Perspective

The rise of intelligent matter

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Artificial intelligence (AI) is accelerating the development of unconventional computing paradigms inspired by the abilities and energy efficiency of the brain. The human brain excels especially in computationally intensive cognitive tasks, such as pattern recognition and classification. A long-term goal is de-centralized neuromorphic computing, relying on a network of distributed cores to mimic the massive parallelism of the brain, thus rigorously following a nature-inspired approach for information processing. Through the gradual transformation of interconnected computing blocks into continuous computing tissue, the development of advanced forms of matter exhibiting basic features of intelligence can be envisioned, able to learn and process information in a delocalized manner. Such intelligent matter would interact with the environment by receiving and responding to external stimuli, while internally adapting its structure to enable the distribution and storage (as memory) of information. We review progress towards implementations of intelligent matter using molecular systems, soft materials or solid-state materials, with respect to applications in soft robotics, the development of adaptive artificial skins and distributed neuromorphic computing.

Intelligence can be understood as the ability to perceive information and to retain it as knowledge to be applied towards adaptive behaviour within a changing environment. Although there is no generally acknowledged definition of intelligence, corresponding concepts in the field of intelligence research embrace two main traits: first, the ability to learn and, second, the capacity to adapt to an environment[1–3]. Both abilities are thus far mostly found in living organisms. Yet, with the proliferation of AI, intense efforts are being made to implement learning and adapting skills in increasingly complex systems that co-integrate various functional components[4–6]. Going beyond such functional architectures, the realization of synthetic matter that itself shows basic features of intelligence would constitute an entirely new concept of AI. Even though such matter which we term here intelligent does not show the same level of intelligence as would be understood in a psychological sense (including, for instance, the ability for cognition or language), its functionality would go far beyond the properties of static matter. Inspiring examples of potential applications include artificial skin[7,8] that self-regulates temperature and absorbance, intelligent clothing[9] that, depending on the wearer's sensation, turns into a warming or cooling garment, as well as soft robotics[10,11] with intelligent tactility. However, because of the vast amount of data that needs to be processed in advanced AI applications, regulating the behaviour of intelligent matter in a central manner will be very challenging. In particular, centralized information processing with conventional computers based on the von Neumann architecture will quickly reach its limits. This is because shuffling data from memory to processor and back not only greatly reduces the speed of the computation, but also requires substantial power consumption[12]. New approaches and computing paradigms are thus required to be implemented directly at the matter level, thus allowing for local pre-processing of data using, for instance, in-memory computing[13,14]. In this way, intelligent matter itself could interact with the environment, self-regulate its action, and even learn from the input it receives.

For the design of intelligent matter, inspiration from nature is beneficial: bottom-up assembly is nature's way of achieving material properties that outperform the properties of their individual constituent units. The macroscopic functionalities of natural matter emerge from sophisticated design motifs and the interplay of molecular, nanoscale and macroscale building blocks[15]. In artificial matter, a combination of bottom-up and top-down methods enables architectures with a variety of novel characteristics and functionalities[15,16]. We can use the concept of increasing functionality and complexity to define intelligence for artificial matter in a hierarchical manner, as illustrated in Fig. 1. This form of intelligence can be realized on a material level by combining four key functional elements (see Box 1): (1) sensors to interact with the environment and receive input and feedback; (2) actuators to respond to the input signal and adapt the material's properties; (3) memory for long-term storage of information and (4) a communication network to process feedback. Ideally, these elements form functional processing continua, which do not require a centralized processing unit, but rather provide the capability for local and distributed information processing[17].

Four categories of matter can be identified, each of which contain different functional elements, depending on their complexity. The most basic group is structural matter without any functional elements. It may comprise highly complex but static structures, which, despite having a wide range of functions, cannot change their properties after synthesis. At a more advanced level, responsive matter is capable of changing its properties (shape, colour, stiffness, and so on) in response to an external stimulus, such as light, electrical current or force.

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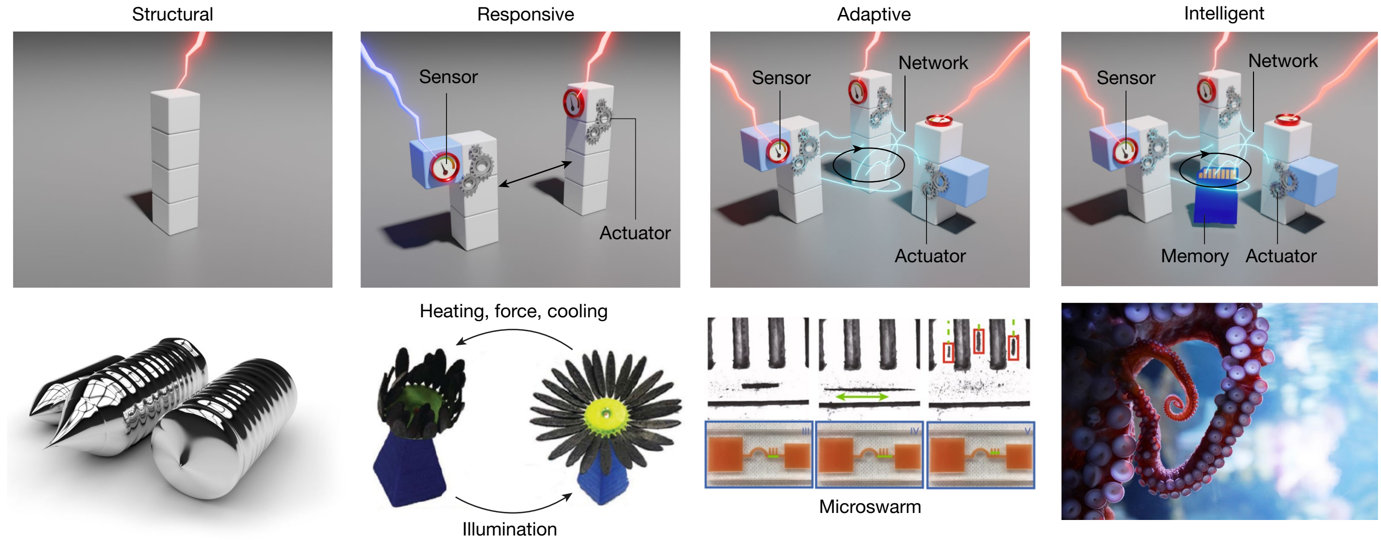


Fig. 1 | Conceptual transition from structural to intelligent matter with increasing functionality and complexity, and corresponding examples. Structural matter is static and cannot change its properties after synthesis, such as pure silicon. Responsive matter can change its properties upon application of an external stimulus (illustrated as red lightning) and comprises embedded sensors and actuators. When an orthogonal counter-stimulus (illustrated as purple lightning) is applied, responsive matter switches back to its original state. The opening and closing of a 3D-printed sunflower made of a photoresponsive shape memory composite[42] is an example of responsive matter. Adaptive matter can modify its properties in response to a stimulus using internal feedback. In addition to sensors and actuators it features a network (illustrated as light blue connections). The magnetic microswarm depicted[27], which can move within obstructive channels, shows adaptive behaviour. Intelligent matter is able to interact with its environment, learns from the input it receives and self-regulates its action. All four key functional elements—sensor, actuator, network and long-term memory—need to be incorporated. The arm of an octopus, with its embedded sensors, actuators and nervous system, represents intelligent matter. Copyright for lower leftmost panel: Peter Sobolev/Shutterstock.com. Copyright for lower rightmost panel: ND700/Shutterstock.com.

The response results strictly from the application of the stimulus, is always equal for specific inputs and, thus, cannot change. But responsive matter can be reversed, that is, switched back to the original state, by a relaxation process or by an orthogonal counter-trigger[18–20]. To provide this active response, both embedded sensors and actuators are needed.

Intense efforts are underway to move beyond responsive matter to adaptive matter, which has the inherent capability to process internal feedback and, thus, not only changes its properties, but even regulates them in response to different environments and stimuli[18]. Thus, adaptive matter relies on a further functional element—namely, a network—to provide feedback in addition to sensors and actuators. Feedback can arise from a combination of multiple responsive units integrated into the same system, realized by coupled chemical reactions or electronically, optically or magnetically coupled nanoscale components[21]. Although, in this way, the properties change over time depending on the input history, the evolution of the properties still depends on external input. A recent viewpoint article by Walther offers a particularly articulate view, arguing that truly adaptive materials can only arise in out-of-equilibrium systems (generally called 'active matter')[18]. This definition brings adaptive materials into the realm of 'life-like materials', which are synthetic materials that are inspired by biological and living matter[19].

Moving beyond adaptive matter will lead eventually to the development of what we term intelligent matter. Intelligent matter is able to interact with its environment, learns from the inputs it receives and self-regulates its action. Learning is enabled by an inherent memory functionality in which the acquired knowledge or skill is stored long-term as experience and can be recalled to produce future behaviour. Thus, intelligent matter includes all four functional elements (sensors, actuators, network and long-term memory) and shows the highest level of complexity and functionality. Here, we outline the development trajectory of these classes of functional matter, give examples of complex systems with various degrees of functionality, and show recent trends towards the ultimate development of intelligent matter.

Swarm-based, self-organized materials

A prominent form of complex behaviour relies on the collective interaction of a large number of individual agents in groups or swarms. Here, multiple individually responsive entities can self-organize in such a way that large-scale adaptive phenomena emerge, for example, pattern formation to protect the collective. In nature, this behaviour is observed in insect colonies[22], schools of fish[23], birds[24] and even mammals[25]. The global response of the collective is often considered to exhibit features of intelligent behaviour, and typically goes beyond the capabilities of the individual elements, which only communicate with their nearest neighbours. Hence, the actions of the individual agents are coordinated in a decentralized manner. This concept of basic intelligence is particularly interesting for the realization of intelligent matter when using building blocks that are implemented on the nanoscale. Nevertheless, on such length scales it is challenging to integrate all of the four key functional elements—in particular long-term memory—as individual components. An illustrative example for emulated swarm-behaviour is the interaction of a large group of small robots, each about one centimetre tall and with limited capabilities[26], which can arrange in complex, predefined shapes (Fig. 2a). The individual robots are responsive agents, merely follow their programmed individual algorithm and communicate only with their nearest neighbours. However, since an external programmer predefines the targeted shape and gives instructions in form of an algorithm, the whole group of robots is not intelligent according to our definition, but rather adaptive. When considering swarm behaviour on the nanoscale, similar restrictions remain and so such systems constitute examples of adaptive matter, as described in the following.

Nanoparticle assemblies

In self-assembled material systems, local communication between the weakly coupled and highly dynamic components takes place in the form of particle–particle interactions. Yu et al.[27] describe the application of

Box 1

Key functional elements of intelligent matter

Intelligent matter interacts with its environment, receives information, and self-adapts based on knowledge gained from past events. To realize a basic form of intelligence within artificial matter, the integration of four key functional elements is essential (see Box 1 Fig. 1).

(1) A sensor unit is required to receive information about both the current state and changes in the environment, as well as to receive feedback signals. This process of sensing or detecting is usually an energy transformation, where the energy of the input signal is converted into a form of energy that can be further processed, such as, for example, the conversion of heat into an electrical potential or the absorbance of light to provide a different molecular structure.

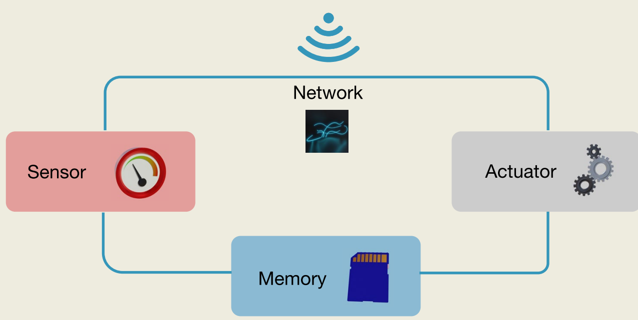
(2) In response to an external stimulus, synthetic matter can respond with a modification of its properties. This requires actuator mechanisms, which provide an output to the environment, such as a change in shape, colour, phase, conductivity and so on.

(3) To retain the received information as knowledge, inherent memory capability is necessary. Memory enables long-term storage and processing of information, which can be recalled as knowledge in the future. In addition to the input signals, feedback signals can also be stored, so that observed consequences of actuation can be used for learning processes.

(4) The final key functional element constitutes the interconnection of sensor, actuator and long-term memory elements. Such connections can be realized via signal pathways in a matter network, which enables the delivery of information and further allows for feedback to be provided.

Different combinations of the four key functional elements—sensor, actuator, network and memory—in synthetic matter result in different levels of complexity and functionality. Whereas for responsive matter a sensor and actuator are both clearly necessary, adaptive matter further requires network pathways in order to provide feedback. The close interplay between all four functional elements is essential for processing information, which is generated during the entire process of interaction between matter and the environment, to enable learning. Hence, if one of the key functional elements is lacking, then, according to our definition, the material is not considered intelligent.

We note that our definition of intelligence in matter cannot be readily compared to the intelligence of living beings in a psychological sense. The four key functional elements are essential to implement artificial intelligent matter, but at the same time they are not sufficient to enable the emergence of will or cognition, which distinguishes synthetic matter from intelligent living beings.



Box 1 Fig. 1 | Intelligent matter is composed of embedded sensors, actuators and signal pathways in internal networks and within-matter, long-term memory.

programmed oscillating magnetic fields to arrange paramagnetic nanoparticles into a ribbon-like dynamic microswarm. Based on repulsive fluidic and attractive magnetic interactions between the chain-forming, structural nanoparticles and depending on the initial shape, the microswarm can perform reversible anisotropic deformation, controlled splitting and merging with high pattern stability as well as navigated locomotion (Fig. 2b). These shape adaptions rely on the input of an external programmer who manipulates the magnetic field and therefore the particles do not show intelligent behaviour by themselves.

Colloidal particles similarly provide promising building blocks for material systems exhibiting self-organization properties. Steered by osmotic and phoretic effects, synthetic bimaterial colloids in a basic solution form two-dimensional 'living crystals' when illuminated by blue light[28]. More complex three-dimensional crystals or microtubes are grown out of Janus colloids in a precessing magnetic field[29]. A leader–follower relationship[30] between microparticles or a cargo transport[31] can be obtained if the size and dielectric properties of different colloids are varied and they are exposed to an alternating-current electric field or ultraviolet light (Fig. 2c). Additionally, the swarm performs negative or positive phototactic motions depending on the light intensity to which it is exposed. Thus, the particle system shows adaptive behaviour to ambient illumination conditions. Phototaxis, that is, the ability to sense and orient to the illumination direction of a light source, has also been realized in artificial microswimmers, which have the structure of a Janus nanotree and propel by self-electrophoresis[32]. Tagliazucchi and co-workers show another intriguing example of adaptive swarm behaviour. The simulations reveal that dissipative self-assembly gives rise to particle configurations of pH-responsive colloids that are not available in equilibrium. As soon as the continuous input of energy is stopped, the assembled structures decompose[33].

Molecular materials

Intriguing adaptive behaviour has been reported in synthetic molecular systems in which feedback arises from reaction networks and coupled intermolecular interactions[34,35]. Limited availability of the required building blocks leads to the successive emergence of two different sets of co-existing replicators, each consuming only their preferred feedstock. This can be understood as an adaptation to the availability of 'food'. Moreover, information transfer regarding the size of the self-replicating molecules was observable from the ancestor to the descendent replicator. This behaviour has parallels to specification in biology. In a different dynamic molecular network, the substrate of a chemical reaction in combination with a second molecule transiently forms its own catalyst. After the reaction is completed, the catalyst is automatically decomposed. In this way, the concentration of the catalyst is regulated, reminiscent of the continuous regulation of enzyme concentration in biological systems giving rise to adaptive behaviour. Furthermore, positive feedback of self-replicators was demonstrated, in which the self-replicators recruit a cofactor for the production of their own precursors[36]. These related examples clearly describe adaptive systems in which feedback arises from reaction networks and coupled interactions. There is no doubt that communication takes place between individual components and that an appropriate action is derived from the 'sensed' information, indicating feedback.

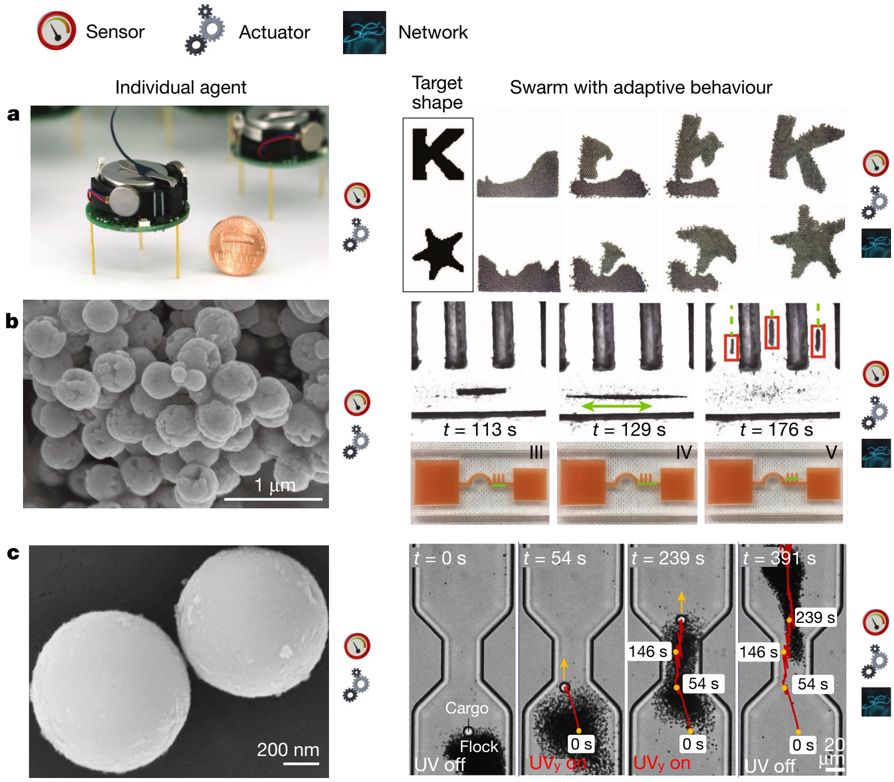


Fig. 2 | Adaptive swarm behaviour of autonomous robots and clusters of colloids. a, autonomous, individually responsive robots merely follow their programmed algorithm and communicate with closest neighbours. In a swarm of a thousand robots, they self-assemble in complex 2D patterns[26]. Since an external programmer predefines the target shape, the swarm is adaptive and not intelligent. **b**, Paramagnetic nanoparticles form a moving microswarm in an oscillating magnetic field[27]. An external programmer can change the field, such that the adaptive swarm can split and circumvent obstacles. The insets show an overview of the path and of the current location of the swarm (indicated by the green line). **c**, A group of phototactic TiO_2 colloids, which cooperatively transport a larger cargo particle by producing a collective diffusiophoretic repulsion. Scale bars: left, 200 nm; right, 20 µm. This repulsion is controlled by an external programmer via ultraviolet light pulses, which makes it an adaptive swarm[31]. Icons show which of the four key functional elements are present.

However, in-matter memory is lacking, which prevents learning from past events and adapting behaviour in an intelligent manner according to the concept shown in Fig. 1.

Soft-matter implementations

In biological systems, softness, elasticity and compliance are salient features, which enable a continuous deformation and, hence, a smooth motion within a congested environment[37]. Natural skin further exhibits striking properties of basic intelligence as defined above, including the tactile sensation of force, pressure, shape, texture and temperature, a haptic memory and the capability of self-healing[38]. The field of soft robotics aims to translate these properties into soft-matter implementations. Soft robots are able to emulate biological motion by adapting their shape, their grip and their tactility. Compared to their rigid counterparts, the risk of harm is dramatically reduced when they are in contact with humans or other fragile objects owing to compliance matching of materials[10,11,37]. Intelligent soft matter, which unifies all four building blocks outlined in Box 1, could thus assist soft-robotic devices to mimic organisms[37]. In the form of an artificial skin, it could further provide a variety of possibilities in health care and medical applications. Multifunctional wearables, which monitor health parameters with a potential subsequent drug delivery[39], human motor assistance via supplying mechanical work after stroke[11] or prosthetics with tactile sensations can be envisioned.

Although full integration of all four key functional elements in soft matter is still elusive, various implementations that combine at least two of the functional elements have been reported.

Responsive soft matter

Soft matter can receive inputs from the environment via sensing elements and provide a direct response through embedded actuators, which is the basic requirement for classification as responsive matter. The most common actuation is a change in shape and softness as a function of the input. One example is a self-contained artificial muscle consisting of a silicone elastomer matrix in which actuation relies on the liquid–vapour phase transition of embedded ethanol micro-bubbles upon heating[40]. This responsive artificial muscle is capable of repeatedly lifting a weight of more than 6 kg as well as agonist–antagonist based skeleton-arm motions and can be used in soft grippers for lifting objects (Fig. 3a). Another approach to realizing the macroscopic mechanical operations of soft robots is the responsive hydrogel based on DNA hybridization-induced double crosslinking shown by Zhao et al.[41]. Gestures of a human hand were mimicked by locally controlling the volume shrinkage of the material with the help of external DNA triggers. Similarly, 3D-printable photoresponsive shape-memory composites alter their 3D forms in response to light and promise large varieties of applications, such as mimicking the open and closed states of a sunflower[42]. All three examples exhibit neither network pathways nor a memory element in which to store feedback information about too strong or weak actuation forces, for instance.

Especially for artificial skins and multifunctional wearables, untethered devices are essential. Thus, the ability to self-power in order to feed sensors, actuators or memory with the required power is vital to device success. Using the embedded actuation to self-generate

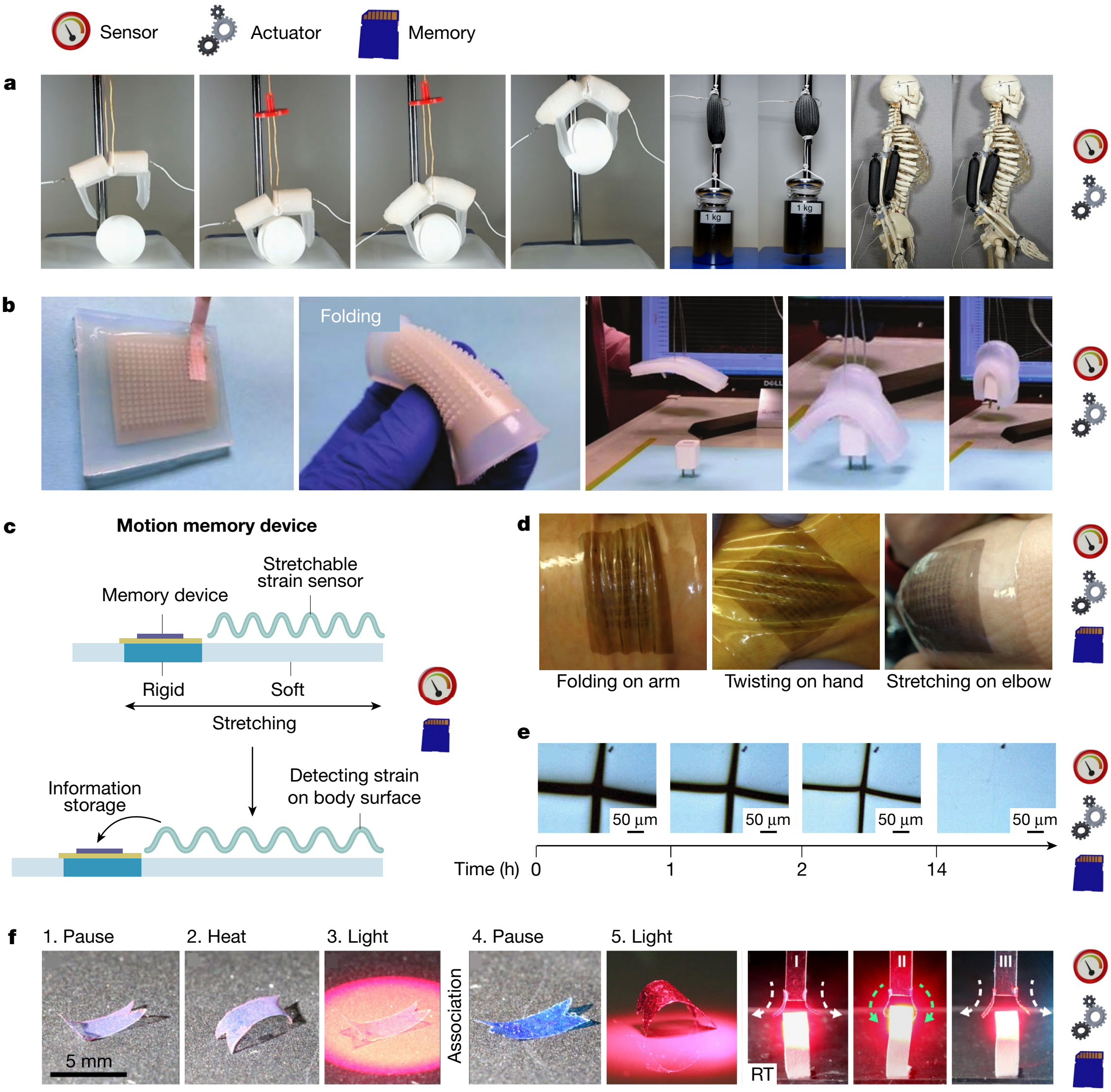


Fig. 3 | Responsive soft matter and soft matter with embedded memory functionality. **a**, Soft grippers and artificial muscle (consisting of a silicone elastomer matrix with embedded ethanol bubbles) lifting objects and acting as an agonist–antagonist actuator pair[40]. The material senses heating induced by an embedded resistive wire and changes its shape, which results in an actuation. **b**, Soft artificial skin using the triboelectic effect to sense proximity, contact and pressure[43]. In addition to the sensing capability, the self-powered material can also embrace objects and lift them up. **c**, Mechanical hybrid substrate that combines memory devices with strain sensors in a wearable device[45]. **d**, Various deformations of a thin-film organic transistor with self-healing properties attached to human limbs[46]. **e**, Self-healing process of a copolymer: after around 14 h, cuts in the material have completely healed up[47]. **f**, Conditioning process of a liquid crystal network actuator; scale bar, 5 mm. After the initially neutral light stimulus is associated with a heat stimulus, the material also responds to light. The material can also be conditioned to certain wavelengths: only soft gripper number II was associated with red light, closing upon irradiation[53]. Icons show which of the four key functional elements are present. **a** and **b** clearly show responsive systems, while examples in **c** and **d** additionally feature a memory element, and thus go beyond responsive behaviour.

electrical power in response to external inputs is a highly attractive approach. One promising attempt by Lai and co-workers takes advantage of the triboelectric effect[43]. Their artificial skin can actively sense proximity, contact, pressure and dampness of touched objects without the need of an external power source and the skin produces electricity in response (Fig. 3b). Another striking example from Schroeder et al.[44] uses a biomimetic concept to generate power inspired by the electric eel. The authors used gradients of ions between miniature polyacrylamide hydrogel compartments bounded by a repeating sequence of cation- and anion-selective hydrogel membranes. The 'artificial eel' uses a scalable stacking or folding geometry that generates 110 V upon simultaneous, self-registered mechanical contact activation of thousands of gel compartments in series. Unlike typical batteries, these systems are soft, flexible, transparent and potentially biocompatible.

Soft matter with embedded memory

A further class of functional soft matter combines in-matter memory with sensing capability. While such matter would not classify as adaptive matter owing to the lack of a network, it goes beyond responsive capability. The following examples are able to receive input from the environment and alter their response as a function of the input history using embedded memory elements. An attractive approach lies in combining the sensor and memory elements within a soft and flexible material, which enables them to work cooperatively. Liu et al.[45] realized this concept in a mechanical hybrid material (Fig. 3c), where resistance-switching devices serve as memory elements on rigid polymerized photoresist (SU-8) islands, which are embedded in stretchable polydimethylsiloxane (PDMS). Microcracks in a thin gold film evaporated onto the PDMS act as both an electrode and a stress sensor

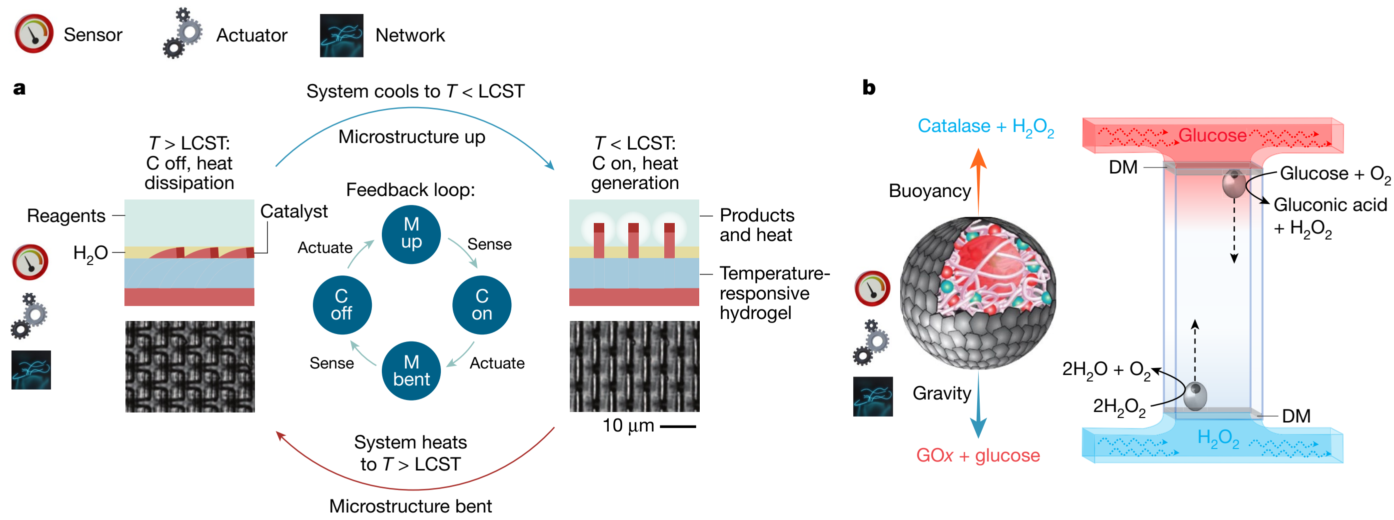


Fig. 4 | Adaptive soft materials with homeostatic properties and enzyme-powered motility. a, Temperature regulation mechanism around a certain temperature, the lower critical solution temperature (LCST), of a self-regulated mechanochemical adaptively reconfigurable tunable system[21]. A temperature-responsive hydrogel, which triggers the degree of bending of micro-pillars, is coupled with an exothermic reaction that takes place when the tips of the micro-pillars reach into the upper reactant-rich layer. 'M' denotes a mechanical action, whereas 'C' stands for a chemical reaction. **b**, Schematic mechanism of oscillatory motion of microcapsules in a water column, which contain both catalase and glucose oxidase (GO*x*). Reactions in hydrogen peroxide or glucose-rich zones realized by dialysis membranes (DM) at the top and bottom of the column lead to a growth or shrinkage, respectively, of an encapsulated oxygen bubble and hence to a change in buoyant forces[54]. Icons show which of the four key functional elements are present. Both examples feature sensors, actuators and a network and thus can be classified as adaptive matter, according to our definition.

at the same time. Attaching this motion memory device to the joints of the limbs allows for detection of human motion based on changes in stress and subsequent information storage.

Self-healing is an important property as it allows a material to permanently restore its original properties after a disturbance/fracture and is a way of erasing memory of past wounding. Oh et al.[46] reported an organic thin-film transistor fabricated from a stretchable semiconducting polymer that is operational even when folded, twisted and stretched on a moving human limb (Fig. 3d). Remarkably, this polymer is capable of self-healing after solvent and heat treatment with almost fully recovered field-effect mobility. Moreover, materials that self-heal without external intervention have been developed[47–49] (see Fig. 3e). A self-healing ability greatly improves the durability of the material and eliminates the need for costly overdesigning.

Information processing usually involves counting, which requires a sensing capability as well as a memory element to store the latest value. Beyer et al.[50] present a design concept for counting matter based on subsequent biochemical reactions. The actual counting procedure is realized by the release of a specific output molecule or enzyme depending on the detected number of light pulses. Another approach towards implementing information processing in soft matter is to involve the inherent properties of the soft material in the computing device[51]. The soft body and its complex dynamics feature nonlinearity and memory capabilities, which are used as a reservoir for reservoir computing (see also examples of solid-state matter implementations below). More specifically, the motor that generates the movements of a soft robot and the sensors that monitor the bending of the soft body together comprise the reservoir. By weighing and summing up the values the corresponding output of the computing device is generated. This method seems a promising way to make use of readily available properties of soft robots for computational resources.

Materials that can be conditioned to learn a desired new response are extremely promising. Zhang et al.[52] developed a hydrogel capable of associative learning, which is one of the simplest form of learning. In the hydrogel embedded and initially randomly distributed gold nanoparticles act as memory elements. Initially, the gel–sol transition, which is naturally triggered by heating, does not occur when the gel is exposed solely to laser irradiation. Simultaneous exposure to light and heat induces a photoacid-driven pH-change, which in turn leads to a clustering of the nanoparticles in the gel, producing a higher absorbance and thus an increase in temperature upon illumination. Consequently, the previously neutral (no effect) light stimulus now leads to melting of the gel. In a follow-up study, the authors demonstrate the association of light irradiation with the intrinsically effective stimulus of heating within a thermoresponsive liquid-crystal polymer network[53]. The actuator responds to the stimuli via bending, which allows the locomotion of microrobots or the closing of grippers (Fig. 3f). Even a selective response to various colours (wavelengths) of irradiation is achieved if different dyes are used as the absorbing memory element. In this form of material, the learned response to a previously neutral stimulus is limited to one stimulus, which follows the same pathway as the initially known stimulus. Thus, the behaviour is algorithmically programmed within a limited parameter range and does not allow for conditioning of a response to an arbitrary input, which would constitute intelligent behaviour.

Adaptive soft matter

Going beyond responsive examples to adaptive soft matter, He et al.[21] demonstrate a strategy for creating autonomous homeostatic materials, which in addition to sensing and actuation also include precisely tailored chemo-mechano-chemical feedback loops (that is, a network) (Fig. 4a). A bilayer thin film containing hydrogel-supported, catalyst-bearing microstructures is separated from a reactant-containing 'nutrient' layer. Reconfiguration of the gel in response to a temperature change induces the reversible actuation of the microstructures into and out of the nutrient layer and serves as a highly precise on/off switch for chemical reactions. Exploiting a continuous feedback loop between an exothermic catalytic reaction in the nutrient layer and the mechanical action of the temperature-responsive gel results in an autonomous, self-sustained system that maintains temperature within a narrow range.

Another implementation of adaptive soft matter that contains an elegant combination of sensing and actuation coupled by a reaction

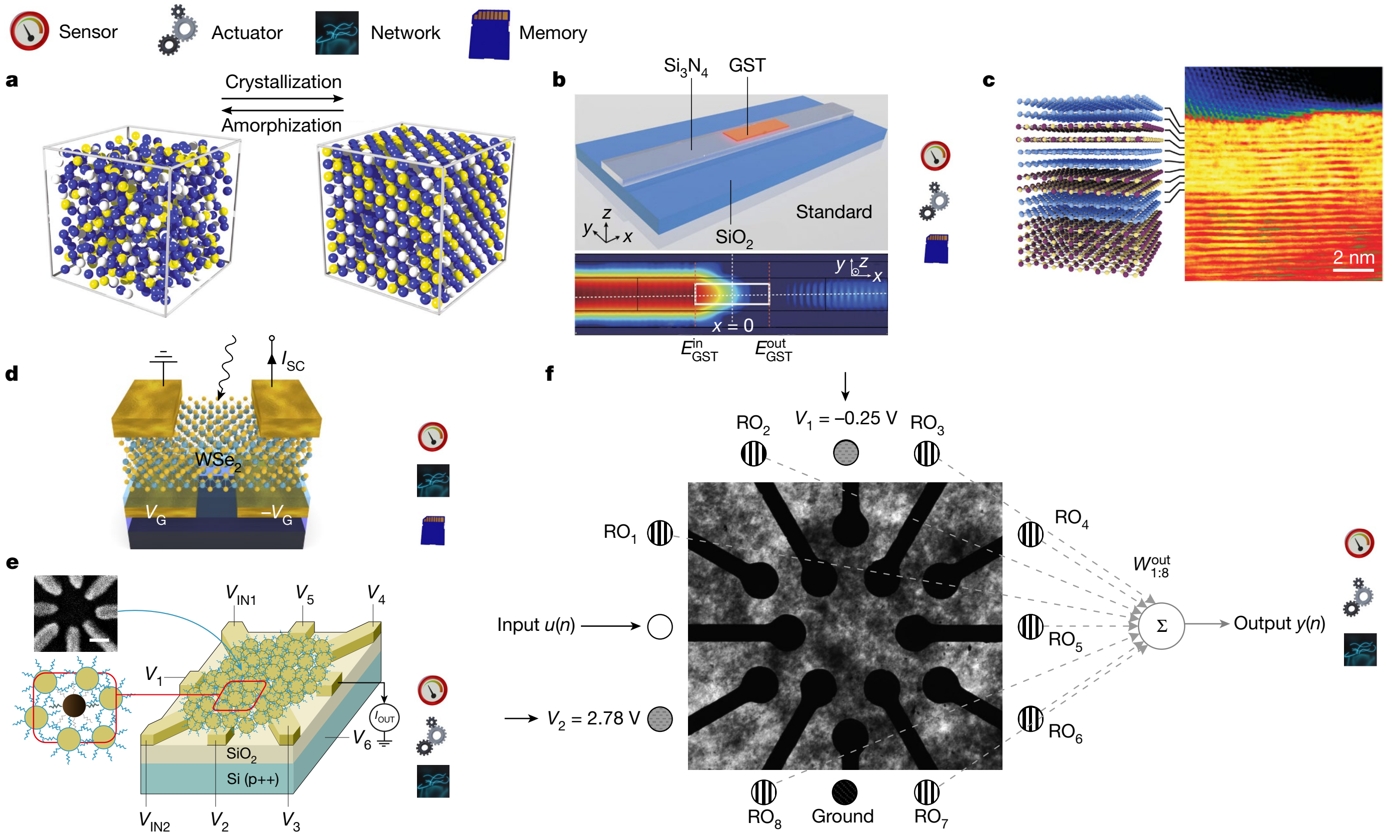


Fig. 5 | Neuromorphic materials and systems. a, Phase-change materials change their degree of crystallization—and thus their electrical conductance and optical absorption—upon exposure to a certain temperature[61]. **b**, Schematic of the phase-change material $Ge_2Sb_2Te_5$ (GST) deposited on an integrated silicon nitride waveguide and the corresponding simulation of the *E*-field distribution of the transverse electric mode at the surface of the waveguide[66]. The optical absorption of the GST is modulated and therefore also the intensity in the photonic waveguide as shown by the *E*-field distribution before (E^{in}_{GST}) and after (E^{out}_{GST}) the phase-change material deposited on the waveguide. Working as a photonic synapse, the demonstrated system exhibits a sensor, actuator and memory element. **c**, Schematic and transmission electron microscope images of a 2D material stacked into a van der Waals heterostructure[68]. These materials exhibit unique and tunable physical properties, which renders them suitable for neuromorphic systems. **d**, The photoresponsivity of a photodiode consisting of the 2D material WSe_2 can be modulated with two-gate electrodes, which are biased at V_G and $-V_G$, respectively[79]. I_{SC} denotes the short-circuit photocurrent of the device. The image sensor presented itself constitutes an artificial neural network with a sensor and memory element, as well as a network. **e**, Schematic representation of an adaptive gold nanoparticle network that can be controlled electronically to represent any Boolean logic gate and hence combines sensor, actuator and network. The upper inset shows an electron microscope image; scale bar is 100 nm (ref. [80]). **f**, Schematic representation of the carbon-nanotube-based reservoir computer with input $u(n)$ and control voltages V_k. The values of the readout electrodes (RO_x) are linearly combined using the learnable weight matrix W^{out}, resulting in output $y(n)$ (ref. [118]). This system features a sensor, an actuator and a network and can be classified as adaptive matter.

network is the model system for autonomous particle motility shown by Kumar et al.[54]. Organoclay/DNA microcapsules loaded with the enzymes catalase and glucose oxidase regulate the growth or shrinkage of encapsulated oxygen bubbles in hydrogen peroxide or glucose-rich environments, respectively. The counteractive reactions lead to an antagonistic regulation of the size of the oxygen bubbles and hence of the effective buoyant force (Fig. 4b). Thus, an enzyme-powered oscillatory vertical movement of colloids in a water column can be achieved.

Garrad et al.[55] demonstrate an integrated soft-matter computational system for both analogous and digital computation, which should enable the realization of adaptive, compliant robots. Opposing conductive fluid receptors are connected when a conductive fluid is injected into the soft matter tube, which is located between the receptors. The electrical current generated can be used to control, for example, actuators of soft robots.

Solid-state matter implementations

Whereas sensing and actuation in synthetic matter can be prominently implemented using self-organized and soft materials, the realization of matter-based information processing seems to be more challenging. Instead, the technology for information processing in solid-state materials is much more advanced, which provides attractive opportunities. In fact, physical and chemical processes themselves can be thought of as a form of computation. Although conventional computers are built from physical devices (such as transistors), they are based on a symbolic notion of computation (that is, on whether a voltage is below or above a certain threshold). Unconventional computing goes beyond the standard models of computing. Living organisms, in particular, can be considered as unconventional computing systems. A close look at complex organisms spawned by nature reveals that the workflows of information processing build directly on physical principles[56]. It was therefore suggested by Feynman[57] and later by Yoshihito[58] to use matter itself for computing. As Feynman puts it: “why should it take an infinite amount of logic to figure out what one tiny piece of space-time is going to do?”[57]. Programmable and highly interconnected networks are particularly well suited to carrying out these tasks and brain-inspired or neuromorphic hardware aims at providing physical realizations. Although in the semiconductor industry top-down fabrication, using established (inorganic) materials, has enabled neuromorphic hardware (for example, IBM's TrueNorth[59] and Google's Tensor Processing Unit[60]), bottom-up approaches exploiting nanomaterials may provide pathways towards unconventional, efficient computation. In combination with the aforementioned matter implementations, hybrid approaches may eventually lead to the realization of intelligent matter.

Neuromorphic materials

Phase-change materials have been a key enabler for brain-inspired or neuromorphic hardware, allowing for the realization of artificial neurons and synapses in artificial neural networks[61]. Their programmability in either an amorphous or a crystalline state via Joule heating is exploited to realize fast, accessible, room-temperature, non-volatile memory devices (Fig. 5a). Their memristive behaviour—that is, the continuous transition between the two phases—and the cumulative change in crystallization, further renders phase-change materials suitable for brain-inspired computation[61,62], where they typically embody synaptic weights and/or the nonlinear activation function. Electrical devices rely on the dependence of the electrical resistance on the material's state, and use an applied electrical voltage for both switching and reading out[63]. In contrast, in photonic devices, a high-power-density light pulse is used to adjust the degree of crystallinity, which changes the absorption of light in the material[64–66] (Fig. 5b).

Furthermore, two-dimensional (2D) materials, such as graphene, MoS_2, WSe_2 or hexagonal boron nitride (hBN), have emerged in the realization of neuromorphic devices, allowing compact artificial neural networks to be devised. Consisting of a single atomic layer, they exhibit unique physical properties distinct from their three-dimensional counterparts[67,68]. When various 2D crystals are stacked, they build so-called van der Waals heterostructures, which enable the engineering of artificial materials and devices with flexible properties[68,69] (Fig. 5c). In particular, bandgap tuning of 2D materials, that is, engineering the size of the bandgap and even choosing between a direct and indirect gap, offers excellent opportunities for electronic and optoelectronic devices, in particular for emulating hardware mimics of neural tissue. Such changes can be achieved by simply changing the number of stacked layers[70,71], intercalation (see ref. [72] and references therein) or by inducing a certain amount of strain (by, for example, deforming the supporting substrate)[73]. Since 2D materials are atomically thin, devices with high mechanical flexibility can be fabricated. This property is especially useful for wearable devices or implants[74]. Importantly, the resistance-switching devices[75,76], memristors[77] and memory devices[78] have been realized that are essential requirements for neuromorphic systems. An intriguing example from Mennel et al.[79] is an image sensor that simultaneously processes the sensed data. The heart of the device is a WSe_2 photodiode array in which the synaptic weights are stored by modulating the photoresponsivity via multi-gate electrodes (Fig. 5d). The sensor can be trained to classify sensed images and, thus, acts as an artificial neural network.

Using material learning, computational functionality was experimentally realized in disordered nanomaterial networks[80]. Arbitrarily interconnected gold nanoparticles functionalized with organic molecules and situated in the centre of eight radially arranged nanoelectrodes could be configured into any Boolean logic gate using artificial evolution at sub-Kelvin temperatures (Fig. 5e). The current response of the nanoparticle network depends in a complex, but deterministic, way on the input and configuration voltages applied to the device. This is therefore an adaptive materials system. A more recent study showed that a similar approach could be used to perform nonlinear classification and feature extraction in a disordered network of boron dopant atoms in silicon at 77 K (ref. [81]). Instead of realizing functionality through artificial evolution, it was shown that a deep neural network model of a nanoelectronic device can be used to tune the device efficiently to perform various classification tasks via gradient descent[82]. Such models are also very useful for studying more complex devices consisting of interconnected nanomaterial networks[83]. These works reveal the potential for exploiting the intrinsic physical properties of matter to achieve efficient computing at the nanoscale. The logical next step would be to let these systems operate stand-alone and allow them to self-adapt their potential landscape to solve computational problems. To arrive at such intelligent systems, the element of memory should be introduced.

Distributed neuromorphic systems

In neuromorphic systems, information processing and memory are co-localized, which rigorously distinguishes them from conventional von Neumann architectures. A further merging of the individual components—that is, the computational (pre-)processing and storing of information with the sensing and actuating part—into a processing continuum can be envisioned, which would enable the implementation of distributed neuromorphic systems that mimic the entire human nervous system. Such network architectures require both unconventional processing designs and efficient signalling pathways between the individual components. Promising candidates are optical neural network models, since light itself can carry out the computation by interacting with matter or interfering with itself without the need for predefined pathways. In addition, they allow for data processing at the speed of light (in the medium) and with an extremely low power consumption compared to their electrical counterparts. An illustrative example of an optical neuromorphic system is given by Lin and co-workers[84]. The authors present an all-optical deep-learning neural network based on several layers of 3D-printed diffractive optical elements. Each micrometre-sized pixel of a diffractive optical element represents a neuron with a certain reflection or transmission coefficient. Thus, the densely packed neurons build a continuous layer, in which each neuron is connected to the next layer's neurons by optical diffraction. Hence, when light is propagating through the different diffractive layers, information is simultaneously processed, similar to the pre-processing of data in human skin before it is transferred to the brain via the nervous system. A similar, but integrated example is the inverse-designed metastructure proposed by Estakhri et al.[85], which can solve linear integral equations with the help of microwaves. The permittivity of a wide waveguide section is modulated in such a way that the guided modes interfere and perform the desired integral operator. In both examples, communication and computation take place at the site of memory, whereas there is no sensor or actuator element in the above-defined sense. Hirano et al. reported on stochastic resonance without tuning for weak periodic input signals and thermal noise in a self-organized Mn_{12}/DNA redox network exhibiting nonlinear current–voltage characteristics[86].

Feed-forward artificial neural networks are not capable of handling a time-dependent input, whereas recurrent neural networks are. Recurrent neural networks have feedback loops, which make the input of a neuron dependent on its output, introducing dynamic memory[87]. Recurrent neural networks may even show self-sustained temporal activation dynamics along its network connections without any input at all. However, recurrent neural networks are computationally very costly and therefore only feasible for small networks[88]. A solution is provided by reservoir computing, a term that covers three independently developed methods for creating and training recurrent neural networks: echo state networks[89], liquid state machines[90], and the backpropagation-decorrelation on-line learning rule[91]. The reservoir computer consists of a randomly connected network, the 'reservoir', which is able to create nonlinear projections of inputs into a high-dimensional space. To train these networks, a simple supervised readout layer is used to learn linear combinations of network states. As only the weights of the output layer need to be trained, and the random network itself is untouched during the process, the learning is relatively fast and efficient compared to other neural network methods. Reservoir computing is used for temporal problems such as chaotic time-series analysis or prediction and speech recognition. These tasks require short-term memory, also called fading memory, with a timescale comparable to that of the input signals. This type of memory should not be confused with the long-term memory that we have identified as being one of the required elements for realizing intelligent matter. As long as the weights of the output layer need to be trained in a supervised fashion, these systems do not self-adapt and are therefore not intelligent according to our definition.

Implementations in dynamic systems include electronic circuits[92,93], a bucket of water[94], gene regulation networks of *Escherichia coli* bacteria[95,96], DNA reservoir computing[97] and a cat's primary visual cortex[98]. In addition, there have been demonstrations of reservoir computing in optical systems using delay lines[99–103], memristor devices[104–110], atomic switch networks[111–113] as well as carbon nanotube systems[114–116].

Every matter-based reservoir tends to have its own physical problems. For memristive cross-bar arrays, variation in memristors is considered as a common problem. Alternatively, there are potential drawbacks in the reservoir model used, for example, optoelectronic systems are based on a single nonlinear node and a delay line[103,117], making them sequential in nature and often quite bulky—however, they get around being sequential simply through the speed and bandwidth at which they can operate. Instead of designing a material substrate to be a good reservoir, one can also use material learning to let the reservoir emerge from the system. Different material configurations can have very different reservoir performance[114,118]; see Fig. 5f. Recent advances in physical reservoir computing are reviewed by Tanaka et al.[119].

Outlook and perspectives

Challenges ahead lie in developing effective methods for fabrication, upscaling and control of intelligent matter. Intelligent matter must contain dynamic materials that possess a substantial degree of conformational freedom, mobility and exchange of nanoscale components. This implies that the interactions between nanoscale components must be weak enough to be manipulable by external stimuli. Moreover, such matter must show a certain degree of internal organization of nanoscale components, so that feedback and long-term memory can be embedded. Furthermore, to adequately receive and transmit external input, addressability with spatial and temporal precision is needed. These requirements are to a large extent contradictory and potentially incompatible. Evidently, the key elements of intelligent matter are more easily realized separately in different material types, which may be potentially incompatible with other materials. We expect that hybrid solutions will be required to address challenges in incompatibilities.

Clearly, none of the examples highlighted here exhibits intelligence in the sense of perceiving information, storing it and learning from it to express adaptive actions and behaviour. So, what could a roadmap towards intelligent matter look like? First, we will need demonstrators and design rules for the development of adaptive matter with inherent feedback pathways by integrating nanoscale building blocks that enable reconfigurability and adaptivity of self-assembled and top-down fabricated nanostructures. Second, we must proceed from adaptive matter that can process feedback to matter with learning capability ('learning matter'). These materials will be empowered by embedded memory functionality, material-based learning algorithms and sensing interfaces. Third, we must proceed from learning matter to truly intelligent matter, which receives input from the environment via sensory interfaces, shows a desired response encoded via embedded memory and artificial networks, and can respond to external stimuli via embedded transducers. The development of intelligent matter will thus require a concerted, interdisciplinary and long-term research effort.

Ultimately, complete system-level demonstrations are necessary to expedite the use of intelligent matter given that overall performance is the collective response of components and connections. A wide variety of technological applications of intelligent matter can be foreseen and the co-integration with existing AI and neuromorphic hardware will be particularly attractive. In this respect, bio-compatible implementations will also be required for applications in the life sciences and bio-cybernetic organisms.

Online content

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