

Prediction-Window Aided Fluid Antenna Systems for High-Mobility Communications



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Abstract: Fluid antenna systems (FAS) provide continuous spatial degrees of freedom for next-generation wireless networks. However, deploying FAS on high-speed mobile embodied intelligent agents introduces Doppler shifts that shorten the channel coherence time, causing conventional full-port scanning to incur excessive pilot overhead. To address this issue, this paper proposes a prediction-aided adaptive communication architecture that constructs a dynamic local sounding window centered on upper-layer prediction results. By exploiting the spatial channel correlation among FAS ports, the proposed approach balances pilot overhead and spatial diversity gain under prediction deviations. We establish a quantitative model for the long-term expected throughput by integrating a nonlinear bounded hit probability function and a gain bridging model based on the zeroth-order Bessel function of the first kind. We then formulate a discrete optimization problem under practical constraints to maximize the expected transmission capacity, and develop a two-stage low-complexity algorithm that decouples the online computational complexity from the number of antenna ports. Simulation results show that the proposed mechanism adaptively adjusts the sounding window size according to moving velocity and prediction accuracy, reducing pilot overhead in high-mobility scenarios and achieving higher throughput than fixed-window and global scanning schemes.

Keywords: fluid antenna system; embodied intelligent agent; overhead catastrophe; prediction window; discrete zeroth-order gradient optimization

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1 Introduction

With the evolution of 6G networks toward space-air-ground-sea integration and autonomous operation, embodied intelligent agents with autonomous sensing, decision-making, and execution capabilities are gradually becoming core nodes at the network edge^[1–2]. In typical applications of vertical industries such as industrial inspection and environmental monitoring, such mobile agents need to complete continuous tasks in highly dynamic physical environments, which imposes stringent requirements on the reliability and effective throughput of wireless communication links.

Fluid antenna systems (FAS), as a revolutionary reconfigurable antenna technology, enable the radiating element to slide freely within a fixed physical aperture, thereby obtaining continuous spatial degrees of freedom in a very compact size to ac-

tively adapt to time-varying wireless channel states^[3–5]. Compared with conventional fixed antenna arrays, FAS can achieve superior channel gain in complex multipath environments due to its flexible spatial reconfiguration capability, and has demonstrated remarkable performance advantages in scenarios such as multi-user access interference suppression and integrated sensing and communication (ISAC). It has thus become a key research direction for next-generation wireless networks^[6–8].

However, existing FAS-related studies are generally based on the underlying assumption that user nodes are stationary or quasi-static, which presupposes that the channel coherence time is sufficient to support the full-port pilot sounding process. In the field of channel estimation and port selection, existing solutions include linear minimum mean square error (LMMSE), compressed sensing, and sparse Bayesian learning^[9–11], as well as various deep learning-assisted schemes^[12–14], all of which are validated under quasi-static block fading channel scenarios. When FAS is deployed on a high-speed moving embodied intelligent agent, the mechanical movement of the agent will induce severe Doppler shift, causing the channel coherence time to shrink sharply and non-linearly as the moving speed increases. If the global blind scanning mechanism that traverses all virtual

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ports is still adopted, the pilot sounding overhead will exhaust all coherence time slots, leaving zero time for effective data transmission and resulting in the performance dilemma of “overhead catastrophe”^[15].

To address this challenge, the most straightforward solution in existing research is to compress sounding overhead based on port prediction: By mining the temporal evolution patterns of channels or environmental sensing information, the optimal port position at the next moment is directly predicted, reducing the original N full sounding operations to single-point sounding, which fundamentally cuts down the pilot temporal overhead^[16]. Traditional methods include the Vec Prony algorithm and the matrix pencil moving port (MPMP) algorithm, which realize port tracking through angle-delay domain features. With the expanding application of large language models (LLMs) in physical layer communications, the state-of-the-art Port-LLM model, built on the GPT-2 backbone with a Low-Rank Adaptation (LoRA) fine-tuning architecture, achieves prediction of future optimal ports through temporal extrapolation of historical channel tables, and outperforms traditional prediction algorithms in spectral efficiency under medium- and high-speed scenarios^[17]. All the above studies have verified the significant overhead compression effect of port prediction, which serves as the core technical foundation for solving the overhead catastrophe in highly dynamic scenarios.

Nevertheless, existing port prediction studies generally have two limitations. First, they aim to output a single optimal port, assuming the prediction result is completely accurate without considering the performance degradation caused by prediction deviation. In fact, any prediction mechanism has errors, and pure single-point prediction has zero fault tolerance capability. Once the predicted port deviates from the true optimal port, the communication gain will directly drop to the channel level at the deviated position, with no buffer margin^[18]. Second, existing studies have not established a joint tradeoff mechanism among prediction confidence, moving speed, sounding overhead, and spatial diversity gain: They either adopt extremely compressed single-point sounding at the cost of robustness, or fall back to full scanning at the cost of transmission efficiency, failing to adaptively adjust the balance between overhead and fault tolerance according to real-time dynamic scenarios.

From the perspective of physical essence, there exists a gain spillover effect caused by spatial correlation among FAS ports^[19]: When there is a small deviation between the true optimal port and the sounding port, the channel gain does not drop sharply to zero, but presents a smooth attenuation characteristic constrained by the zeroth-order Bessel function of the first kind over spatial distance. This physical property implies that moderately expanding the sounding range on the basis of single-point prediction can cover high-probability prediction deviation intervals and obtain significant fault tolerance gain with only a tiny amount of additional pilot overhead. Conversely, completely abandoning window expansion and relying solely on single-point

prediction is equivalent to actively wasting the inherent spatial fault tolerance potential of FAS; yet blindly expanding the window will offset the overhead reduction benefit brought by prediction and slide back to the overhead catastrophe. Therefore, a key issue for further enhancing the performance robustness of highly dynamic FAS systems is how to design an adaptive local sounding mechanism based on the overhead compression capability of port prediction, while improving prediction fault tolerance with controllable additional overhead.

To fill the above research gap, this paper proposes a prediction-aided fault-tolerant window-enhanced adaptive communication mechanism for fluid antenna systems. The proposed mechanism assumes the existence of a generic port prediction module at the upper layer, whose prediction accuracy is uniformly characterized by a baseline hit rate parameter. Instead of focusing on the specific implementation of the prediction algorithm, this paper concentrates on the adaptation enhancement layer between the prediction results and the underlying hardware. Specifically, a local search window containing K consecutive virtual ports is constructed around the predicted anchor port. By leveraging the inherent spatial channel correlation of FAS to bridge prediction deviations, this design achieves substantial fault tolerance and spatial diversity gains at the expense of minimal and controllable pilot overhead. Furthermore, we designate the window size K as the core control variable to conduct a joint optimization coupled with the terminal moving velocity and the baseline prediction accuracy. In extreme high-speed and high-Doppler scenarios, the algorithm adaptively shrinks the window to $K = 1$ to ensure effective data transmission duration under critically short coherence times. In medium- and low-speed scenarios, the window is moderately expanded to maximize fault-tolerance robustness and channel capacity while keeping the pilot overhead affordable. Consequently, an optimal dynamic balance between pilot overhead and spatial diversity gain is achieved, fundamentally mitigating the overhead catastrophe in highly dynamic environments.

The main contributions of this paper are summarized as follows:

1) We propose a fundamentally new overhead management paradigm for FAS in highly dynamic scenarios. By constructing a dynamic local sounding window anchored on upper-layer port prediction results, we transform the conventional global blind search into a spatially localized precision sounding process. This architecture effectively compresses the pilot temporal overhead while robustly retaining critical fault-tolerance capabilities against algorithmic prediction deviations.

2) We establish a comprehensive mathematical model to evaluate the long-term expected throughput of the proposed system. To quantitatively characterize the intrinsic relationship between prediction accuracy and search window size, we introduce a nonlinear bounded-growth hit probability function. Furthermore, we derive an equivalent gain bridging model based on the zeroth-order Bessel function of the first kind to accurately capture the spatial spillover effect of channel correlation under pre-

diction miss scenarios. Leveraging this analytical framework, we formulate a non-convex optimization problem that captures the dynamic tradeoffs among motion timeliness, pilot overhead, and spatial diversity gain under stringent task deadline constraints.

3) To meet the stringent real-time communication requirements of mobile agents, we design an efficient computational framework combining offline spatial expectation decoupling with online discrete zeroth-order (ZO) gradient tracking. The offline stage decouples the computationally intensive multi-path channel statistical integration from real-time motion states, translating core expectation parameters into constant-time algebraic lookups. The online stage utilizes a discrete ZO gradient ascent engine equipped with heuristic initialization and early stopping criteria. This two-stage design enables microsecond-level adaptive tracking of the optimal window size, with an online time complexity entirely decoupled from the massive number of antenna ports.

2 System Model

2.1 Physical Scenario and Mobility Modeling

Consider a single-antenna base station serving an embodied intelligent agent performing environmental inspection tasks, such as an unmanned surface vehicle (USV). The agent is required to travel from the starting point to the destination within a specified task deadline T_{deadline} , and the total straight-line physical travel distance is denoted as D . During task execution, the instantaneous moving speed of the agent is defined as a continuous variable v .

As the agent travels through the environment, its relative motion and variations of surrounding scatterers induce Doppler shift, resulting in rapid fading of the wireless channel. Let f_c denote the carrier frequency of the system, c denote the speed of light, and f_{env} denote the inherent baseline frequency shift of the surrounding environment. The term $f_d = f_c v/c$ represents the maximum geometric Doppler shift caused by the high-speed mechanical movement of the embodied intelligent agent. The channel coherence time T_c of the system is modeled as:

$$T_c = \frac{1}{f_{\text{env}} + \frac{f_c v}{c}} \quad (1).$$

This model indicates that the faster the moving speed v of the agent, the stronger the Doppler effect, and the shorter the channel coherence time T_c ^[20]. To quantitatively analyze the boundary characteristics of this mobility model, this paper discusses two extreme asymptotic scenarios as follows.

- Quasi-static boundary: When the moving speed of the agent node approaches zero ($v \rightarrow 0$) or the agent travels at an extremely low speed, the term $f_d \rightarrow 0$, and the channel coherence time degenerates to $T_c \approx 1/f_{\text{env}}$. At this point, the wireless channel is mainly dominated by macroscopic environmental scatter-

ing, exhibiting the traditional block fading characteristic with relatively sufficient temporal coherence.

- High-Doppler regime: When the agent has to travel at full speed ($v \rightarrow v_{\text{max}}$) to meet the tight task deadline, i.e., extremely small T_{deadline} , the dominant term in the denominator evolves into the self-induced Doppler shift f_d . In this case, the Doppler spread expands dramatically, causing the channel coherence time T_c to shrink sharply and non-linearly.

To ensure coherent transmission in highly dynamic environments, the system specifies that the length of each data transmission cycle must be equal to the current channel coherence time $T_c(v)$.

2.2 Multipath Channel and Physical Gain Modeling for FAS

As shown in Fig. 1, the agent node is equipped with a one-dimensional linear FAS. To accurately capture the channel correlation of FAS within an extremely small space, this paper adopts the Sum of Sinusoids (SOS) method to physically model the spatial channel^[21–22].

Assume that radio waves, after being scattered by the surrounding environment, form M independent multipath rays arriving at the agent node. Let the m -th ray, $m \in \{1, 2, \dots, M\}$, have a random angle of arrival $\theta_m \in [0, 2\pi]$ following a uniform distribution, and a random initial phase $\phi_m \in [0, 2\pi]$ following a uniform distribution. Let the total physical length of the fluid antenna be W times the signal wavelength λ . Within this fixed physical length, N virtual communication ports for antenna sliding are uniformly distributed. Taking one end of the antenna as the origin of the physical coordinate system, the precise physical spatial coordinate x_n of the n -th virtual port, $n \in \{1, 2, \dots, N\}$, is expressed as:

$$x_n = \frac{n-1}{N-1} W\lambda \quad (2).$$

Due to the tiny differences in spatial coordinates of each port,

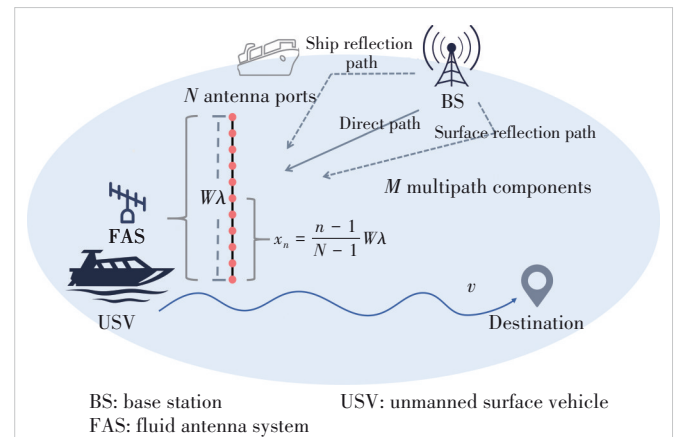


Figure 1. System Diagram of an FAS-enabled agent served by a base station in a multipath environment

continuous phase shifts occur when multipath rays arrive at different ports. The complex channel state h_n received at the n -th virtual port is the superposition of M rays:

$$h_n = \frac{1}{\sqrt{M}} \sum_{m=1}^M \exp \left(j \left(2\pi \frac{x_n}{\lambda} \cos(\theta_m) + \phi_m \right) \right) \quad (3)$$

where $1/\sqrt{M}$ is the normalization coefficient to ensure the conservation of average channel power. The physical channel power gain of the n -th virtual port is defined as:

$$g_n = |h_n|^2 \quad (4)$$

As x_n varies continuously, the spatial channel formed by the gain set $\{g_1, g_2, \dots, g_N\}$ exhibits a continuously fluctuating correlated fading characteristic. There exists a global optimal channel gain over the entire antenna aperture, denoted as:

$$g_{\max} = \max_{n \in \{1, \dots, N\}} g_n \quad (5)$$

To quantitatively characterize the inherent non-independence of FAS at the spatial hardware level, the spatial correlation coefficient between any two virtual ports n and n' is defined as $\rho_{n,n'}$. In the classic rich scattering environment with isotropic scattering, according to Clarke's channel model, the spatial correlation between any two points can be obtained from the zeroth-order Bessel function of the first kind^[4]:

$$\rho_{n,n'} = J_0 \left(\frac{2\pi |x_n - x_{n'}|}{\lambda} \right) \quad (6)$$

Substituting the port physical coordinate formula into the above equation, the spatial correlation between ports can be expressed as a function of the discrete index difference:

$$\rho_{n,n'} = J_0 \left(2\pi W \frac{|n - n'|}{N - 1} \right) \quad (7)$$

The above spatial correlation model demonstrates that the spatial channel formed by the gain set $\{g_1, g_2, \dots, g_N\}$ is not spatially independent across all positions, but exhibits a continuous undulating correlated fading characteristic in space. When the index difference $|n - n'|$ is small, ports maintain a strong positive spatial correlation. This physical property serves as the theoretical cornerstone of the mechanism proposed in this paper: If there exists a minor spatial deviation between the optimal port predicted by the high-level embodied intelligence algorithm and the true global optimal port $g_{\max}$, constrained by the envelope of the correlation coefficient $\rho_{n,n'}$,

opening a local window with K consecutive ports around the predicted port for adaptive sliding sounding can still achieve channel gain close to the global optimum with a very high probability. On the contrary, if ports are mutually independent, any small deviation of the high-level prediction would result in complete detection failure.

2.3 Embodied Artificial Intelligence (EAI) Prediction and Channel Sounding Overhead Model

Acquiring channel state information (CSI) consumes time-domain resources. Let the pilot overhead duration for testing a single FAS port be a constant τ_0 . To obtain the global optimal gain $g_{\max}$, the traditional full scanning mechanism traverses all N ports across the entire aperture, resulting in a delay overhead of $N\tau_0$.

In the proposed mechanism, the embodied intelligent agent leverages the perception model to predict the local interval where the optimal channel is most likely to exist, and instructs the FAS to perform sounding only within a local search window containing K consecutive virtual ports, where the discrete control variable K satisfies $1 \leq K \leq N$. Under this mechanism, the pilot sounding duration per cycle is reduced to $K\tau_0$. Within one coherence time T_c , after deducting the pilot overhead, the time ratio factor $\eta(v, K)$ available for effective service data transmission is modeled as:

$$\eta(v, K) = \max \left[0, 1 - \frac{K\tau_0}{T_c} \right] = \max \left[0, 1 - K\tau_0 \left(f_{\text{env}} + \frac{f_c v}{c} \right) \right] \quad (8)$$

As shown in Fig. 2, this formula reveals the core tradeoff in highly dynamic scenarios that either an excessively large window K or an excessively high speed v will cause the effective transmission time to approach zero. Among them, the perceptual computation phase with negligible time overhead consists of two sub-processes: The EAI perception model outputs the predicted optimal port, and the online ZO optimization algorithm determines the optimal search window size.

Due to the uncertainty in the embodied intelligence's prediction of the environment, this paper defines the probability that

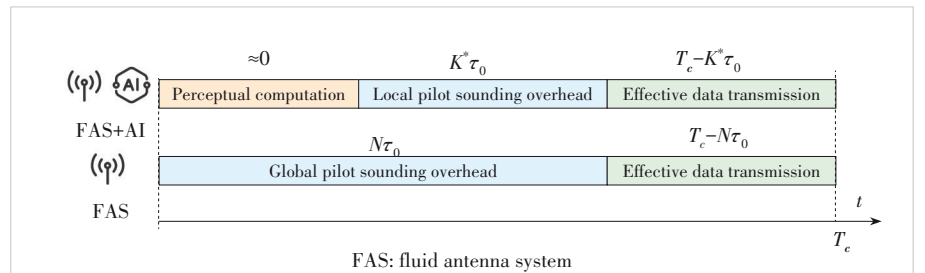


Figure 2. Timing diagram of pilot overhead and effective data transmission within one channel coherence time T_c , comparing the proposed prediction-aided local sounding (FAS+AI) with conventional full-port scanning (FAS)

the embodied intelligence accurately includes the global optimal port within a window of size K as the hit probability $p(K)$. A nonlinear bounded growth function is introduced to characterize this behavior:

$$p(K) = 1 - (1 - p_0) \left(1 - \frac{K-1}{N-1}\right)^\alpha \quad (9).$$

In the formula, the constant $p_0 \in (0,1)$ denotes the baseline perception hit rate under a minimal window ($K=1$); the constant $\alpha \geq 1$ is the confidence index that reflects the performance decay rate of the embodied perception model. This hit probability model satisfies the following boundary characteristics of fluid antennas:

- Single-point baseline: When the system relies entirely on the EAI's single-point prediction ($K=1$), the function rigorously degrades to $p(1) = p_0$, representing the inherent baseline perception confidence of the prediction model.
- Full-aperture scan: When the search window expands to traverse the entire physical antenna aperture ($K=N$), the system invariably captures the global optimum, correctly yielding $p(N) = 1$.

The exponent $\alpha > 1$ serves as a crucial non-linear shape parameter. It mathematically maps to the precision metric (e.g., the scale parameter λ of the Laplace distribution) of the underlying error distribution, characterizing the diminishing marginal probability gain as the search window expands toward the aperture boundaries.

2.4 Hit Probability and Expected Transmission Capacity Model

In summary, when the FAS performs sliding sounding within a window of size K , the system communication presents two mutually exclusive statistical states as follows.

- Prediction hit scenario ($p(K)$): The FAS performs sliding sounding within window K and successfully captures the global optimal gain; that is, the effective gain satisfies $g_{\text{hit}} = g_{\text{max}}$.
- Prediction miss scenario ($1 - p(K)$): The global optimal port lies outside the search window, and the FAS can only obtain a suboptimal instantaneous maximum gain in the erroneous local region, denoted as $\tilde{g}_{\text{local}}(K) = \max_{n \in K_{\text{miss}}} g_n$, where K_{miss} represents the set of consecutive virtual port indices that exclude the true global optimal port.

Based on the microscopic spatial correlation theory derived above, the local extremum $\tilde{g}_{\text{local}}(K)$ in the miss scenario is not spatially independent of the global optimal point g_{max} ; instead, it is constrained by the physical envelope of the spatial correlation coefficient. Furthermore, the parametric multipath model for fluid antennas proposed by Wong et al.^[3] demonstrates that the correlated channel states across the entire FAS aperture can be decoupled into a linear superposition of a global baseline state and local independent fluctuations in the complex voltage do-

main. To overcome the computational bottleneck in calculating the joint expectation of non-independent multivariate Rayleigh distributions and to quantitatively characterize this spatial spillover effect, this paper constructs an asymptotic bridging function. It treats the uncaptured gain $\tilde{g}_{\text{local}}(K)$ within the sounding window as an independent fluctuation, combining it with the global state weighted by the squared Bessel factor $\rho_{\text{eff}}(K)^2$, which maps the expected minimum physical distance into the power domain. Consequently, the conditional effective instantaneous gain in the miss scenario is modeled as a continuous mixed variable that evolves with the window size K :

$$\tilde{g}_{\text{miss}}(K) = \left| \rho_{\text{eff}}(K) \right|^2 g_{\text{max}} + \left(1 - \left| \rho_{\text{eff}}(K) \right|^2\right) \tilde{g}_{\text{local}}(K) \quad (10),$$

where $\rho_{\text{eff}}(K)$ denotes the equivalent spatial correlation factor between the window edge and the true optimal port in the miss scenario. Under the miss event, the true optimal port is assumed to follow a uniform distribution among the remaining $N-K$ ports outside the window. The expected index distance from the optimal port to the nearest boundary of the sounding window can be quantitatively expressed as $\mathbb{E}[d_{\text{min}}] \approx \frac{N-K}{4(N-1)} W\lambda(1 - p_0)$. Accordingly, the equivalent spatial correlation factor $\rho_{\text{eff}}(K)$ can be directly derived from the zeroth-order Bessel function of the first kind:

$$\rho_{\text{eff}}(K) = \max \left(0, J_0 \left(2\pi W \frac{N-K}{4(N-1)} (1 - p_0) \right) \right) \quad (11).$$

Some recent cutting-edge studies have derived closed-form approximations for the average spatial correlation across the entire antenna aperture to break through the integral calculation bottleneck of multipoint joint distributions^[19]. However, such macroscopic averaging algorithms are mainly applied to evaluate the global ergodic capacity of FAS. In the embodied intelligence-assisted architecture proposed in this paper, the underlying FAS performs local sliding sounding based on the dynamic window K . Directly adopting the global static average correlation parameters would eliminate the microscopic distance evolution characteristics between the local window edge and the optimal point. Therefore, to accurately capture the high-resolution spatial dynamics under the local search mechanism, the proposed bridging model does not adopt macroscopic simplification algorithms, but retains the precise physical mapping of the Bessel function.

This model conforms to the underlying physical limits of FAS: When the window is extremely small, i.e., $K \rightarrow 1$, a prediction miss will most likely leave the erroneous single-point sounding far from the optimal solution, and the correlation factor will drop to a low level, resulting in severe attenuation of $\tilde{g}_{\text{miss}}(K)$. As the window gradually expands, i.e., $K \rightarrow N$, even if the high-level algorithm still judges it as a "miss", the physi-

cal edge of the large window statistically approaches the true optimal port continuously, i.e., $\mathbb{E}[d_{\min}] \rightarrow 0$, and the spatial correlation recovers rapidly, $\rho_{\text{eff}} \rightarrow 1$, making $\tilde{g}_{\text{miss}}(K)$ approach g_{max} .

When calculating the system transmission capacity, the dual physical fading from macroscopic distance and microscopic multipath propagation needs to be considered. Since the macroscopic physical displacement of the embodied intelligent agent is negligible relative to the distance to the base station within the extremely short cycle (millisecond level) of local sounding and transmission, this paper assumes that the large-scale path loss dominated by absolute distance remains quasi-static within each local cycle, and models it as a constant local baseline received Signal-to-Noise Ratio (SNR), denoted as γ .

On top of this baseline, the small-scale instantaneous physical gain captured by the fluid antenna sliding within the tiny physical aperture, i.e., g_{max} or $g_{\text{miss}}(K)$, is the real cause of dramatic fluctuations in communication quality. Therefore, the full instantaneous received SNR of the system can be decoupled into the product of the baseline constant and the instantaneous gain. Combined with Shannon's theorem, given the system channel bandwidth B and baseline SNR γ , under a given strategy (v, K) , the instantaneous effective transmission capacity $C_{\text{instant}}(v, K)$ under a single random multipath realization is expressed as:

$$C_{\text{instant}}(v, K) = \eta(v, K) \cdot B \cdot [p(K) \log_2(1 + \gamma g_{\text{max}}) + (1 - p(K)) \log_2(1 + \gamma \tilde{g}_{\text{miss}}(K))] \quad (12)$$

The long-term average expected effective throughput $R(v, K)$ within one communication cycle is modeled as:

$$R(v, K) = \eta(v, K) \cdot B \cdot \mathbb{E}_h \left[p(K) \log_2(1 + \gamma g_{\text{max}}) + (1 - p(K)) \log_2(1 + \gamma \tilde{g}_{\text{miss}}(K)) \right] \quad (13)$$

$$R(v, K) = \eta(v, K) \cdot B \cdot [p(K) \bar{C}_{\text{hit}} + (1 - p(K)) \bar{C}_{\text{miss}}(K)] \quad (14)$$

where $\mathbb{E}_h[\cdot]$ denotes the mathematical expectation over all possible realizations of the continuous spatial multipath channel.

2.5 System Extension for 2D FAS

The above work constructs a spatial bridging model for FAS based on one-dimensional linear topology. As the demand for spatial degrees of freedom within a physical aperture rises, two-dimensional planar fluid antennas (Planar FAS) have emerged as a key evolutionary direction for terminal antenna design. Recent studies demonstrate that two-dimensional fluid antennas deliver superior geometric packing performance and spatial diversity gain under a constrained aperture^[23], and have been deployed in sophisticated network architectures such as simultaneous wireless information and power transfer (SWIPT) and feder-

ated learning^[24]. To verify the scalability of the theoretical framework proposed in this paper, this section extends the one-dimensional baseline model to a two-dimensional planar space.

In the two-dimensional extended model (Fig. 3), the physical panel of the fluid antenna is defined as a rectangular region with dimensions $W_y \lambda \times W_z \lambda$, on which $N_y \times N_z = N_{\text{total}}$ discrete virtual ports are uniformly arranged. Accordingly, the single spatial index is extended to a two-dimensional coordinate pair (m, n) . Under the assumption of isotropic scattering, the microscopic spatial correlation coefficient $\rho_{(m, n), (m', n')}$ between any two ports still follows the zeroth-order Bessel function of the first kind, but its argument is replaced with the two-dimensional Euclidean distance:

$$d_{(m, n), (m', n')} = \lambda \sqrt{\left(\frac{m - m'}{N_y - 1} W_y\right)^2 + \left(\frac{n - n'}{N_z - 1} W_z\right)^2} \quad (15)$$

When the underlying hardware is extended to a two-dimensional panel, the local detection window output by the upper-layer perception model changes from a one-dimensional line segment to a two-dimensional rectangular search box containing K ports. For the prediction miss state, solving the expected minimum physical distance $\mathbb{E}[d_{\min}]$ from the unknown global optimal port to the edge of the search box involves complex two-dimensional boundary integration. Existing literature usually adopts multivariate distribution tools such as Copula theory for accurate planar correlation modeling^[25], but the high analytical complexity of Copula-based methods is not applicable to the cross-layer joint optimization problem in this paper. Therefore, the equivalent area method is adopted for dimensionality reduction and approximate analysis. The total area of the two-dimensional panel is $A_{\text{total}} = W_y W_z \lambda^2$, and the equivalent to-

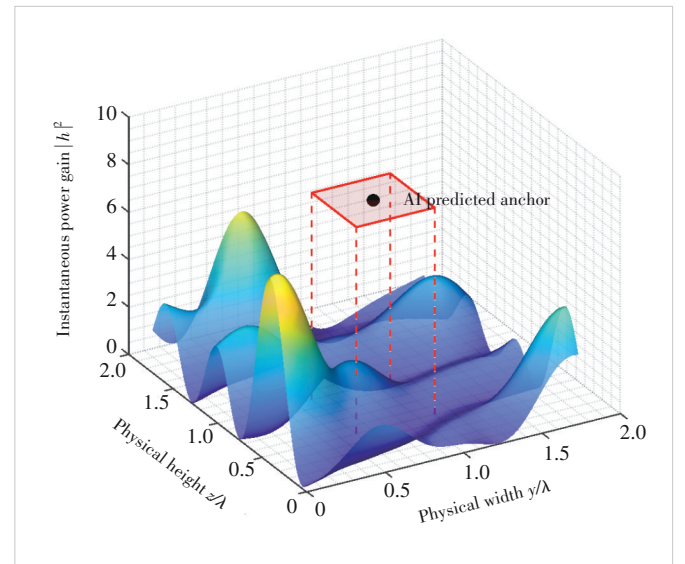


Figure 3. Schematic diagram of spatial relationship for 2D FAS

tal side length is $D_{\text{total}} = \sqrt{W_y W_z} \lambda$. The area of the search box with K ports is $A_K = \frac{K}{N_{\text{total}}} W_y W_z \lambda^2$, and the equivalent inner side length is $D_K = \sqrt{A_K} = \sqrt{\frac{K}{N_{\text{total}}}} \sqrt{W_y W_z} \lambda$. When the remaining length is $D_{\text{total}} - D_K$, the expected distance from a uniformly distributed random point to the nearest edge is $\frac{1}{4} (D_{\text{total}} - D_K)$. The derived two-dimensional expected minimum physical distance $\mathbb{E}[d_{\text{min}}^{2D}]$ is approximated as:

$$\mathbb{E}[d_{\text{min}}^{2D}] \approx \frac{\sqrt{W_y W_z}}{4} \left(1 - \sqrt{\frac{K}{N_{\text{total}}}} \right) \lambda \quad (16).$$

Substituting this expected distance into the correlation envelope function yields the equivalent spatial correlation factor in the two-dimensional space:

$$\rho_{\text{eff}}^{2D}(K) = \max \left(0, J_0 \left(\frac{2\pi \mathbb{E}[d_{\text{min}}^{2D}]}{\lambda} \right) \right) \quad (17).$$

Furthermore, the equivalent suboptimal gain under two-dimensional conditions can also be expressed in a linear bridging form:

$$\tilde{g}_{\text{miss}}(K) = |\rho_{\text{eff}}^{2D}(K)|^2 g_{\text{max}} + \left(1 - |\rho_{\text{eff}}^{2D}(K)|^2 \right) \tilde{g}_{\text{local}}(K) \quad (18).$$

Via mapping based on the equivalent area method, the physical dimensions of the antenna are mathematically unified and abstracted into a single discrete resource variable K , which denotes the total number of ports within the search window. Accordingly, the expected throughput objective function $R(v, K)$ formulated earlier and the subsequent two-stage offline-online algorithm are formally compatible with one-dimensional and two-dimensional FAS via this approximation.

It should be noted that the above treatment is a dimension-reduction approximation. It neglects subtle physical characteristics, including the azimuth offset of the two-dimensional rectangular window, abrupt corner gain variations, and differences in the planar distribution of multipath arrival angles, leading to a precision gap compared with the rigorous model for two-dimensional planar FAS. Full-dimensional precise modeling for two-dimensional topologies, optimization of the aspect ratio and shape of rectangular windows, and dedicated joint scheduling algorithms tailored to two-dimensional spaces can be systematically investigated as independent research directions in future work.

3 Joint Optimization Problem Formulation

To maximize the communication efficiency of embodied intelligent agents during the execution of highly dynamic tasks, this

paper focuses on optimizing the underlying fluid antenna adaptive sensing mechanism. In practical operational scenarios for embodied intelligence, the agent's instantaneous moving speed v is strictly governed by high-level mechanical navigation and motion planning. Meanwhile, the prediction accuracy p_0 of the environmental perception model fluctuates in real time due to physical conditions such as local illumination and occlusions.

Therefore, from the perspective of the physical-layer communication link, the variable pair (v, p_0) is not a decision-control variable that can be actively tuned by the communication system; instead, it represents instantaneous state variables determined by the external environment and task requirements. Under such rapidly time-varying states, the core decision-making authority of the communication physical layer lies in flexibly adjusting the local search window size K of the FAS. Given the system channel bandwidth B and local average received SNR γ , the long-term expected effective throughput over a single communication cycle under the current instantaneous state (v, p_0) is defined as the objective function. The joint optimization problem P1 is formulated as follows:

$$\begin{aligned} \text{P1: } \max_K \quad & R(K|v, p_0) = \eta(v, K) \cdot B \cdot \\ & [p(K)\bar{C}_{\text{hit}} + (1 - p(K))\bar{C}_{\text{miss}}(K)] \\ \text{s.t.} \quad & \text{C1: } K\tau_0 < T_c(v) \\ & \text{C2: } K \in \{1, 2, \dots, N\} \end{aligned} \quad (19).$$

3.1 Offline Decoupling of Spatial Channel Expectation

The objective function consists of two components. The constant $\bar{C}_{\text{hit}}$ denotes the expected channel capacity when the globally optimal antenna port is successfully captured within the search window. The variable $\bar{C}_{\text{miss}}(K)$ denotes the conditional expected capacity under prediction miss, which is bounded by the Bessel-based spatial correlation envelope and increases with K as the window edge approaches the true optimal port. The time-ratio factor $\eta(v, K) = 1 - \tau_p K / T_c(v)$ characterizes the fraction of the coherence time remaining for data transmission after pilot sounding.

Constraint C1 is the timing constraint, which guarantees that the pilot sounding overhead is strictly less than the current channel coherence time. Constraint C2 restricts the search window to a positive integer that does not exceed the total number of physical antenna ports N .

3.2 Coupling Structure of the Objective Function

Problem P1 is a one-dimensional discrete nonlinear programming problem subject to hard timing constraints. Although the decision variable is a single scalar K , the objective function exhibits a coupled structure in which three physical mechanisms evolve with K in opposing directions:

- Time-ratio factor $\eta(v, K)$: monotonically decreasing with K , since window expansion increases pilot time consumption and

reduces the time available for effective data transmission.

- Sensing hit probability $p(K)$: monotonically increasing with K , since a larger window statistically raises the probability of covering the true optimal port.
- Miss-state expected capacity $\bar{C}_{\text{miss}}(K)$: monotonically increasing with K , since window expansion shortens the physical distance between the search boundary and the true optimal port, thereby elevating the equivalent Bessel spatial correlation factor and the local suboptimal gain.

The product of the decreasing time-ratio factor and the increasing spatial gain term creates a competing structure that generally favors an intermediate window size. However, because the spatial gain term further involves the nonlinear bounded hit probability function $p(K)$, the Bessel-based correlation factor in $\bar{C}_{\text{miss}}(K)$, and Monte-Carlo-smoothed statistical expectations, its precise shape depends on system parameters and may exhibit local fluctuations. A rigorous analytical proof of global unimodality or quasi-concavity is therefore not available. Numerical experiments across the parameter range considered in this study consistently indicate a predominantly unimodal trend (i.e., the throughput first increases and then decreases with K), which provides a heuristic basis for the gradient-based search algorithm developed in Section 4. The algorithm further mitigates the risk of local irregularities through heuristic anchor initialization and early termination.

Since the underlying integral operator of the objective function has no explicit closed-form analytical solution, and the environmental state (v, σ) switches frequently in real time, directly evaluating all candidate windows online induces severe latency. This motivates the low-complexity algorithm design in the following section.

4 Algorithm Design

To address the non-convex nature of the optimization problem and the stringent constraint of ultra-short coherence time for embodied intelligent agents, this paper proposes a two-stage algorithm framework termed “offline spatial expectation decoupling and online discrete zeroth-order tracking”. This framework offloads computationally intensive electromagnetic statistical integration to the offline phase, while adopting a discrete ZO gradient algorithm to accomplish adaptive optimization with minimal computational overhead during the online phase.

4.1 Offline Decoupling of Spatial Channel Expectation

Based on the ergodicity assumption of wireless channels, the spatial fading probability density function of multipath channels follows a time-invariant distribution within a broad class of physical scenarios (e.g., rich-scattering environments). Accordingly, the intricate statistical integration operations can be fully decoupled from real-time motion states.

Offline precomputation of the algorithm is implemented on a ground server. Given the system physical parameters and reference SNR γ , we generate N_{sim} sample realizations of Clarke’s

isotropic scattering multipath channel, then compute the expected hit upper bound $\bar{C}_{\text{hit}}$ corresponding to the global extreme point of the system. Next, we traverse all candidate search windows $K \in \{1, \dots, N\}$, and compute the array of bridged expected capacities under miss conditions $\bar{C}_{\text{miss}}(K)$ with the equivalent Bessel spatial correlation factor incorporated. To eliminate spurious numerical peaks (ripples) induced by finite Monte Carlo sampling, a moving average filter is applied to the one-dimensional array $\bar{C}_{\text{miss}}(K)$ to restore smoothness.

Upon completion of offline computation, the system only needs to transmit one scalar value and a one-dimensional array of length N to the on-board memory of the agent. In this way, the integral operator $\mathbb{E}_h[\cdot]$ embedded in the objective function is decoupled and converted into an algebraic memory lookup with $\mathcal{O}(1)$ computational complexity.

4.2 Online Algorithm Based on Discrete ZO Gradient

During task execution by the agent, high-frequency fluctuations of the instantaneous state (v, p_0) cause the unimodal optimal point K^* of the objective function to drift continuously. This algorithm adopts the discrete ZO gradient ascent method to realize microsecond-scale adaptive tracking without exhaustive global search and state-space quantization errors inherent to conventional large lookup tables.

Prior anchor initialization: A heuristic starting point is constructed based on perception confidence. When p_0 is large, the optimal solution tends to correspond to a small search window. The initial point is defined as:

$$K_{\text{curr}} = \max\left(1, \lfloor N \cdot (1 - p_0) \cdot \beta \rfloor\right) \quad (20),$$

where β denotes a tuning constant.

ZO two-sided difference estimation: At the current iterate K_{curr} , single-step perturbations are applied to its left and right discrete neighbors. The lightweight objective function is evaluated to obtain $R(K_{\text{curr}} - 1)$, $R(K_{\text{curr}})$, and $R(K_{\text{curr}} + 1)$. The discrete gradient is approximated via central difference:

$$\hat{\nabla}_K R = \frac{R(K_{\text{curr}} + 1) - R(K_{\text{curr}} - 1)}{2} \quad (21).$$

Adaptive step sizing and early termination: The estimated gradient is normalized adaptively in magnitude to guide the search window toward the extremum with dynamic step sizes. Benefiting from the unimodal property of the objective function, the optimization process is considered to have reached the global maximum once $R(K_{\text{curr}}) \geq R(K_{\text{curr}} - 1)$ and $R(K_{\text{curr}}) \geq R(K_{\text{curr}} + 1)$. A hard stopping criterion is then activated to output the optimal K^* .

The execution logic of the online phase is summarized in Algorithm 1.

Algorithm 1. Online Adaptive Tracking via Discrete ZO Gradient Ascent

Input: Instantaneous state vector (v, p_0) , pre-computed offline constant $\bar{C}_{\text{hit}}$, pre-computed offline array $\bar{C}_{\text{miss}}[1 \cdots N]$, learning rate μ , tuning constant β .

```

1: Calculate coherence time bound:  $T_c = 1/(f_{\text{env}} + f_c v/c)$ 
2: Calculate maximum permissible window constraint:
    $K_{\text{max}} = \lfloor T_c / \tau_0 \rfloor$ 
3: if  $K_{\text{max}} < 1$  then
4:   return Exception (Velocity exceeds physical tracking limit)
5: end if
6: Initialize heuristic anchor:
    $K_{\text{curr}} = \max\left(1, \min\left(K_{\text{max}}, \lfloor N \cdot (1 - p_0) \cdot \beta \rfloor\right)\right)$ 
7: for iter = 1 to MaxIter do
8:   Define discrete neighborhood:
      $K_{\text{left}} = \max(1, K_{\text{curr}} - 1)$ ,  $K_{\text{right}} = \min(K_{\text{max}}, K_{\text{curr}} + 1)$ 
9:   Evaluate  $R(K_{\text{left}})$ ,  $R(K_{\text{curr}})$ , and  $R(K_{\text{right}})$  using
     decoupled algebraic components
10:  if  $R(K_{\text{curr}}) \geq R(K_{\text{left}})$  and  $R(K_{\text{curr}}) \geq R(K_{\text{right}})$  then
11:     $K^* = K_{\text{curr}}$ 
12:    break
13:  end if
14:  Estimate discrete central difference gradient:
15:    if  $K_{\text{curr}} == 1$  then  $\hat{\nabla}_K R = R(K_{\text{right}}) - R(K_{\text{curr}})$ .
16:    else if  $K_{\text{curr}} == K_{\text{max}}$  then  $\hat{\nabla}_K R = R(K_{\text{curr}}) - R(K_{\text{left}})$ 
17:    else  $\hat{\nabla}_K R = (R(K_{\text{right}}) - R(K_{\text{left}}))/2$ 
18:  end if
19:  Compute adaptive step size: step = round( $\mu \cdot \hat{\nabla}_K R_{\text{norm}}$ )
20:  Update current window:
      $K_{\text{curr}} = \max\left(1, \min\left(K_{\text{max}}, K_{\text{curr}} + \text{step}\right)\right)$ 
21: end for
Output: Optimal search window size  $K^*$ 

```

4.3 Time Complexity and Real-Time Performance Analysis

To verify the feasibility of the proposed framework under the hard real-time communication constraints of embodied intelligence, this section conducts an asymptotic complexity analysis from both temporal and spatial dimensions.

1) Spatial complexity analysis

In terms of storage overhead, the system decouples complex physical integration from macroscopic environmental states, eliminating the need for the agent's on-board terminal to store massive multi-dimensional state grids required by the conventional lookup table (LUT) method. The online optimization only permanently retains one constant of expected upper bound $\bar{C}_{\text{hit}}$ and a one-dimensional expected array $\bar{C}_{\text{miss}}[K]$ of length N in memory. Accordingly, the spatial complexity of the system is bounded by $\mathcal{O}(N)$, and its RAM footprint imposes nearly negligible load on on-board tiny NPUs or microcontrollers.

2) Temporal complexity and real-time performance analysis

If the conventional exhaustive global search is adopted, the system must evaluate all N candidate windows within each communication cycle, resulting in an online time complexity linear

in the number of antenna ports, namely $\mathcal{O}(N)$. This approach incurs severe latency when deployed for large-scale fluid antenna systems. By contrast, the discrete ZO tracking framework proposed in this paper achieves a significant reduction in computational overhead:

- Complexity of single function evaluation: Benefiting from offline expectation decoupling, computationally expensive integration and Bessel series calculations are removed from the online objective function. Each single evaluation of $R(K)$ merely involves constant-level algebraic multiplication-addition operations and an $\mathcal{O}(1)$ memory lookup.

- Convergence complexity of optimization iterations: The ZO gradient iteration is hard-constrained within a predefined maximum iteration count I_{max} . Moreover, owing to the inherent unimodal property of the objective function, combined with heuristic anchor initialization and an early stopping mechanism, the actual number of iterations required by the algorithm is generally much smaller than I_{max} .

Hence, the worst-case time complexity of online adaptive optimization is $\mathcal{O}(I_{\text{max}})$. Since I_{max} is a constant bound independent of the antenna scale N , the algorithm achieves complete decoupling from system size in the asymptotic sense. When deployed on mainstream on-board computing hardware, the optimization procedure with $\mathcal{O}(I_{\text{max}})$ complexity runs on a sub-microsecond timescale, which is much shorter than the millisecond-scale coherence time limit $T_c(v)$ induced by the Doppler shift in highly dynamic scenarios. This characteristic fully satisfies the hard real-time communication requirements for high-frequency autonomous operation of embodied intelligent agents.

5 Simulation Results and Analysis

This section validates the performance of the proposed embodied intelligence-aided FAS algorithm. The key parameter settings are specified as follows: carrier frequency $f_c = 2.4$ GHz, total number of antenna ports $N = 100$, antenna length $W = 2$, number of multipath components $M = 20$, pilot time consumption per port τ_0 , and prediction accuracy of the EAI perception model p_0 .

5.1 Analysis of Effective Throughput and Overhead Catastrophe Avoidance

As illustrated in Fig. 4, theoretically, the optimal window size K^* that maximizes the effective throughput R increases as τ_0 , p_0 , or v decreases. The rise in the agent's moving speed v and the growth of single-port pilot overhead τ_0 jointly squeeze the system's available time budget. As shown in the partial enlarged view for $\tau_0 = 0.05$ ms, the throughput R drops to zero at $K = 80$ under $v = 30$ m/s, which corresponds to the overhead catastrophe.

A higher prediction accuracy p_0 eliminates the necessity of selecting K sampling points around the predicted position for pilot transmission to expand fault tolerance. According to the ini-

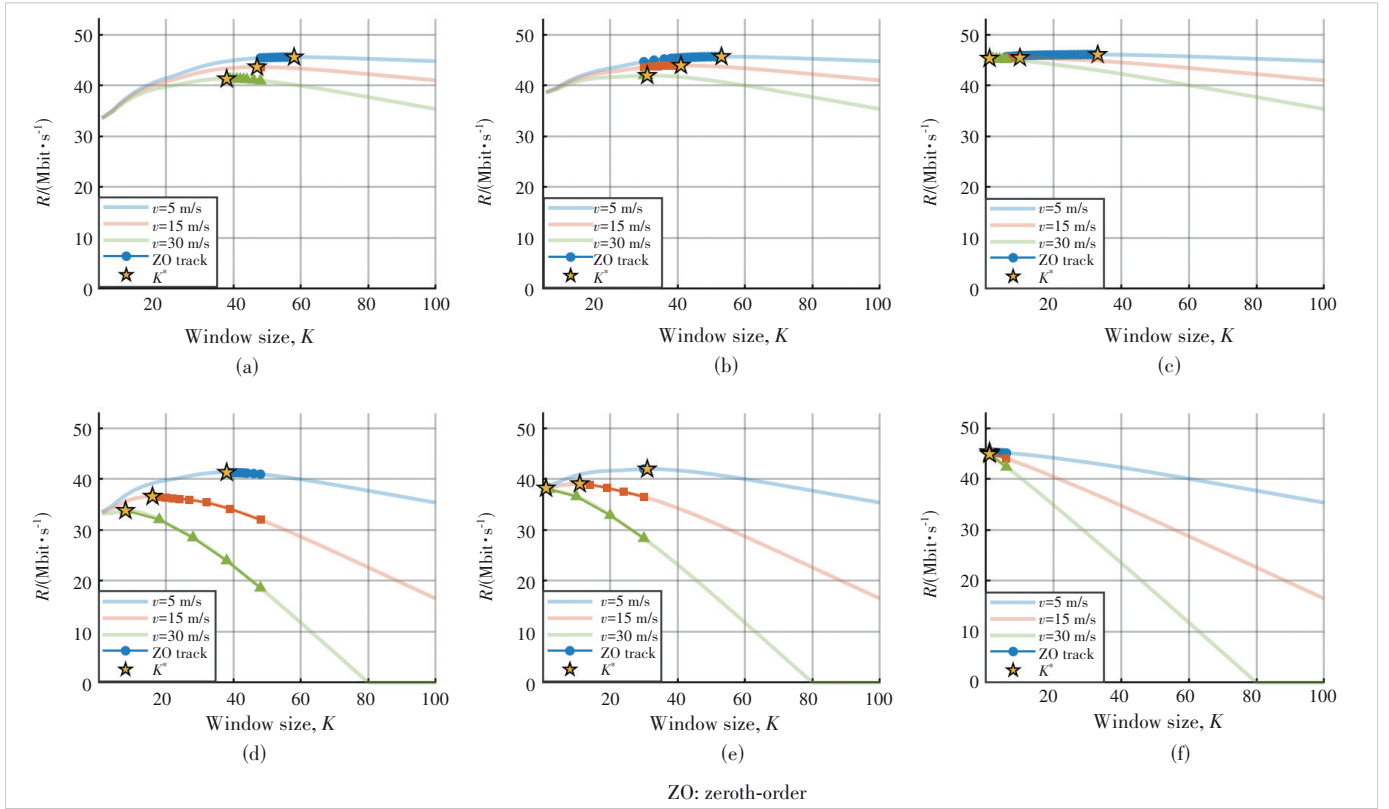


Figure 4. Simulation results of R versus K : (a) $\tau_0 = 0.01$ ms, $p_0 = 0.2$; (b) $\tau_0 = 0.01$ ms, $p_0 = 0.5$; (c) $\tau_0 = 0.01$ ms, $p_0 = 0.9$; (d) $\tau_0 = 0.05$ ms, $p_0 = 0.2$; (e) $\tau_0 = 0.05$ ms, $p_0 = 0.5$; (f) $\tau_0 = 0.05$ ms, $p_0 = 0.9$

tialization formula $K_{\text{curr}} = \max(1, \lfloor N \cdot (1 - p_0) \cdot \beta \rfloor)$ in the proposed algorithm, the initial sensing window size exhibits a negative correlation with the prediction accuracy p_0 of the EAI perception model. Under poor sensing conditions, the algorithm adaptively anchors the starting point to a region with larger K to compensate for sensing degradation by exploiting spatial diversity gains.

5.2 Adaptive Regulation of Optimal Window and Perception Accuracy Gain

Fig. 5 plots the variation of R against v under diverse operating conditions, where the three curves correspond to the proposed algorithm, the fixed-window scheme with $K = 20$, and the exhaustive global search with $K = N$, respectively. Simulation results reveal that in low-mobility scenarios with low pilot overhead, the channel coherence time is sufficiently long. Conventional scanning schemes can attain full spatial diversity gains and deliver decent system performance, exhibiting marginal performance gaps compared with the proposed algorithm. Nevertheless, as v and τ_0 rise, the throughput of traditional approaches drops sharply and eventually falls to zero beyond a certain velocity threshold, namely the overhead catastrophe. In contrast, the algorithm developed in this paper dynamically shrinks the search window K according to the moving velocity. At the cost of a slight loss in maximum spatial diversity gain, it significantly

reduces pilot overhead time, thereby sustaining high and stable throughput even in highly dynamic operating regions.

Fig. 6 reveals the adaptive mechanism of the system. The adaptive window adjustment reflects the tradeoff between spatial domain gain and time domain overhead. When the perception accuracy p_0 is low, the system expands the search window K^* to obtain spatial diversity gain to compensate for sensing degradation. When an increase in moving velocity v leads to temporal compression, the system adaptively shrinks the search window to guarantee valid transmission duration. Under conditions of extremely high moving velocity or extremely high perception accuracy, the system tends to select a smaller optimal window and eventually converges to single-point prediction. This indicates that in high-mobility scenarios, the system must rely on high-precision prediction mechanisms to fundamentally avoid the overhead catastrophe.

5.3 Validation of Spatial Correlation Bridging Model

Fig. 7 verifies the gain boundary of the high-level perception accuracy p_0 of the embodied intelligence model over underlying wireless transmission performance. The sensitivity of throughput to perception accuracy increases significantly with moving velocity. In low-speed scenarios, the dependence of system performance on prediction accuracy is relatively weak. In high-speed scenarios, the channel coherence time is extremely short, and

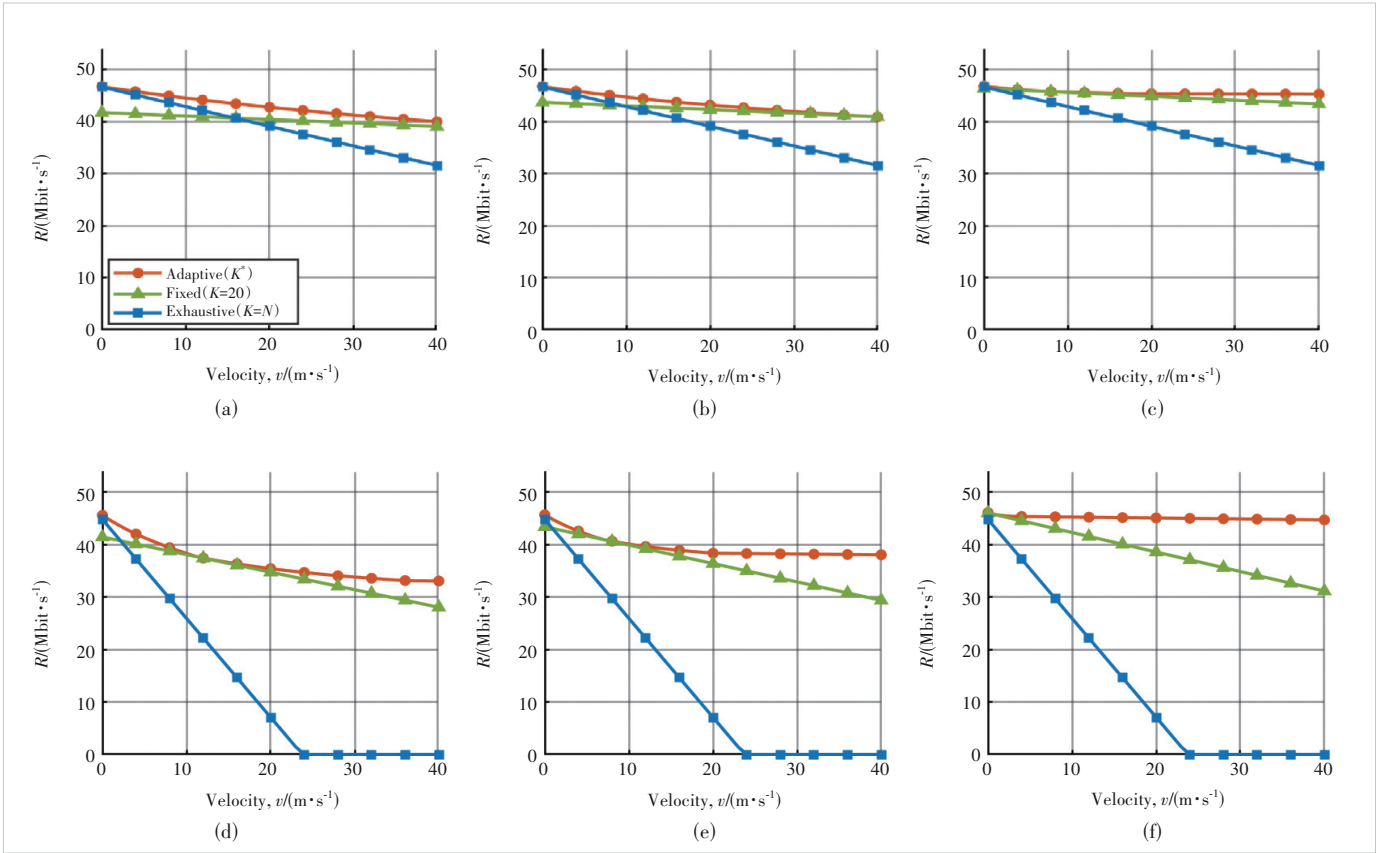


Figure 5. Simulation results of R versus v : (a) $\tau_0 = 0.01$ ms, $p_0 = 0.2$; (b) $\tau_0 = 0.01$ ms, $p_0 = 0.5$; (c) $\tau_0 = 0.01$ ms, $p_0 = 0.9$; (d) $\tau_0 = 0.05$ ms, $p_0 = 0.2$; (e) $\tau_0 = 0.05$ ms, $p_0 = 0.5$; (f) $\tau_0 = 0.05$ ms, $p_0 = 0.9$

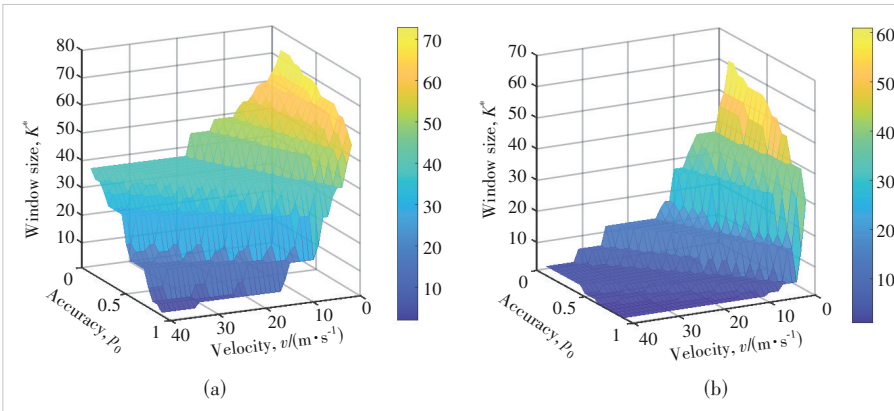


Figure 6. Adaptive adjustment of optimal window size with prediction accuracy and moving velocity: (a) $\tau_0 = 0.01$ ms; (b) $\tau_0 = 0.05$ ms

the system becomes highly sensitive to pilot overhead; improving perception accuracy allows the underlying fluid antenna to complete high-confidence detection within an extremely narrow window, thereby substantially increasing the system throughput. As the perception accuracy continues to improve, the optimal throughputs at different velocities rise steadily and show a convergence trend. This demonstrates that a high-precision embodied perception model can effectively compensate for the physi-

cal transmission deterioration caused by high mobility.

Fig. 8 presents Monte Carlo validation for the theoretical spatial bridging model proposed in Section 2.4. The results reveal that the equivalent suboptimal capacity attainable upon system prediction miss is not a constant. As the local detection window K expands, the physical boundary of the error window gradually converges toward the true optimal port from a macroscopic statistical perspective. Benefiting from the very small port spacing of fluid-state antennas, the underlying Bessel spatial correlation generates a spatial spillover effect, enabling the

conditional miss capacity to converge smoothly and non-linearly to the theoretical upper bound $\bar{C}_{\text{hit}}$. This verifies the physical rigor of the proposed bridging model.

6 Conclusions

To address the overhead catastrophe incurred by full-port scanning of fluid antennas in highly mobile dynamic scenarios,

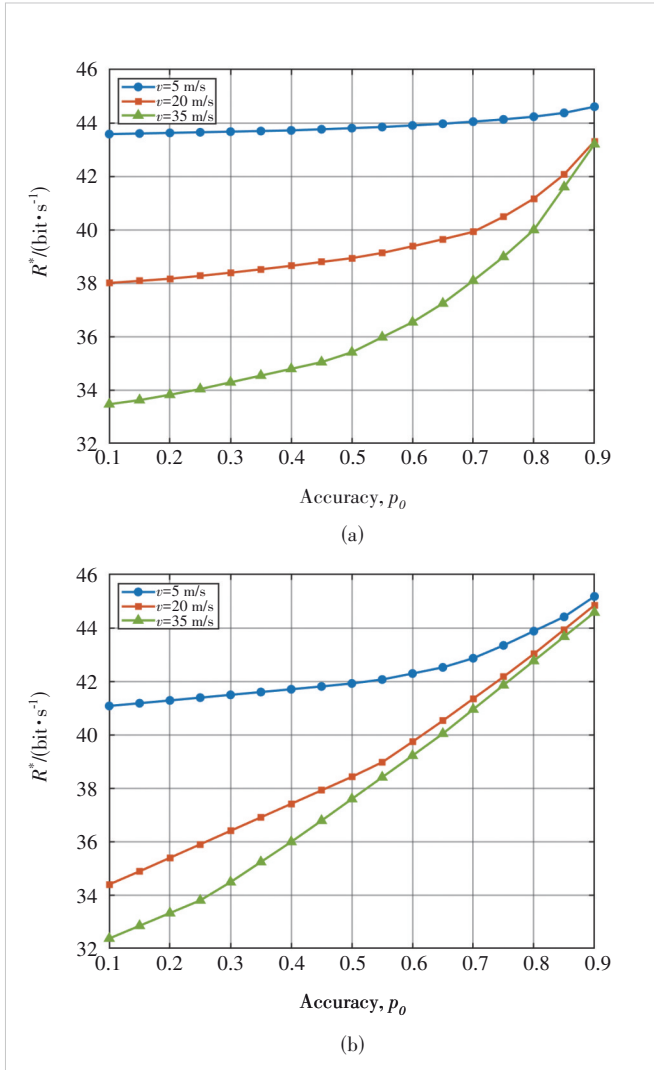


Figure 7. Effective throughput R versus prediction accuracy p_0 under different moving velocities: (a) $\tau_0 = 0.01$ ms; (b) $\tau_0 = 0.05$ ms

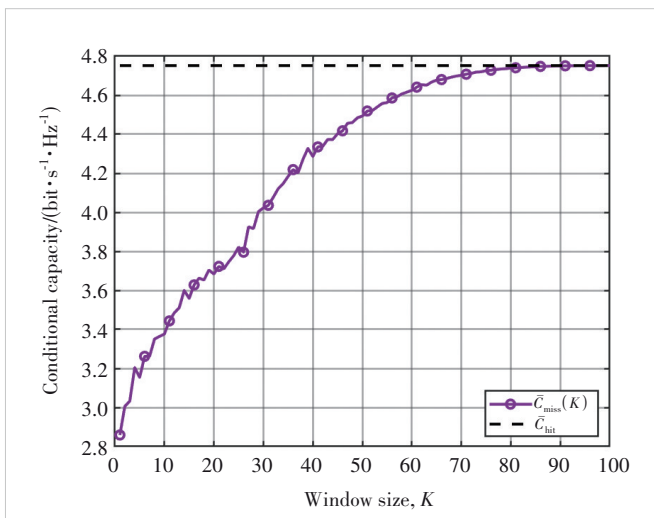


Figure 8. Monte Carlo validation of the spatial bridging model

this paper proposes a predictive error-tolerant window-enhanced adaptive communication mechanism for fluid antennas. Built upon the overhead compression capability of port prediction, the proposed scheme compensates for prediction deviations via a local search window, improves system fault tolerance and channel gain under controllable overhead, and achieves a dynamic tradeoff between overhead and robustness.

This paper establishes a quantitative analysis model for long-term expected throughput. It characterizes the inherent correlation between prediction accuracy and window size via a nonlinear hit probability function, derives a gain bridging model for miss cases based on the zeroth-order Bessel function of the first kind, quantifies the gain overflow effect brought by spatial channel correlation, and formulates a discrete optimization problem subject to timing constraints. The model further reveals the dynamic tradeoffs among moving speed, prediction accuracy, pilot overhead, and spatial diversity gain.

A low-complexity two-stage offline-online solving algorithm is designed in this work. In the offline stage, multipath channel statistical integration is decoupled from real-time motion states, and core expected parameters are precomputed, simplifying online objective function evaluation to constant-time table lookup operations. In the online stage, discrete ZO gradient ascent serves as the core optimization engine. Combined with heuristic initialization and early stopping mechanisms, the algorithm realizes microsecond-scale adaptive tracking of the optimal window without explicit analytical gradients. Its online time complexity is decoupled from the total number of antenna ports, satisfying the hard real-time communication requirements of high-dynamic environments.

Simulation results validate the performance superiority and adaptive mechanism of the proposed scheme: The system dynamically adjusts the window size according to moving speed and prediction accuracy. It fully harvests spatial diversity gains under low-speed conditions and automatically converges to single-point prediction mode at high speeds, fundamentally avoiding overhead catastrophe. Improvements in prediction accuracy can further cut window overhead, and such performance gains are particularly prominent in high-mobility scenarios.

The core model and algorithm developed herein are designed for one-dimensional linear fluid antennas only, while two-dimensional planar scenarios are validated within the framework via dimension-reduction approximation. Future research may extend to precise modeling of two-dimensional fluid antennas, multi-agent joint channel scheduling, and dynamic adaptation of prediction confidence.

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