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Optical Lace for Synthetic Afferent Neural Networks

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Abstract

While vision dominates sensing in robots, animals with limited vision deftly navigate their environment using other forms of perception such as touch. Efforts have been made to apply artificial skins with tactile sensing to robots for similarly sophisticated mobile and manipulative skills. The ability to functionally mimic the afferent sensory neural network, required for distributed sensing and communication networks throughout the body is still missing. This limitation is partially due to the lack of cointegration of the mechanosensors in the body of the robot. In this paper, lacings of stretchable optical fibers distributed throughout 3D printed elastomer frameworks create a cointegrated body, sensing, and communication network. This soft, functional structure can localize deformation with sub-millimeter positional accuracy (Err = 0.71 mm), and sub-Newton force resolution (~0.3 N).

Summary

A soft optical sensor network distributed within a soft body to measure the location and degree of deformation.

Introduction

Many biological systems have adapted to functionally interact with the external environment by developing an entwined brain to body relationship. This complex arrangement allows the latter to perceive the world and the former to interpret it in a closed-loop manner. As robots become more physically complex and cognitively advanced, we can take inspiration from animal nervous systems to create the necessary groundwork for controlling robotic artifacts.

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Through sight, hearing, smell, taste, touch and even interpretation of magnetic and electric fields, animals and plants feed a sense of exteroception. Proprioception, knowledge of position and state of their own body parts, is achieved through some combination of these sensory organs as well; animals, in particular, use vibrations and forces felt through mechanoreceptors under skin (1) and through deformation and stress measurements within muscles and tendons (2, 3). From this information, they perform complex tasks such as maneuver when blind or alter their behavior when injured.

Presently, autonomous robots mainly use visual and tactile detectors placed at end effectors for exteroception, (4) and sensors at joints and the center of mass for proprioception (4) to complete complex tasks. A more distributed sensor network, as in the neural circuitry of animals, would allow robots to interact at higher tactile resolutions and measure mechanical damage (i.e. bent or broken limbs) accumulated over time. The importance of distributed, volumetric sensing is even more pronounced in the field of soft robotics where every part of the machine deforms. In these robots, the stretchable sensors distributed throughout the body have only recently been used for feedback control.(4–12)

These stretchable sensors typically use electrical properties (e.g., resistance (4, 13), capacitance (14, 15), voltage (16), and current (17)) in planar arrays (or “skins”) to localize surface deformations (17–21). Compared to electricity, light carries information faster and with higher data densities through changes in intensity, phase, polarization, or wavelength. (22) It can also be carried in multiple directions simultaneously and is less susceptible to electromagnetic interference.(22) As a result, optical sensors provide an excellent alternative to electrical ones.(7, 23–28) Optical skins have used light loss through bent fibers (29–31), fiber Bragg gratings (24), and frustrated total internal reflection (32–35) to measure planar shape change but have not been used to directly measure complex, volumetric deformation due to their 2D fabrication limitations. Stretchable lightguides sensitive to tensile strain and external forces through Beer’s law can be easily embedded into a volume, but lack the spatial differentiation of skins (7, 23, 25–28). The optical sensor network we present here uses an entirely different principle—frustrated total internal reflection—to measure deformation through light coupled from the physical interaction of neighboring lightguides (Figure 1A, left). By measuring these coupling interactions, we can differentiate between simultaneous multiple and singular deformations throughout a volume.

In this manuscript, we introduce a platform, which we call Optical Lace (OL), for creating arbitrary 3D grids of soft, stretchable lightguides for spatially continuous deformation sensing (Figure 1A). This 3D sensory array provides similar function to the afferent neural network in organisms. We distribute these lightguide networks throughout the volume of a 3D printed soft scaffold. To determine the extensive capabilities of this system, we performed mechanical analysis, optical simulation, x-ray imaging, and sensor characterization of our system. We concluded with devices composed of OL that show (i) exteroception that can locate multiple finger presses simultaneously, and (ii) proprioception that monitors volumetric structural deformation.

Results

System design

Using a commercially available high resolution, rapid 3D printing technique (CLIP (36); Carbon M1), we created a scaffold from elastomeric material (EPU 40; Supplemental Figure S1; Materials and methods: System fabrication) to house a four cored OL (Figure 1B, left). We label the network as OL_{1,3}, where the notation **1,3** represents **one** powered input core and **three** un-powered output cores. As the 3D printed structural framework we created is of variable stiffness (to demonstrate arbitrary deformable interfaces), we co-designed the OL_{1,3} to be at the top of the scaffold, where it is softest (Figure 1B, right), so force can be best transferred to the sensor in the exteroceptive case.

Our demonstrative structure deforms through the bending and buckling of the struts in a 3D printed lattice; we programmed the stiffness gradients by varying the strut thickness (t). For example, by making the struts thinner, they bend and buckle more easily, creating a softer section. Equations 1 and 2 show rectangular beam bending and buckling forces (37)

$$F_{buckle} = \frac{\pi^2 E t^4}{12 l^2} \quad (1)$$

$$F_{bend} = \frac{3 \delta E t^4}{12 l^3} \quad (2)$$

where E is the elastic modulus, δ is the deflection, and l is the length of a strut. For our printed geometry, this quartic dependence on thickness results in large behavior differences of the softer top layer, $t \sim 0.75$ mm, which buckles at $F_{comp} \approx 6$ N, and stiffer bottom layer, $t \sim 1.125$ mm, which bends until $F_{comp} = 12$ N (Figure 1B, right) and does not exhibit buckling behavior upon compression. This complex response to force is ideal for touch interfaces as a finger press provides sufficient force to completely deform the top while the bottom layer provides significant resistance to deformation. The difference in stiffness also increases the sensitivity of the OL by transferring forces directly to the mechanosensor, the air gap separating the input and output lightguides (Figure 1C, left). We fix the cores in place within this area of interest using lattice-work guide channels printed into the scaffold.

Optical array design and lace fabrication:

After printing, we thread the polyurethane lightguides (StretchMagic, Pepperell Braiding Co.; MA, (23) diameter $d_{out} = 1$ mm for outputs, and $d_{in} = 1.5$ mm for the input; Materials and methods: System fabrication) into the lattice-work channels which loosely hold the cores in place. The channel wall's porosity, $\phi_{air} = \frac{A_{air}}{(A_{air} + A_{EPU})} = 0.53$, allows our cores to guide more light by increasing the numerical aperture ($NA=0.174$ without and $NA=0.880$ with porosity) and critical angle ($\theta_{crit}=83.42^\circ$ without and $\theta_{crit}=54.02^\circ$ with porosity) due to the increased difference in refractive index between the air and printed polyurethane scaffolding and polyurethane cores ($n_{core}=1.52$; (23) $n_{air}=1.0$; $n_{EPU}=1.51$ (Figure S2); $n_{porous}=1.24$ at $\lambda=850$ nm).

The interconnected guide channels allow the contact and coupling of light between input and output lightguides. The optically powered input core leaks light into the unpowered outputs only when deformations cause the lightguides to contact (Figure 1C, right). In the OL presented in this paper, the outputs are U-shaped, lined up next to each other, and optically separated from the input lightguide with a small air gap (0.4 mm) in the resting state (Figure 1C). This configuration allows the outputs to be parallel to the input core so that line (not point) contact occurs and increases the dynamic signal range through the increasing coupling lengths with compression.

We measured the power from all the output lightguides to interpret the position of localized deformations with photodiodes (Materials and methods: Electronic setup for reading signals). In the exteroceptive structures, we designed the receptive field of each mechanosensor to be comparable to the size of a typical fingertip measured by a ruler, $w_1 = 6.4$ mm (Figure S3), so that a press centered on the output would produce only one signal for simple processing. To measure the location of touch continuously over a distance, we placed the outputs close together ($w_2 = 8.35$ mm; Figure S3) so that the receptive fields overlapped allowing a single finger press to cause signal in multiple mechanosensors at once. In the case where multiple outputs are contacted, the touch position can be calculated using the ratio of intensities in the neighboring lightguides.

Experimental validation

To visualize the scaffold deformation and core contact, we used x-ray micro computed tomography (μ -CT) to image the OL_{1,3} (Figure S4; Materials and methods: Micro CT scan). The 3D reconstructions show the variable stiffness scaffolding deformed as designed with the stiff scaffold undisturbed even with full compression of the soft segment (Figure 2A, left). Additionally, due to the high compliance of the soft scaffold, external forces result in highly localized deformation to ensure that only one or two receptive fields are activated with one touch. We also confirm that the coupling length (i.e., physical contact between input and output cores) does increase to its maximum length, 3.5 mm, at high forces. Under the large deformation applied (e.g. $h = 5$ mm), light remains coupled; however, the CT scan reveals that these extreme deformations cause the input to roll around the output core instead of simply contacting from above (Figure 2A, middle, right).

We ran simulations on the lace (COMSOL Ray Optics; Materials and methods: Optical Simulation) which, as expected, indicate a linear increase in the normalized coupled signal transmitted from the input as the coupling length increases (Figure 2B). We modeled the lightguides as lossless cylinders ($d = 1$ mm) with $n_{core} = 1.52$, clad by air, $n_{air} = 1.00$. We set them to contact over a straight section of varied length, $0.1 \text{ mm} < L < 4.5 \text{ mm}$ (Figure 2B), on the output core. We also set the cores to overlap by 0.050 to 0.55 mm to simulate a changing contact width when they are slightly deformed into each other. From the measured power of light at the end of the output, we see that a minority fraction of the input light ($< 12\%$; Figure S5) coupled. This ensures that multiple signals can be read simultaneously from a single input. Importantly, the correlation of signal intensity to core contact makes it possible to measure force or extent of deformation in addition to position. Additionally, our experimental results from testing two straight, cylindrical lightguides coupling with a

constant contact width and varying length, L , matches well to the simulated results (Figure 2B; Figure S6). The signals in Figure 2B are normalized to their signal at 4 mm coupling length.

While the change in coupling length produces the majority of the signal, the contact width is also a control variable (Figure S7). Very small contact widths lead to a small contact area and low signal; too large implies significant deformation of the cores, causing more light loss to the environment (Supplemental text, Figure S7). We experimentally confirmed that our sensor network functions mainly due to changes in contact length which can be seen in Figure 2A, where even at high deformations there is limited change in core shape.

Sensor Characterization

We characterized the force response of an OL_{1,3} by attaching an IR LED to the end of the input core, and photodiodes to the ends of one leg of each output core to read the coupled light intensity (Materials and methods: Force and positional accuracy measurements). To measure the force response, we used a z-axis stage to repeatedly press a force gauge into the centers of each of the three outputs between 1.5 - 3.5 N at 0.5 N intervals and recorded the signal (Figure S8; Materials and methods: Force and positional accuracy measurement). The signals were normalized to the maximum possible value that the electronics can produce (Figure 3A; Materials and methods: Electronics setup for reading signals). The minimum and maximum indentation needed for a reliable, linear signal response was ~ 1 mm and 3 mm with the current scaffold. The signal output was highly repeatable with an average standard deviation $\overline{SD} = \frac{1}{n} \sum_{i=1}^n \frac{SD}{avg\ signal} = 0.02$ in normalized output signal across the $n=300-400$ total data points. The low standard deviation of the signal implies a force resolution (~0.3 N) comparable to the skin in the human hand (i.e., humans can perceive 7% change in applied force between 2.5 - 10 N (38)) and is better than typical resistive or capacitive soft sensors (~10% variation of signal (9, 11)). The minimum indentation required for this particular OL_{1,3} is much larger for our sensor than the human hand (OL: 1 mm; human hand: 10 - 500 μ m (39, 40)), or electronic soft sensors which are typically on the scale of a few mm thick (4, 13, 14, 18, 19). While the design of our scaffold OL_{1,3}, has a reliable minimum readable force of 1.5 N and a maximum of 5 N (for comparison, resistive and capacitive soft sensors can measure minimum forces around 0.01 N (9, 11) and the human hand 0.001 N (1)), we can tune the sensitivity and dynamic force range via lattice geometry. The lace itself, without being encapsulated in a lattice, has a minimum detectable force of 0.06 N for the particular fiber mechanical properties used in this study.

To assess the frequency response of our sensors, we shot a 4.5 mm diameter projectile into an OL_{1,3} at ~0.23 km s⁻¹ (Movie S1, Materials and methods: impulse measurement). While collecting sensor data, we visualized the impact using high speed camera (Phantom LAB 310) data for ground truth. The OL embedded in the 3D printed framework could measure an impulse between 0.2 - 2.5 ms long from six samples while the actual impact was about 0.1 ms (Figure 3B, S9). From high speed video, we estimate that the OL can measure deformation rates of at least 46 kHz $frequency = \frac{velocity\ of\ projectile}{deformation\ observed} = \frac{230,000\ mm / s}{5\ mm}$. The sensor response, however, is slightly delayed from the time of impact by 0.7 - 26.4 ms. The

inconsistent time between analog readouts suggests that the error is due to the microcontroller as the Arduino can read analog signal at about 4 kHz and the OPAMP used will produce an attenuated signal above 6 kHz. Another source of delay is in the finite time it takes for the compression wave to collapse the elastomer matrix.

To measure the positional accuracy of the OL_{1,3}, we pressed the sensor every millimeter between the left and right outputs (Figure 3C) with the same z-axis stage and force gauge (Materials and methods: Force and positional accuracy measurements). We took the maximum value from each output during the press to calculate position and plotted it against the actual position measured by a ruler. From Figure 3C, we see the overlapping receptive fields of each mechanosensor as there are signals from both neighboring outputs when the sensor is pressed directly between, but not when pressed directly above their centers. From the ratio of the output intensities, we interpolate the position of touch between two outputs using the empirically determined (Figure S10) equation 3:

$$x_{\text{calc}} = x_{\text{base}} + 5.09 * \left(\frac{I_{\text{Right}}}{I_{\text{Left}} + I_{\text{Right}}} \right)^{.34} \quad (3)$$

where x_{base} is the center of the closest output to the left, I is the maximum signal during a press of either the left or right neighboring output (Figure S10). We fit the ratio to the true position, for one set of data, to find the nonlinear equation above (Figure S10). When only one output core has a signal, the ratio is zero so the system assumes the press is directly above the center of that output. This introduces greater error (maximum error, $Err_{\text{max}} = 2.7$ mm, average error, $Err = 0.71$ mm) near the centers of the receptive fields where there is no overlap (i.e. near the center of an output, Figure 3C). While the data was taken with presses of around 4-5 N, this model does not require prior knowledge of the magnitude of applied force since it relies on the ratio of intensities and not their absolute value. It also has sub-millimeter average positional accuracy ($Err = 0.71$ mm, $SD = 0.69$ mm; Figure 3D) which is comparable to the spatial resolution of touch sense in a human hand (2-3 mm (41)). Typical electronic soft sensors are often shown to have spatial resolution on the 0.1 mm scale (17, 42) but, like OL, can likely have much higher upper limits in positional accuracy with improved manufacturing methods.

Exteroception

To demonstrate the exteroceptive abilities of this system, we fabricated a musical instrument (OL_{1,15}) with fifteen output cores over a single, 12.5 cm long input line (Figure 4A) using the same core geometries as the OL_{1,3} shown previously. Due to the light propagating through the input in one direction, the coupled light primarily travels in the same direction, and thus preferentially down one leg of the contacting output (Figure 1C). We took advantage of this directionality and placed an LED (IR on the right, visible on the left) on both sides of the input core. In Figure 4, we used a blue LED to visualize the pathway for data collection; however, we took data using an IR light source which would not have been visible in our illustration. We threaded the right leg of the output to the left side to read the coupled IR light with a photodiode (Figure 4A, output: data, Figure S11) and the remaining leg to the front of the scaffold as a visual indicator of ground truth (Figure 4A output: visual,

Figure S11). The IR signals were interpreted by an Arduino microcontroller communicating with the software package “Processing” on a laptop computer (Figure S12) to produce auditory signals based on position of touch in real time (Movie S2). The calculated position is also plotted on a number line from 0-14 representing each of the 15 outputs. The program also measures the intensity of the signal to play notes of varying volume (Movie S2). Figure 4,B–D shows the calculated positions for a press directly above, between, and over multiple outputs, along with a representation of the press in the same position.

Proprioception

To demonstrate a proprioceptive use case, we collected data from an OL_{1,12} (Figure 5A; Materials and methods: System fabrication) to reconstruct the 3D deformation state of a cylinder, with embedded stiffness gradients, undergoing uniaxial compression (Figure 5B, Movie S3,4). We varied the stiffness within the cylinder by varying the strut thickness (Figure 5B, S13; from bottom to top: $t_{stiff}=1$ mm, $t_{soft}=0.75$ mm, $t_{medium}=0.875$ mm). By adding a stiff spiral (Figure 5A, scaffold) with a powered waveguide core (Figure 5A, input), we increased the sensitivity of the OL and swept out a larger volume for sensory information. The variable stiffness and added stiffness from the spiral allowed the cylinder to measure forces from 0.5 N – 22 N allowed Figure 5A shows this spiral input core, illuminated using a blue and green LED, and the 12 output cores positioned normal to it and along its length.

To calculate the compression of each section, we obtain 18 sets of simulated force vs localized compression for every 2.2 mm of height from finite element analysis (FEA) of the scaffold and selected the 12 that correspond to the innervated area (Materials and methods: Proprioception accuracy measurements). We measured the force in each section of the cylinder using a linear model of signal intensity to force and calculated the displacement of each section with a compression vs force model fit to the simulated FEA model (Table S2). The model and our reconstructed data are shown in Fig. 5C,D. For model validation, we compared the calculated strains to those measured using a Digital Image Correlation (DIC) extensometer during single axis compression tests. The average magnitude of error over nine tests is 0.033, 0.33, 0.24 mm with a standard deviation of ± 0.01 , 0.24, 0.25 mm (Figure 5E) for the stiff, medium, and soft sections respectively. These errors are a little larger but on the same order of magnitude as human perception of skin indentation in the hand, ~ 0.1 mm (40), and can be decreased (0.021, 0.029, 0.19 mm) if using a model fit to DIC data (Movie S4).

Limits of the Optical Lace

Innervating large and tortuous 3D structures will require knowledge of the power transfer limits of the OL, which has inherent length limitations due to optical losses through and between fibers. We modeled these losses using Beer’s law under two specific use cases: (i) The first one defines the OL length as if we are looking for only a few signals at one time over as large an area as possible. This situation is useful in exteroception where knowing when and where a robot has been contacted is important. In this case, presently, the input can be ~ 80 cm long for the material and electronics system we have chosen (See SI Text, Figure S14). (ii) The second defines how long the OL can be if we want to interpret all

signals simultaneously. This situation is useful for proprioception where constantly measuring local curvatures globally would be important. In this case, presently, the input can be 31 cm long with 37 outputs (See SI Text, Figure S14).

Discussion

In this work, we demonstrated a 3D mechanosensor network, which we call Optical Lace, co-integrated with variable compliance structures that performs similar functions as, but does not mimic the mechanisms of, an afferent nervous system. We demonstrated the OL's ability to repeatably sense localized, volumetric deformations within a 3D printed polyurethane lattice. While the OL itself could detect .06 N forces, the OL embedded in the lattice could detect ~0.3 N with sub-millimeter average positional accuracy (0.71 mm) that is comparable to human skin.

While we only demonstrate two simple examples of computer interfaces with extero- and proprio-ception, the OL and scaffold can be tuned for sensitivity, spatial resolution, and accuracy as well as designed to be responsive to both the direction and type (tension, compression, bending, twisting) of deformation. Changing the scaffolding to be selectively stiff to better transfer forces to the mechanosensor, removing the air gap so the sensor starts at a non zero value, and adding mechanical amplifiers (like hair on animals, or feathers on birds; Figure S15) can decrease the measurable force to ~0.035N (corresponds to a ~0.5 mm displacement).

The minimum detectable force of the OL without the scaffold can be further reduced by lowering the elastic modulus of the core, allowing more contact area with smaller forces. Higher accuracy, especially between outputs, can be increased by changing the output geometries to be flatter and overlapping (Figure S16). We can also increase both the spatial resolution and accuracy of the OL by narrowing the widths of the outputs. Finally, to measure direction and multiple types of deformations, we can combine multiple OLs (Figure S17; Movie S5) and even use different geometries altogether (Figure S18, Movie S6). Larger volumes can be innervated by a single input using improved lightguide materials, higher power LEDs, or more sensitive photodetectors. Finally, fewer accompanying electronics may be required if we take inspiration from biology to combine signals from individual mechanosensors without losing information (43).

In the future, we would like to take advantage of the higher information density that can be carried through optical systems to create integrated sensori-motor networks. These networks could combine not only deformation sensing, but temperature (44), humidity (45), and chemical monitoring. We can also better incorporate the cores through directly 3D printing the lightguides (46). By mimicking the inherent link between sensory and motor signals in animals, which are employed not only for action execution but also for action "selection," (47) we may be able to use Optical Lace to simplify controls and electronics and improve the efficiency of robots.

Materials and Methods

Materials testing

To characterize the mechanical properties of the 3D printed material, we performed uniaxial tensile tests according to the ISO 37 method with a type 4 dumb-bell sample geometry. The test was run at 200 mm min^{-1} on a Z010 Zwick Roell using a 10 kN load cell with pneumatic grips pressurized at 85 psi. The graph in Fig. S1 shows the averaged data with standard error of 11 samples. The data shows slightly exaggerated strains due to the sample slightly slipping out of the grips. All compression tests were run on the Zwick with a 10kN load cell between 2 parallel plates. The sample below was a solid cylinder (diameter = 29 mm, height = 12.5 mm) and was compressed at a strain rate of 12 mm min^{-1} . The lattices in Figure 1 were compressed at 10 mm min^{-1} .

Measuring Signal change due to varying contact length and width

With a constant coupling length rig Figure S15, the contact width between cores is changed by spacers that limit the amount of compression between cores. We see that at first, the output signal increases as the compression and coupling length increases, but then drops off (Figure S15). This may be caused by loss of higher order modes that can be carried by the lightguide due to large change in core diameter and increased loss due to a change in the angle at which rays hit the core surface as previously noted by Harnett et al (23). The initial increase in signal may imply that more light couples as the contact area increases due to greater contact width.

System Fabrication

We designed the variable stiffness scaffolding using Fusion 360 (Autodesk, Inc.; Figure S3) and stereolithography 3D printed the OL scaffolding from a commercial elastomeric polyurethane (EPU) material on a Carbon M1 printer. We designed the top ~8 mm to have a thinner strut thickness, $t_{soft} = 0.75 \text{ mm}$, compared to the rest of the scaffold, $t_{stiff} = 1.125 \text{ mm}$, which created an area that was sensitive to external touch. Within the scaffolding are lattice walled channels to hold the lightguides with thin, $t_{clad} = 0.4 \text{ mm}$, walls to minimize the effect on the mechanical properties of the structure. The scaffold was fully cured after being in an oven for eight hours at 120°C after excess resin was removed in an isopropyl alcohol wash.

We threaded a thin monofilament string (Darice jewelry designer, 8lb) through each channel in the printed scaffold and super glued the end to a commercial, clear, soft, polyurethane core (Stretch Magic, Pepperell) with a refractive index of 1.52 (23) and diameter $d_{out} = 1.0 \text{ mm}$ for the outputs and $d_{in} = 1.5 \text{ mm}$ for the input. We then pulled the cores into place with the string.

For the proprioception cylinder, as the output u size and spacing have changed to fill the available space to be innervated. The outputs U'S are 6.8 mm wide and spread out to be every 9 mm along the input so that each one represents about 2.5 mm of height on the cylinder. They are parallel to the compression axis as this causes the inputs and outputs to be pressed together during compression. The U's are also curved to match the spiral so that the

output and input core line contact increases with more compression. The input was designed as a spiral as opposed to a zig zag or s-curve to avoid any sharp curves that would introduce more light loss.

Micro CT scan

We designed and printed a rig to hold the CT sample in the deformed state for the duration of the scan as seen in Figure S4. The sample was scanned on an Xradia Zeiss Versa XRM-520 run at 100kV/9W with 0.7 second exposure time and 36.7 μm resolution. We reconstructed the scan into a 3D part in the software Aviso (ThermoFisher Scientific) after removing the bar causing the deformation from the slices. We then removed background noise and testing rig before slicing the reconstruction to show the cores in Figure 2A.

Electronics Setup for Reading Signals

We designed and 3D printed elastomeric parts to hold the photodiodes (380 nm-1100 nm, SFH 229 from OSRAM Licht AG) and IR LEDs (peak 875nm, TSHA4400 from Vishay Intertechnology, Inc.) in contact with the cores using friction fits. The setup used to take data for the OL1,3 is shown in Figure S9. All data for force and positional accuracy was taken with photodiodes amplified with an OPAMP (LM324A, Texas Instruments Inc.) that has a 2M Ω gain and a 4,700 pF capacitor acting as a low pass filter with a maximum signal value of 800. The signal from the photodiodes were sent through a simple current-to-voltage (I/V) converter circuit (Figure S19) and read through the analog pins on an Arduino microcontroller (Arduino MEGA 2560) at a baud rate of 9600.

All the photodiodes for the exteroceptive sensor use a 2M Ω resistor (R1) while the proprioceptive sensor used 2, 4.99, or 10 M Ω resistors as listed in Table S1. The IR LEDs have 33 Ω resistors (R2). The circuits were powered by two wall outlets for a +V = 5V and -V = -5V. Data was transferred to Processing about 50 times per second.

Optical Simulation

We modeled a straight input and single output in COMSOL's Ray Optics package as lossless, cylindrical, 1 mm diameter lightguides. Walls were setup at both ends of each core to measure the light intensity through those areas. Input light was set up through the "Release from Grid" module, entering from one of the input ends in a uniform density cone of 400 rays with a cone angle of $\pi/9$ and a total power of 1 Watt to simulate the LED. Rays leaving the cores were suppressed. The mesh had a minimum element size of 0.009 mm, a maximum of 0.25 mm with a curvature factor of 0.1 and maximum element growth rate of 1.1. The simulation was solved using the ray tracing solver over a path length of 0 – 300 mm with a step size of 0.1 mm. We ran a parametric sweep of the coupling length from 0.1 – 4.5 mm with a step size of 0.1. To simulate varying levels of core deformation, we also ran a parametric sweep of the overlap between the two cores from 0.05 mm - 0.55 mm in steps of .1 (Figure S7).

Impulse Measurement

To measure an impulse, we first removed the capacitor (Figure S19, C1) which was inserted as a low pass filter. We recorded 4002 points of data on an Arduino set at a baud rate of

2,000,000 which took roughly 1 second. The actual amount of time it took to get 400 analog readings varied from 904 – 1093 ms. We shot seven sensors with 0.177 caliber bb pellets as the projectile and measured the signal from the impact. Using a high speed camera (phantom LAB 310) set to take 23,000 frames per second and a flashing LED to sync the data to the video (Figure S20). From the high speed video, we determined the projectile took ~0.00009 seconds (2 frames) to pass through the entire sensor. Movie S1 shows one test with the high speed video brightened and contrast increased for better viewing.

Force and Positional Accuracy Measurements

We mounted a digital force tester to a vertical lift stage and attached a 3D printed finger phantom to its end (Figure S9). We attached the OL_{1,3} to a delrin block and a ruler to the acrylic sheet under it so we could measure presses every millimeter along the length (Figure S9). To apply a force, we lowered the vertical lift stage to press the finger phantom into the sample until the desired force was read. From the collected data, we use the maximum value from each output for each press, defined as a chain of non-zero signal values, and normalize them by 800, the maximum value possibly read from the sensor (Figure 3A,C). To find the nonlinear portion of equation 3, we divided the actual position, x_{true} , by the ratio of neighboring output signals, $x = \frac{I_{Right}}{I_{Left} + I_{Right}}$, to get a multiplication factor. We then plotted the factor by the ratio and fit a curve in Excel (Microsoft, Inc.) (Figure S10). The factor was multiplied by the ratio and added to x_{base} to get the final equation.

Proprioception Accuracy Measurements

We placed the cylinder between two parallel plate attachments of the Z010 Zwick Roell tensile tester using a 10 kN load cell and ran the compression test at 10 mm min⁻¹ while acquiring data from the sensors and filtered with an exponential filter with a smoothing constant of 0.9 using an Arduino. To measure the localized deformations experimentally, we marked the front face of the cylinder with silver sharpie every 2.5 mm and tracked the dots using digital image correlation (DIC) extensometer with VIC Snap and VIC-2D (Correlated Solutions, Inc.) and convert the pixel positions of the dots to displacements. From the sensor data, we correlate the signal magnitude to force with a linear model. We then create our model using MATLAB to fit a sixth degree polynomial to the localized displacement and force values from the FEA simulation done in ANSYS (Movie S7). We find the error of the calculated displacements using $error = abs(dis_{calc} - dis_{DIC})$. Since the simulation can only solve up to 35% compression, we show two models in the supplementary movies; Movie S3 shows the FEA model and Movie S4 shows a model based on experimental data up to 35% compression.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Fig. 1. Fabrication and design overview.

(A) Examples of OL without supporting structure showing light coupling (circled in red) in a 2D array (left) and a 3D geometry (right). (B) 3D printed soft scaffolding with embedded channels for elastomeric lightguide cores (left). Eight compression tests of the 3D printed lattice with one standard deviation above and below the average in gray (right). (C) Schematic cross section showing the lightguides with close-up of the mechanoreceptor (left). LED illuminating the straight input core and light coupling to an output core when deformed (right).

Fig. 2. Experimental validation.

(A) Sliced micro X-ray CT scan reconstructions of lightguide-lattice composites with contact between cores labeled. (A bottom) Magnified isometric and side view of CT reconstructions showing the contact and orientation of the cores at the deformation site under high deformation. (B) Normalized simulated and experimental signal coupled from input to output with varying coupling length and constant contact width (~0.3 mm).

Fig. 3. Sensor characterization.

(A) Normalized averaged signal from each output when pressed over 20 times with increasing force reported with one standard deviation above and below (B) Fastest (black square) and slowest (green triangle) of eight sensor responses to a ~ 0.1 ms impulse which impacts at time = 0 (marked by a red vertical line). (C) Signal from all three outputs as the OL_{1,3} is pressed every millimeter along the input from the middle of the left to right outputs. (D) Average calculated vs actual position of eight samples of presses with a dotted line showing where the points would lie if 100% accurate (ground truth).

Fig. 4. Exteroception.

(A) Musical instrument with 15 output cores. A red LED for visual feedback and the photodiodes for each output core are located on the left side. On the right side, we placed a blue LED to show light to be read by the photodiodes. Direct visual and computed locations of press positions (B) directly on an output, (C) between outputs, and (D) over four outputs simultaneously.

Fig. 5. Proprioception.

(A) CAD model of each component of the cylinder and the completed device with three different stiffness sections. (B) Actual structure, (C) FEA simulated model with strain, and (D) computer reconstructed cylinder shown during compression. (E) Average displacement error in mm between calculated and measured vs normalized displacement for each stiffness section with one standard deviation above and below over nine single axis compression tests.