

Bit-propelled active matter

Informational active matter

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For an amateur sailor cruising through rough seas keeping course becomes increasingly difficult with the growing strength of the winds, but the skilled seaman thrives in rough waters, confidently steering the vessel to harness the powerful winds so he can sail towards the next harbor at greater and greater speeds. The sailboat propels by harnessing the kinetic energy of the winds through the sails' lift, but crucially the speed and direction of motion depend on the point of sail, so that the boat captain must continuously assess the direction of the wind to steer the bow and adjust the sails appropriately [1]. Formally, the sailor implements a feedback control loop consisting of measurement (of the wind) followed by a change of “state” of the vessel (e.g., to one of the possible bow and sail angles) that biases the motion of the vessel towards the desired course. This intelligent decision process is difficult to master, so that many more amateur sailors choose instead to navigate in motorboats that keep course by opposing the winds and thrusting forward thanks to the fuel-burning rotation of their propellers.

Let us scale our vessels down to below the size of unicellular organisms (i.e., somewhere on the micron scale). We can immediately identify the analog of the motorboat. Imagine taking a micron sized polymer sphere embedding an hematite block on one side (a so-called Janus particle) and placing it in an index-matched solvent containing hydrogen peroxide. When the experimenter shines light of the appropriate wavelength on the system they will observe that the Brownian particle begins thrusting forward due to the catalytic decomposition of hydrogen peroxide, mediated by the hematite under blue-light illumination [2]. Now place many of these particles together and you will have a paradigmatic synthetic active matter system giving rise to clusters in the absence of cohesive interactions between the particles [3] — a phenomenon known as motility-induced phase separation [4, 5] — so that when the light is turned off the clusters fall apart and we recover the much less interesting Brownian suspension. It is clear that clustering is occurring at the expense of chemical energy that is used to overcome noise, meaning that as thermal motion increases relative to the self-propulsion, the system will cluster less and less.

Can we design a system that does not try to overcome noise, but rather harnesses it so as to achieve greater directed thrust in a noisy environment (somewhat like a sailboat in rougher

seas)? In a recent preprint [6], VanSaders and Vitelli show us that the answer is “yes”, by introducing a system of “thinker” particles that can sense their state (e.g., their velocity and distance from the nearest particle) and implement a feedback that biases noise-induced transitions to certain microstates (e.g., ones for which the particle moves preferentially in a given direction). Crucially, the thinkers do not change the current state of the system (as defined by the particles’ positions and velocities), but instead bias the transition to an unoccupied microstate in the future.

It is instructive to see how the analogy to a sailboat breaks down. A sailboat harnesses currents (the wind) by deterministically adjusting its state so as to move in the right direction. So, even though the direction of wind is noisy, this noise is just a disturbance and, unlike for thinker particles, fluctuations do not propel the sailboat. Furthermore, in an equilibrium bath of passive particles, we have no net currents (no wind!) by virtue of being in equilibrium, so how can a particle propel without doing work on the system? The answer is that it can do so by measurement and control actions alone, while exerting a negligible amount of work, $W < \epsilon$, on the system. For instance, this can be achieved by expanding/contracting the particle’s radius when it is sufficiently far from other particles so as to not interact/do work on the system.

For $\epsilon \rightarrow 0$, such a thinker particle amounts to a Maxwell’s daemon [7] (following our analogy, perhaps we should call it *Maxwell’s pirate*) that converts information into work (self-propulsion), so that for each measurement a particle can extract $\mathcal{W} \leq k_B T I$ to propel itself, where I is the information gained about the state of the system following the measurement (viz., with each measurement the reduction in uncertainty about the state of the system is $\Delta S_{sys} = -k_B I$ and the extractable work is $\mathcal{W} \leq -T \Delta S_{sys}$) [8]. In other words, the particles use information as fuel (they are bit-propelled!). Naturally, we must pay the energetic price of erasing the memory of the thinker particle after each controller action (precisely $k_B T I$), so that the Second Law is not violated, and the system is driven out of equilibrium at a net positive energy cost (as it should be evident by the positive entropy production associated with the particles’ motion [9]). The authors dub the resulting activity as *informational activity* (vs. mechanical activity of Janus particles) and a system of many such particles as *informational active matter*.

VanSaders and Vitelli thus complete the taxonomy of active matter systems. Just like passive matter can be divided into systems whose properties are controlled by energetic or entropic forces, active matter can be classified into energy-driven and information-driven systems. For the system of expanding/contracting thinker particles (the “thinker fluid”), the authors develop a kinetic theory that allows them to predict collective properties such as the distribution of self-propulsion speeds, pressure, and heat flux. Finally, they show how a reinforcement learning strategy can be used to learn optimal schemes to harness fluctuations and form patterns both in thermal and nonthermal systems (such as poured and vibrated granular materials), and how for informational active systems more noise leads to greater drive/control, while it acts as a disturbance for mechanically active systems.

In conclusion, VanSaders and Vitelli show us that in microscopic intelligent systems informational-driving can be the sole source of self-propulsion (though, they note, it need not be), giving rise to unique features that cannot be observed in energetically-driven systems. It will be enticing to see how the study of living systems will embrace this organizational principle, as well as how it will be used in the design of microrobotic systems. Finally, as I reflect on the relationship between information and action at microscopic scales, I cannot think of a more succinct way of summarizing this relationship than by restating Descartes' principle [10] as “Cogito, ergo moveo” (“I think, therefore I move”).

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