

Autonomously designed pulses for robust, site-selective control of atomic qubits

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Quantum computers based on cold-atom arrays offer long-lived qubits with programmable connectivity, yet the relatively low fidelity of site-selective, single-qubit control limits their programmability. We introduce an artificial-intelligence (AI) framework that overcomes this limitation. Trained on atom-laser dynamics in the presence of atomic motion in optical tweezers, a deep neural network autonomously designs robust composite pulses that increase local control fidelities tenfold while remaining compatible with existing control hardware. We further demonstrate the robustness of these pulses regarding optical aberrations and beam misalignment. This approach establishes AI-trained pulse compilation for high-fidelity qubit control, and can be readily extended to other atomlike platforms, such as trapped ions and solid-state color centers.

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I. INTRODUCTION

Neutral-atom arrays are emerging as a leading platform for large-scale quantum information processing [1–5]. Each atom trapped in an optical tweezer hosts long-lived qubit states that are precisely manipulated with the use of near-resonant laser illumination [6–8]. Control fidelity approaching 0.9999 for single-qubit gates [9] and 0.999 for two-qubit gates [10] has been demonstrated with global laser illumination across entire atom arrays. However, extending this level of precision to site-selective, individual qubit control remains a major challenge for increasing the programmability of quantum operations [4]. Global illumination combined with atom shuttling [11] enables individual qubit control [12,13], but this approach limits the gate speed and increases the complexity of compiling quantum circuits [14].

The use of localized laser beams for individual qubit control [Fig. 1(a)] offers several advantages, such as efficient use of laser power, reduced off-resonant scattering [9], lower idling errors [12], and native circuit implementation [15]. However, this local qubit control generally shows a lower control fidelity [4,16–18] compared with global illumination: the atom motions within the tweezers introduce large fluctuations in the atom-laser interaction

[Fig. 1(b)], leading to the qubit control errors and decoherence [19]. Increasing the beam diameter can reduce these effects, but this approach compromises the laser power efficiency and isolation from the adjacent atoms. Although motional ground-state cooling [20] can minimize such errors, residual motions still impose a limit on control precision.

The atom motions need not permanently restrict control precision; instead, engineered laser pulses can coherently eliminate the motion-induced effects. Techniques such as dynamical decoupling [21–23] and robust composite pulses (CPs) [24–26] effectively counteract the quasistatic errors. However, these methods become ineffective when localized laser beams are used, since the atom motions induce rapidly varying amplitude errors in the qubit control [Figs. 1(c) and 1(d)]. While model-based stochastic optimizations [27–31] have been explored to identify robust pulses for specific target rotations, generalizing these approaches to arbitrary qubit rotations remains a significant challenge.

To address this challenge, we adopt machine-learned control approaches [32–37] for robust, site-selective control of atomic qubits. A deep neural network (DNN), trained on a Hamiltonian describing motion-dependent atom-laser interactions, autonomously generates CPs that cancel motion-induced amplitude errors. Compared with robust CPs currently in use, the learned sequences increase single-site gate fidelity by an order of magnitude and broaden the accessible range of qubit rotations. We further benchmark their resilience to optical aberrations and alignment errors using a programmable focus array [38].

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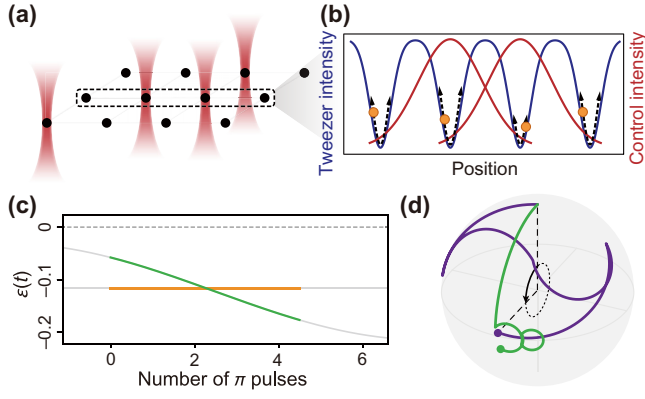


FIG. 1. Site-selective control of atomic qubits in optical tweezers. (a) Addressing target atoms with tightly focused beams enables efficient site-selective qubit control. (b) Atom motions in optical tweezers induce amplitude fluctuations in the local control field. (c) These fluctuations introduce a time-dependent Rabi-frequency error $\epsilon(t)$ (green) with a nonzero mean $\langle \epsilon(t) \rangle$ (orange). (d) Under $\epsilon(t)$, conventional composite pulses (e.g., BB1) deviate from the target rotation (green), whereas the AI-trained pulses compensate for $\epsilon(t)$ and reach the target rotation (purple).

II. AUTONOMOUS PULSE DESIGN

Figure 2(a) shows the schematic of the DNN to produce the trained CPs. The CP comprises a series of n rectangular pulses to implement target qubit control while mitigating the motion-induced amplitude error $\epsilon(t)$. We denote the trained CP with n pulses as CP(n); the k th pulse ($k = 1, \dots, n$) is characterized by Rabi frequency $\Omega_{c,k}$, detuning Δ_k , and pulse duration τ_k . Note that $\epsilon(t)$ perturbs $\Omega_{c,k}$ in the interaction Hamiltonian as $\Omega_k(t) = \Omega_{c,k}(1 + \epsilon(t))$ (see Sec. A in Supplemental Material [39]). For each target rotation

$$\mathcal{U} = \exp\left(-i\frac{A_{\text{tg}}}{2}\hat{\mathbf{n}}(\theta_{\text{tg}}, \phi_{\text{tg}}) \cdot \boldsymbol{\sigma}\right),$$

with the Pauli matrices $\boldsymbol{\sigma} = (\hat{\sigma}_x, \hat{\sigma}_y, \hat{\sigma}_z)$, the DNN receives the desired pulse area A_{tg} and polar angle θ_{tg} of $\hat{\mathbf{n}}$, and returns the required parameters for the n constituent pulses. The subscript “tg” stands for “target”. Adding the global phase ϕ_{tg} to all $\Omega_{c,k}$ completes the implementation of $\mathcal{U}$ by CP(n).

The DNN is trained with reinforcement learning [40,41]. For the reward of the learning, we use the control fidelity

$$F_{\text{CP}(n)}(\epsilon(t)) = \frac{1}{4} \left| \text{Tr}[\mathcal{U}^\dagger U_{\text{CP}(n)}(T; \epsilon(t))] \right|^2$$

of implementing $\mathcal{U}$. Here, $U_{\text{CP}(n)}(T; \epsilon(t))$ is the time-evolution operator due to CP(n) under $\epsilon(t)$, where $T = \sum_{k=1}^n \tau_k$ (see Secs. B and C in Supplemental Material [39]). The angle brackets $\langle \dots \rangle$ refers to the ensemble average over the thermal atoms in a tweezer. The radius ($1/e^2$)

TABLE I. Parameters for the trap and atom motions. $\sigma_r(\sigma_z)$ denotes the standard deviation of the atom’s position along the radial (axial) direction.

Parameter	Value
Tweezer beam $1/e^2$ radius R_{tweezer}	0.7 μm
Trap depth	0.8 mK
Trap frequency $\omega_r/2\pi$ ($\omega_z/2\pi$)	155 kHz (42 kHz)
Atom temperature	30 μK
Atom distribution σ_r (σ_z)	78 nm (201 nm)

of the laser beam for local qubit control R_{control} is set to 1 μm . The parameters for the trap and atom motions are summarized in Table I, and are commonly found in neutral-atom experiments [12,42,43].

We specifically train the DNN for $n = 3$ and $n = 4$ so that the resulting sequences can be compared with conventional CPs, SK1 [25] and BB1 [24], respectively, each of which uses the same number of pulses. Figures 2(b) and 2(c) show the pulse parameters of CP(3) and CP(4), respectively, obtained from two independently trained DNNs. Unlike SK1 and BB1, which are restricted to rotations with $\theta_{\text{tg}} = \pi/2$, the trained CPs can accommodate arbitrary target rotation axes within the training range $A_{\text{tg}} \in [\pi/4, \pi]$ and $\theta_{\text{tg}} \in [\pi/5, 4\pi/5]$. To ensure experimental feasibility, we constrain the pulse parameters such that $|\Omega_{c,k}|, |\Delta_k| \leq 2\pi \times 1 \text{ MHz}$ (see Secs. D–F in Supplemental Material [39] for details on the training process).

The trained CPs suppress $\epsilon(t)$ through distinct error-cancellation strategies. In CP(3), the first two pulses have durations comparable to the motional period ($\omega_r \tau_k / 2\pi \sim 0.5$ for $k = 1, 2$), so they coherently accumulate the dominant components of $\epsilon(t)$. The final pulse ($k = 3$) then cancels the accumulated error by reversing the precession axis [see the phase flip in $\arg(\Omega_{c,k})$]. The spectral analysis in Sec. IV confirms that the dominant components occur at dc and $2\omega_r$. In contrast, CP(4) uses short pulses ($\omega_r \tau_k / 2\pi \sim 0.05$ for all k) and rapidly alternates the precession axis, which averages out $\epsilon(t)$ without relying on a specific motional spectrum. This comes at the cost of reduced cancellation of the dc component that BB1 is designed to suppress. Figure S7 in Supplemental Material [39] depicts the accumulated error during the sequence and illustrates these behaviors.

Figure 3 shows the control fidelity of CP(n). As shown in Fig. 3(a), the conventional CPs are ineffective at mitigating $\epsilon(t)$, exhibiting higher errors than a single rectangular pulse. By contrast, artificial intelligence (AI)-trained CP(3) and CP(4) both coherently suppress this error, yielding an order-of-magnitude increase in fidelity across a wide range of qubit rotations [Figs. 3(b) and 3(c)]. For this assessment, we generated an independent validation set of 10 000 thermal atoms whose initial conditions were not used during the training.

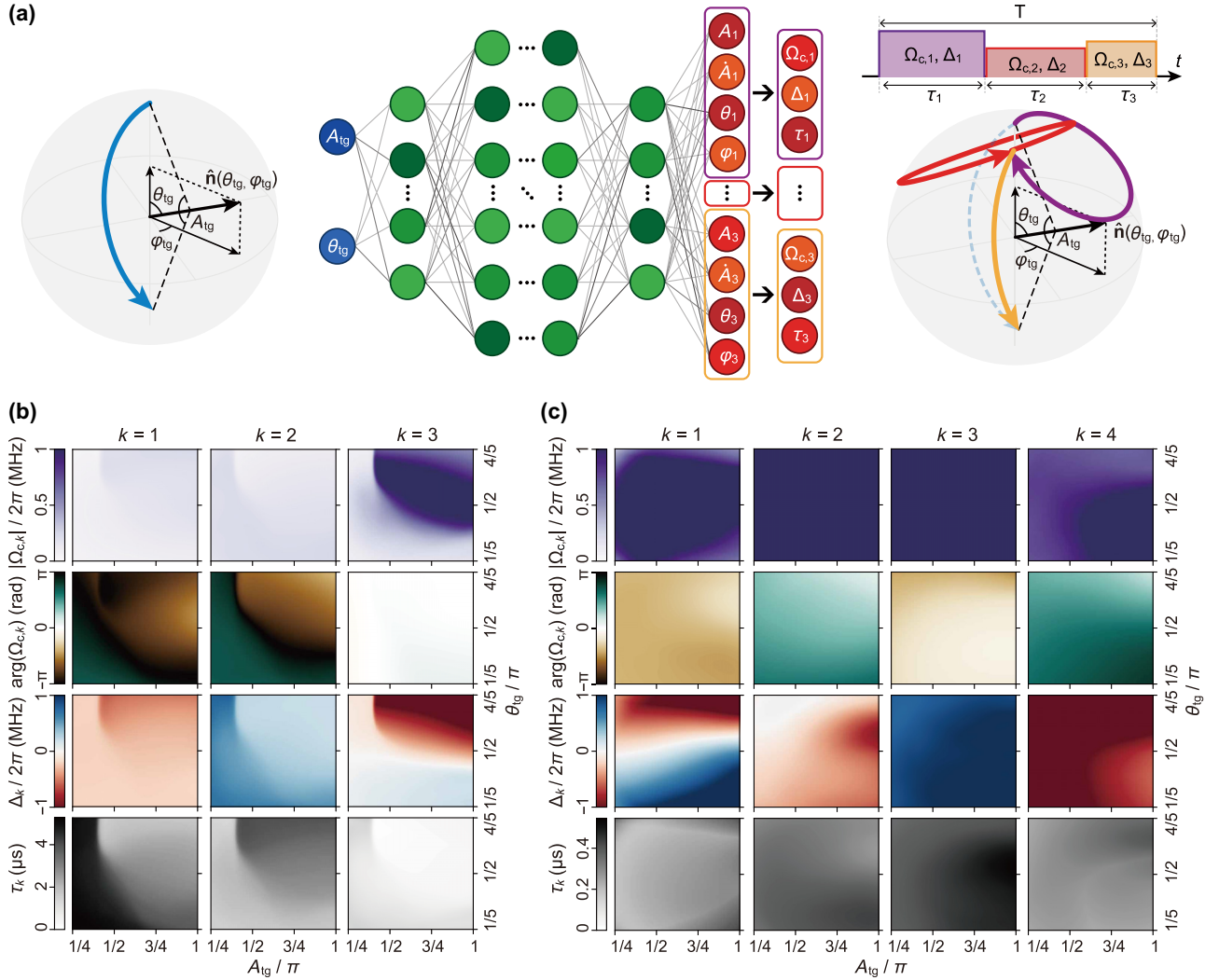


FIG. 2. Trained composite pulses. (a) A target qubit rotation (left) on the Bloch sphere is encoded into a series of pulses (right). The trained deep neural network (middle) identifies the required pulse parameters. (b),(c) Pulse parameters of trained CP(3) and CP(4) implementing the target rotation ($A_{\text{tg}}, \theta_{\text{tg}}$), respectively. Detailed pulse parameters for representative single-qubit gates are provided in Tables SII and SIII in Supplemental Material [39].

This study applies directly to the local control of microwave clock-state qubits (e.g., $|0\rangle = |F=1, m_F=0\rangle$ and $|1\rangle = |F=2, m_F=0\rangle$ of ^{87}Rb) via two-photon Raman transitions [4], since other time-varying effects such as detuning error (due to differential light shift [44, 45]), qubit loss from polarization mixing [46], and incoherent scattering [9] are negligible compared with motion-induced amplitude error (see Sec. G in Supplemental Material [39]).

III. FIDELITY UNDER OPTICAL SYSTEM IMPERFECTIONS

Gate implementations using tightly focused control beams are inherently more sensitive to optical system imperfections than schemes relying on global illumination.

Residual aberrations [47] and misalignments [42] between the control beam and the tweezer alter the distribution of motion-induced errors, thereby degrading the fidelity of CPs trained under ideal conditions.

To quantify these effects, we generate a 40×40 optical focus array [Fig. 4(a)] with phase-only digital holography [38] (see Sec. G in Supplemental Material [39])—a core technique for both the generation [11] and the control [5,48] of neutral-atom qubit arrays. After adaptive aberration correction and intensity homogenization, residual variations in peak intensity and $1/e^2$ radius persist across the array [Fig. 4(b)]. We treat these distributions as realistic inhomogeneities in the intensity and radius of the control and tweezer beams, and evaluate the fidelity accordingly.

When evaluated over the measured residual aberrations, CP(3) and CP(4) outperform both conventional CPs and

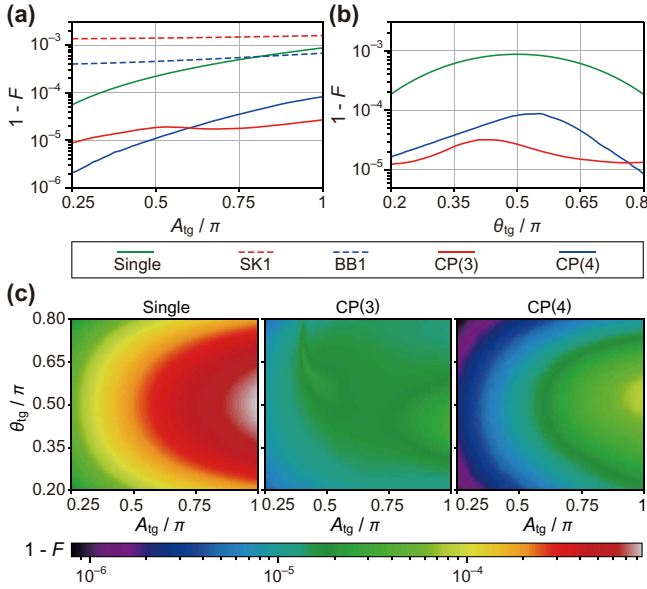


FIG. 3. Control fidelities of trained composite pulses. (a),(b) Fidelity of CPs implementing target rotations with $\theta_{\text{tg}} = \pi/2$ and $A_{\text{tg}} = \pi$, respectively. (c) Control fidelities over the training range.

a single rectangular pulse [Figs. 4(c)–4(f)]. The fidelity dependence on the control beam inhomogeneity reflects the spatial landscape of the Rabi frequency experienced by atoms as they traverse the beam. Although the trained CPs remain somewhat sensitive to the intensity variation $\delta I_{\text{control}}$ of the control beam [Fig. 4(c)], they still achieve markedly higher fidelities than conventional robust CPs. Because a larger control beam radius mitigates motion-induced error [4], fidelity increases monotonically with beam radius [Fig. 4(d)].

Meanwhile, inhomogeneities in the tweezer beams modify the trap depth and frequency, changing both the range and the characteristic frequency of the atom motion in tweezers (see Sec. A in Supplemental Material [39]). As shown in Figs. 4(e) and 4(f), a narrower and deeper trap increases control fidelity due to tighter atom localization. CP(3) shows a notable dependence on $\delta R_{\text{tweezer}}$, suggesting it has been trained to suppress specific trap frequencies. The spectral properties of the trained CPs are analyzed in the next section.

We next evaluate how relative displacements between the control beam and the tweezer reduce control fidelity. Misalignments modify the local Rabi frequency experienced by the atom: rather than the ideal quadratic dependence, the frequency exhibits a linear variation with displacement. Consequently, fidelity decreases, as shown in Figs. 5(a) and 5(b); radial offsets produce a much larger loss than axial ones. Notably, CP(3) quickly loses its error-mitigation capability, whereas CP(4) remains relatively robust regarding misalignment. This contrast arises from

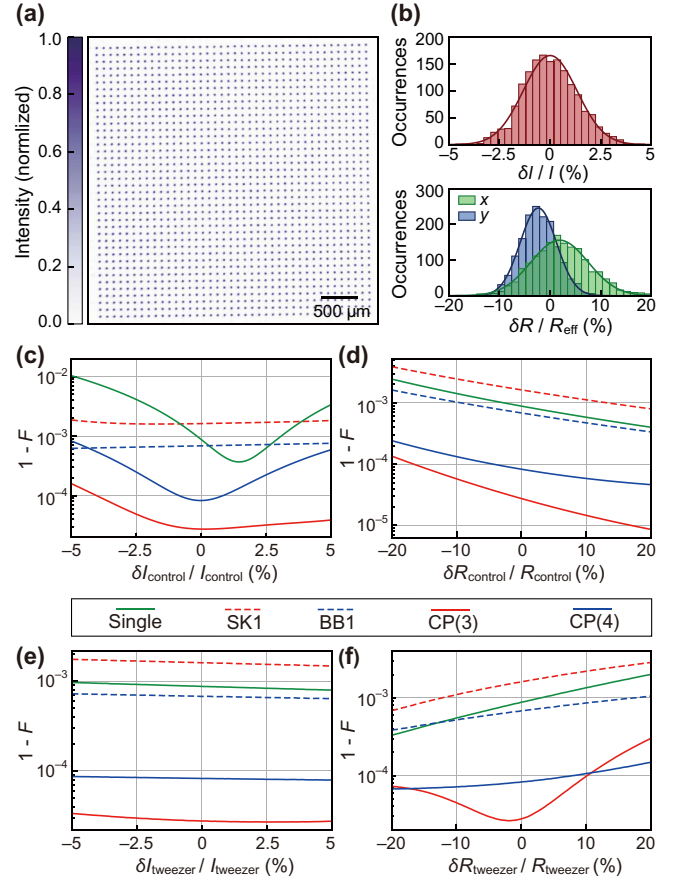


FIG. 4. Control fidelities under optical focus array. (a) Camera image of a 40×40 focus array generated by a phase spatial light modulator. (b) Distributions of peak intensity (top) and $1/e^2$ radius (bottom); solid lines are Gaussian fits with a standard deviation of 1.3% for the intensity and 6.8% (5.1%) for the radius along the x (y) axis. δR denotes the deviation from the effective radius $R_{\text{eff}} = \sqrt{R_x R_y}$, where R_x (R_y) is the mean radius along the x (y) axis. (c)–(f) π -pulse fidelities plotted against deviations in peak intensity and radius for (c),(d) the control beam and (e),(f) the tweezer.

the distinct error-filtering characteristics of the two trained CPs with the additional spectral components in $\epsilon(t)$ due to misalignments, as analyzed in the next section.

IV. SPECTRAL ANALYSIS

In this section, we analyze the spectral characteristics of the trained CPs that suppress the motion-induced amplitude error $\epsilon(t)$. In the composite-pulse frame defined by U_c (see Sec. B in Supplemental Material [39]), we show that to the leading order in $\epsilon(t)$,

$$1 - F \simeq G(\langle \epsilon(t) \rangle) + \frac{1}{2\pi} \int d\omega |\mathbf{r}(\omega)|^2 S(\delta\epsilon; \omega),$$

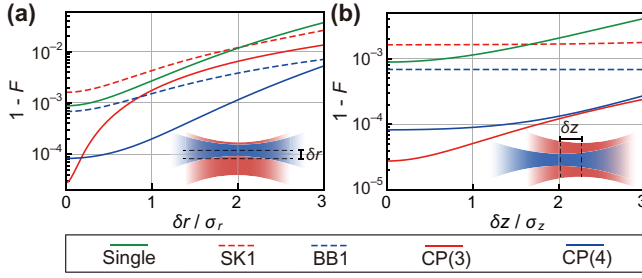


FIG. 5. Control fidelities under misalignments. (a),(b) π -pulse fidelities plotted against misalignment in the radial and axial directions, respectively. The insets show the control beam (red) offset from the tweezer (blue).

where the two contributions stem from (1) imperfect cancellation of the mean amplitude error $\langle\epsilon(t)\rangle$ (i.e., bias),

$$G(\langle\epsilon(t)\rangle) = |\langle\epsilon(t)\rangle\mathbf{r}(0) - \mathcal{D}|^2,$$

and (2) incomplete filtering of the zero-mean fluctuation $\delta\epsilon \doteq \epsilon(t) - \langle\epsilon(t)\rangle$ characterized by its power spectrum $S(\delta\epsilon; \omega)$. Here, $\mathcal{D} = \frac{1}{2} \text{Im}[\text{Tr}[\sigma \ln(\mathcal{U}^\dagger \mathcal{U}_c)]]$, and

$$\mathbf{r}(\omega) = \frac{1}{2\hbar} \int_{-\infty}^{\infty} \text{Tr}[\sigma \tilde{H}_c^\perp(t)] e^{-i\omega t} dt$$

is the filter amplitude obtained from the transverse CP Hamiltonian $\tilde{H}_c^\perp(t)$ (see Sec. I in Supplemental Material [39]). Note that $G(\langle\epsilon(t)\rangle)$ captures the residual error bias, while $\mathbf{r}(\omega)$ characterizes the spectral response of the CP.

Figures 6(a) and 6(b) show $G(\langle\epsilon(t)\rangle)$ and $|\mathbf{r}(\omega)|^2$, respectively, with the experimentally inferred distributions

of $\langle\epsilon(t)\rangle$ and $S(\delta\epsilon; \omega)$ overlaid. These distributions are obtained from the measured intensity and beam-radius variations across the 40×40 focus array shown in Fig. 4(a). For a single rectangular pulse, the residual bias $G(\langle\epsilon(t)\rangle)$ reaches its minimum at zero mean error, $\langle\epsilon(t)\rangle = 0$. By contrast, the trained CPs are optimized to minimize $G(\langle\epsilon(t)\rangle)$ at the mean error due to the atom's harmonic motion [dashed black line in Fig. 6(a)]. This designed shift effectively displaces the implemented rotation $\mathcal{U}_c$ from the target gate $\mathcal{U}$, such that $\mathcal{D} \simeq \langle\epsilon(t)\rangle\mathbf{r}(0)$, thereby canceling the leading-order error bias. Moreover, the broader width of $G(\langle\epsilon(t)\rangle)$ for the trained CPs indicates increased robustness regarding variations in the control beam intensity $\delta I_{\text{control}}$ and alignment imperfections that modify the spatial intensity profile.

The filter functions $|\mathbf{r}(\omega)|^2$ of the trained CPs are tailored to suppress the dominant ac components in $S(\delta\epsilon; \omega)$, particularly at $\omega = 2\omega_r$ and $2\omega_z$. These components arise from the atom motions in the control beam's quadratic Rabi-frequency envelope. While both trained CPs exhibit saturated filtering near dc [see the inset in Fig. 6(b)], their effectiveness in suppressing motion-induced fluctuations hinges on the targeted reduction of these harmonic components. Notably, the two trained CPs demonstrate distinct spectral characteristics. CP(3) features narrow-band filtering centered at the dominant $2\omega_r$. By contrast, CP(4) exhibits broadband filtering that extends over all relevant spectral components, including $\omega = 2\omega_z$. This broadband profile results in resilience under alignment errors (Fig. 5), which introduce additional spectral weight at $\omega = \omega_r$ and $\omega = \omega_z$ [cyan (magenta) points in Fig. 6(b), respectively] due to the linear Rabi-frequency gradient

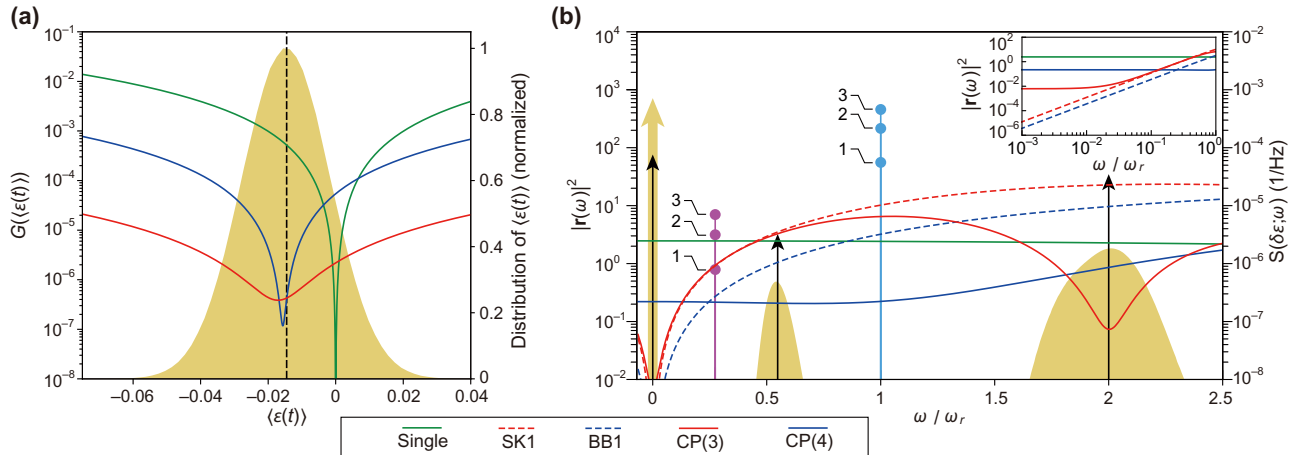


FIG. 6. Spectral characteristics. (a) Residual bias $G(\langle\epsilon(t)\rangle)$ of the trained CPs for a π pulse, with the error bias $\langle\epsilon(t)\rangle$ for an ideal optical focus (dashed black line) and foci with measured δI and δR in Fig. 4(b) (yellow distribution) overlaid. $G(\langle\epsilon(t)\rangle) = 0$ for SK1 and BB1 (not shown). (b) Filter functions of the CPs, with the power spectra of the ideal optical focus (black arrows) and foci with measured δI and δR in Fig. 4(b) (yellow distribution) overlaid. The cyan (magenta) points denote spectral components due to radial (axial) misalignments. Numbers labeling the points indicate the magnitude of misalignment in units of $\delta r/\sigma_r$ for radial displacements and $\delta z/\sigma_z$ for axial displacements. The inset shows an enlargement near the dc component.

sampled by off-centered atoms. Similar spectral responses are observed generically for the trained CPs implementing different target rotations (see Fig. S8 in Supplemental Material [39]).

V. CONCLUSION

We demonstrate that AI-trained composite pulses enable robust and efficient single-qubit control with spatially localized laser fields. By use of deep reinforcement learning to model the interaction dynamics of atoms oscillating in optical tweezers, the trained CPs effectively suppress motion-induced amplitude errors that arise from the nonuniform intensity profile of the control beam. We show that the resulting localized control yields gate fidelities exceeding those of analytic sequences such as BB1 and SK1 by an order of magnitude, even in the presence of optical aberrations and alignment imperfections. In addition, the trained neural network exhibits generalization over the space of $SU(2)$ rotations, enabling automated identification of composite pulses for arbitrary single-qubit gates. By replacing the CPs already used in neutral-atom experiments [4,16,18], our method provides a general pathway to high-precision qubit control and increases the capabilities of neutral-atom quantum processors.

The AI-optimized control enables the agent to learn and generalize complex atom-laser interactions relevant to qubit control. By defining the learning reward using calibrated Hamiltonians, our approach can be extended to autonomously synthesize composite pulses, for example, for Rydberg-mediated entangling gates [49] and recoil-free gates [50,51] in neutral-atom qubits. More broadly, because it adapts to system-specific error landscapes, the same approach is readily applicable to other platforms where composite pulses are already used, including mitigation of motional-amplitude errors in trapped ions [52], suppression of population leakage in transmon qubits [53,54], and reduction of spin decoherence in solid-state color centers [55].

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DATA AVAILABILITY

The data that support the findings of this article are not publicly available. The data are available from the authors upon reasonable request.

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