Neuromorphic Metamaterials for Mechanosensing and Perceptual Associative Learning

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Physical systems exhibiting neuromechanical functions promise to enable structures with directly encoded autonomy and intelligence. A neuromorphic metamaterials class embodying bioinspired mechanosensing, memory, and learning functionalities obtained by leveraging mechanical instabilities integrated with memristive materials is reported. The prototype system comprises a multistable metamaterial whose bistable dome-shaped units collectively filter, amplify, and transduce external mechanical inputs over large areas into simple electrical signals using embedded piezoresistive sensors. Dome deformations in nonvolatile memristors triggered by the transduced signals, providing a means to store loading events in measurable material states are recorded. Sequentially applied mechanical inputs result in accumulated memristance changes that allow us to physically encode a Hopfield network into the neuromorphic metamaterials. This physical network learns the history of spatially distributed input patterns. Crucially, the neuromorphic metamaterials can retrieve the learned patterns from the memristors’ final accumulated state. Therefore, the system exhibits the ability to learn without supervised training and retain spatially distributed inputs with minimal external overhead. The system’s embodied mechanosensing, memory, and learning capabilities establish an avenue for synthetic neuromorphic metamaterials that learn via tactile interactions. This capability suggests new types of large-area smart surfaces for robotics, autonomous systems, wearables, and morphing structures subjected to spatiotemporal mechanical loading.

1. Introduction

The nervous systems of animals comprise networks of distributed sensory, memory, and control elements that enable perception, reaction, and adaptation in response to varied external stimuli. The coevolution of the nervous system and body morphology is thought to reduce the complexity of sensed signals due to morphological computing and short neuronal connections. This results in a form of neuromechanical control that requires few inputs to fulfill complex functions.[1,2] Some organisms, such as comb jellies (phylum Ctenophora[3]), perform complex tasks even without a central nervous system. This capability stems from coevolved neuromechanical systems that exploit morphological and sensory couplings to create autonomic responses.[2] which constitute one of the simplest forms of learned behavior. Typical autonomic behaviors include reflexes,[4] preflexes, and central pattern generators,[5] all of which leverage fast, decentralized sense–compute–actuate control loops.[1] At the most basic level, this is achieved through the synergy of morphology, sensing, computation, and actuation systems that perceive stimuli,[6] filter noise,[7] and store only valuable information as physical states of systems. Achieving similar capabilities in synthetic systems is important for realizing the next generation of autonomic, multifunctional, power-efficient materials, devices, and systems. Single artificial neuromechanical functions encoded into material systems have been demonstrated, including sensing,[8,9] filtering and thresholding,[10,11] and different forms of mechanically encoded memory.[12,13]

Learned autonomic biological responses are thought to be created when groups of neurons reinforce synaptic connections, resulting in simultaneous firing.[14,15] Inspired by synapses and neurons, neuromorphic computing has emerged as a field leveraging history-dependent responses and the electrical tunability of materials and devices to approximate brain-inspired computation.[16] Many neuromorphic systems exploit memory resistive, or memristive, materials to achieve the characteristics of synaptic plasticity, memory storage, and even threshold-gated neural spiking. Furthermore, memristor arrays operate with very low power, offering an analog route for highly parallelized
computation. Recently, neuromorphic materials have been integrated with sensory systems to encode and process external inputs that enable the formation of memory and learning. In a seminal work, afferent nervous functions have been mimicked via neuromorphic circuits to convert information from mechanical inputs into motor functions, thereby completing a synthetic reflex arc. Artificial neuromechanical perception has also been demonstrated in flexible substrates embedding synaptic transistors and Nafion-based memristors capable of durably encoding spatiotemporal tactile excitations into signals amenable for ex-situ classification using supervised learning. Spatiotemporal, long-term memory formation, and retention have also been shown using a 3 × 3 array of carbon nano-tubes (CNT)/polydimethylsiloxane (PDMS) piezoresistive sensors and Pt/HfO2/TiN memristors.

Online learning (implying adaptation or plasticity as data is sensed) is a crucial function of neuromechanical systems that has so far been much less explored in mechanically reconfigurable, neuromorphic material systems. Thus, synthetic material systems enabling integrated mechanosensing, memory, and autonomic learning capabilities remain rare. Realizing systems that embody neuromechanical functions promises to allow structures to display advanced functionalities such as autonomy and intelligence. We report on a class of neuromorphic metamaterials exhibiting bioinspired mechanosensing, memory, and learning functionalities achieved by leveraging local mechanical instabilities that trigger electrical memristance changes in soft materials. Our prototype consists of a multistable metamaterial whose unit cells filter, amplify, and transduce external mechanical inputs into simple electrical signals. The unit cell consists of a piezoresistive sensor at the base of a bistable dome. Structural bistability is critical to achieving inherent filtering, thresholding, and signal amplification capabilities. The metamaterial is scalable and may cover large areas (c.a. 10² cm²) at tunable sensitivity and resolution levels (Figure 1a.i). We encode the transduced signals by firing nonvolatile memristor adaptation, thus providing a means to store spatially distributed mechanical signals in analog material states (Figure 1a.ii).

Notably, our voltage-controlled memristors display additive resistance accumulation when triggered by physical events exceeding a designed amplitude threshold for each dome-shaped unit. This process allows us to reproduce the additive process that encodes several patterns of distributed forces (or displacements) into the connectivity matrix of physically realized Hopfield networks whereby successively applied spatially distributed inputs continuously update the states of the network (Figure 1a.iii). Crucially, the learned, mechanically applied patterns can be retrieved from the memristor’s final electrical resistance states, i.e., the measured memristive states encode the time history of prior loading. Therefore, our system displays the ability to learn online, retaining spatially distributed inputs exceeding a critical threshold with minimal external overhead.

Figure 1. a) i) Neuromorphic metamaterial composed of mechanosensing unit cells with inherent filtering, transduction, mechanoelectric signal amplification, and memory capabilities. ii) The bistable units transduce mechanical inputs exceeding a desired amplitude threshold into electrical resistance changes mediated by the dome stable state-dependent piezoresistive sensor. iii) These characteristics allow for realizing physical Hopfield networks capable of encoding several spatiotemporal patterns as attractors of the network’s interaction matrix, the synaptic weights of which are stored as the final (current) states of the memristors. b) The physical Hopfield networks enabled by our neuromorphic metamaterials are trained online by continuously changing distributed mechanical inputs (such as pressures over wings). This allows for realizing substrates exhibiting event camera-like tactile perception with online learning and reduced external memory as several patterns can be retrieved from the memristors’ latest states, i.e., the current memristive states encode the time history of loading as distinct patterns stored in the Hopfield network’s connectivity matrix.
A neuromorphic metamaterial that combines mechanosensing and thresholding behaviors is reminiscent of event cameras\[28,29\] in which pixels asynchronously record events when light intensity exceeds a specified threshold, offering power-efficient and low-latency visual perception. In such systems, pixel triggering events are timestamped and recorded in silicon-implemented memory components. Our metamaterial embodies a tactile analog of an event camera augmented with a memory capable of in-hardware learning, whereby mechanical inputs exceeding the designed threshold values of each dome-shaped pixel are learned sequentially and encoded in the final memristance states (Figure 1a.i–iii). This capability is needed in scenarios where histories of mechanical forces (pressures) can be used to learn and refine the operation of autonomous systems. For example, our metamaterial could filter and record different flow features exceeding the desired pressure threshold as attractors in the physically embodied Hopfield network (Figure 1b). This concept of in-hardware learning can be applied to the wings of drones and other morphing aircraft to enhance aerodynamic control in challenging flight conditions. Given that the Hopfield network is continuously updated as tactile events exceed a threshold, a neuromorphic metamaterial such as this offers a new route for realizing engineering systems with online learning through tactile perception for applications in robotics, autonomous systems, wearables, and morphing structures.

2. Mechanosensing

The mechanosensing unit cell is comprised of a bistable, compliant dome with a piezoresistive sensor embedded in the flat membrane surrounding the dome. This membrane may connect multiple dome unit cells to form a metasheet. The geometry of the unit cell is defined by the dome height, \( h \); thickness, \( t \); radius, \( r_d \); as well as the base width, \( w \), and piezoresistive sensor dimensions (Figure S1, Supporting Information).\[22\] Each dome-shaped unit is geometrically bistable with two stable states: the stress-free, as-printed ground state and the inverted state (Figure 2a). The state of the dome determines the deflection and strain in the surrounding base membrane (Figure 2b).

**Figure 2.** a) The bistable unit cell in its ground and inverted states. The sensor is flat in the ground state and curves out-of-plane in the inverted state. Scale bars are 16 mm, the diameter of the dome. b) Finite element analysis (FEA) stress plots of the unit cell dome without an embedded sensor. c) The resistance of the sensor, \( R \), over 18 inversion cycles with 30 s intervals between snap-through events. After the initial increase in resistance, the unit cell displays two distinct, consistent levels of resistance corresponding to the stable states. The dome has dimensions \( h = 7 \) mm, \( t = 0.8 \) mm, and \( r_d = 8 \) mm. d) The bistability thresholding functionality is schematically illustrated. Forces below the threshold, \( F < F_{th} \), do not induce snap-through and are filtered out: the sensor’s initial and final resistances correspond to the ground state, \( R_g \). Forces at or above the threshold, \( F \geq F_{th} \), cause the dome to undergo snap-through to the inverted state, and the event is recorded via the sensor’s final resistance corresponding to the inverted state, \( R_i \). e) The filtering tunability is experimentally demonstrated by the changing snap-through load for unit cells of two different thicknesses, \( t = 0.8 \) mm and \( 0.9 \) mm \((h = 7 \) mm, \( r_d = 8 \) mm). f) Linear and curved sensors at distances of 10, 12, and 14 mm from the center of the dome \((h = 7 \) mm, \( t = 0.8 \) mm, \( r_d = 8 \) mm) are compared to demonstrate changing nonlinear signal amplification. g) Isolated FEA strain plots for the linear and curved sensors at 10 mm from the center of the dome in the inverted state.
The bistability of the dome consequently means the sensor at the base also exhibits two stable configurations with corresponding resistance levels. Thus, the electrical resistance of the piezoresistive sensor, $R_s$, and the structural behavior of the dome are intrinsically linked. Unlike previous research that leveraged the hierarchical behaviors of metasheets with closely spaced domes,\(^{[22,23]}\) we use sufficient spacing, $w$, in the metasheet to ensure that neighboring unit cells do not significantly affect each other. Thus, characterization studies can be performed on individual unit cells.

We demonstrate this mechatronic coupling over multiple inversion cycles using 3D printed unit cells composed of thermoplastic polyurethane (TPU) with conductive polylactic acid (PLA) sensors (Figure 2c). The initial cycles differ from the steady-state largely due to the strain softening behavior of the TPU substrate, which is most significant in the first few inversion cycles (Figure S2, Supporting Information).\(^{[30]}\) This effect is compounded by permanent damage induced by strain in the stiffer and more brittle conductive PLA sensor.\(^{[31]}\) Thus, repeatedly strained sensors show higher ground state resistance than the as-printed resistance.\(^{[30]}\) This baseline drift can be reduced by inverting the domes several times before use. After this initial phase, the unit cell has two distinct, repeatable resistance levels (Figure 2c), with the lower resistance level, $R_c = R_{g}$, indicating the ground state and the higher resistance level, $R_e = R_i$, indicating the inverted state. The difference in resistance between the two states is on the order of several hundred Ohms. The transient spikes of resistance in between the steady-state values are due to the high strains experienced during dome snap-through between states, which cause the sensors to briefly lose conductivity (Figure S3, Supporting Information).\(^{[11,30]}\) Because we are only interested in the steady-state values of the ground and inverted states before and after dome inversion, these spikes are generally not shown in full in the presented plots.

### 2.1. Filtering and Thresholding

Filtering is a critical function of neuromechanical systems that allows them to consolidate external stimuli to those which meet a particular threshold. Rather than targeting a lower detection limit, as previous studies have done,\(^{[34–36]}\) it is advantageous to set an inherent threshold level to filter out the noise and extraneous inputs. In our neuromorphic metasheet, switching between the stable states of the dome is a threshold-dependent process: a minimum force, $F_{\text{th}}$, is required to trigger the snap-through of the dome from the ground state to the inverted state. The force and energy required for snap-through are proportional to the material properties and geometry as follows, where $E$ is the elastic modulus and $\nu$ is the Poisson’s ratio:\(^{[22,37]}\)

$$F_{\text{th}} \propto \text{Inversion energy} \propto \frac{E t^3}{1 - \nu^2} \left( \frac{4h^2}{r_d^4} \right) \quad (1)$$

Forces below the inversion threshold, $F < F_{\text{th}}$, do not cause the dome to snap-through to the inverted state. Therefore, when a subthreshold force is removed, the deflected dome returns to the ground stable state, and the sensor reverts to its ground state resistance, $R_g$. Consequently, no memory is written into the structure. However, forces at or above this threshold, $F \geq F_{\text{th}}$, trigger snap-through to the inverted stable state, and memory of the force application event is encoded in the structure. The strains associated with the inverted state cause the sensor to remain at $R_i$ (Figure S4, Supporting Information). This filtering capability is schematically illustrated in Figure 2d.

To demonstrate tunable thresholding capabilities in our metasheet design, we compare unit cells with domes of two different thicknesses: 0.8 and 0.9 mm (Figure 2e). All other parameters are preserved for both domes ($h = 7 \text{ mm}$, $r_d = 8 \text{ mm}$). Using a tensile testing machine, we apply point loads to the top of each dome (Figure S6, Supporting Information). When the load is limited to 16 N, $F < F_{\text{th}}$, for both domes, so neither dome inverts, and the applied load is filtered out: the sensors return to their original ground state resistance values once the load is removed. When the load is increased to 18 N, the inversion threshold is met for the $t = 0.8 \text{ mm}$ dome, and the final resistance of the sensor shifts to its inverted state value, thereby demonstrating memory of the event. For the thicker $t = 0.9 \text{ mm}$ dome, $18 \text{ N} < F_{\text{th}}$, so the load is again filtered out. By increasing the applied load to 22 N, the inversion threshold is met for the $t = 0.9 \text{ mm}$ dome, and this is remembered by the change in the sensor resistance. This comparison illustrates the geometry-dependent thresholding that enables the filtering of insufficient mechanical signals. The same threshold force tunability can also be achieved by varying the dome height (Figure S7, Supporting Information). Thus, it is possible to have a metasheet with distributed sensing thresholds by varying the heights and/or thicknesses of the domes in each unit cell. This spatially distributed filtering can be exploited to efficiently manage large amounts of data, a well-known problem in tactile sensors.\(^{[36]}\) Previous work on pressure sensors with learning did not incorporate this bioinspired filtering capability,\(^{[20,21]}\) which would be critical for creating a tactile event camera equivalent.\(^{[28,29]}\)

### 2.2. Nonlinear Signal Amplification

The second key function of mechanosensing units is the amplification of input signals for easier detection. Switching the states of the bistable domes amplifies the local mechanical strain in the metasheet, a nonlinear response that produces large changes in sensor resistance in response to dome inversion. This amplification is critical for writing memory to the linked memristors: at least a 10% change in sensor resistance is preferred. To quantify this amplification of the local mechanical strain, we conducted finite element analysis (FEA) to examine the stresses and strains in the membrane surrounding the dome, where the sensors are located. These simulations reveal that the stresses and strains in the membrane are inversely proportional to the radial distance from the center of the dome, $r$ (Figure 2b, S1b, Supporting Information). This relationship between $r$ and the radial and tangential stresses, $\sigma_r$ and $\sigma_\theta$, follows the following analytical expressions, where $D_2$, $D_3$, and $D_4$ are constants:\(^{[23]}\)

$$\sigma_r = D_2 (1/r^4) + D_3 + D_4 \log(r) + \ldots \quad (2)$$

$$\sigma_\theta = -D_2 (1/r^4) + D_3 + D_4 (1 + \log(r)) + \ldots \quad (3)$$
Therefore, changing the location of the piezoresistive sensor relative to the dome changes the effective amplification factor of the mechanosensing unit, which governs the magnitude of the change in sensor resistance in response to dome inversion. We experimentally demonstrate this first with a basic linear sensor, measuring 24 mm × 1.75 mm × 0.3 mm. Using a dome radius of 8 mm, we print unit cells with sensors placed at 14, 12, and 10 mm from the dome center (Figure 2f). To compare the changes in sensor resistance and remove the variations due to 3D printing, we normalize the resistance values using each sensor’s as-printed resistance. At a distance of 14 mm, there is little discernible change in the sensor’s resistance value when the dome is inverted. At 12 mm, the observed spikes indicate snap-through, but the sensor lacks two distinct resistance levels. At 10 mm, the sensor exhibits both the snap-through spikes and distinguishable ground and inverted state resistance levels. By placing the sensor closer to the dome, we increase the strain in the sensor in the inverted state, and therefore its corresponding change in electrical resistance. The reasons for not going so far as to place the sensors directly on the dome itself are twofold. First, it would be impractically difficult to print the sensors on the curved surface of the dome. Second, the surface of the dome may show high strains under only partial inversion (Figure S5, Supporting Information), while the base remains relatively unstrained until snap-through. Thus, placing the sensor on the dome rather than the metasheet base would amplify \( F < F_B \), eliminating the filtering capability.

The amplification can be further increased by changing the geometry of the sensor. To target the region of high strain close to the dome perimeter, we print and test sensors with the same dimensions but following circular arcs with varying radii from the center of the dome. At \( r = 14 \text{ mm} \) and \( r = 12 \text{ mm} \), the spikes indicating snap-through are clearly displayed. Unlike a linear sensor at a distance of 12 mm, the curved sensor displays two distinct levels of resistance, differing in value by 10–15%. At 10 mm away, the difference between the two resistance levels is 90% of the initial resistance, compared to only a 40% difference for the linear sensor. This increase in signal amplification may be explained by inspecting the longitudinal (1-direction) strain in each type of sensor with FEA (Figure 2g). We are most interested in the 1-direction strain because the conductivity is highly directionally dependent due to the internal alignment of conductive microparticles in the direction of extrusion.\(^{[38]}\). The linear sensor shows bands of very low strains, which should not significantly contribute to a change in resistance. Furthermore, the presence of both tensile and compressive strains in the linear sensor causes resistance fluctuations that result in partial signal cancellation. In contrast, the curved sensor shows a uniform compressive strain, with no regions of strain below 1%. This uniform strain means the effects of dome inversion are more strongly displayed throughout the sensor, resulting in increased signal amplification. For simplification purposes and to avoid the increased damage that occurs with more highly strained curved sensors (Figure S8, Supporting Information), we use metasheets with linear sensors to connect to memristors. Curved sensors could be made more practical by using a less brittle conductive filament; this is left to future work.

3. Spatiotemporal Memory

The mechanosensing functionality of our metasheets can be used to encode the transduced distributed mechanical inputs into memories. When mechanical inputs cause certain domes to invert, the occurrence of events and spatial pattern are recorded by the metasheet’s deflection. The pattern formed in the metasheet indicates the sites experiencing a force exceeding the programmed threshold, \( F \geq F_{B1} \). The spatial resolution of the metasheet can be made finer or coarser by scaling the unit cells’ local geometry and spacing.\(^{[22,23]}\) Unlike previous sensing skin devices aiming for high sensitivity over a small area, similar to a fingertip,\(^{[34,35]}\) we target large area applications, such as pressure sensing over an aircraft wing (Figure 1b). Such large-scale applications further underscore the necessity of filtering and nonlinear amplification to avoid data overload.\(^{[16]}\)

To catalogue sequentially applied patterns, we couple the dome strain sensors to nonvolatile memory resistors, resulting in an auxiliary memory layer. Specifically, this layer consists of voltage-dependent polymeric memristors based on flexible polymer films and off-the-shelf components and aims to electrically remember dome inversion events transduced by the mechanosensing units. Figure 3a illustrates the scheme we used to convert discrete (and even repeated) changes in dome sensor resistance, \( R_{\text{d}} \), into multi-bit memristive states, \( M \). Other integration schemes are also feasible, such as for a 1:1 dome–memristor pair (Figure 3a) or scaled in parallel across larger \( m \times n \) arrays.

Because the dome sensors are passive devices and the memristors are voltage-activated, a fixed amplitude voltage waveform, \( V(t) \), is supplied to induce a current through the sensor and a proportional voltage drop across a resistor in series with the sensor. A rectangular voltage waveform (where \( V_{\text{min}} = 0 \) and \( V_{\text{max}} > 0 \)) is chosen to reduce the DC power consumption and enable incremental programming of the memristor during times when the dome is inverted (i.e., the applied force is \( \geq F_{B1} \), and thus the sensor resistance is high: \( R = R_{\text{d}} \)). To enable this signal to program a voltage-controlled memristor, we implemented a fixed gain amplification circuit that outputs a voltage proportional to \( \Delta R_{\text{d}} \) and fed this through a switch regulator with a 5 V switching threshold (see Figure S9, Supporting Information, for details). The switch regulator ensures that the voltage transmitted to the memristor, \( V_{\text{in}}(t) \), has a consistent amplitude, even when successive dome inversions affect the total change in \( R_{\text{d}} \). In this way, \( V_{\text{in}}(t) \) represents the convolution of \( V(t) \) and the time when the dome is inverted (i.e., \( R = R_{\text{d}} \)): the resulting response yields \( V_{\text{in}}(t) \) equal to 0 V when the dome is not inverted and a peak voltage value of 5 V when the dome is inverted. The voltage signal \( V_{\text{in}}(t) \) is then applied to the memristor and a resistor wired in series (see Section A.6, Supporting Information, for details on how \( R_{\text{d}} \) was selected), which enables the divided voltage across the memristor, \( V_{\text{m}}(t) \), to be sampled as a measurable state of electrical memory for the corresponding dome. Table 1 shows the scheme’s logic, illustrating that changes in memristance (\( |\Delta M| > 0 \)) can only occur when the dome is inverted and \( V_{\text{m}}(t) \) (which is also proportional to \( V(t) \)) is sufficiently high to induce a change in \( M \).

The polymeric memristors used herein consist of a poly (3,4-ethylenedioxythiophene) (PEDOT):poly-styrene sulfonic acid
(PSS) thin film (~60 nm thick) sandwiched between indium tin oxide (ITO) and copper (Cu) electrodes (effective electrode diameter ≈ 1.8 mm; see Figure S11, Supporting Information, for device architecture). PEDOT:PSS forms a strong, flexible polymer matrix\cite{39,40} that enables mixed ionic-electronic transport, and it has been used to create organic memristive devices interfaced with reactive and noble metal electrodes displaying high OFF/ON ratios.\cite{41,42} Furthermore, the fact that PEDOT:PSS films can be fabricated through simple, low-temperature processing to make functional memristors makes this memristor material a promising candidate for enabling a conformal memory layer in mechanosensitive neuromorphic metasheets.

Representative voltage-controlled current measurements obtained on six distinct PEDOT:PSS memristors are shown in Figure 3b. The arrows denote the direction of the measured current path in response to one cycle of a 100 mHz sinusoidal voltage. The significant hysteresis in these current–voltage (i–v) curves indicates that the devices can reversibly switch between a high resistive state (HRS ≈ 15.2 kΩ) and a low resistance state (LRS ≈ 1.31 kΩ) in response to varying the applied voltage. The counterclockwise direction of current flow at positive voltages and the clockwise direction of current flow at negative voltages shows that these memristors exhibit a nonvolatile memristance.\cite{43,44} Specifically, when the applied voltage on the Cu electrode relative to the grounded ITO electrode increases above +3 V (V_{th}) (See Figure S12, Supporting Information, for measurement technique details), the devices switch (i.e., SET) from the HRS to the LRS as reflected in the sharp increase in current. Only when the probe voltage is lowered below −4 V do the devices RESET to the HRS. This means that programmed states of resistance can be stored in the sample even when the voltage to the device is removed (or set to zero). While the precise mechanism of voltage-activated resistive switching in these devices is still under investigation, these simple, low-cost, potentially conformal devices yield consistent performance across dozens of batches (Figure S12, Supporting Information) and suitable cycle-to-cycle stability (Figure S13, Supporting Information).

The 1:1 dome–memristor pair operation scheme described earlier and shown in Figure 3a seeks to incrementally reduce from the HRS the memristance of a specific memory device in response to discrete dome inversions. Based on the i–v behaviors in Figure 3, we tested the ability to incrementally program the memristors using a series of 5 V rectangular pulses. Each pulse lasts 5 s and occurs once every 15 s, an intentional choice that corresponds closely to the 100 mHz sweep frequency used for i–v measurements (Figure S14, Supporting Information). As the average estimated time constants for memristors used here were estimated to be 2.69 and 4.34 s (growth and decay respectively), a 5 s time ON guarantees the recording of only the steady-state response of the memristors. A low-amplitude voltage (1 V < V_{th}) is used to read the new resistance state of the memristor between pulses. Figure 3c shows the incremental reductions in M(t) induced by successive 5 V pulses, i.e., it is partially switched from HRS to LRS with each pulse.

Adjusting the pulse width and tuning the pulse amplitude relative to the SET voltage can be used to design the memristance variation per event and extend the number of programmable resistance states that each memristor can access. By varying the amplitude of V_{in}(t) from the switch regulator, we observed
that a 4 V amplitude of $V_m$ results in a steady cumulative change in resistance across subsequent pulses (Figure S15, Supporting Information). For $V_m$ values below 3.5 V, we observe smaller total changes and greater variability per subsequent pulse. This information allowed us to determine the necessary amplitude of $V_{in}(t)$ supplied by the switch regulator. We also explored the duration of the writing pulses to determine a suitable pulse width. We compared the cumulative reductions in a memristor’s resistance for three different pulse widths ($T_{on}$), revealing that for 1 and 2 s pulses, the cumulative changes in the resistance are small and unsteady (Figure 3d). This is because the pulse is too brief to drive adequate memristance changes. In contrast, using 5 s pulses yielded consistent, monotonic changes in device resistance, validating the 1:1 dome–memristor operational scheme. Also, from Figure 3d, we can estimate a net change in 0.4 kΩ after 6 simulated dome inversion events which is comparable to the net change in the nominal value of memristance from 6 physical dome inversion events as shown in Figure 3c. While this writing pulse is long compared to other memristors, we expect they could respond significantly faster by reducing the thickness and electrode dimensions, and unveiling the mechanisms of switching. For comparison, PEDOT:PSS-based organic electrochemical transistors can exhibit voltage-driven conductance changes in less than one millisecond.[45]

4. Spatially Distributed Input Learning: Physical Hopfield Networks

The combined mechanosensing and history recording capabilities of our metamaterial allow us to implement a physical learning system based on Hopfield networks[28] and the Hebbian learning rule.[46,47] Hopfield networks consist of interconnected artificial neurons and synapses that learn a series of input patterns stored as minima (i.e., attractors) in their energy landscapes. These patterns can be retrieved following the associative memory paradigm.[46] Hopfield networks achieve this by utilizing a fully connected network architecture that strengthens the synaptic connection between activated artificial neurons. Specifically, patterns ascribed to neuron states, such as images represented by pixels, are stored in the network’s interaction matrix, $J$ (Section A.12 for details, Supporting Information). Stored patterns form different attractors in the networks’ energy landscape (Figure 4d).[47] We leverage the cumulative resistance changes in our memristors, triggered by dome inversions, to capture the interactions between dome units, thus updating the network’s synaptic weights $J_{ij}$ and storing the spatial patterns sequentially input into our metamaterial.

The physical Hopfield network consists of a $m \times n$ dome metasheet array (Figure 4a), with each unit cell (dome + sensor) acting as an individual artificial neuron (The term artificial neuron refers to a unit in Hopfield network jargon; however, the terminology does not imply biomimetic neural functionality.) and the interconnecting memristors acting as synapses. Each unit can adopt two possible states: (+1) ground state and (−1) inverted state (Figure 2a). The interactions between unit cells can be captured by connecting different dome pairs to an XOR gate, as illustrated for a $2 \times 2$ ($n = m = 2$) array in Figure 4a (more detail in Figure S18, Supporting Information). This writes a resistance change for every “on” and “off” neuron pair interaction (Figure S19, Supporting Information). The number of memristors was reduced by considering the convergence properties of the networks ($j_{ij} \leq 0$ and $j_{ij} = j_{ji}$), which reduces the number of needed interactions to the upper triangular portion of the $m n \times m n$ interaction matrix, labeled as $U_i$ ($i = 1, 2, \ldots, M = m^2(n \times n - 1)$; see Figure 4a). By using this scheme, the Hopfield network can be trained directly by physical inputs with different external patterns as they occur, i.e., the network is trained online. This approach enables us to autonomously program new memristance values and thereby assemble and update the connectivity matrix based on physical events, unlike previously implemented physical Hopfield networks[48–50] in which memristance values in the weight matrix were iteratively adjusted offline using applied voltage pulses to achieve a desired connectivity matrix.

A 3-stage measurement scheme was implemented to capture the interactions between dome units by using the cumulative memristor response (Figure 4b). In stage 1, an initialization pulse (INIT) of 4.3 V for 20 s was used to pre-set each memristor to a value that changes linearly in response to subsequent voltage pulses (described in Figure S16, Supporting Information). Stage 2 involves a calibration procedure consisting of a series of four 4.3 V, 5 s writing pulses (simulating dome inversion events) preceded and followed by 1.5 V, 10 s reading pulses. The voltage across the memristor ($V_m$) is measured correspondingly, which directly reflects the resistance state of the memristor. The first read pulse reflects the initial HRS of the memristor ($V_m^0$), and the second read pulse reflects the current resistance state of the memristor after the four calibration writing pulses ($V_m^C$). The difference between the two read pulses accounts for the net change $\Delta V^i = (V_m^C - V_m^0)/4$ due to four simulated dome inversions. Stage 3 constitutes the actual learning phase, where the memristor network is subjected to a series of training pulses generated by actual dome inversion events (physically induced inversion patterns), which are also preceded and followed by reading pulses. The measured difference in $V_m$ read between the third ($V_m^T$) and final ($V_m^F$) read events reflects the net change in $V_m^T$ (resistance) due to pair-wise interactions between dome inversion events. The entries to the interaction matrix are calculated as $U_i = \text{round}(\frac{V_m^T - V_m^F}{\Delta V^i})$. By performing this procedure across the six memristors in parallel, we can automatically store and update interaction values between units (Figure 4c and S18, Supporting Information), generate the interaction matrix between dome units, and learn the input sequence patterns using the physical Hopfield network.

We demonstrate the Hopfield network’s online learning capability with a $2 \times 2$ metasheet array ($n = m = 2$, with unit cell dimensions $w = 30 \text{ mm}$, $h = 7 \text{ mm}$, $t = 0.8 \text{ mm}$, $r_d = 8 \text{ mm}$; see Figure S1, Supporting Information). The array was trained by applying a sequence of patterns using manual dome inversions (see Movie S1, Supporting Information). Any noise from the manual process of inverting the domes is filtered by the thresholding and amplification properties of the mechanosensors, illustrating the robustness of the method conferred by the morphological signal filtering and amplification of our
metamaterial. The resulting inter-unit firing is captured by constructing the interaction matrix from the memristor voltages read before and after the patterns are input (Figure 4c dark gray shaded regions). As the Hopfield network’s interaction matrix stores several patterns additively in the latest values of the weights (i.e., final values of this specific loading sequence, see Section A.12, Supporting Information), only the differences between initial and final memristance measurements are necessary to retrieve the stored collection weights of the trained network. Once the interactions are stored, the network’s weights are set, and the unique patterns are retrieved offline by presenting corrupted images to the network and performing an energy minimization process with asynchronous neuron update (see Section A.12, Supporting Information).

The training performance of our physical system was evaluated by performing three different dome inversion patterns (Figure 4c) and extracting the interaction matrix from each sequence. The Hopfield network’s energy landscape was examined to determine whether the physically input patterns were successfully stored as energy minima (Figure 4d). To achieve this, we utilized the principal component analysis (PCA) dimensionality reduction technique that uses random data generated based on the trained interaction matrix and the energy function to visualize the network’s attractors using the two largest variance directions ($Z_1$ and $Z_2$). The analysis reveals different attractors within the landscape (Figure 4d), each corresponding to the input patterns ($\xi_i$) and their reflections ($-\xi_i$). This behavior is expected as the Hopfield network’s energy
function is quadratic, yielding equal values for $\xi^i$ and $-\xi^i$. This leads to the system learning both configurations (i.e., $\xi^i$ and $-\xi^i$) since both are energy minima. This quadratic behavior can be avoided by having a larger number of dome units and using an energy function for a continuous state. Moreover, it is worth mentioning that $\xi^2$ and $\xi^2$ for the first input sequence are the reflections of one another, which implies that for this case, there would be four different attractors instead of six as in the other sequences. The obtained results indicate that the training procedure captures all interactions between dome units, and the memristor-encoded Hopfield network successfully remembers the input patterns. The classification accuracy of the physical training is evaluated by presenting 3000 different corrupted patterns to the network and then determining the number of correct identifications (i.e., implying no errors with respect to the stored patterns during training). Each corrupted pattern is a variation of one of the original input patterns, with normally distributed noise, which is utilized to test the accuracy of the network with nonbinary initial patterns. A 90%, 95%, and 95% overall accuracy, respectively, is found for the three pattern sequences shown in Figure 4c, which has a 4% average difference from the offline trained (perfectly trained) Hopfield network (Table S5, Supporting Information). These results show that one of the learned patterns during the physical training is consistently retrieved with zero error more than 90% of the time a pattern is given to the network. The energy minimization process involving the weights’ updating when several corrupted patterns are presented to our physically trained network is shown in Movie S2, Supporting information.

5. Conclusion

We introduce a new class of flexible metamaterials showing spatiotemporal mechanosensing and neuromorphic online learning. Our prototype leverages the structural bistability of cm scale dome-shaped units to filter, amplify, and transduce external mechanical signals into electrical states that are used to induce nonvolatility (permanent) changes in memristance. The proposed architecture allows for producing neuromorphic properties in metamaterials that can cover large areas ($10^2$ cm$^2$), in contrast to many examples of neuron-inspired sensing and perceptual systems designed for sub-mm scale sensing resolution. Nonetheless, the temporal resolution of our system is comparable to other flexible neuromorphic sensing systems for which incremental writing of the memory elements takes 2–5 s. We use the spatial organization of our dome units and the cumulative changes in memristance of our metamaterial to realize a physical Hopfield network capable of learning sequences of mechanical input patterns online. Specifically, we leverage the dome units’ bistability-based filtering and amplification to generate threshold-dependent changes in sensor resistance that can trigger shifts in the corresponding memristor state. We use the memristance value to populate physically realized Hopfield networks’ interaction matrix weights, thus capturing the firing of units following a well-known Hebbian rule. Crucially, the cumulative resistance changes of our metamaterial’s memristors allow for retrieving all the stored patterns from their final (i.e., current) states. As a result, our metamaterial encodes several input patterns without the need to store continuous temporal information. In this sense, our metamaterial exhibits analogous behavior to threshold-dependent event cameras augmented with nonvolatile memory that encodes the captured episodes directly into the physical network’s weights. We envision this unique capability as providing a route for systems that continuously learn spatiotemporal mechanical inputs and adapt depending on different external stimuli. This can be utilized to trigger different control policies with minimal time delay using a reduced number of mechanical sensors and an optimal amount of analyzed data. For example, known pressure patterns associated with dangerous aerodynamic conditions could be presented to the current state of the physical Hopfield network connectivity matrix (see Equation (7)). Reaching an energy minimum would indicate that such a pattern was learned (see Figure 1b), signaling that control action is needed with minimal computational cost. This allows for embodying decentralized sense–compute–control loops capable of recognizing when to trigger autonomous behaviors in response to unknown and varying input conditions. Thus, our mechanosensitive neuromorphic metamaterials reduce the need for costly online data storage, transmission, and processing of spatiotemporal inputs, especially in situations where tactile pattern identification is of interest, including for robotics, autonomous systems, wearables, and morphing wings.

6. Experimental Section

Unit Cell and Metasheet Fabrication: The unit cells are 3D printed using fused deposition modeling (FDM) on a Raise3D Pro2 printer using the settings in Table S1, Supporting Information. Ninjatek Cheetah TPU filament ($E = 26$ MPa) was used for the dome and base and BlackMagic3D PLA + graphene composite filament ($E = 3767$ MPa) for the sensor. Due to the PLA + graphene material being two orders of magnitude stiffer than the TPU, the sensors were embedded in the TPU base to avoid delamination. A connection point was left exposed at each end. To address the high contact resistance of conductive filament, each connection point was painted with a thin layer of highly conductive carbon paint (Pelco, Electrodog 502) before attaching a copper wire, using another layer of conductive paint. After drying, a dot of hot glue was applied on each connection to secure the wire in place. Metasheets were manufactured following the same procedure, with one continuous 3D print.

Unit Cell Resistance Measurements: The resistances of the dome sensors were measured using a voltage divider circuit with a 2 kΩ shunt resistor. The voltage drop over the sensor was measured using a National Instruments USB-6251 data acquisition system and a simple National Instruments LabVIEW multimeter program. The DC power supply (Keysight E36313A) applied 2 V to the circuit.

Mechanical Tests: Inversion force and thresholding tests were performed on an Instron 3345 Universal Testing Machine with Bluehill software. Test domes were printed with a 2 mm diameter hole in the center, where an M2 screw is attached with a nut and washer. The other end of the screw was attached to a machined aluminum block, which was held by the Instron machine grips. The dome sample to be tested sat on a 3D-printed base with a 20 mm × 20 mm square hole centered under the dome to allow for free inversion (Figure S6, Supporting Information). The sensor was hooked up to the same voltage divider circuit as used for other resistance measurements. Resistance data was gathered for 10 s before the Instron test began to capture the initial state of the sensor. For each test, the head of the machine moved down at a rate of 20 mm min$^{-1}$. Once inversion was detected via a drop in the reaction force, the test stopped, and the machine returned the dome to the starting position. The sensor data was collected until the total test time reached...
2 min. The dome was then reset manually and the test was rerun. Each specimen first underwent 10 full inversion tests. Then, the threshold behavior was tested following the same settings as for the inversion force, but with the end of the test triggered by a maximum applied load. This maximum load was incrementally increased for each test until the inversion force threshold was reached.

FEA: The unit cells were modeled in Abaqus using linear elastic material properties and S4R shell elements. To capture the bistable behavior, geometric nonlinear analysis was used. The unit cell was initially modeled in the stress-free ground state. Snap-through was triggered using an enforced displacement applied to the center node of the dome while the edges were pinned. These boundary conditions were then released while the center node was fixed to show the free inverted state of the unit cell.

**Fabrication of Memristors:** ITO glass slides (10–15 Ω sq⁻¹) were cleaned with (in the following order) soap-water, de-ionized water, ethanol, acetone, and propanol via sonification for 15 min each and dried using ultra-pure nitrogen. The conductive face of the clean ITO slide was oxidized in an oxygen plasma chamber using a PE 50 XL Benchtop low-pressure plasma system for 1 min to increase the hydrophilicity of the surface, which encouraged wetting of PEDOT:PSS solution resulting in uniform distribution. 3 wt% PEDOT:PSS solution bought from Sigma-Aldrich was spin-coated onto a clean ITO glass slide at 3000 rpm for 40 sec. It was then dried at 120 °C for 20 min and vacuum annealed for more than 24 h. This results in a thin film (~60 nm thickness) measured using an F20 device from Filmetrics. Portions of the ITO were covered with insulating tape, which when removed post-fabrication recovered a naked ITO surface to be used as a bottom electrode as seen in Figure S11b, Supporting Information.

**Characterization of Memristors:** Electrical characterization of the fabricated devices was done using an SP 200 Potentiostat from Biologic. Spring-loaded copper contacts were used as the top electrode as shown in Figure S11b, Supporting Information. Bipolar sinusoidal voltage waveforms of 5 V and 100 mHz were used for the characterization

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**Supporting Information**

Supporting Information is available from the Wiley Online Library or from the author.

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**Conflict of Interest**

The authors declare no conflict of interest.

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**Data Availability Statement**

The data that support the findings of this study are available from the corresponding authors upon reasonable request.

**Keywords**

associative memory, bistability, embodied intelligence, mechanosensing, neuromorphic metamaterials

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