum communication networks, urban and wide-area fiber quantum networks are rapidly moving from laboratory principle verification to engineering and large-scale practical application stages, putting

unprecedented stringent requirements on the coupling efficiency of free-space light to single-mode fiber, as well as the long-term stability and broadband environmental anti-interference capability of the coupling system [3]. The latest field demonstration results of quantum networks show that entanglement distribution nodes enhanced by quantum storage have achieved long-term stable operation in multiple scenarios, which further confirms that high-performance and highly stable fiber coupling links are an indispensable core support for practical quantum networking [4]. However, most existing studies focus on the impact of strong environmental disturbances on fiber coupling systems in field engineering deployment scenarios, but often ignore the coupling stability in laboratory principle verification scenarios, which is a prerequisite core for determining the upper limit of key technical indicators of quantum networks, and the reliability and repeatability of basic research conclusions. As an inevitable link for the key technologies of quantum networks to move from principle verification to engineering implementation, although the laboratory environment has greatly suppressed environmental disturbances through vibration isolation platforms, precision temperature control, sealed optical paths and other means, the coupling system is still inevitably subject to the continuous action of a variety of inherent dynamic micro-disturbances: periodic thermal drift remaining from the closed-loop control of temperature control systems, background micro-vibrations that cannot be completely filtered by vibration isolation platforms and vibration conduction from equipment such as pump lasers and vacuum systems, residual stress deformation after solidification of optical components and thermal stress release induced by temperature changes, nanoscale creep of precision translation stages, local refractive index fluctuation of the optical path caused by air flow in clean rooms, etc., all

will cause submicron pointing drift and low-order wavefront distortion of the coupled beam [5].

Adaptive Optics (AO) is a commonly used method to suppress and eliminate such aberrations and perform real-time wavefront correction [6]. A 2024 review systematically summarized adaptive optics technology for free-space to fiber coupling under strong turbulence, emphasizing the core position of algorithm real-time performance [7]. The widely accepted physical evaluation criterion in the industry is to reduce the wavefront residual to below a quarter of the wavelength ($\lambda/4$) to ensure performance close to the diffraction limit [8]. In extremely sensitive systems such as quantum communication, this threshold is often further tightened to $\lambda/10$ or even $\lambda/20$ [9].

In view of the stringent real-time requirements of quantum communication links, the selection of optimization algorithms is crucial. Although a variety of algorithms have been proposed for wavefront shaping, their actual effectiveness depends not only on convergence accuracy, but also on physical interpretability and hardware compatibility [10]. A 2022 study showed that Quantum-behaved Particle Swarm Optimization (QPSO) has stronger global search capability, higher precision and faster convergence rate [11], and a 2025 study proposed an improved Stochastic Parallel Gradient Descent (SPGD) algorithm, which achieved a faster convergence speed in wavefront control for quantum communication [12]. To further explore which algorithm, QPSO or SPGD, is more suitable for ensuring the stability of fiber links, considering that Genetic Algorithm (GA) and Simulated Annealing (SA) are commonly used optimization algorithms, this study compared the performance of four representative algorithms—GA, SA, SPGD, QPSO—in fiber coupling optimization. Among them, GA and SA are used as reference for SPGD and QPSO, which can more clearly reflect the superiority of SPGD and QPSO. Instead of blindly

pursuing the ultimate mathematical precision, this paper demonstrates from the perspective of engineering practicality why SPGD is the optimal solution for real-time fiber coupling scenarios in quantum networks. On this basis, the optimization effects of more optimization algorithms on fiber coupling can be studied and verified in the follow-up to further explore the optimal optimization algorithm, providing guidance for the development of subsequent fiber link stability experiments.

This paper first elaborates on the principle of combining these four algorithms with fiber coupling scenarios, determines the optimal parameters of each algorithm to improve the coupling efficiency, then briefly describes the simulation settings of the four algorithms, compares their convergence rates and wavefront correction effects, and finally draws conclusions.

2. Adaptive Optics and Algorithm Principles

2.1. AO

AO is a key technology for restoring or improving imaging quality and signal transmission efficiency by dynamically compensating wavefront distortion in optical systems in real time, and is widely used in quantum communication, Free-Space Optical (FSO) communication, biomedical microscopic imaging and other fields [13]. Its basic structure is shown in Fig. 1, where the optical path is represented by blue arrows and the circuit by green arrows. Its main principle is to use wavefront correctors (such as Deformable Mirrors (DM) and Spatial Light Modulators (SLM)) to perform targeted compensation for wavefront distortion caused by atmospheric turbulence, uneven refractive index of media, thermal deformation of optical components and other factors.

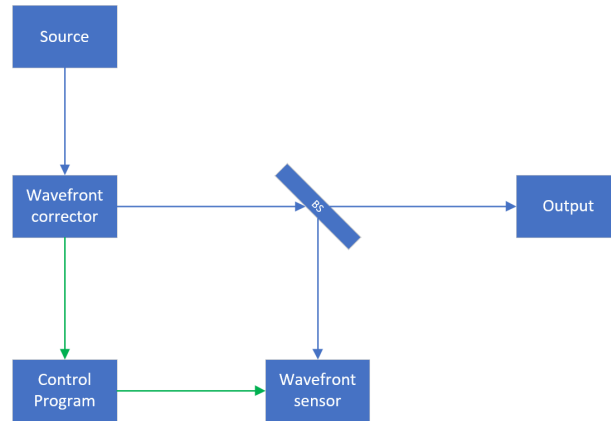


Fig 1. Adaptive optics system

For the wavefront phase correction and optimization scenario, this paper selects four optimization algorithms: GA, SA, SPGD and QPSO, to construct a model-free adaptive optimization framework. Taking the RMS phase residual as the objective function, the core optimization problem is defined as:

$$\min J(V) = \sqrt{\frac{1}{N_{\text{valid}}} \sum_{(i,j) \in \Omega} [\Phi_{\text{rec}}(i,j) - \Phi_{\text{cor}}(V,i,j)]^2} \quad (1)$$

where V is the actuator control vector, Φ_{rec} is the target phase, Φ_{cor} is the fitted phase of the corrector influence function, Ω is the effective pixel domain, N_{valid} is the

number of effective pixels, and a smaller $J(V)$ indicates a higher fitting accuracy.

2.2. GA

Proposed by John Holland in 1975 inspired by Darwin's theory of biological evolution and Mendel's genetic laws, GA is a classic evolutionary global optimization algorithm. This algorithm encodes the feasible solutions of the optimization problem into heritable "chromosome individuals", maps the solution space to the genetic coding space, and iteratively executes three core genetic operators—selection, crossover and mutation—on population individuals by simulating the evolutionary mechanism of "survival of the fittest" in nature.

It continuously eliminates inferior solutions with low fitness, retains and propagates superior solutions with high fitness, and after multiple generations of evolution, the population converges to the individual with the highest fitness, i.e., the global optimal solution of the problem. This algorithm is independent of the gradient information of the problem, has natural parallelism and strong global search capability, and can be adapted to complex optimization problems with nonlinearity, multi-modality and high dimensionality [14].

In wavefront correction, the main process of this algorithm is shown in Fig. 2. The GA first directly maps the

"population" to the Zernike coefficients V that the AO system corrector should generate; then enters the core Iteration link, combines the advantages of different Zernike coefficients through the crossover formula (simulating gene recombination to screen better correction configurations), and applies random perturbations to the Zernike coefficients through the mutation formula (exploring new correction spaces to avoid local optimum); after the Converged judgment of continuous no improvement, the optimal Zernike coefficients V_{opt} are output to make the corrected wavefront approach the target wavefront.

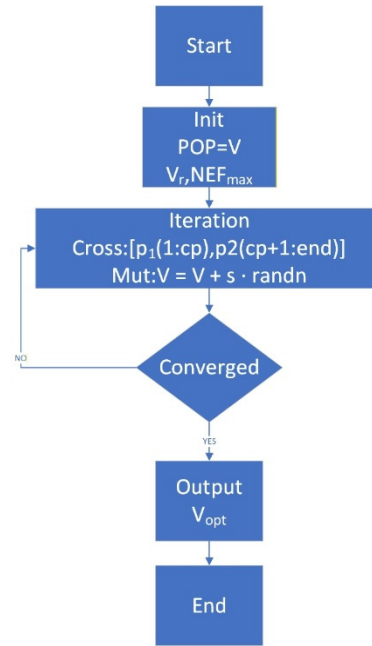


Fig 2. Flow chart of GA

GA evolves and optimizes through selection, crossover and mutation operations [15]. In wavefront control, these operations correspond to discrete mutations of actuator voltages. Such "gene mutations" will cause jump changes in the wavefront phase, leading to the instantaneous destruction of the partially coherent optical field and severe fluctuation of coupling efficiency, and high-frequency and large-amplitude actuator actions may also damage the hardware [16]. Recent studies have shown that although GA can converge to the global optimal in wavefront correction, the severe oscillations before convergence will cause system instability, making it particularly unsuitable for quantum communication links with high real-time requirements [17]. Therefore, despite its global search capability, GA is difficult to apply to scenarios requiring smooth and continuous adjustment such as real-time fiber coupling due to its discontinuous physical behavior.

2.3. SA

Proposed by Kirkpatrick et al. in 1983 based on the solid physical annealing process and Monte Carlo iteration strategy, the SA algorithm takes temperature as the core control parameter. It first endows the algorithm with the ability to escape from local optimum at an initial high temperature, accepts inferior solutions with a certain probability through the Metropolis criterion, and then gradually reduces the probability of accepting inferior solutions by slowly cooling down, finally making the algorithm only accept better solutions and converge to the global optimal solution. This algorithm has a theoretical guarantee of global convergence,

is independent of gradient information, and can be adapted to both continuous and discrete optimization problems, and its convergence performance is mainly determined by the cooling strategy [18].

In wavefront correction, the main process of this algorithm is shown in Fig. 3. The SA algorithm first initializes the Zernike coefficients $V=0$ that the AO system corrector should generate and annealing parameters (initial temperature T_0 , termination temperature T_{min} , cooling coefficient α); then enters the core Iteration link, generates new Zernike coefficients V_{new} by applying small adjustments to the current Zernike coefficients through the perturbation formula, and decides whether to adopt them through the probability acceptance formula—if the wavefront error (energy E) decreases, it is accepted directly; if the error increases, it is accepted with a temperature-dependent probability $\exp(-\Delta E/T)$ (high probability at high temperature for global exploration to avoid local optimum; low probability at low temperature for local fine-tuning to lock the optimal correction effect); after the Cooling step of gradual cooling and Converged judgment, V_{opt} is output to drive the corrector.

SA simulates the solid annealing process and accepts inferior solutions with a certain probability according to the Metropolis criterion, thus escaping from local optimum [19]. In the high-temperature stage at the initial stage of the algorithm, SA will accept solutions that worsen wavefront distortion with an extremely high probability, which is equivalent to introducing "disordered thermal motion" physically, wasting a lot of detection time and leading to an

extremely low convergence speed [20]. For energy-sensitive systems such as fiber coupling, the early disordered exploration is fatal. The latest research compared the application of SA with other algorithms in adaptive optics and

found that SA has a much lower convergence accuracy than gradient-based algorithms under the same number of measurements [21].

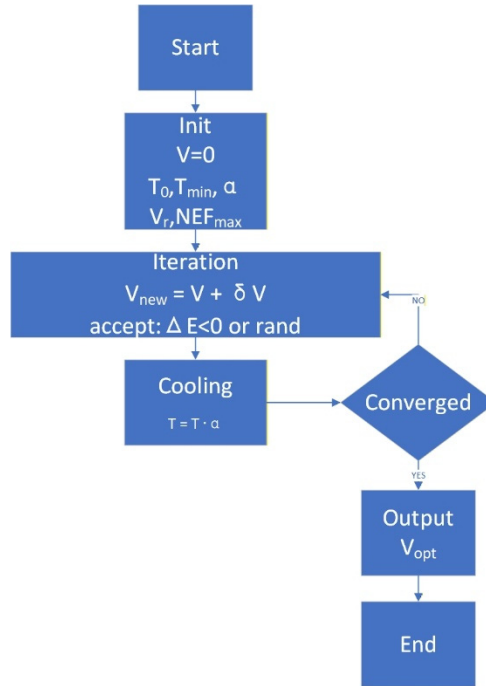


Fig 3. Flow chart of SA

2.4. SPGD

Proposed by Vorontsov et al. in 1997, the SPGD algorithm is a model-free real-time stochastic optimization algorithm. Without knowing the precise mathematical model of the controlled system and the analytical gradient expression, this algorithm only applies small random perturbations conforming to statistical characteristics to all control variables at the same time, makes an unbiased estimation of the gradient direction by using the correlation between the

variation of the objective function before and after perturbation and the perturbation vector, and then updates all control variables in parallel along the optimization direction to achieve fast closed-loop optimization. The algorithm has the advantages of no model dependence, full parallel update, small amount of calculation and fast convergence speed, and is the mainstream algorithm for high-dimensional strongly coupled real-time control systems such as adaptive optics wavefront correction and beam shaping [22].

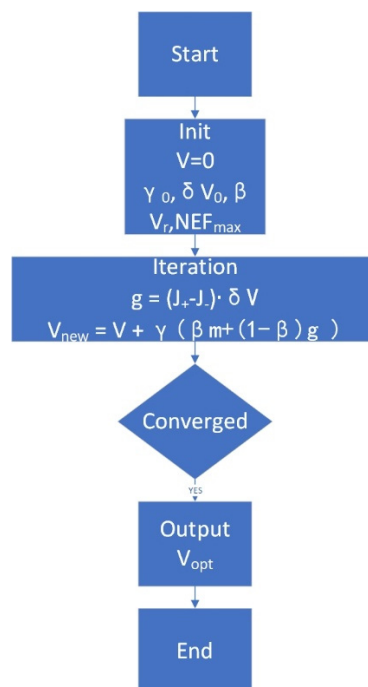


Fig 4. Flow chart of SPGD

In wavefront correction, the main process of this algorithm is shown in Fig. 4. The SPGD algorithm first initializes the Zernike coefficients $V=0$ that the AO system corrector should generate and real-time optimization parameters (initial step size γ_0 , perturbation amplitude δV_0 , momentum coefficient β); then enters the core Iteration link, performs bidirectional positive and negative perturbations on the Zernike coefficients through the gradient formula, obtains the gradient g by using the error difference (reflecting the influence direction of the change of Zernike coefficients on the wavefront error), and smoothly adjusts the Zernike coefficients by combining the historical momentum m through the momentum update formula to optimize rapidly along the direction of error reduction; after the Converged judgment, V_{opt} is output to drive the corrector to realize real-time and accurate wavefront correction.

SPGD applies small random perturbations to all control channels at the same time, estimates the gradient according to the change of the objective function (coupling efficiency), and updates the voltage along the gradient direction [23]. This method is naturally consistent with the continuous fine-tuning characteristics of adaptive optics hardware: positive and negative small perturbations imitate the continuous deformation process of the deformable mirror. SPGD quickly climbs to the local maximum in a way that least damages the current optical field, with an extremely fast convergence speed and minimal physical perturbation [24]. In recent years, SPGD has been widely used in free-space optical communication and quantum key distribution systems, and its improved algorithms have further improved the anti-noise capability and convergence speed [25-26]. These are exactly the characteristics most needed for real-time fiber coupling.

2.5. QPSO

Proposed by Sun Jun et al. in 2004 on the basis of the

traditional Particle Swarm Optimization (PSO) algorithm combined with the basic principles of quantum mechanics, the QPSO algorithm describes the quantum motion behavior of particles based on the Schrödinger equation and the probability distribution of the wave function, making the particles in a quantum potential well with the weighted center point of individual optimum and global optimum as the core. It breaks through the local optimum constraint through the quantum tunneling effect, and completely eliminates the velocity term of the traditional PSO at the same time, only controlling the particle iteration through the contraction-expansion coefficient, which greatly simplifies the algorithm structure. The algorithm has a strict theoretical guarantee of global convergence, better population diversity, can effectively avoid premature convergence, and is suitable for complex optimization problems with high dimensionality, multi-modality and nonlinearity [27].

In wavefront correction, the main process of this algorithm is shown in Fig. 5. The QPSO algorithm first directly maps the "particle swarm" to the Zernike coefficients V that the AO system corrector should generate, and initializes the contraction factors a_s/a_e and individual/global optima p_b/g_b ; then enters the core Iteration link, combining the parallel search capability of the particle swarm with quantum behavior characteristics: calculating the local attractor point P through the local attractor point formula (combining p_b and g_b to guide the particles to gather towards excellent Zernike coefficient configurations), updating the particle position (Zernike coefficients) through the quantum update formula, and the contraction factor α dynamically controls the search range (large α in the early stage for global exploration; small α in the later stage for local fine-tuning); after Update p_b/g_b to retain significant improvements and Converged judgment, V_{opt} is output to drive the corrector to complete the global optimal correction of complex wavefronts.

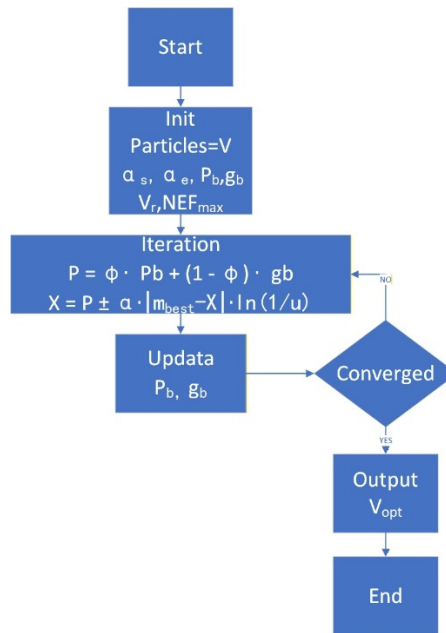


Fig 5. Flow chart of the Quantum-behaved Particle Swarm Optimization algorithm

QPSO abandons the velocity term of traditional PSO, assumes that particles are in a quantum potential well, their states are described by wave functions, and particles appear in the search space with a certain probability density [28]. This mechanism allows global exploration without causing

severe jumps of the actuator. The potential well model makes the particle motion trajectory relatively smooth, maintains optical coherence, and avoids the instantaneous collapse of system energy [29]. Therefore, among global optimization algorithms, QPSO has the most gentle and physically

reasonable performance. Recent experiments have shown that QPSO can effectively balance exploration and exploitation in wavefront correction, with convergence accuracy close to gradient algorithms, but the number of measurements required is still significantly higher than that of SPGD [30].

3. Simulation and Results

To evaluate the performance of various optimization algorithms under a unified benchmark close to real physical systems, this section elaborates on the construction mechanism of the closed-loop adaptive optics simulation optical path and the physical definition of evaluation metrics, and conducts a rigorous sensitivity analysis and optimal calibration of the key hyperparameters for each algorithm.

3.1. Simulation Optical Path and Physical Propagation Evolution Model

In practical adaptive optics systems for fiber coupling, wavefront correction devices (e.g., deformable mirrors, DM) and wavefront detection terminals (e.g., focal-plane CCD) are often located on non-strictly conjugate planes. To accurately reproduce this physical characteristic, a wavefront-sensorless closed-loop simulation model involving free-space diffraction propagation is established in MATLAB. The dynamic closed-loop optimization procedure of the system is described as follows: First, an initial distorted wavefront modulated by the Kolmogorov turbulence model or environmental micro-vibration model is imposed at the system entrance pupil. After being projected onto the deformable mirror plane, the distorted wavefront undergoes phase compensation via the surface profile modulation of the DM. Subsequently, the compensated near-field complex amplitude propagates to the detector focal plane through Fresnel diffraction, forming a far-field interferometric intensity distribution. The terminal detector calculates the root-mean-square (RMS) error of the wavefront residual by extracting morphological features of the focal spot, which is fed back to the control algorithm as a scalar objective function. The algorithm independently computes the actuator voltage update vector based on the feedback to drive the deformation of the DM. This physical closed-loop process iterates continuously until the wavefront RMS converges to a stringent threshold required by quantum network links (e.g.,

0.1 λ) or reaches the maximum physical sampling constraint set by the system.

3.2. Reconstruction of the Evaluation System

When comparing control algorithms with different underlying mathematical mechanisms (gradient-based methods vs. swarm intelligence heuristic methods) horizontally, adopting the conventional "number of algorithm iterations" as the horizontal evaluation axis will significantly deviate from the real time cost of hardware control. In actual quantum links, the pure software computation time of the algorithm is far less than the hardware physical sampling cycle consisting of "issuing drive voltages $\rightarrow$ approaching the mechanical response of the DM $\rightarrow$ approaching CCD exposure and readout". Therefore, this paper introduces the Number of Function Evaluations (NFE) as the core evaluation metric for measuring the "convergence speed" and "time overhead" of algorithms. NFE strictly corresponds to the total number of detection executions by the physical system: for swarm intelligence algorithms (e.g., GA, QPSO), completing one population "iteration" requires evaluating all particles with population size N one by one, consuming N NFEs; for local gradient algorithms (e.g., SPGD), a single iteration usually only applies positive and negative bidirectional voltage perturbations, consuming only 2 NFEs. Using NFE as the benchmark can most realistically reflect the absolute physical time cost consumed by the algorithm in the experimental optical path.

3.3. Hyperparameter Sensitivity Analysis and Optimal Configuration Calibration

The convergence dynamic characteristics of optimization algorithms are extremely sensitive to their hyperparameter settings. To eliminate performance misjudgment caused by suboptimal parameters and ensure absolute objectivity in horizontal comparisons, a detailed sensitivity analysis of the core parameters of four algorithms—GA, SA, SPGD, and QPSO—is performed using the control variable method before formal closed-loop verification. Figs 6 to 9 show the distribution evolution of the final wavefront convergence RMS for the four algorithms under different parameter steps, respectively.

For the Genetic Algorithm (GA):

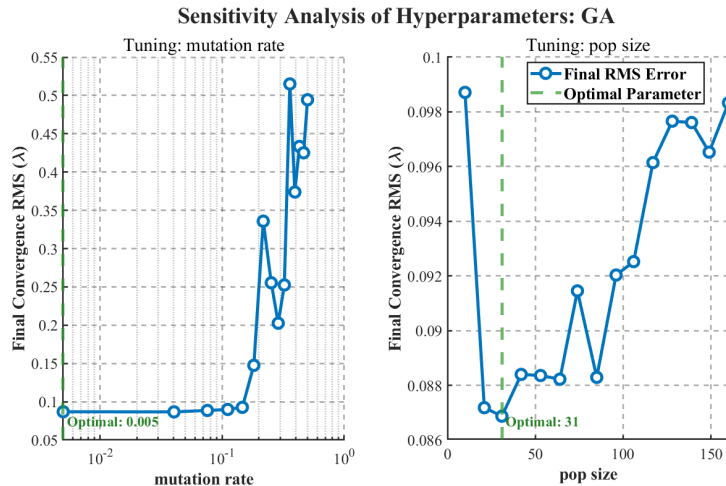


Fig 6. Convergence speed and convergence effect of different parameters in the GA algorithm

As shown in Fig.6, the mutation rate and population size determine the spatial exploration capability of the algorithm.

When the mutation rate is excessively high, the system exhibits a random walk behavior leading to divergence; an

overly large population size, on the other hand, results in redundant and ineffective measurements. Through simulation, the optimal mutation rate is determined to be 0.005 and the

optimal population size is 31.
For the Simulated Annealing (SA) algorithm:

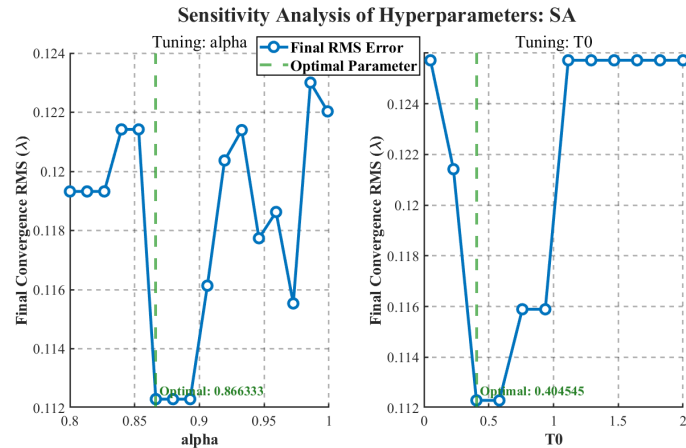


Fig 7. Simulated Annealing (SA) algorithm

As shown in Fig.7, the cooling coefficient α and initial temperature T_0 govern the probability of the system escaping from local minima. Sensitivity scanning reveals that the algorithm achieves the optimal balance between early-stage

exploration and late-stage convergence at $\alpha = 0.866333$ and $T_0 = 0.404545$.

For the Stochastic Parallel Gradient Descent (SPGD) algorithm:

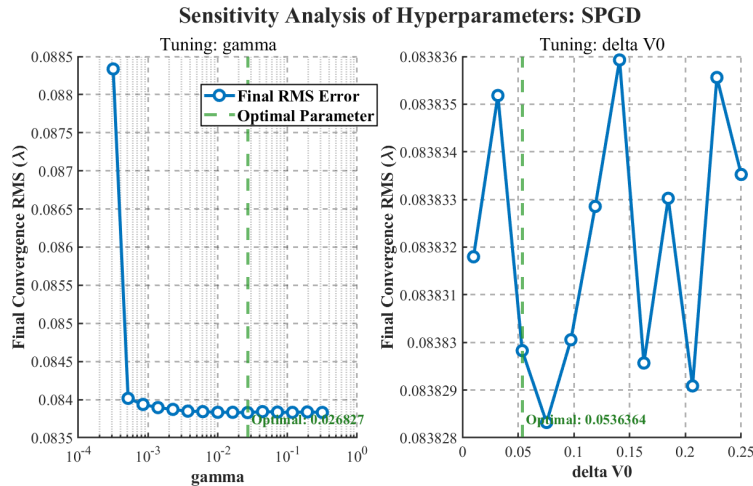


Fig 8. Convergence speed and convergence effect of different parameters in the SPGD algorithm

As shown in Fig. 8, the gain step size γ and the applied perturbation amplitude ΔV_0 are key to controlling the estimation accuracy of the gradient direction. Since the algorithm requires maintaining the coherence of the optical field, excessive perturbation will destroy the steady state of

the system. After fine optimization, the optimal step size γ is calibrated as 0.026827, and the perturbation amplitude ΔV_0 is set to 0.0536364.

For the Quantum Particle Swarm Optimization (QPSO) algorithm:

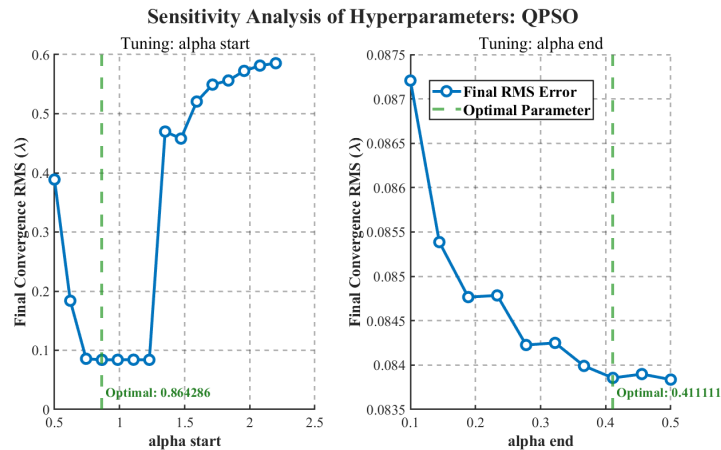


Fig 9. Convergence speed and convergence effect of QPSO algorithm with different parameters

As shown in Fig. 9, the algorithm regulates the width of the quantum potential well through dynamic contraction-expansion factors (α_{start} to α_{end}). When α_{start} equals 0.864286 and α_{end} equals 0.411111, the particles possess sufficient global quantum tunneling capability in the early stage of iteration and can effectively collapse to the optimal solution

domain in the later stage. Based on the above sensitivity analysis, the optimal core parameters of the four algorithms are extracted.

The core parameters of the four algorithms are summarized in Table 1:

Table 1. Core parameters of the four algorithms

Algorithm	Parameter_1_Name	Best_Value_1	Parameter_2_Name	Best_Value_2
GA	Mutation Rate	0.005	Population Size	31
SA	Cooling Factor (alpha)	0.866333333	Initial Temp (T0)	0.404545455
SPGD	Gain (gamma)	0.026826958	Perturbation (Delta V0)	0.053636364
QPSO	Alpha Start	0.864285714	Alpha End	0.411111111

The configuration is shown in Table 1. All subsequent convergence dynamics comparisons and robustness statistical simulations are strictly carried out based on this calibrated parameter library. Table 1 Optimal Core Hyperparameter Configurations of the Four Algorithms Algorithm Name Core Parameter 1 (Optimal Value) Core Parameter 2 (Optimal Value) Evaluation Threshold GA Mutation rate = 0.005 Pop size = 31 0.1 λ SA Cooling coefficient (α) = 0.866333 Initial temperature (T_0) = 0.404545 0.1 λ SPGD Gain step size (γ) = 0.026827 Disturbance amplitude (ΔV_0) = 0.0536364 0.1 λ QPSO Initial contraction factor (α_{start}) = 0.864286 Termination contraction factor (α_{end}) = 0.411111 0.1 λ .

4. Conclusion

4.1. Comparison of Convergence Speed and System Detection Overhead

The optimal hyperparameters calibrated in Table 1 were introduced into the simulation model to drive closed-loop control under the same initial turbulent distortion. The wavefront residual convergence trajectories of the four algorithms (with the total number of physical measurements NFE as the horizontal axis) are shown in Fig. 10, and the relevant key performance statistics are detailed in Table 2.

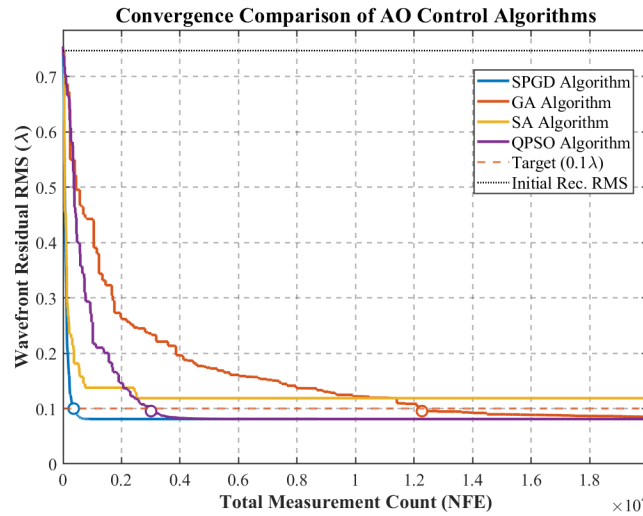


Fig 10. Comparison of Convergence Processes and Final Convergence Judgment Points of the Four Algorithms

Table 2. Performance Statistics of the Four Algorithms

Algorithm name	Root Mean Square Error (λ)	Standard deviation	variance	Average improvement rate (%)	Improvement in standard deviation (%)
SPGD	0.100617921	0.04461679	0.001990658	0	0
QPSO	0.098882892	0.050256849	0.002525751	1.724373709	-12.6411132

4.2. Analysis of Correction Accuracy and Engineering Applicability

To eliminate the contingency caused by a single random initial distortion and further explore the ultimate accuracy and robustness of the algorithms in complex wavefront environments, 500 groups of distorted initial wavefronts were randomly generated in this paper, and closed-loop correction statistical experiments were carried out using SPGD and QPSO algorithms respectively.

Fig.11 shows the scatter distribution and mean values of the final residual RMS of the two algorithms after 500

independent runs. From a macroscopic statistical perspective, the average final RMS of QPSO is 0.0989 λ , while that of SPGD is 0.1006 λ . Judging only by the mean value, it is easy to draw the wrong conclusion that "the accuracy of QPSO is slightly higher than that of SPGD". However, in practical engineering applications, the system pays more attention to the winning rate of the algorithm in "stably finding the optimal solution" in each independent run, rather than the mathematical mean pulled by extreme values. For this reason, the "performance improvement distribution histogram" shown in Fig. 12 was plotted in this paper (i.e., under the same initial distortion in each group, the difference between the

final convergence RMS of QPSO and SPGD, $\Delta RMS = RMS_{QPSO} - RMS_{SPGD}$). After removing 137 abnormal outliers where both algorithms diverged due to excessively

severe distortion, the remaining 363 groups of valid head-to-head data were analyzed, leading to a completely different conclusion.

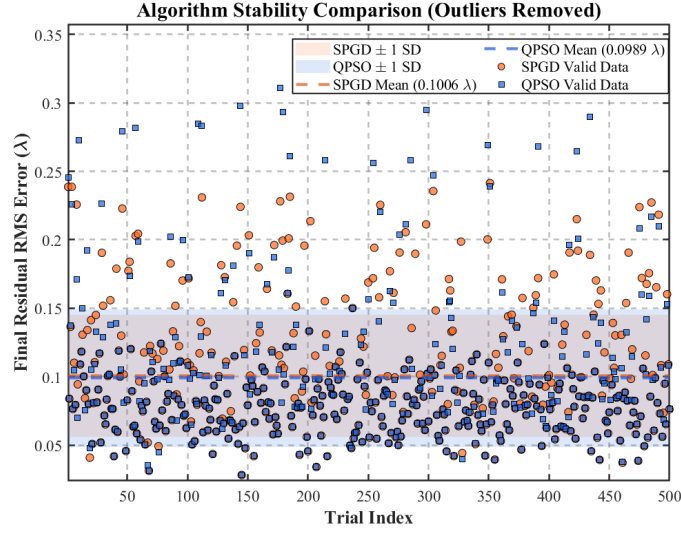


Fig 11. Mean Error and Variance Distribution of the Two Algorithms after 500 Runs

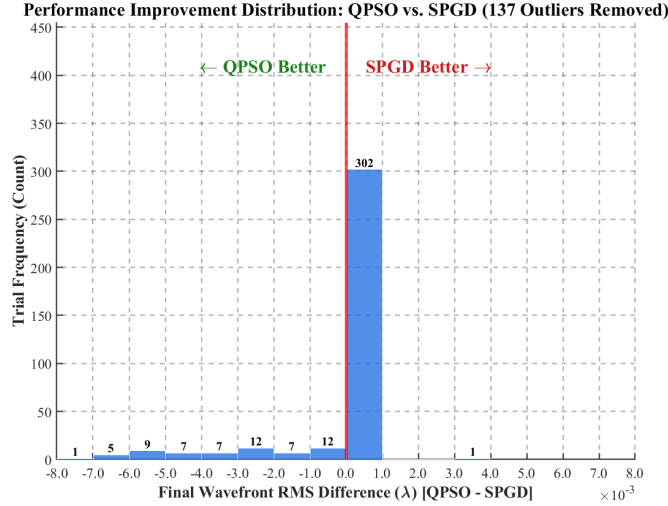


Fig 12. Final Wavefront RMS Difference between SPGD and QPSO Algorithms

Table 3. Average Error and Variance Values of the Two Algorithms after 500 Runs

Row	Average_RMS	Variance	Standard_Deviation	Improvement_Pct
SPGD_Absolute_Error	0.025017895	0.000050026	0.007072906	0
QPSO_Absolute_Error	0.023632287	0.000052755	0.007263241	0
Difference_QPSO_minus_SPGD	0.001385608	0.000001254	0.001119961	5.538467565

SPGD has an overwhelming positive winning rate: in Fig. 12, the interval representing "SPGD Better ($\Delta RMS > 0$)" highly concentrates 302 test results. This means that in up to 83.2% (302/363) of practical head-to-head comparisons, SPGD found a smaller or equal minimum wavefront residual compared with QPSO.

Statistical truth of mean deviation: the reason why QPSO can achieve a slight mean advantage in Fig. 11 is that there is an extremely long but sparse tail distribution on the left side of Fig. 12 (QPSO Better interval), such as occasional excellent solutions as low as $-8.0 \times 10^{-3} \lambda$ order. This indicates that QPSO only "happened" to tunnel to a deeper local minimum in a few cases (less than 17%), thus mathematically lowering the overall mean.

Physical insignificance of extreme value differences: combined with the abscissa order of Fig. 12 ($10^{-3} \lambda$), even in

the few cases where QPSO performs better, the accuracy improvement brought by it compared with SPGD is only on the order of a few thousandths of a wavelength. In a real quantum network fiber coupling system, such a small theoretical improvement will be completely overwhelmed by environmental thermal noise and mechanical micro-vibration, belonging to "invalid improvement".

Analysis summary: considering that SPGD only requires about 1/7 of the measurement time (NFE) in Section 4.1, as well as the head-to-head winning rate of up to 83.2% in this section, it can be conclusively proved that in the physical closed-loop model with spatial propagation, the SPGD algorithm does not sacrifice accuracy for speed. On the contrary, it comprehensively surpasses global algorithms such as QPSO in convergence speed, detection action cost, and final optimization accuracy in most cases.

5. Conclusion

In the context of quantum network fiber coupling tasks, the evaluation of wavefront correction algorithms must take into account both physical measurement overhead and stringent robustness requirements. Based on the adaptive optics closed-loop simulation model including the actual diffraction propagation process, this paper systematically calibrated and statistically compared four optimization algorithms: GA, SA, QPSO and SPGD, and drew the following conclusions.

Engineering limitations of global algorithms: genetic algorithm (GA) and simulated annealing (SA) cannot meet the real-time requirements of the system due to huge physical measurement overhead or easy iteration stagnation. Although quantum particle swarm optimization (QPSO) can show extremely high theoretical optimization depth under a few specific distortions, its huge population iteration cost (high NFE) and low universal winning rate make it difficult to perform high-frequency dynamic correction tasks.

Comprehensive optimality of the SPGD algorithm (core conclusion): this study revises the inherent cognition that "the accuracy of gradient algorithms is inferior to that of global algorithms". A large number of independent statistical results show that the SPGD algorithm not only has an absolute advantage in convergence speed (taking only about 14% of the time of QPSO), but also achieves correction accuracy better than or equal to that of QPSO in up to 83.2% of homologous wavefront comparison tests. With extremely low hardware computing power burden, minimal applied perturbation, and extremely stable local extreme value locking capability, SPGD is the best control algorithm balancing high bandwidth and high precision in the current quantum network fiber coupling scenario.

The simulation results of this study have provided clear and rigorous theoretical support for the selection of adaptive optics control algorithms. However, non-ideal factors such as low-frequency mechanical drift, airflow disturbance, and detector shot noise inevitably exist in the actual laboratory optical path.

Based on the above conclusive results, the next work of this project will directly adopt the optimized SPGD algorithm to drive the real deformable mirror (DM) hardware system. The experiment will focus on exploring whether the SPGD algorithm can reproduce the efficient optimization performance in the simulation when facing real continuous laboratory environmental noise under the physical limitation of DM's own Zernike mode fitting ability, so as to effectively and long-term guarantee and improve the dynamic coupling efficiency of single-mode fibers.

References

- [1] Nielsen M A, Chuang I L. Quantum Computation and Quantum Information[M]. Cambridge: Cambridge University Press, 2010.
- [2] Li Y. Efficient and Robust Spatial-to-Fiber Coupling for Multimode Quantum Networks via Cascaded Adaptive Feedback Control[R]. IEEE Dataport, 2025.
- [3] Liao S K, et al. Satellite-to-ground quantum key distribution[J]. Nature, 2017, 549(7670): 43-47.
- [4] Bhaskar M K, et al. Experimental demonstration of memory-enhanced quantum communication[J]. Nature, 2020, 580 (7801): 60-64.
- [5] Fujii Y, Kashiwagi K, Suzuki R, et al. Long-term stability of squeezed light in a fiber-based system using automated alignment[J]. Review of Scientific Instruments, 2024, 95(9): 093004.
- [6] Vorontsov M A, Sivokon V P. Stochastic parallel-gradient-descent technique for high-resolution wave-front phase-distortion correction[J]. Journal of the Optical Society of America A, 1998, 15(10): 2745-2758.
- [7] Wang Y, Zhang H, Liu J. Adaptive optics for free-space to fiber coupling under strong turbulence: a 2024 review[J]. Photonics Research, 2024, 12(3): 456-469.
- [8] Hardy J W. Adaptive Optics for Astronomical Telescopes[M]. New York: Oxford University Press, 1998.
- [9] Cao Y, et al. Long-distance free-space quantum key distribution in daylight towards intercontinental satellite-based quantum communication[J]. Optica, 2021, 8(8): 1078-1085.
- [10] Zhang H, Xu L, Guo Y, et al. Application of AdamSPGD algorithm to sensor-less adaptive optics in coherent free-space optical communication system[J]. Optics Express, 2022, 30(5): 7477-7492.
- [11] Fallahi S, Taghadosi M. Quantum-behaved particle swarm optimization based on solitons[J]. Scientific Reports, 2022, 12: 13977.
- [12] Xu L, Wang J, Yang L, Zhang H. Design and performance analysis of NadamSPGD algorithm for sensor-less adaptive optics in coherent FSOC systems[J]. Photonics, 2022, 9(2): 77.
- [13] Chen B, Zhou Y, Li Z, et al. Adaptive Optical Closed-Loop Control Based on the Single-Dimensional Perturbation Descent Algorithm[J]. Sensors, 2023, 23: 4371.
- [14] Holland J H. Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence[M]. Ann Arbor: University of Michigan Press, 1975.
- [15] Goldberg D E. Genetic Algorithms in Search, Optimization, and Machine Learning[M]. Reading: Addison-Wesley, 1989.
- [16] Lam F, Li B, Garcia M A G. Real-time wavefront correction using genetic algorithms for free-space optical communication [J]. Optics Express, 2020, 28(5): 7123-7136.
- [17] Xu J, Zhang X, Zhang D, et al. Phase optimization of wavefront shaping using genetically assisted harmony search algorithm[J]. Laser & Optoelectronics Progress, 2024, 61(21): 2126001.
- [18] Kirkpatrick S, Gelatt C D, Vecchi M P. Optimization by simulated annealing[J]. Science, 1983, 220(4598): 671-680.
- [19] Kirkpatrick S, Gelatt C D, Vecchi M P. Optimization by simulated annealing[J]. Science, 1983, 220(4598): 671-680.
- [20] Zhang Y, et al. Wavefront correction using simulated annealing algorithm for fiber coupling in free-space optical communication[J]. Optics Communications, 2018, 410: 123-129.
- [21] Chen L, Yang H, Wang J. Performance evaluation of metaheuristic algorithms for adaptive optics in satellite-to-ground laser communication[J]. Optics & Laser Technology, 2022, 156: 108521.
- [22] Vorontsov M A, Carhart G W, Ricklin J C. Adaptive phase-distortion correction based on parallel gradient-descent optimization[J]. Optics Letters, 1997, 22(12): 907-909.
- [23] Vorontsov M A, Carhart G W, Ricklin J C. Adaptive phase-distortion correction based on parallel gradient-descent optimization[J]. Optics Letters, 1997, 22(12): 907-909.
- [24] Pan Z, Li Y, Shen Y, et al. Multi-aperture adaptive fiber-coupled free-space optical communication system: scintillation mitigation and turbulence compensation experiment based on

- gamma-gamma channel modeling[J]. IEEE Photonics Journal, 2025, 17(2): 1-7.
- [25] Song H, et al. Deep learning enhanced SPGD for wavefront correction in free-space optical communications[J]. Photonics Research, 2021, 9(10): 1987-1995.
- [26] Long J, Xiong Y, Zhou Z, et al. High-precision, real-time wavefront sensing via sparse diffractive deep neural networks[J]. Optics Express, 2024, 32(18): 32468-32484.
- [27] Sun J, Feng B, Xu W. Particle swarm optimization with particles having quantum behavior[C]//Proceedings of the 2004 Congress on Evolutionary Computation. Piscataway: IEEE Press, 2004: 325-331.
- [28] Sun J, Feng B, Xu W. Particle swarm optimization with particles having quantum behavior[C]//Proceedings of the 2004 Congress on Evolutionary Computation. Portland: IEEE Press, 2004: 325-331.
- [29] Liu Z, Zhu X, Bi D, Zhang Y. Distortion spot correction based on improved particle swarm optimization algorithm[J]. Chinese Journal of Lasers, 2024, 51(13): 1305001.
- [30] Zhang Y, Chen B, Gu H, et al. Design of a fiber alignment coupling system based on spiral scanning and the DAS SPGD algorithm[J]. Laser & Optoelectronics Progress, 2025, 62(5): 0506008.