Physical learning

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Motorized paperclip learns functional reflexes

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A wire of motorized hinges learns, forgets, and relearns automatic responses on demand, uncovering the physical principles necessary to emulate autonomous learning of living matter.

Shaping paperclips into animals can be excellent entertainment for idle moments, but any creative pinching efforts remain frustratingly limited by the original shape of the paperclip. Traditional materials are designed for one shape only. By contrast, living materials adapt their mechanical properties after fabrication, learning to adopt different shapes on demand. Now, writing in *Nature Physics*, Yao Du and colleagues[1] have embedded the ability to learn into a wire of motorized hinges. By locally adapting the motors' mechanical properties, they trained their metamaterial wire to learn, forget, and relearn multiple shapes on demand.

When a traditional material — like the titanium–nickel wire of a paperclip — is manufactured, its designated shape is forged to be the global mechanical equilibrium[2]. So even when a paperclip is pinched into an animal shape and thereby moved into a different local mechanical equilibrium, heating and cooling the paperclip will restore the original shape — the global mechanical equilibrium. The carefully pinched animal shape is forgotten and cannot be retrieved.

To train a shape that can be recovered upon a local pinch as input, the mechanical properties of the material need to be adapted so that the desired shape corresponds to the mechanical equilibrium upon pinch input. The problem of global optimization of mechanical properties to achieve the desired mechanical equilibrium can be readily solved by machine learning. The emerging field of physical learning has shown that physical systems can also achieve machine learning-like global

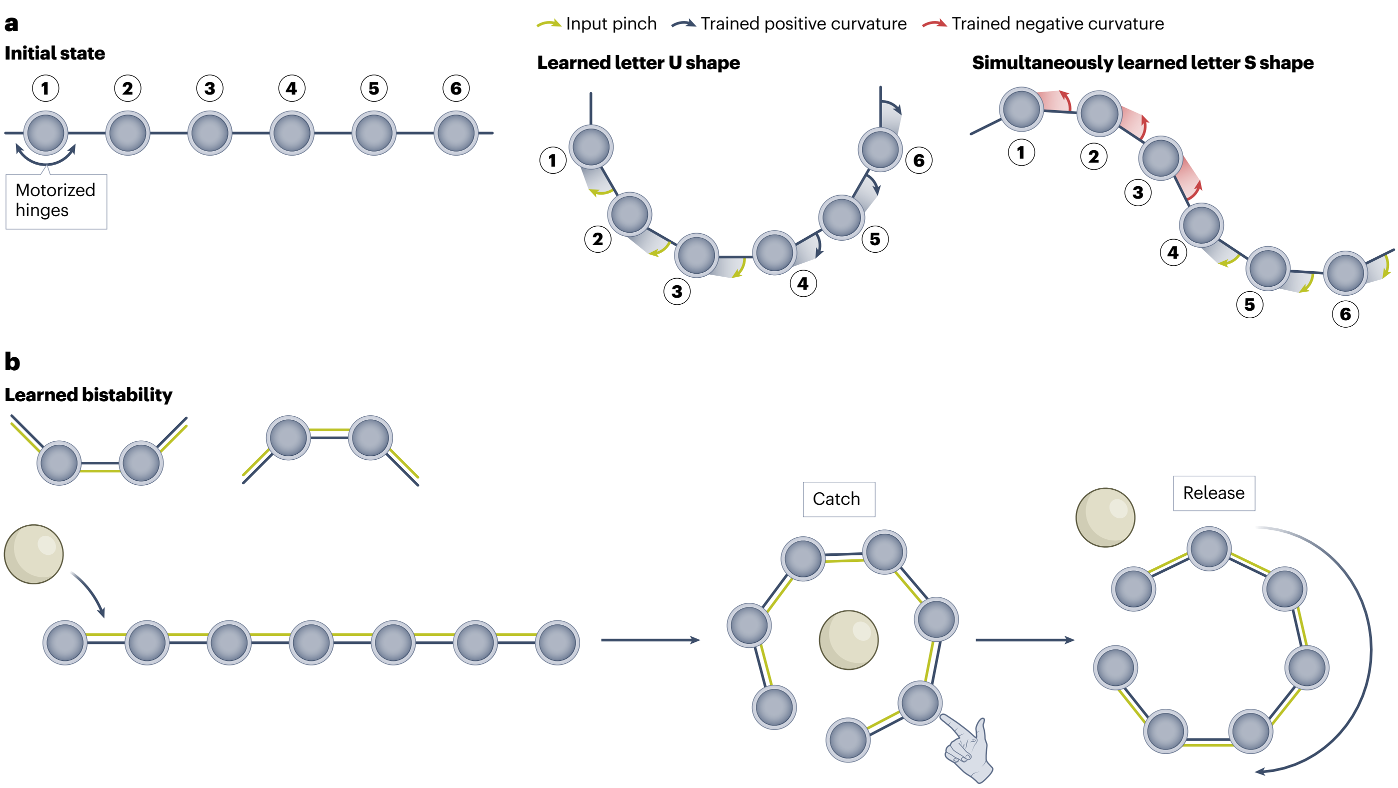

Fig. 1 | Motorized wire learns multiple shapes through non-reciprocity. **a**, The team constructed a wire of motorized hinges (circles). The arrows show the directions in which the wire can bend around each hinge, and the shading shows the potential curvature of each wire segment. The stiffnesses of motorized hinges in a wire were trained so that the wire adopted the desired shape — the letter U in this case — as an equilibrium configuration upon a local pinch at the input hinges. Non-reciprocal coupling between hinges enabled learning of multiple shapes. For the letter U, a positive curvature input at hinge number 2 induced positive curvature at hinge number 5, while a positive input at hinge number 5 induced a negative curvature at hinge number 2 for the letter S. **b**, Bistability trained into pairs of hinges (highlighted in green) allowed a reflex-like catch of an impacting ball and release by manual perturbation as both ball and hand activate the bistable switches.

optimization by processing only local information autonomously[3]. The trick is to uncover the laws of local adaptation that empower materials to learn a new mechanical equilibrium.

The physical learning concept of contrastive learning uses the difference between two states of mechanical equilibrium[4,5] – the free state the system relaxes to under the input, and the desired state it should relax to under the input – to adapt the local mechanical properties step by step. The local difference between free and desired states drives the adaptation of mechanical properties until the system relaxes on its own into the desired equilibrium upon input. Understanding the physical principles of those local learning rules is critical, since they require only local information and therefore scale well with system size compared to global optimization.

Du and colleagues[1] constructed a wire of motorized hinges that learned to adopt desired shapes upon input pinches. Each hinge was equipped with a microcontroller that measured its own curvature and its immediate neighbours' curvature. Then, based on these two measurements, it exerted a motorized torque. The local stiffnesses of the microcontrollers determined the torques at each hinge and, in turn, the equilibrium shape of the metamaterial wire. By adapting the stiffnesses according to contrastive learning, the metamaterial wire learned to form the shapes of letters in response to a designated input pinch at one of the hinges. Additionally, the wire was able to forget a previously learned shape and learn a new one without reinitialization.

Notably, non-reciprocal interactions were essential for learning multiple shapes at once. Non-reciprocal in this context means that a positive curvature pinched into hinge number 2 induces positive curvature at hinge number 5, but a positive curvature pinched into hinge number 5 induces a negative curvature at hinge number 2. Thanks to this non-reciprocity, the motorized wire could be simultaneously trained such that an input pinch at hinge number 2 induced the letter U, while an input pinch at hinge number 5 induced the letter S (Fig. 1). Instead of learning only a single shape at a time, non-reciprocal coupling enabled concurrent learning of multiple distinct shapes.

Conceptually, non-reciprocity implies that learning is not driven by mechanical equilibrium but by the minimization of work. In fact, the team showed that the full complexity of learning capabilities of the motorized wire was captured by a dynamical systems description. Nonlinearity of the motorized torques due to their finite maximal torque stabilized unstable curvatures. This way, pairs of hinges could have two or even four stable curvatures instead of just one without nonlinearity.

The combination of the multiple stable curvatures, made possible by nonlinearity, and the ability to learn multiple shapes simultaneously, thanks to non-reciprocity, enabled even more complex behaviours. The metamaterial wire could learn the reflex to coil upon deformation of bistable hinge pairs and de-coil upon nudging the hinge pairs into opposite curvature (Fig. 1). Training for four stable curvatures even made the wire crawl.

Breaking down the complexity of learning in artificial intelligence systems and the brain into physical concepts appears to be an insurmountable task. The programmable metamaterial wire presented by Du and colleagues is a brilliant reduction in complexity that is key to disentangling the essential physics concepts that enable learning and constrain the space of learnable states. In particular, the core roles of non-reciprocity and multistability point to dynamical systems as a promising field for understanding the physical principles of learning. These principles may guide advanced robotic functionality that closely emulates the autonomous and adaptive behaviour of living matter.

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Competing interests

The author declares no competing interests.