

Optimal Area Exploration by Resetting Active Particles

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Identifying optimal strategies for efficient spatial exploration is crucial, both for animals seeking food and for robotic search processes, where maximizing the explored area is a fundamental requirement. Here, we propose position resetting as an optimal protocol to enhance spatial exploration in active matter systems. Specifically, we show that the area covered by an active Brownian particle depends non-monotonically on the resetting rate, demonstrating that resetting can optimize spatial exploration. Our results are based on experiments with active granular particles undergoing Poissonian resetting and are supported by simulations of active Brownian dynamics. The covered area is analytically predicted for both large and small resetting rates, leading to a scaling relation between the optimal resetting rate and the self-propulsion speed.

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Effective navigation and exploration of an environment are crucial tasks for a wide range of systems, spanning from the microscale to the macroscale. Specifically, this need arises in many active and living systems, which convert energy from the environment into directed motion [1–3]. In the realm of synthetic active matter, such as robotics, efficient exploration has numerous applications, including mapping uncharted territories and conducting lifesaving rescue missions [4–6]. The need for efficient spatial exploration also extends to bioinspired technologies, such as microrobotic drug delivery and cargo transport [7,8]. Likewise, for living organisms, the constant quest for nutrients and other resources is essential for survival [9,10]. In all these systems, an agent is more likely to achieve its goal when spatial exploration is efficient, i.e., when the covered area is maximized during the search process.

Recently, resetting problems [11,12] have stimulated research in nonequilibrium statistical physics and stochastic processes, with a surge of interest following the seminal work by Evans and Majumdar more than a decade ago [13,14]. Resetting consists of intermittent returns to a fixed location and produces nonequilibrium steady states with nontrivial relaxation properties [15–18], as well as a high degree of entropy production [19–24]. A large proportion

of studies focus on first-passage properties under resetting, which have shown the potential to mitigate long search times [25–33]. The first-passage time, i.e., the minimal time to reach a target, can in many cases be minimized by tuning the resetting rate. This strategy cuts off unfavorably long trajectories that do not encounter the target, while favorable trajectories reach the target without strong influence from resetting [26]. The theoretical picture developed has also been validated experimentally, for instance, by considering colloids in optical tweezers [27,34,35]. In addition, beyond the first-passage time, several theoretical studies have focused on other functionals [36–38] under resetting, as well as on convex-hull problems [39]. Resetting fits naturally within the broader class of intermittent search strategies, where phases of local exploration are interrupted by rapid relocation events such as those found in Lévy flights or alternating ballistic and diffusion modes [40]. In this structural analogy, resetting plays the role of a rapid relocation step.

Beyond the well-known passive scenario, increasing attention has been devoted to resetting in nonequilibrium systems, such as active matter, where resetting has been studied extensively from a theoretical perspective. Several recent results have been obtained for one-dimensional run-and-tumble particles [41–51], as well as in higher dimensions with both run-and-tumble dynamics [44,52,53] and active Brownian dynamics [54–58], even in confining geometries [59]. Experimental studies, however, remain sparse, except for recent works using hexbugs and programmable robots [60–62].

However, while it is known that resetting affects the first-passage time, its role in the covered-area problem is not clear. Intuitively, once a region has been mapped, there is no benefit in revisiting it. From this perspective, resetting

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could, at first glance, appear to be a poor strategy, since it forces the active particle to reexamine already visited locations. However, resets also facilitate a dense exploration of the neighboring region around the resetting location, a feature that is likely lost in the absence of resets in favor of sparse exploration.

Here, we discover that resetting provides an efficient strategy to enhance the area covered by active matter systems. In particular, we experimentally and numerically study the dynamics of an active particle confined to a circular plate and subject to stochastic resetting. This Letter is performed using an active vibrobot [63,64], whose position is reset to the center of the plate after a random time drawn from an exponential distribution. At each reset, the particle orientation is randomized. The exploration process ends once the boundary of the system is reached [Fig. 1(a)]. We demonstrate the existence of an activity-dependent optimal resetting rate that maximizes the covered area, as evident from direct inspection of particle

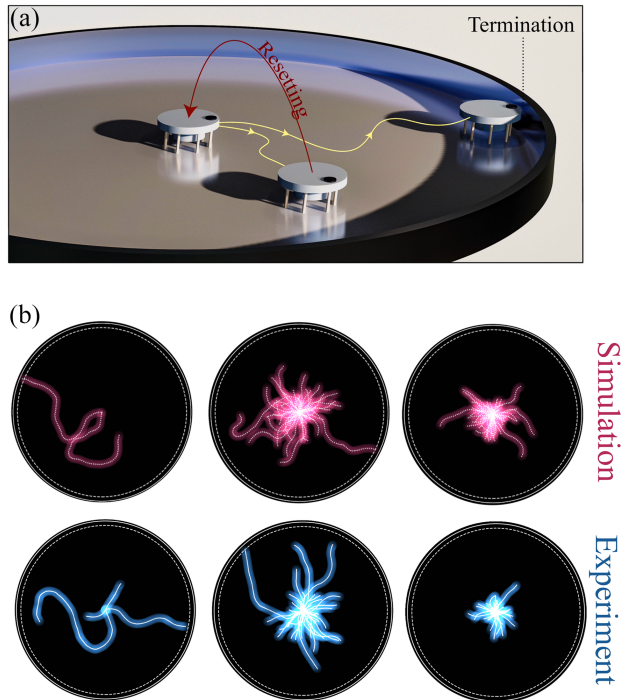


FIG. 1. Active granular particle under resetting. (a) Visualization of the experimental setup showing a vibrobot moving on a circular plate. The particle is reset (red arrow) to its initial position with a randomized orientation at times drawn from an exponential distribution. This process continues until the particle reaches the boundary of the plate. (b),(c) Time trajectories of finite-sized active particles in a circular plate of radius R , for three different resetting rates, $r = 0.5, 1.0, 2.5$ Hz. The covered area is visualized by coloring the center-of-mass trajectory with a thickness corresponding to the particle diameter. (b) Shows experimental data, while (c) shows the simulation results. These typical trajectories qualitatively reveal a nonmonotonic dependence of the covered area on the resetting rate r , observed both in experiments and simulations.

trajectories for a vibrobot [Fig. 1(b)] obtained both experimentally and numerically. Our Letter implies that resetting can be adopted as an optimal strategy to enhance spatial exploration in robotics applications, for example, to improve the efficiency of searching for targets.

Setup—We consider an active granular particle [65–73], called a vibrobot [63,74], moving on a circular plate under the action of an electromagnetic shaker. A vibrobot is a 3D-printed plastic-made particle consisting of a cylindrical body with a height of 7 mm and a diameter of $\sigma = 15$ mm. Seven legs are attached to the particle body and are in contact with the plate. All legs are tilted in the same direction with an angle of 4° , breaking the translational symmetry of the particle. In this way, when the shaker is on, the vibrobot exhibits active motion [74], which is well described by active Brownian particle dynamics with a typical speed [63,75]. We note that the active Brownian particle model is a coarse-grained description that does not capture the microscopic stick-slip dynamics of vibrobots, and its validity is restricted to the Stokes-like regimes identified in prior works [64,73]. Further details on the particle design and the shaker working conditions are reported in End Matter. When the vibrobot hits the container boundary, the measurement is stopped, and the particle is manually placed in the center of the plate with the same orientation. These trajectories serve as the basis for trajectories with stochastic resetting, as explained in detail later.

The dynamics of an active vibrobot are well described by the equation of motion for a two-dimensional active Brownian particle [3]. This has been experimentally verified in Ref. [63]. In our Letter, we consider shaker conditions such that inertia is negligible (as reported in Ref. [76]), leading to effectively overdamped dynamics. Consequently, the particle's orientation denoted by θ and its position represented by the two-dimensional vector $\mathbf{x}$ evolve according to

$$\dot{\mathbf{x}} = v_0 \mathbf{n} + \sqrt{2D_t} \boldsymbol{\xi}, \quad (1a)$$

$$\dot{\theta} = \sqrt{2D_r} \eta. \quad (1b)$$

In this dynamics, D_t is the translational diffusion coefficient, while $\boldsymbol{\xi}$ and η are a vector and a scalar delta-correlated Gaussian white noise with zero mean, respectively, modeling spatial translational noise and rotational noise. The term v_0 represents the self-propulsion speed of the vibrobot, with a direction of motion given by $\mathbf{n} = [\cos \theta, \sin \theta]$. The orientation angle θ undergoes diffusive behavior with rotational diffusion coefficient D_r . Finally, the ratio v_0/D_r defines the persistence length due to the activity, i.e., roughly the distance traveled by the particle before its direction of motion changes. We emphasize that the vertically vibrating plate influences the vibrobot dynamics through two independent mechanisms [63]:

(i) activity, or self-propulsion, arising from the vibrobot's structural asymmetry, and (ii) an additional translational noise reminiscent of thermal noise in microscopic systems but originating from imperfections in both the plate and the vibrobot. While all parameters in the active Brownian particle model can be varied independently, this is not the case in the experiments. The model therefore serves as a complement to the experiments, enabling the exploration of regions of parameter space that are inaccessible experimentally. The dynamics (1) is complemented by absorbing boundary conditions at the container circular wall, which is placed at a radial position R from the center of the plate.

Resetting events are realized in experiments and simulations by interrupting the particle trajectories after a time τ drawn from an exponential distribution $p(\tau) \propto \exp(-r\tau)$ characterized by a resetting rate r . In the latter, the protocol requires manually resetting the particle at the center of the circular plate only when the vibrobot reaches the boundary and the recording is stopped, rather than at every resetting event. This greatly simplifies the protocol for performing resetting experiments (see End Matter).

Here, we focus on calculating the space explored by the particle, referred to as the covered area. After discretizing the space into cells of size approximately equal to the particle radius, the covered area is defined as the fraction of occupied cells. This quantity is computed by tracking the trajectory of the vibrobot's center of mass with a thickness equal to the particle diameter (see End Matter for details on the discretization scheme). Consequently, a second visit to the same cell does not increase the covered area, which thus corresponds to the number of “distinct sites” in random-walk studies [77,78]. We emphasize that defining the covered area based on the particle size provides only a lower bound on the total area explored, as many realistic systems may have a larger radius of exploration.

Specifically, we focus experimentally and numerically on the mean covered area $\mathcal{A}$ explored up to the time τ_S required for the particle to reach the boundary. If the particle is reset in the middle of the container at a time $\tau < \tau_S$ due to a random resetting event, the calculation of $\mathcal{A}$ continues, since the particle has not yet touched the boundary. However, we include an upper cutoff time t_c , at which the measurement is stopped even if the container's boundary is not reached. This mimics the desire to achieve a goal in finite time and excludes unfavorable exploration strategies that are too slow. Hence, we are interested in the mean area explored up to a time $\min\{\tau_S, t_c\}$.

Results—By visual inspection of the particle trajectory [Fig. 1(b)], we observe that both experiments and simulations consistently display nonmonotonic behavior in the area covered by the particle as a function of the resetting rate r . To quantify this observation, we study $\mathcal{A}$ as a function of r for three experimental configurations corresponding to different self-propulsion speeds, $v_0 = 11.4, 26.1, 63.3 \text{ mm s}^{-1}$ (Fig. 2). Experimentally, different

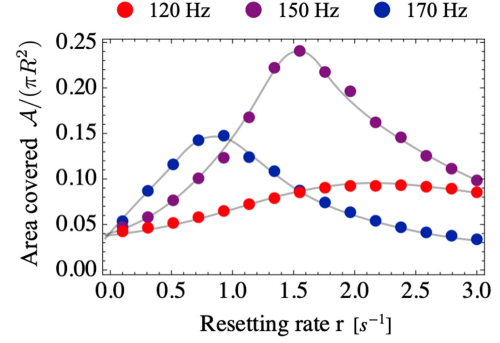


FIG. 2. Resetting induces optimal covered area. Covered area $\mathcal{A}$ normalized by the plate area πR^2 as a function of the resetting rate r . The analysis is performed for three different shaker frequencies, as indicated in the legend, corresponding to different particle parameters (see End Matter). Dots represent the data points, while the gray solid lines serve as guides to the eye. Optimal resetting rates are identified as the values of r that maximize the covered area.

self-propulsion speeds are obtained by varying the shaker frequency (see End Matter). The case $r = 0$ corresponds to the absence of resetting, while the maximal, statistically relevant, resetting rate shown corresponds to 3 Hz. The mean covered area displays a nonmonotonic behavior with r : It increases until a maximum (up to 30%) and then decreases again for further increases in r .

Simulations allow us to systematically explore the role of the particle speed v_0 and the resetting rate r beyond experimental conditions [Fig. 3(a)]. In the heat map, bright and dark colors correspond to higher and lower values of the mean covered area $\mathcal{A}$ (up to a covered-area fraction of 40%). In the absence of resetting, $\mathcal{A}$ decreases monotonically with the self-propulsion speed. Indeed, as the persistence length v_0/D_r becomes large compared to the plate radius, the particle moves ballistically toward the container boundary, exploring only a narrow region of the domain.

In the presence of resetting, two competing effects arise. Resetting generates an effective attraction toward the origin, forcing the particle to repeatedly explore the central region of the circular plate, while simultaneously extending the exploration time by preventing absorption at the boundary. Although this behavior is reminiscent of intermittent search strategies, the underlying mechanism is fundamentally different: Resetting does not promote the exploration of new regions but instead repeatedly restarts the active trajectory within the same confined domain, thereby modifying how the particle samples space before first passage. This leads to a nonmonotonic dependence of the covered area $\mathcal{A}$ on r [Fig. 3(b)], a behavior observed systematically across several values of the self-propulsion speed [Fig. 3(a)]. The cutoff time t_c does not qualitatively alter the results, preserving the nonmonotonic behavior of the covered area (see End Matter). In addition, this

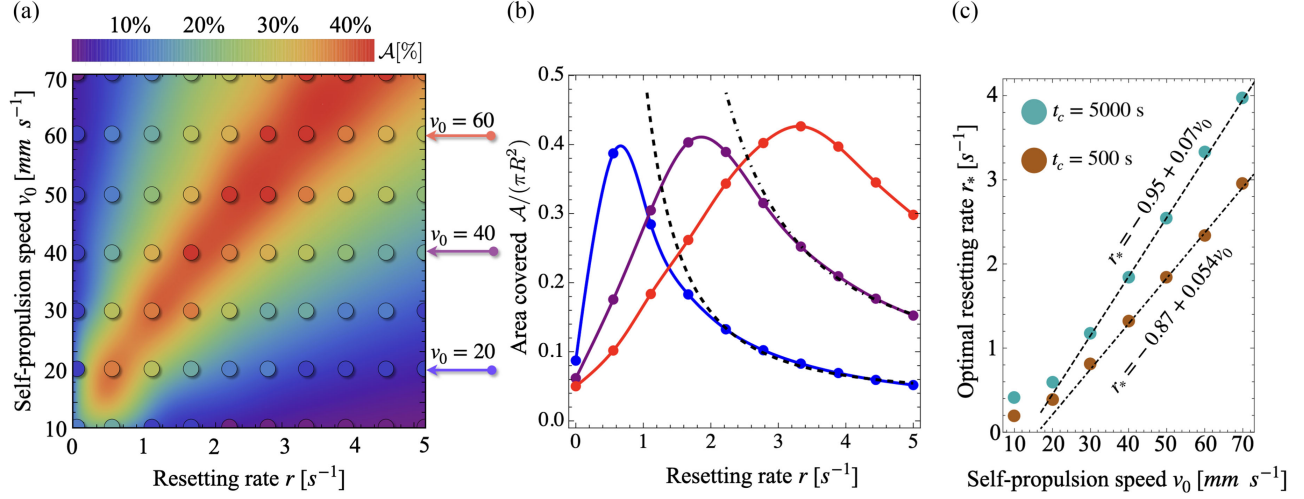


FIG. 3. Resetting-induced optimal area covered by an active particle. (a) Covered area $\mathcal{A}$ (color gradient) normalized by the area of the circular plate, as a function of the resetting rate r and self-propulsion speed v_0 . Colored dots represent simulation data, and the background is obtained by interpolation. (b) Normalized $\mathcal{A}$ versus r for selected v_0 values indicated by arrows in (a). The two dashed lines denote the predicted $\sim r^{-2}$ scaling at large r . The cutoff time is $t_c = 5000$ s. (c) Optimal resetting rate as a function of v_0 , showing the predicted linear behavior (dotted black lines). Blue and red points correspond to cutoff times $t_c = 500$ and 5000 s, respectively. The remaining simulation parameters are $D_r = 0.85\ s^{-1}$, $\gamma_t = 10.0\ g\ s^{-1}$, and $D_t = 1.59\ mm^2\ s^{-1}$.

nonmonotonicity also occurs for other resetting-time distributions, as verified for gamma-distributed resetting times (see End Matter), demonstrating the generality of the observed phenomenon.

To gain analytical insights into the experimentally and numerically observed covered area, we consider the regime where the particle's persistence length v_0/D_r is large compared to the system size. Consequently, except when interrupted by resetting events, the particle moves ballistically toward the boundary with speed v_0 . This allows us to extract the behavior at small and large r , as well as an estimate of the optimal resetting rate r_* . At small resetting rates, the exploration process is dominated by a small number n of approximately independent trajectories, each covering an area A_1 . Since the process ends upon first passage to the boundary, we have $n \approx r\langle\tau_S\rangle$, where $\langle\tau_S\rangle$ is the mean first-passage time. For a ballistic trajectory, $A_1 = 2\sigma v_0/r$, using the particle width 2σ and persistence length v_0/r to estimate the area. Because the first-passage problem in the high-persistence regime is rotationally symmetric, it can be reduced to a one-dimensional problem along a ray from the origin to the boundary. The mean first-passage time can be computed using standard methods based on the backward Fokker-Planck equation [79]. For a system described by a Fokker-Planck operator $\mathcal{L}(x)$, the mean first-passage time $\langle\tau_S(x_0)\rangle$, as a function of the initial position x_0 , satisfies a differential equation in x_0 , namely, $\mathcal{L}^\dagger(x_0)\langle\tau_S(x_0)\rangle - r\langle\tau_S(x_0)\rangle + r\langle\tau_S(x_R)\rangle = -1$, with boundary condition $\langle\tau_S(R)\rangle = 0$ corresponding to an absorbing boundary at the edge of the circular plate. Here, $\mathcal{L}^\dagger$ denotes the adjoint of the Fokker-Planck operator [79,80]. In the present high-persistence regime, x_0 parametrizes a ray

connecting the center of the circular plate to the boundary, and $x_R = 0$ denotes the resetting location at the origin, i.e., the center of the plate. Since the high-persistence dynamics reduces to ballistic motion, we have $\mathcal{L}^\dagger(x_0) = v_0(d/dx_0)$. The solution of this differential equation evaluated for particles initiated in the center of the plate is $\langle\tau_S\rangle = (e^{rR/v_0} - 1)/r$. Combining these results, we expect at small resetting rates:

$$\mathcal{A} \approx 2\sigma v_0 \langle\tau_S\rangle = 2\sigma R + \frac{\sigma R^2}{v_0} r + \frac{\sigma R^3}{3v_0^2} r^2 + \dots \quad (2)$$

When no resetting takes place, the covered area coincides with that of the area swept by a straight trajectory from the origin to the boundary $2\sigma R$, while resetting increases this area, with a linear leading-order correction.

At large resetting rates, we can no longer assume that the areas are independent as in the small- r limit, since overlaps become significant. In this regime, rapid resetting generates a densely explored region near the origin, with an effective radius given by the typical distance a particle travels before a reset, v_0/r . Hence, we expect that the particle covers a dense region with area $\mathcal{A} \approx (v_0/r)^2$. Moreover, the exploration process terminates once a rare event occurs, allowing the particle to reach the boundary before a resetting event. Consequently, we expect the covered area to scale as

$$\mathcal{A} \approx \pi(v_0/r)^2 + 2\sigma R \quad (3)$$

for large resetting rates.

To estimate the optimal resetting rate r_* , we equate the leading scaling behaviors at small and large rates

$\pi(v_0^2/r_*^2) = (\sigma R^2 r_*/v_0)$. This yields a simple linear relation between the optimal resetting rate and the self-propulsion speed $r_* \sim v_0$,

$$r_* \sim \frac{v_0}{R^{2/3} \sigma^{1/3}}, \quad (4)$$

which holds in the high-persistence regime, where the persistence length exceeds the size of the plate, i.e., $v_0/D_r \gg R$. This behavior is confirmed in Fig. 3(c), where the same linear scaling is observed even outside the high-persistence regime. This can be explained through Cavalieri's principle, which states that the area of a weakly curved trajectory (i.e., large but finite persistence) is equal to that of its straight, ballistic counterpart, as shown in the End Matter. As long as self-intersections are sufficiently rare, the high-persistence scaling results are expected to hold. Furthermore, the scaling of the optimal resetting rate $r_* \sim v_0$ implies that the area at optimality $\mathcal{A}_*$ is approximately independent of the self-propulsion speed. This observation has interesting implications for optimal area-covering strategies in situations where each reset carries a cost, for example, fuel expenditure for a robot or animal, or thermodynamic costs associated with experimental resets. Since, at the optimal resetting rate, the total covered area is largely insensitive to the self-propulsion speed, it is advantageous to choose the speed that minimizes the required resetting rate. Doing so reduces the cumulative cost of performing resets. In our system, this corresponds to operating at a lower self-propulsion speed, while remaining in the active regime where the scaling $r_* \sim v_0$ holds. The approximate independence of the covered area at optimality with respect to activity is confirmed in our analysis [Fig. 3(b)], although we observe a slight increase in $\mathcal{A}_*$ with v_0 . This indicates that, beyond the high-persistence regime, particles with higher activity are more effective probes of the environment. Finally, although the temporal cutoff quantitatively affects the optimal resetting rate, the linear scaling remains robust when the cutoff is varied by an order of magnitude, as shown in Fig. 3(c). We therefore expect that, provided the cutoff exceeds the characteristic timescales of the system, such as the mean first-passage time to the boundary, it does not qualitatively affect the underlying physics.

Discussion—We have demonstrated an optimal strategy to maximize spatial exploration in active matter systems, a problem of broad relevance to search processes in living organisms, synthetic microswimmers, and macroscopic robots. Our results show that active particles benefit from intermittently restarting their exploration from a central location. This effect is quantified by an activity-dependent optimal resetting rate that maximizes the covered area. Our findings are demonstrated experimentally using active granular particles (vibrobots) and confirmed by active Brownian particle simulations, which systematically establish the robustness of the results by varying the activity

beyond the experimental conditions. The simulations further clarify that our results originate solely from the competition between persistence dynamics and the resetting rate. Other forces typically governing the vibrobot dynamics, such as self-alignment and dry friction, are not essential for our findings. Importantly, we discover that the optimal resetting rate scales linearly with the self-propulsion speed, such that the characteristic length scale v_0/r remains constant at optimality. This scaling relation provides a simple yet powerful design principle for efficient search in active systems.

Our findings connect a predominantly theoretical topic in statistical mechanics, namely, stochastic resetting, to applications involving granular robots, including efficient spatial exploration and resource acquisition. We anticipate that this study will stimulate further research, ranging from theoretical efforts aimed at rationalizing our results within frameworks based on the Feynman-Kac formalism, stochastic functionals, or large deviation theory [81–83], to the development of more efficient strategies employing different resetting-time distributions; for instance, see End Matter for a discussion of gamma-distributed resetting times. The experimental strategy employed here (and presented in Ref. [84]) to investigate resetting overcomes limitations due to insufficient statistics, a common challenge in experimental studies. This approach can also be applied to colloidal systems or more complex biological organisms, where efficient spatial exploration underlies critical processes such as resource acquisition, avoidance of harmful conditions, and surface colonization for biofilm formation.

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K. S. O., H. L., and L. C. designed and conceptualized the research. L. C. designed and performed the experiment. K. S. O. performed the numerical simulations. All authors equally contributed to the manuscript writing.

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End Matter

Details of the experiment—

Vibrobot design: The active vibrobot is fabricated from a proprietary photopolymer by stereolithographic 3D printing and consists of a cylindrical core, a cap, and seven legs attached to the cap. The core has a diameter of 9 mm and a height of 4 mm, whereas the cap placed on top of the core has a diameter of 15 mm and a height of 2 mm. Seven cylindrical legs with a diameter of 0.8 mm and a length of 5 mm are attached to the cap and arranged in a regular heptagon around the core. The resulting particle has a total height of 7 mm and covers a circular area on the plate with a diameter of 15 mm [Figs. 4(a) and 4(b)]. All legs are tilted by 4° relative to the vertical in the same direction, breaking the translational symmetry of the body and giving rise to active motion. The vibrobot has a mass $m = 0.83$ g and an approximate moment of inertia $J = 17.9$ g mm². A black sticker with a white circle is placed on the particle cap, aligned with the direction of the leg tilt.

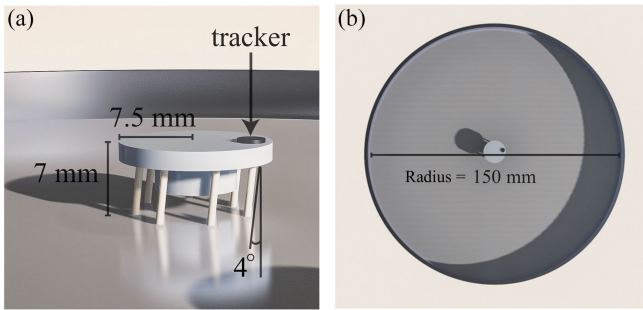


FIG. 4. Vibrobot and setup illustration. (a) Schematic side view of the vibrobot. (b) Top-view illustration of the setup, showing a particle moving on the vibrating plate.

Experimental setup: The vibrobot exhibits active motion when placed on a vertically vibrating circular plate. The plate has a diameter of 300 mm and a height of 15 mm and is positioned horizontally with respect to the ground. Vertical vibrations are generated by an electromagnetic shaker, with frequency f and amplitude A , connected to the plate. A plastic barrier surrounding the plate prevents the vibrobot from falling off.

Data acquisition method: Data are acquired by recording images with a high-speed camera operating at a temporal resolution of 50 frames/s and a spatial resolution of 0.3 mm/pixel. Particle positions are determined from the images using a standard tracking algorithm with subpixel accuracy, while the particle orientation is obtained by tracking the position of the white circle relative to the center of mass. Translational and angular velocities are then computed as $\mathbf{v} = [\mathbf{x}(t + \Delta t) - \mathbf{x}(t)]/\Delta t$ and $\omega = [\theta(t + \Delta t) - \theta(t)]/\Delta t$, respectively, with $\Delta t = 0.02$ s corresponding to the acquisition rate of 50 frames/s.

Parameter extraction for active vibrobots: As shown in Ref. [63], the vibrobot can be described as an inertial active Brownian particle with velocity $\mathbf{v} = \dot{\mathbf{x}}$ and angular velocity $\omega = \dot{\theta}$, namely,

$$m\dot{\mathbf{v}}(t) = -\gamma_t \mathbf{v}(t) + \gamma_t v_0 \mathbf{n}(t) + \gamma_t \sqrt{2D_t} \boldsymbol{\xi}(t), \quad (\text{A1a})$$

$$J\dot{\omega}(t) = -\gamma_r \omega(t) + \gamma_r \sqrt{2D_r} \eta(t), \quad (\text{A1b})$$

where m and J denote the particle mass and moment of inertia, respectively. The coefficients γ_t and γ_r represent the translational and rotational friction, while D_t and D_r are the translational and rotational diffusion constants. The term

$\gamma_t v_0 \mathbf{n}$ accounts for the active force driving the motion, with v_0 being the characteristic running velocity of the vibrobot and $\mathbf{n} = [\cos \theta(t), \sin \theta(t)]$ its orientation, i.e., the direction along which the legs are tilted.

To estimate the five free parameters of dynamics (A1), we match five observables between experiments and simulations. In particular, we compute the velocity distribution $P(\mathbf{v})$, the angular velocity distribution $P(\omega)$, the mean-square displacement $\langle [\mathbf{x}(t) - \mathbf{x}(0)]^2 \rangle$, the angular mean-square displacement $\langle [\theta(t) - \theta(0)]^2 \rangle$, and the cross-correlation between the velocity and orientation $\langle \mathbf{v}(t) \mathbf{n}(0) \rangle - \langle \mathbf{n}(t) \mathbf{v}(0) \rangle$. These observables are evaluated from both experimental data and numerical simulations initiated with a trial set of parameters. The total deviation between the experimental and simulated results is then computed and minimized iteratively using a Nelder-Mead optimization scheme.

Compared to Ref. [63], here we consider three different shaker conditions with frequencies $f = 120, 150$, and 170 Hz, while keeping the amplitude fixed at $A = 45(3) \mu\text{m}$. This choice leads to different sets of vibrobot parameters:

f (Hz)	120	150	170
v_0 (mm s ⁻¹)	63.6	26.1	11.4
D_t (mm ² s ⁻¹)	1.59	0.57	8.56
D_r (s ⁻¹)	0.85	0.29	0.11
γ_t (g s ⁻¹)	10.0	75.8	281.5
γ_r (g mm ² s ⁻¹)	305	325	311.

In all three cases, the inertial time m/γ_t and the rotational inertial time J/γ_r are significantly shorter than the persistence time $1/D_r$. Consequently, the evolution of the velocity $\mathbf{v}$ and the angular velocity ω can be neglected, leading to overdamped equations of motion for the position $\mathbf{x}$ and the orientation angle θ . This simplification reduces the parameter space to be explored in the numerical study. Specifically, since the particle size and the system size are fixed, the only relevant parameter is the persistence length v_0/D_r , as discussed in the main text.

Resetting implementation: Our resetting experiment follows a three-step protocol. (i) A particle is manually placed at the center of the container with a random orientation. (ii) We record its trajectory until it reaches the container boundary, in a time τ_S . Steps (i) and (ii) are repeated to obtain N trajectories, where the particle reaches the boundary after a time τ_S for each trajectory. (iii) We extract a time τ from an exponential distribution $p_r(\tau)$ with rate r and compare it with the first measured value of τ_S . The entire trajectory is retained if $\tau > \tau_S$; i.e., the particle reaches the boundary before the resetting time. Otherwise, if $\tau < \tau_S$, the trajectory is truncated at time τ , meaning the particle is reset before reaching the boundary. In this case, after the reset, the particle trajectory continues by concatenating it with the next trajectory. This process is repeated

until the particle reaches the boundary (so that the extracted τ is larger than the corresponding measurement of τ_S). If the time accumulated from these trajectories is larger than t_c , the process is stopped because the particle has not reached the boundary within the cutoff time. Our experimental strategy offers several advantages. First, it allows us to use the same set of N trajectories to compute any observable for different resetting rates. Second, it reduces experimental error, as the resetting time is imposed *a posteriori* rather than manually in each experiment. Similar numerical methods have been proposed in the past, including an approach that allows estimation of the steady state under resetting based on measurements of the reset-free process [84].

Discretization scheme for the area fraction—To estimate the covered area $\mathcal{A}/(\pi R^2)$, we discretize the space into cells of linear extent δ (see Fig. 5 for an illustration). At time t , the particle has a center-of-mass coordinate (x_t, y_t) , which upon rounding to the nearest cells translates into a cell coordinate $(x_t/\delta, y_t/\delta)$. The cells covered by the particle at that instant are those with indices (n, m) for which

$$\left(\frac{x_t}{\delta} + n\right)^2 + \left(\frac{y_t}{\delta} + m\right)^2 \leq \left(\frac{r_p}{\delta}\right)^2, \quad (\text{B1})$$

where r_p coincides with the particle radius. This defines, up to time t , a number of occupied $n_O(t)$ and unoccupied cells $n_U(t)$. The normalized covered area is obtained as

$$\frac{\mathcal{A}}{\pi R^2} = \frac{n_O(t)}{n_O(t) + n_U(t)}. \quad (\text{B2})$$

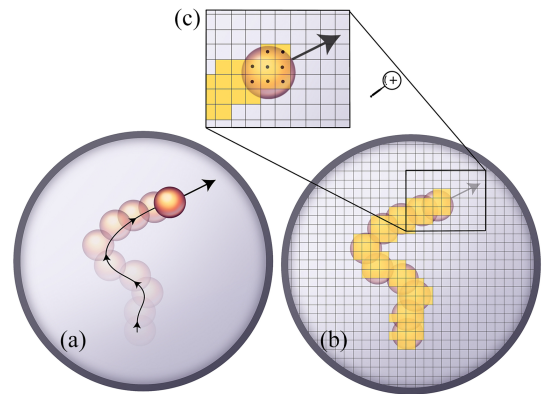


FIG. 5. (a) Illustration of a particle trajectory (colored circle), where the trajectory is represented by the black arrow. (b) Discretized particle path and area with $\delta = 0.133r_p$ and $\mathcal{A}/(\pi R^2) \approx 0.1$. Unoccupied and occupied cells are shown in gray and yellow, respectively. The overlapping black path shows the center-of-mass trajectory. (c) Zoom of panel (b) showing the discretized area at a given time.

Since the rounding error is not crucial for the results considered here, we pick $\delta = 0.4r_p$.

Temporal cutoff and non-Poissonian strategies—

Role of the cutoff time: In our protocol, a temporal cutoff is applied to exclude excessively long exploration strategies, mimicking tasks such as drones, robots, or animals searching for targets or mapping an area within a finite time. The covered area $\mathcal{A}$ is measured for two cutoff times t_c , differing by an order of magnitude [Fig. 6(a)]. The change in t_c does not alter the qualitative trend of $\mathcal{A}$ as a function of the resetting rate r .

Non-Poissonian strategies: Exponential resetting times are not always optimal for minimizing first-passage times in passive Brownian particles [85] or covered areas. This raises the question of whether nonexponential strategies may be relevant to the area-coverage problem studied here. From our experimental data, we report the area-covering fraction for both exponential $p(\tau) = r \exp(-r\tau)$ and gamma-distributed $p(\tau) = \tau^{k-1} \exp(-\tau/\theta)/\Gamma(k)$, inter-reset times [Fig. 6(b)]. This analysis suggests that sharper resetting strategies may further enhance area exploration in active particles.

Correction to the high-persistence regime—Here, we show that the area of straight ribbons in two dimensions remains unchanged when small curvatures are included. Let $\gamma(s)$ be a planar curve with internal coordinate $s \in (0, L)$ and denote the normal vector at a point s as $N(s)$, such that the tangent vector is $\dot{\gamma}(s) = T(s)$. The signed curvature $\kappa(s)$ at s is defined by $\dot{T}(s) = \kappa(s)N(s)$. By considering a parallel curve $\tilde{\gamma}(s) = \gamma(s) + uN(s)$ obtained by displacing a distance u along the local normal, the tangent to the parallel curve is $\tilde{T}(s) = T(s) + u\dot{N}(s)$. Using the planar Frenet-Serret relation $\dot{N}(s) = -\kappa(s)T(s)$, we have $\tilde{T}(s) = [1 - u\kappa(s)]T(s)$. The area element of a

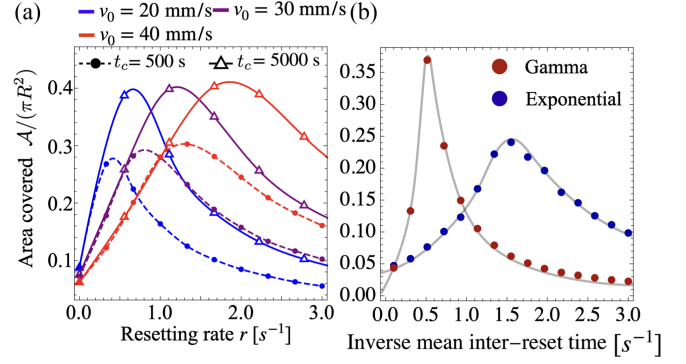


FIG. 6. (a) Covered area $\mathcal{A}$ normalized by the plate area obtained for two temporal cutoff values t_c . (b) Normalized $\mathcal{A}$ calculated for exponential $p(\tau) = r \exp(-r\tau)$ and gamma distributions $p(\tau) = \tau^{k-1} \exp(-\tau/\theta)/\Gamma(k)$, with identical averages and $k = 10$. (a) and (b) are obtained from simulations and experiments at shaker frequency of 150 Hz.

small parallelepiped spanned by increments ds and du along the s and u directions is $dA = [1 - u\kappa(s)]dsdu$, so that the total area of the strip is

$$\mathcal{A} = \int_{-w/2}^{w/2} du \int_0^L ds [(1 - \kappa(s)u)] = Lw. \quad (D1)$$

Here, the term proportional to u cancels immediately due to the antisymmetry of the integral, and $\mathcal{A}$ is the same as if the strip had no curvature. For active particles, the typical paths before resetting have length v_0/r and width 2σ . By the above argument, the high-persistence approximation is expected to hold well as long as path self-intersections are rare, even if the trajectories exhibit curvature due to finite persistence.