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Tensegrity Robotics

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Abstract

Numerous recent advances in robotics have been inspired by the biological principle of tensile integrity—or ''tensegrity''—to achieve remarkable feats of dexterity and resilience. Tensegrity robots contain compliant networks of rigid struts and soft cables, allowing them to change their shape by adjusting their internal tension. Local rigidity along the struts provides support to carry electronics and scientific payloads, while global compliance enabled by the flexible interconnections of struts and cables allows a tensegrity to distribute impacts and prevent damage. Numerous techniques have been proposed for designing and simulating tensegrity robots, giving rise to a wide range of locomotion modes, including rolling, vibrating, hopping, and crawling. In this study, we review progress in the burgeoning field of tensegrity robotics, highlighting several emerging challenges, including automated design, state sensing, and kinodynamic motion planning.

Keywords: tensegrity, robotics, soft robotics, resilient robots

Introduction

Tensegrities are composed of rigid compressive elements (struts) and flexible tensile elements (cables), connected to create a compliant yet stable network (Fig. 1).[1] The inclusion of rigid components and the overall low stiffness (or high ''softness''[2]) of the structure endows tensegrities with desirable properties found in both classically ''rigid'' and ''soft'' robots. Tensegrities have served to inspire art, model biological structures like the human skeleton, and to provide designs for lightweight and strong architecture.[3–5] In fact, tensegrities can form the minimal-mass structure required to sustain a given compressive[6] or bending[7] load, exhibiting great potential for use as lightweight deployable satellites and other structures.[8] Tensegrities have even been explored for use as robotic grippers,[9] manipulators,[10] and shoulder joints for manipulator arms.[11] While the scope of the tensegrity literature is vast, in this review, we focus on locomoting tensegrity robots. We refer to other reviews, when applicable, for further details on nonlocomoting tensegrities.[1,3–5,12–14]

Numerous tensegrity robots have been proposed that utilize a wide range of mechanical designs, locomotion modes, and sensing modalities. For example, some tensegrity robots can adjust the length of either their struts[15] or cables,[16,17] to change their resting shape and induce motion by shifting their center of mass. Others harness thrust generated by jetpacks,[18] vibration,[19] or propellers.[20] Tensegrity robots often exhibit passive compliance, allowing their structure to absorb energy, while providing robustness to damage and pressure.[21] Passive deformation may also be exploited to absorb impacts from unintended falls or extraterrestrial landing (Fig. 1C).[16]

In this review, we survey recent progress and highlight grand challenges for the field of tensegrity robotic locomotion. Although we separate key concepts for organizational clarity, we would like to simultaneously convey the interdisciplinary nature of this field, by discussing interactions between the relevant fields of study. We begin by discussing the mechanical design of tensegrity robots and then overview existing locomotion methods, sensing techniques, and approaches for control and motion planning. While there have been great advancements in each area thus far, fundamental

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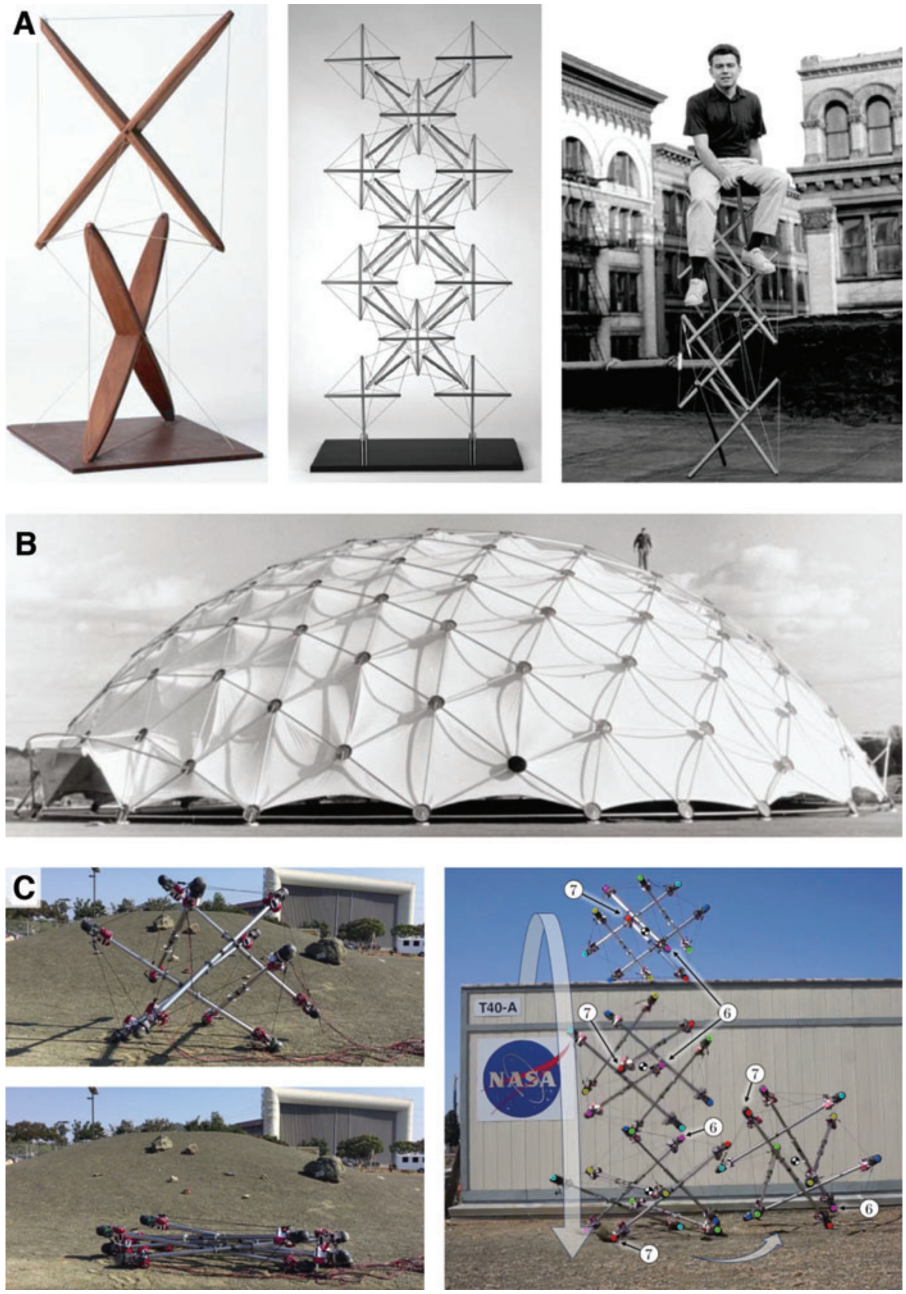

FIG. 1. Tensegrity concepts were originally applied to create **(A)** artwork[3] and **(B)** lightweight architectural structures.[4] **(C)** Recently, roboticists have built tensegrity robots that can withstand significant impacts, such as falling from the roof of a building.[16] Labels 6 and 7 point to nodes 6 and 7, respectively, to help visualize the spinning trajectory followed by the tensegrity as it fell from the roof of a building. Color images are available online.

challenges remain, ranging from automated codesign of sensors, actuators, and the underlying mechanical structures; improved sensors and algorithms for state estimation; and real-time path planning algorithms. As research progresses, we expect tensegrity robots to achieve unprecedented mobility in extreme environments.

Structural Design

There are myriad ways to connect compressive and tensile elements to create tensegrity structures.[1] Various materials could be used for the compressive and tensile elements, depending on the desired balance between competing design objectives (cost, strength, weight, etc.). Fortunately, there are numerous tools to aid in the structural design of tensegrities, including analytic frameworks[22] and robot simulators.[23,24] In this study, we summarize the design of tensegrity structures, that is, the selection and placement of struts and cables.

In the taxonomy delineated by Skelton, tensegrities can be classified by the number of rigid bodies in contact.[6] For example, class 1 tensegrities such as the six-bar icosahedron that forms the structural basis of numerous tensegrity robots[16,21,23,25,26] (Fig. 2A) have only one rigid body contacting each node; no two struts are fixed in contact (however, they could incidentally contact during normal motions). Class 4 ''t-bar'' tensegrities (resembling the kites built by Snelson,[3] but pinned at the two struts' intersection) have four struts connecting at a single node and are proven as the minimal mass structures for compressive loading

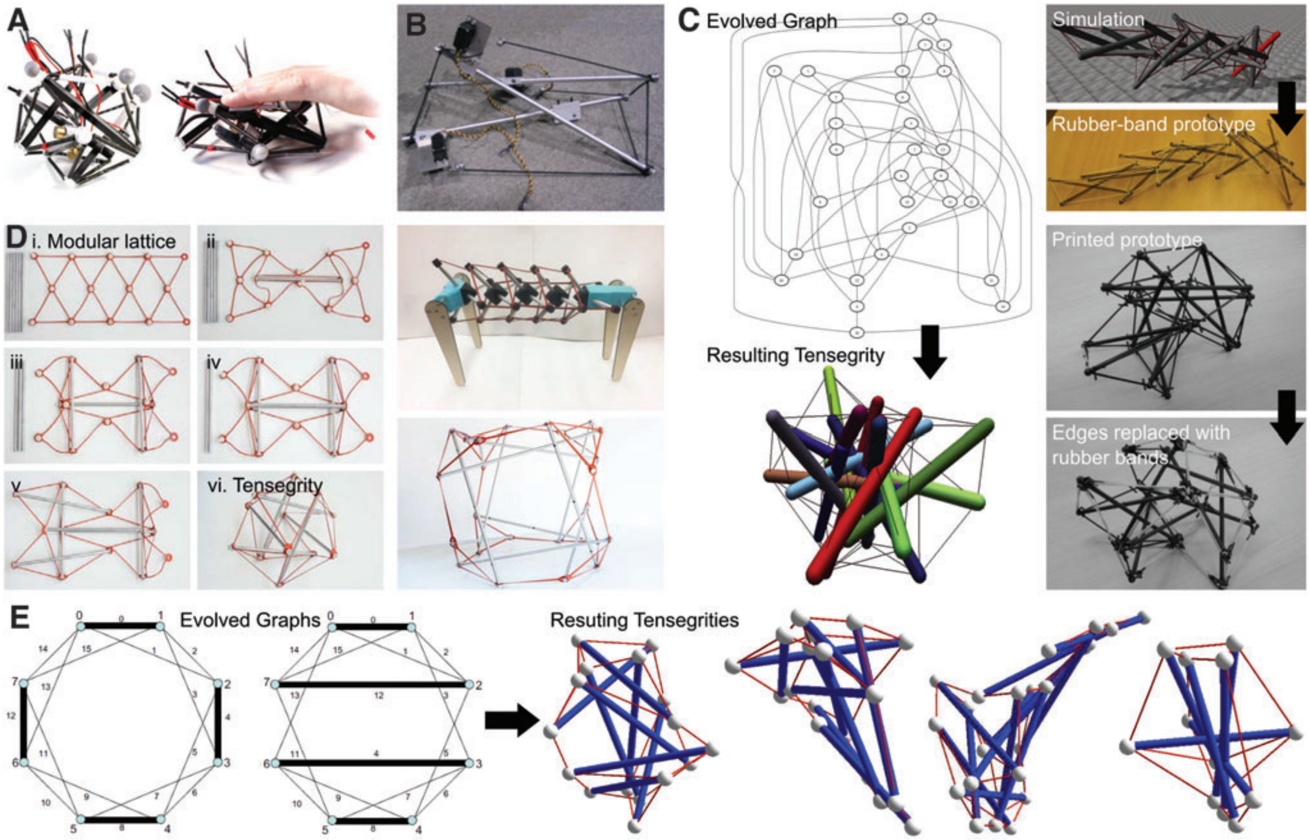

FIG. 2. Many methods exist for designing tensegrity robots, using combinations of automated tools and designer intuition. **(A)** Hand-designed six-bar icosahedron with graphite composite tubes and passive helical springs.[21] **(B)** Hand-designed three-bar crawling tensegrity structure.[29] **(C)** evolutionary algorithms can operate on an abstract connectivity graph to generate novel tensegrity designs of varying size and numbers of struts and cables.[30] Additive manufacturing and rubber bands were used to physically realize the designs. **(D)** Modular elastic prototyping nets for quickly manufacturing the cables for a tensegrity.[31] *Left*: assembly process. Starting with a modular lattice **(i)**, rods are sequentially added **(ii–v)**, to create an equilibrium icosahedron shape. *Right*: additional manufactured structures, including a spine robot (*top*) and a cube-like shape (*bottom*). **(E)** Direct encoding of cable and strut lengths, in addition to connectivity, can be paired with evolutionary algorithms to generate tensegrity designs.[32] Color images are available online.

conditions,[6] suggesting that further developing techniques for automated design of tensegrity structures could lead to mechanically optimal robots. Although most tensegrities are composed of a single base topology, some tensegrities have nested hierarchies of fundamental strut-cable arrangements[6] or a base pattern repeated serially.[27] In addition, researchers have recently proposed changing the stiffness of tensegrities on-demand by switching between a class 1 and a class 2 topology, highlighting the key role that topology plays in performance, even with the same set of parts.[28]

Since each member in a tensegrity primarily only experiences tension or compression, designers often treat the tensegrity as a simple truss.[1] Mechanically, this simplification allows for a high degree of controllability, reliability, and tunability. The truss model also allows for the development of analytic models of deformation, alleviating the need for a more complex finite-element simulation. Many methods have been proposed for form-finding (finding the rest configurations) of tensegrities (as reviewed by Tibert and Pellegrino,[22] and Juan and Tur,[13]) and analyzing their dynamic properties.[12] Importantly, the stiffness of the overall tensegrity structure can be adjusted by increasing the prestress (or resting tension) in the tensile elements.

To reduce prototyping cost and time, tensegrity topologies can be designed in an autonomous or semiautonomous manner in a robot simulator. For example, Paul *et al.* used evolutionary algorithms (EAs) to specify the number and size of rods in addition to the inter-rod connections (Fig. 2B, E).[32] To further generalize the design process, Rieffel *et al.* designed an EA to generate graphs that represent the connectivity of tensegrities and allowed the simulator to determine the resting shape (Fig. 2C).[30] In these examples of EAs in tensegrity design, the simulation environments and search algorithms were formulated to ensure that generated tensegrity *structures* could be manufactured. However, there is not a generalized framework for determining if or how simulated solutions will transfer to functional *robotic* hardware. Promisingly, Zheng *et al.* recently proposed a robustness metric for estimating the likelihood of achieving sim-to-real transfer for tensegrity designs.[33]

Tensegrity hardware design is often achieved through a combination of human intuition and mechanical models (Fig. 2A, B).[21,29] Once a topology has been selected, actuator and sensor placement is often decided heuristically, which can lead to inefficient or redundant designs. Fortunately, several researchers have proposed iterative methods for choosing where to place sensors and actuators within the networks of cables and struts, in an effort to balance the competing requirements of low cost and high performance.[34–36] Many materials for struts and cables have been used, including metal and fishing line (Fig. 2B),[27,29] aluminum and paracord,[16] graphite composite tubes and passive helical springs (Fig. 2A),[21] and acrylic pipes paired with rubber bands.[37] The stiffness of the tensegrity can even be changed to some degree through the use of prestress in the cables and adjusted in an application-specific manner to improve robot performance. For instance, a tensegrity-inspired fish robot used prestretched cables to stiffen its body and improve its swimming speed.[38] Researchers have even begun exploring the use of variable-stiffness materials and mechanisms[39] in tensegrities, allowing robots to change the bending or tensile stiffness of their members and thereby modify their dynamics. For example, Zappetti *et al.* used a low-melting point alloy to change the stiffness of a stationary three-bar tensegrity,[40] while Friesen *et al.* controlled the stiffness of their tensegrity-inspired arm by adjusting its cable tension.[11]

Connecting the cables and struts in a tensegrity is straightforward for simple structures such as a three-bar prism, but quickly becomes complicated. For example, the canonical six-bar icosahedron tensegrity truss has 24 cables that need to be attached. During assembly, the cables' natural tension makes the structure deform into shapes that are difficult to work with. To simplify assembly, one group proposed modular lattices that reduce assembly time from hours to minutes for moderately-complex designs (Fig. 2D).[31] Zappetti *et al.* proposed a three-dimensional (3D) printed lattice structure that was used to make icosahedron modules,[41] while Lee *et al.* simultaneously 3D printed polylactic acid (PLA) struts alongside a dissolvable mold that was later filled with silicone to make the tensile cables.[42] Other researchers have proposed 3D printing tensegrities and then replacing some printed connections with cables, although this technique has not been used to create locomoting tensegrity robots.[30] Additional design considerations for selecting tensegrity hardware include impact resilience,[16] cost,[35] and modularity.[19]

Simulation

Many studies have used simulation to generate and evaluate designs of and control policies for tensegrity robots. There are three main families of simulation tools used in this context: (1) the more traditional physics engines, which are based on first-principles, analytical models, and numerical approximations; (2) analytical formulations, which solve systems of differential equations that represent the dynamics of a tensegrity structure; and (3) the emerging family of differentiable physics engines, which aim to learn a physical model directly from data. In this section, we introduce popular physics engines, discuss several tensegrity robot simulators, and describe the newer differentiable simulators. A high-level comparison of several popular simulators is shown in Table 1. More detailed descriptions of each simulator are presented throughout this section.

Simulators based upon traditional physics engines use first principles from physics to predict the future motions of objects. Since tensegrity assemblies are composed of rigid struts and compliant cables, tensegrity simulators usually include a collision detector and both rigid body and soft body dynamics components. Rigid body physics engines, such as the popular bullet2[48] and Open Dynamics Engine (ODE),[49] can efficiently calculate rigid-body motions in parallel. Soft-body physics engines implement various solution methods, ranging from the bounding box-based bullet3[48] to finite element method (FEM)-based Vega-FEM[50] and simulation open framework architecture (SOFA).[51] These engines can accurately model deformable objects, making them an ideal choice to model soft bodies such as tensegrity cables, skins, and strut endcaps.

The soft and compliant properties of tensegrities can be simulated by extending or combining different physics engines (such as ODE, MuJoCo,[52] or bullet2). For instance, the early tensegrity simulation environment by Paul *et al.*[29] was built upon ODE and supports cables as virtual objects that are massless, volumeless, and do not have any contact characteristics. More recent work by Wang *et al.*[53] built a tensegrity robot over the MuJoCo physics engine.[52] Both Caliper[43] and the open-source NASA Tensegrity Robotics Toolkit (NTRT)[24] extend bullet2 with support for compliant cables. NTRT provides relatively comprehensive support for tensegrity robot modeling and has consequently become the most popular choice for the development of gaits in simulation.

Starting from analytical formulations of the statics and dynamics of a tensegrity structure, several researchers have achieved higher level tasks such as topology optimization and controller design.[54,55] These analytical models make simplifications, such as treating the struts as cylinders, preventing rotation along the axis of the struts, ignoring endcaps, and assuming that there are no collisions between cables. For instance, TensegrityMATLABObjects (TMO)[44] is a Matlab-based tensegrity simulator, which supports strut-ground collision and friction-less contact. Software for Tensegrity Dynamics (STEDY)[45] and Modeling of Tensegrity Structures (MOTES)[46] are Matlab-based comprehensive tools that use nonminimal Cartesian coordinates to describe the dynamics of the system. VirtualTensegrities[56] is a Java-based simulator that can visualize multiple tensegrity structures yet neglects collisions.

As an example of how multiple simulators can be used to model a single robot design, consider the SUPERball v2 robot[16] (Fig. 3), which is composed of six struts and 24 cables. During design, and for predicting dynamic motions using analytic models, TMO[44] simulator is often used to reduce cost, development time, and operational risk. Subsequent controller development and modeling can be done in higher level simulators such as MuJoCo[53] and NTRT.[24] Importantly, TMO can only model dynamic motions and contacts between struts and the ground, while neglecting friction, strut–strut contact, and cable contacts. MuJoCo can additionally model strut–strut contact and friction, but only NTRT can detect collisions between cables and other components. This capability has helped facilitate successful transfer of locomotion policies from NTRT to reality.[57]

Although complicated motions can be generated in simulation, policy transfer from simulation to reality is plagued by inconsistencies. Mitigating this so-called ''reality gap'' between simulation and hardware typically requires an iterative process where simulator parameters are tuned after running experiments on physical robots to more accurately reflect real conditions. For example, hardware validation of the NTRT

Table 1. Comparison of Various Tensegrity Robot Simulators

		Cable		*Ground*		*Rod*		
Simulator	*Physics engine*	*Mass*	*Contact*	*Reaction*	*Friction*	*Reaction*	*Friction*	*Differential*
Paul *et al.*[29]	ODE			✓	✓	✓	✓	
Caliper[43]	Bullet2			✓	✓	✓	✓	
NTRT[24]	Bullet2		✓	✓	✓	✓	✓	
TMO[44]	Matlab			✓				
STEDY[45]	Matlab			✓				✓
MOTES[46]	Matlab	✓		✓				✓
Wang *et al.*[47]	MuJoCo			✓	✓	✓	✓	✓

The main differences of the tensegrity simulators are in (1) the physics engine that the simulator is built on (where MATLAB refers to custom physics engines programmed using MATLAB); (2) modeling of the cable (mass and contact with other objects); (3) modeling of the contact between the robot and the ground (reaction force and friction force); (4) modeling of the rod-rod contact (reaction force and friction force); (5) differentiability.

MOTES, Modeling of Tensegrity Structures; NTRT, NASA Tensegrity Robotics Toolkit; ODE, Open Dynamics Engine; STEDY, Software for Tensegrity Dynamics; TMO, TensegrityMATLABObjects.

simulator has been performed for spine-like tensegrity robots[58] and a six strut icosahedron robot.[23] These studies identified system parameters that could be tuned to increase the accuracy of NTRT and improve its applicability to real systems. To reduce the data requirement during policy generation, Zhu *et al.* used a Bayesian optimization identification framework with a parameter projection to a lower dimensional space through embedding.[59,60] Nevertheless, system identification techniques assume that the underlying analytical or numerical model is conceptually correct and the reality gap can be effectively eliminated by tuning the model's parameters. Frequently the model is imperfect, and significant reality gaps persist, even after tuning model parameters.

To further diminish the reality gap, researchers have begun building physics engines predicated on a differentiable model, such as a deep neural network. Differentiable models help to reduce data requirements, increase the policy update frequency from per-trajectory to per-time step, and allow the robot to learn system dynamics directly from data. One method for defining differentiable physics engines is to model system components as moving particles that interact.[61] Each element in a scene (robot and environment) can be split into multiple modules, and the simulator can then generate a graphical representation of module interactions. Two classes of interactions can be defined: fixed system topology and temporary connections for collisions. This framework gives rise to an *interaction network* that depicts the interactions of different modules.

Recently, Wang *et al.* proposed the first differentiable physics engine focused on tensegrity systems. It uses interaction networks, as well as first principles from physics.[47,53] Namely, the differentiable physics engine models cable tensions as spring forces that depend linearly on an unknown coefficient that needs to be learned from data. The friction and the reaction forces, however, are more complex and involve nonlinear components modeled by neural networks. The combination of first principles and interaction networks results in a more data-efficient, explainable, and modular pipeline for system identification. One limitation of the differentiable physics engine of Wang *et al.* is that it considers cables as virtual objects with no mass, volume, or contact. An inherent limitation of all differentiable engines is that they assume that system dynamics are totally unknown—even though the governing equations of motion are often well understood—and try to learn the dynamics exclusively from data.

Locomotion

A rich variety of locomotion modes have been demonstrated for tensegrity robots (Fig. 4). Many of the tensegrity robots we reviewed move by rolling, or what Kim *et al.* refer to as ''punctuated rolling,'' since the motion is characterized

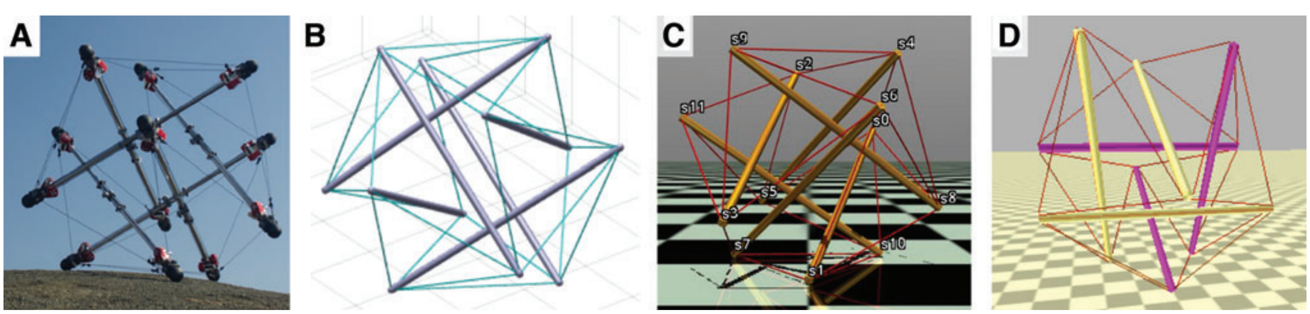

FIG. 3. SUPERball v2[16] **(A)** hardware, and its model in **(B)** the Tensegrity MATLAB Objects (TMO) tensegrity simulation framework,[44] **(C)** the MuJoCo physics engine,[53] and **(D)** the NASA Tensegrity Robotics Toolkit (NTRT). TMO can simulate dynamic motions, while MuJoCo can additionally detect rod-rod collisions, and NTRT can even detect collisions between cables and other components. Color images are available online.

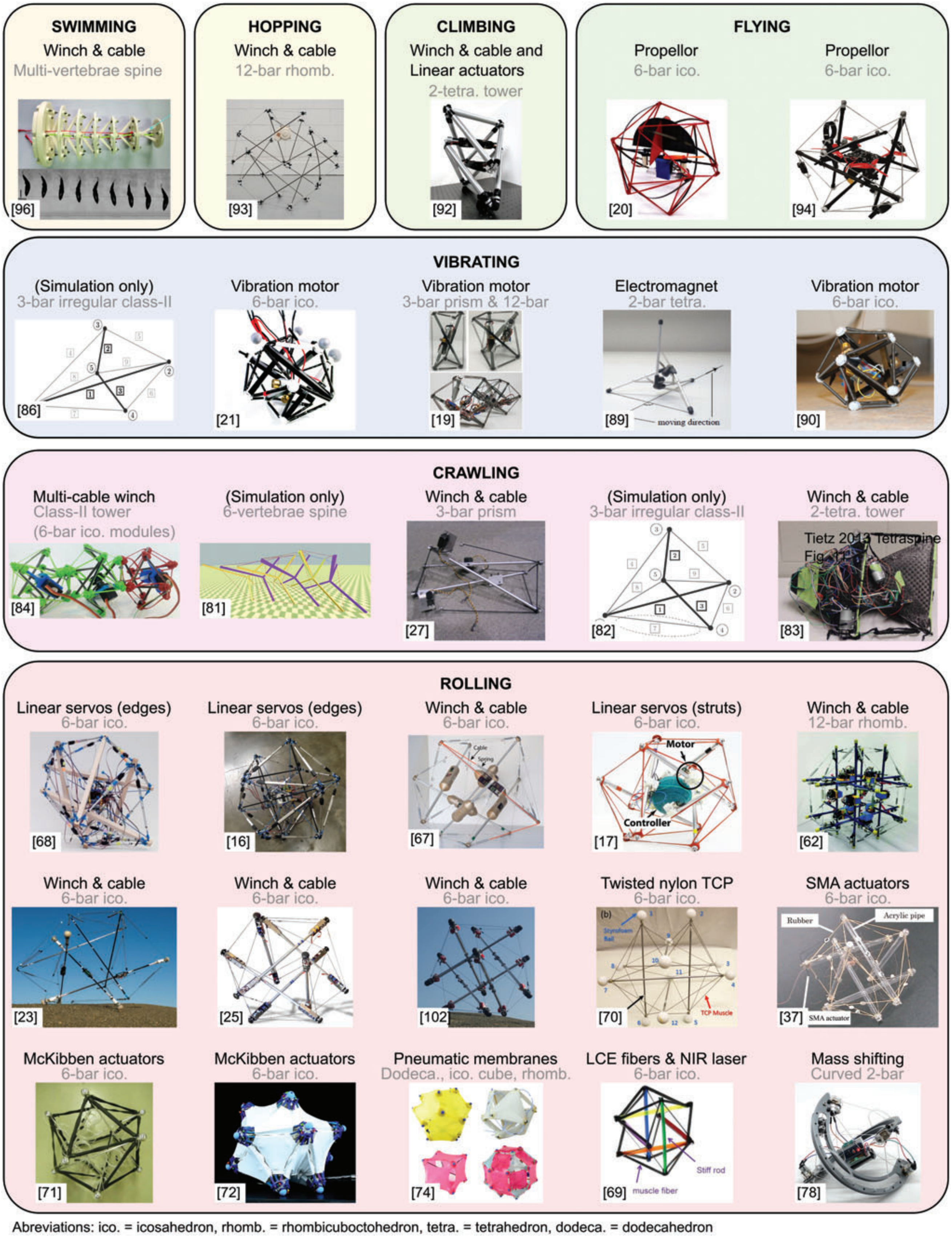

FIG. 4. Representative examples of locomotion strategies utilized by tensegrity robots. Since actuation and topology are often tightly coupled with the locomotion strategy, these are also indicated for each example. Color images are available online.

by discrete, sequential impact events between the strut ends and the ground.[62] Other tensegrity robots locomote by swimming, hopping, climbing, flying, vibrating, or crawling. Often, actuator choice and robot topology are tightly coupled with the desired mode of locomotion. For example, climbing robots are best suited to tower structures, whereas rolling is best suited to symmetric topologies approximating a sphere, such as the widespread six-bar icosahedron.

Rolling

Rolling tensegrities achieve motion by displacing their center of gravity so that it is outside their polygon of stability (the vertical projection of the nodes that are in contact with the ground). The result is a tipping from face to face. Since the mass of a tensegrity is often concentrated in the rigid struts that form the structure, rolling tensegrities must be capable of large structural deformations.

Deformations are typically produced by changing the length of tensile elements along the edges of a tensegrity, which in turn shifts the struts and causes the structure to topple. To achieve a rolling locomotion mode, many tensegrity robots feature motors mounted on their rigid struts to contract the cables that serve as the edges of the tensegrity.[23,25,62–67] Other actuators have been demonstrated for changing the length of the edges, including linear servos in series with springs,[15,17,68] liquid crystal elastomer threads activated with near-infrared light,[69] shape memory alloy springs,[37] silver-coated twisted nylon,[70] and McKibben pneumatic actuators.[26,71,72] Most rolling tensegrity robots are six-strut class 1 structures with an icosahedron resting shape. A few two- and three-strut rolling tensegrities have been shown in simulation, but none was implemented in hardware.[55,73] We have observed the rolling locomotion approach used on robots with characteristic length scale of meters (e.g., Superball[16]) down to a few centimeters (e.g., Wang *et al.*'s light-powered tensegrity[69]), with speeds on the order of a few body lengths per minute ($\approx$3.5 BL/min[16] and $\approx$1.15 BL/min[69]).

While most rolling tensegrities modulate the lengths of their tensile elements to roll, several other strategies have been demonstrated. For example, the TT-4mini has custom linear actuators as its struts and passive elastic elements as its edges.[17] Baines *et al.* designed reconfigurable planar membrane actuators that form the faces of tensegrity robots, capable of extending in-plane to change the tensegrity's shape, or bulging out of plane to tip the tensegrity.[74] In-plane extending membranes were demonstrated on a 6-strut icosahedron, whereas out-of-plane membranes were demonstrated on a rolling 12-bar rhombicuboctahedron, 4-strut cube, a 10-strut dodecahedron, and various others. Curved two-strut tensegrities introduced by Kaufhold *et al.*[75–77] and Rhodes and Vikas[78] roll by shifting masses along tracks embedded in the curved struts.

Crawling

Several tensegrity robots are capable of deforming their structure to use a subset of their strut ends as feet, achieving gaits resembling those of legged animals. All reviewed crawling tensegrities either relied on winch and cable actuation[27,29] or were only realized in simulation.[79–82] For example, Masic *et al.* simulated a class-II tensegrity tower composed of four-bar prism segments.[79] Paul *et al.* demonstrated three-bar[27,29] and four-bar[29] crawling robots in simulation and hardware, resulting in robots 36 cm long, with resulting speeds of $\approx$2 BL/min.[29] SunSpiral and colleagues introduced the TetraSpine, a class of multisegment spine-like robots that could walk and climb over objects in the NTRT simulator, and some progress was made toward building real robots with a similar design.[80,83] A later study on similar simulated robots led to high-DoF multisegment spine-like robots that used central pattern generators (CPGs) to attain various crawling and snake-like gaits.[81] Zappetti *et al.* demonstrated winch-driven, modular six-bar icosahedron tensegrities that could be connected in series to yield a crawling robot.[41,84]

As evidenced by the research referenced above, crawling tensegrities can be made of either single controllable segments or multiple segments that collaborate to control their ground contact and locomote. By expanding the range of shape primitives to include additional geometries, such as the deployable class-II tensegrity tower with pentagonal modular sections introduced by Veuve *et al.*,[85] additional locomotion gaits could be attained.

Vibration

Vibrating tensegrities locomote by harnessing oscillating elements, such as linear electromagnets or eccentric mass motors, to dynamically excite the whole tensegrity structure.[41,82,86–89] The locomotion mode is characterized by complex coupling between multiple physical phenomena, including asymmetrical friction pairings and dynamic ''hopping'' that ultimately yields motion along a surface. For example, by dynamically exciting its structure, a two-bar tensegrity could vibrate in different directions.[89] Other icosahedron tensegrity robots could drift along a surface.[21,90] Varying the frequency of their driving motors (two[21] or three[90]) led to some ability to change the robot's locomotion speed and direction, with Riefell and Mouret reporting an impressive maximum speed of 69 BL/min for their decimeter-scale robot (rod length of 9.4 cm[21]). Notably, since the vibrating class of tensegrity does not require large structural deformations to locomote, some modeling inaccuracies can be avoided, such as those arising when modeling large deformations and calculating strut collisions. The vibrating tensegrity thus boasts the resilience characteristic of tensegrity robots and simplifies modeling efforts.

Other locomotion modes

Other locomotion modes achieved by tensegrities include peristaltic pipe crawling,[91,92] hopping,[18,93] and flying.[20,94] These locomotion modes could potentially allow robots to access difficult-to-reach locations or achieve rapid locomotion.

Friesen *et al.* built a duct climbing robot composed of two tetragonal sections, made of six linear servos each, and winches and cables connecting the two sections.[91,92] The tetragonal section would expand to jam in the duct, while the winches and cables would advance the unjammed section. This approach could have applications in pipe inspection, disaster response, or other highly-constrained environments.

Hopping and flying locomotion modes are promising for switching between rapid, long-distance travel and controlled local motions, allowing the robot to adjust to mission demands. Garanger *et al.* showcased a hopping 12-bar rhombicuboctahedron actuated with winch and cables.[93] To achieve hop and roll locomotion, Kim *et al.* simulated a six-bar icosahedron tensegrity with a single thruster in the center,[18] whereas Mintchev *et al.* built a six-bar icosahedron tensegrity with two propellers inside.[20] A similar robot by Zha *et al.* situates a quadcopter inside a six-bar icosahedron tensegrity. The quadcopter enables flying, while the tensegrity permits the robot to reorient itself after a crash.[94]

Although no terrestrial mobile robots based on bending tensegrities have been shown to date, Bliss, Iwasaki, and Bart-Smith introduced a class-II tensegrity tower composed of two-bar planar modules that are capable of oscillating a fin for generating thrust underwater.[95] Bending motion primitives have been used by free-swimming fish-inspired robots as well.[38,96] Similarly, Sabelhaus *et al.* described a five-vertebrae spine tensegrity called ULTRAspine[97] and Zappetti *et al.* demonstrated a variable stiffness vertebrae spine tensegrity,[28] both of which were capable of executing controlled bending motions.

Sensing

Although many tensegrity robots showcased in the literature operate in a sensor-free, open-loop manner,[21,67,98] state estimation[25] and contact sensing[23] facilitate closed-loop gait control and will potentially enable tensegrity robots to execute controlled dynamic locomotion in unstructured environments. A high degree of control over system dynamics will, in turn, facilitate the transfer of advanced control policies from simulation to physical hardware. Numerous sensing methods for tensegrities have been proposed (Fig. 5), yet only a subset of these have been evaluated in dynamic situations.

Since each member of a class 1 tensegrity is axially loaded, the full state of a tensegrity robot comprises the spatial positions and velocities of its endcaps, ground contact information, tension in the cables, compression of the struts, and orientation of the overall structure (although orientation could be inferred from the spatial positions in a global reference frame). Often, only partial state information is necessary for successful locomotion. For example, the Modular Tensegrity Kit introduced by Kimber *et al.* only requires a six-axis accelerometer to record its vibrations.[19]

One logical method to estimate spatial positions is to measure the distance between nodes. For cable-actuated tensegrities, measuring the amount the actuator has contracted (or extended) does not account for stretch in the cables

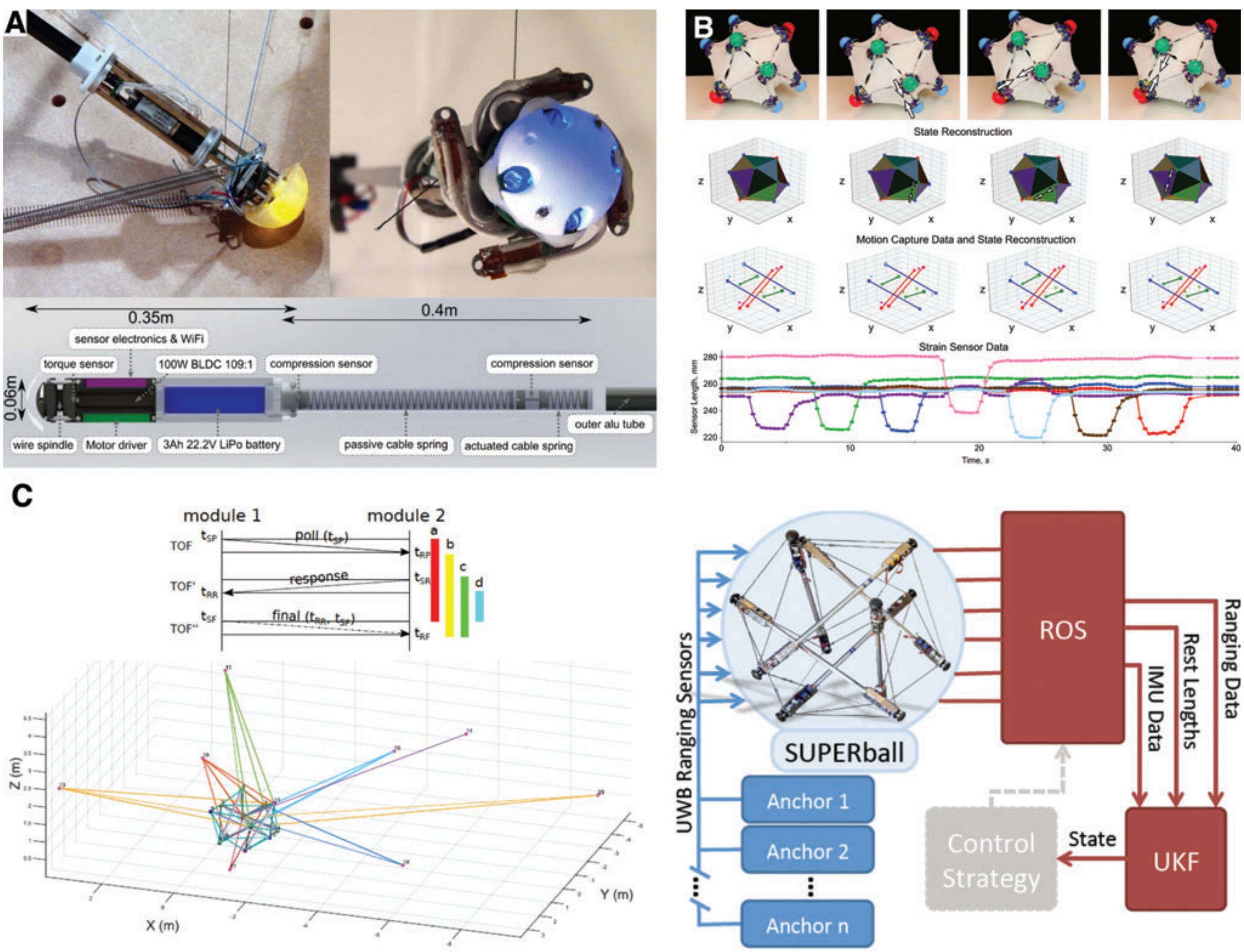

FIG. 5. Sensors allow tensegrities to estimate their 3D shape (state) and detect environmental interactions.[25] **(A)** *Top:* contact measurement using force sensors within the struts' endcaps. *Bottom:* numerous sensors were integrated into REcTeR's struts.[63] **(B)** State estimation using surface-based strain sensors.[26] **(C)** State estimation using external ranging sensors. ROS, Robot Operating System; UKF, Unscented Kalman Filter. Color images are available online.

themselves or deformation of the struts. Stretch sensors[99–101] could potentially be used, but they have only begun to be investigated in the context of tensegrity robotics to measure cable length[83] or strut extension.[91] For cable-driven robots, quadrature encoders[91] or Hall-effect sensors[92] attached to the motors that spool the cables have been utilized to estimate cable length.

Other robots have integrated multiple sensors into the canonical six-bar icosahedron to aid in locomotion. For example, ReCTeR had 24 tension sensors (uncalibrated strain gauges), six ground-reaction force sensors, and three inertial measurement units (IMUs) on the endcaps of several of the six-bar tensegrity's struts (Fig. 5A).[23,63] The tension sensors were input into linear feedback controllers to drive cable lengths to set points determined by an embodied reservoir computer. As a result, the system could recover stable locomotion—even after being physically restrained. Later work by Burms *et al.* used the force sensors to classify terrain.[66] SUPERball was designed to overcome some of the mechanical limitations of ReCTeR, one of those being restricted sensing capabilities.[63] Tension sensors were integrated into SUPERball's 12 passive cables, torque sensors were added to the active cables, and IMUs measured accelerations on the endcaps. Zhang *et al.* used the accelerometers on SUPERball to directly transfer policies from NTRT to hardware, addressing part of the simulation-to-reality (sim2real) gap which prevented open-loop policies from transferring.[57] SUPERball v2 featured accelerometers to detect which of its faces was pointing downward, enabling the robot to determine feasible actions for intuitive real-time teleoperation by a human operator.[102]

Algorithms have also been proposed to intrinsically estimate the shape of tensegrity robots. Caluwaerts *et al.* proposed an Unscented Kalman Filter-based sensor fusion algorithm to estimate the 3D state of a tensegrity using ranging sensors (Fig. 5C).[25] Fusing time-of-flight ranging sensors, IMU, and actuator states, Caluwaerts *et al.* could localize a meter-scale tensegrity within a large testing area (91 m^2) with ~10-cm accuracy. Stretch sensors[99] and McKibben muscles[103] were integrated into robotic skins to create a reconfigurable tensegrity that could roll and achieve simultaneous estimation of the spatial positions of all nodes on a six-bar tensegrity (Fig. 5B).[26,72]

Control

Tensegrities can be actuated to achieve a wide range of goals, from attaining a desired structural shape trajectory in place[104] to locomotion,[57] to accomplishing a mission in the field.[102] Pose or task-level controllers can use open loop or closed loop strategies to determine a desired sequence of actuator commands and associated forces. The appropriate controller formulation strongly depends on the types of actuators and sensors on a tensegrity and the application intent. This section highlights the essential role that control theory has played in developing the field of tensegrity robotics, while conveying how controls can be applied to achieve more effective in-field deployment.

Controllers can operate over different time horizons and at various levels of abstraction (Fig. 6). At a low level, controllers act upon a single strut or cable in a larger network, modulating tension based on the equations of dynamics. Alternatively, controllers can operate at a global level and can be formulated to choose a set of actuation patterns that steer a tensegrity toward a goal. As a hybrid approach, local dynamics controllers can be placed in sequence or hierarchically with controllers of increasing levels of abstraction, to achieve robust global movement policies.

Numerous tensegrity controllers have emerged to achieve closed-loop control objectives, often following several common development models (as summarized in Fig. 7). Classical control strategies rely upon analytical models and convex optimization to regulate intended behaviors.[104] More recently, data-driven[57] and bioinspired techniques[81] have allowed the control of more complex systems that analytical methods cannot handle. However, it is often infeasible to predict the conditions under which data-driven and bioinspired approaches can safely operate.

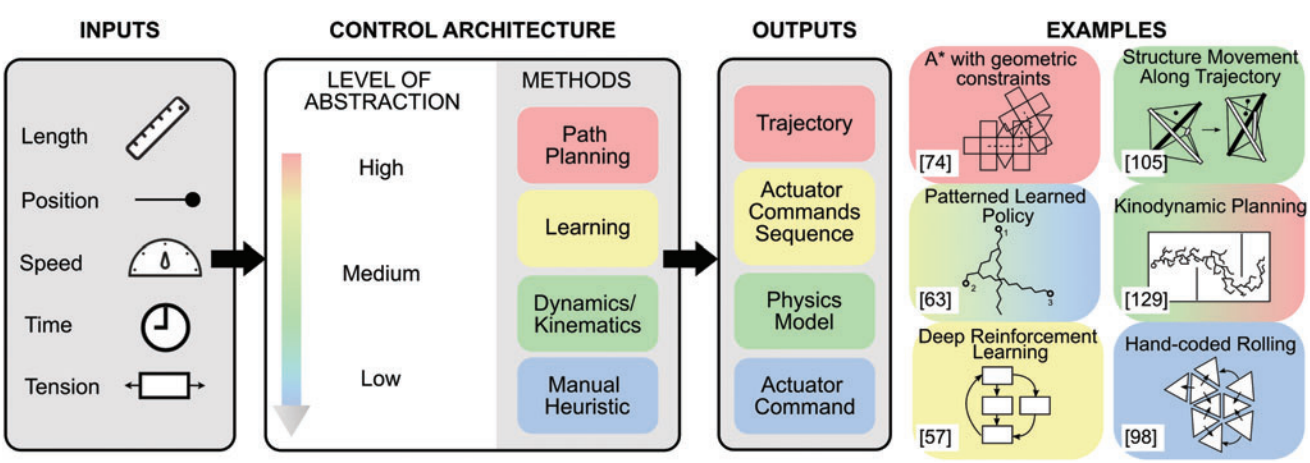

FIG. 6. Tensegrity robots can be controlled at various levels of abstraction, ranging from low-level motion primitives generated from manual experimentation or physical models to high-level motion planning to move the robot through a series of waypoints. Color images are available online.

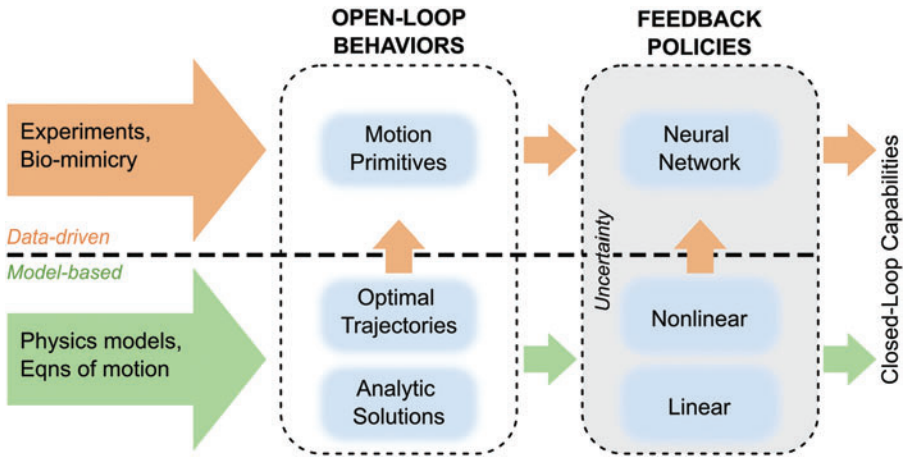

FIG. 7. Information flow in tensegrity control policy development. *Top*: experiments and biomimicry can be used to develop open-loop behaviors and/or feedback policies. *Bottom*: physics models and equations of motion can generate optimal trajectories, analytic solutions, and feedback policies that are useful for improving data-driven behaviors or even generating closed-loop capabilities on their own. This diagram shows enough connections to capture most of the processes used by tensegrity robots, although other development frameworks are conceivable, including bidirectional information flows. Color images are available online.

Analytical approaches

Tensegrity research based on analytical methods has focused on modeling the statics[13,105] and dynamics[12] of a structure to provide effective equations of motion.[14] Given a dynamic model, it is possible to control a tensegrity structure along static equilibrium manifolds.[104] Changing the rest lengths of cables in planar tensegrity structures was the goal of the majority of reported controllers. Dynamic models for such networks are attainable using minimal coordinates and ordinary differential equations of motion (Fig. 6, green shading).[106] Skelton and Oliveira showed that the dynamics of 3D tensegrities cannot be represented by ordinary differential equations, but rather become systems of differential algebraic equations.[14] Alternatively, feedback linearization control laws[107] and Lyapunov-based controllers for 3D dynamic models[106] have also been applied for tensegrity control. Structural control of tensegrities can be coupled with global planning algorithms to move nodes along a desired trajectory.[108–110] The cables connecting the nodes of tensegrity systems are often assumed to behave like linear springs. Sabelhaus *et al.* exploited this feature to design model predictive controllers for moving spine-like tensegrities along a desired configuration trajectory.[111]

The complex dynamics of tensegrity structures makes controlling them for locomotion a challenge, prompting several researchers to develop simpler heuristic controllers (Fig. 6, blue shading). For example, Shibata *et al.* used intuition to design a two-actuator policy to tip a shape-memory alloy driven icosahedron tensegrity between various faces and locomote.[37] Similarly, hand-picked rolling policies were demonstrated for icosahedron tensegrities using pneumatic Mckibben actuators as the tensile elements.[26,71] Despite having 24 candidate edges for actuating, typically only one or two actuators were necessary to tip the tensegrity from face to face in a predictable manner.

Despite their intuitive appeal, hand-coded policies have numerous disadvantages. First, they are highly system dependent and do not abstract to other structures beyond the ones that the policy was developed for. Second, hand-coded policies are not conducive to dynamic rolling, but rather quasi-static locomotion modes, such as tipping face-to-face. Hand-coded policies do not lend themselves to quickly generating actuation sequences to attain many successive face transitions along arbitrary paths. Furthermore, traditional control approaches generally have not accounted for self-collisions or environmental contact dynamics, limiting their real-world applicability. Hardware experiments have not utilized analytical control approaches, because they frequently depend on accurate state information, which is nontrivial to acquire.

Data-driven and bioinspired frameworks

Seeking to expand beyond hand-coded policies, researchers have begun to develop data-driven machine learning, as well as bioinspired approaches (Fig. 6, blue shading and Fig. 7, top). When paired with simulators, data-driven approaches are quite appealing, allowing thousands of control policies to be quickly evaluated. Since an exhaustive search of control possibilities is impractical, EAs are frequently applied to achieve locomotive gaits for tensegrities,[29,112] potentially through multiagent descriptions of the modular system.[113,114] In addition, forward kinematics of tensegrity robots have been solved using feature extraction through supervised learning algorithm[115] and energy-based local node models for changeable edge lengths[116] and strut lengths.[117] The search space can also be reduced by imposing biologically-inspired *a priori* couplings of control inputs through CPGs, which have been applied frequently to soft robots and recently to tensegrities.[58,95] In practice, these approaches that are less dependent on accurate models can make efficient use of sensor data and computing resources by exploiting body dynamics and morphological computation.[112]

In particular, Paul *et al.* introduced a simulation pipeline for developing controllers for three- and four-strut tensegrities with both static and dynamic gaits.[29] In this pipeline, an EA operated upon a population of 200 tensegrity robots in an ODE simulator to implicitly account for the nonlinear dynamics of the tensegrities and maximize a simulated robot's fitness (distance travelled), by modulating the robot's actuator firing patterns. Since Paul's pioneering work, many subsequent articles have utilized learning and simulation to generate dynamic rolling policies for tensegrities. In subsequent research on six-bar tensegrity robots by Iscen *et al.*,[113] the length of each cable was controlled by a sine wave pattern with an independent phase, duration, and amplitude, driven by a centralized synchronization signal, as governed by:

$$y(t) = C + Asin(\omega t + \phi) \quad (1)$$

Here, $y(t)$ is the length of a cable, C is an offset, A is the actuation amplitude, ω is the angular frequency, and ϕ is a phase offset. This formulation resulted in 96 independent parameters, which were calibrated automatically using EA that evaluated several thousand controllers in simulation. Researchers have also proposed phase coupled oscillators inspired by the salamander nervous system,[118,119] applied to spine-like tensegrity robots.[58] To generate policies for spine tensegrities with extremely high DOF, Mirletz *et al.* used a Monte Carlo algorithm to generate initial guesses, followed by iteratively sampling a Gaussian distribution around the best policy parameters.[58]

Another vein of work relates to deep reinforcement learning (RL) and holds promise of generating successful feedback control policies that map directly from sensory data to task-oriented actions.[120] A crucial consideration for extending RL to tensegrities is whether a learned model can be made to generalize over a large part of the state space. This consideration can be addressed, in part, using model-based RL tools, such as Guided Policy Search,[121] that combine several locally valid controllers into a single, more broadly applicable learned policy. RL has successfully facilitated the development of rolling controller policies for SUPERball.[57]

Motion planning

If a robot is able to discern its global position, it can engage in higher level motion planning, exploiting the well-developed literature on robot path planning (Fig. 6, red shading).[122] Motion planning is needed to perform complex tasks with long time horizons, such as goal-directed obstacle-avoiding locomotion or purposeful deformation of a tensegrity structure. Numerous planning algorithms have been proposed for tensegrity robots, ranging from quasi-static approaches to more complex asymptotically-optimal kinodynamic planners.

Early planning methods for tensegrities planned deployment and shape change by applying optimization to generate a sequence of statically stable configurations.[108,123] Further work accounted for self-collision avoidance in this process.[124,125] More recent approaches plan paths for tensegrity mobility, but still assume a control process slow enough to eliminate any dynamic effects.[109,124] This quasi-static assumption is often applicable to tensegrity-based civil structures,[126] but is not amenable to robotic applications.

Other planning strategies chain together several motion primitives using a global planner. This approach decouples planning from dynamics, often yielding relatively simple yet intuitive solutions. For example, Vespignani *et al.* introduced a steerable teleoperation-based controller for icosahedron tensegrities that operated on top of arbitrary tipping control primitives.[102] Seeking to automate the path generation, another group proposed A* for generating actuation sequences for a rolling and hopping icosahedron in simulation.[18] The cost function for weighing the value of possible trajectories was dependent on topographic information (height of adjacent tiles in the search), whether or not hopping or rolling was chosen (equivalent to energy expended), and the travelled distance. Another study proposed a geometric planning algorithm that generalizes to any n-sided polyhedral.[74] The approach combines a weighted A* search with geometric constraints of a given polyhedron and uses an optimization routine to keep track of orientation and generate collision-free paths through the plane. Chaining together motion primitives with a global planner can be effective for some nonlinear systems. However, it is best suited to scenarios in which a feasible trajectory can be generated on a known environmental map *a priori*.

Although the previously discussed planning approaches were shown to generate feasible paths, they did not consider energetic optimality under dynamic conditions. To be efficient during long-term use, a tensegrity planner should be able to select configurations that take advantage of nonlinear dynamics. For example, energetically complex behaviors such as rolling, jumping, and climbing all involve nonlinear dynamics and may enable highly efficient traversal. As well as monitoring energy, a planner should accommodate a high-dimensional state space, avoid self-collisions, and consider the topography of the current terrain. These needs can individually be met by strictly geometric methods, but addressing all of them with a single tool is presently infeasible.

In attempts to converge on physically-realistic, dynamic planners for tensegrities that tackle the aforementioned concerns, researchers have begun to look toward kinodynamic motion planning. Kinodynamic motion planning is often framed as a nonconvex trajectory optimization problem in which costs are minimized under certain constraints. Sequential convex optimization can be used to iteratively correct a trajectory toward a local minimum.[127] An alternative, probabilistically complete methodology is sampling-based motion planning. Unlike global roadmap-based approaches in this planning family, the popular incremental Rapidly-Exploring Random Trees (RRT) algorithm can directly accommodate dynamics.[128] RRT samples control inputs, rather than states, and grow the tree by propagating inputs' effects forward from states that have already been reached, eventually building broad coverage. Littlefield *et al.* introduced the first kinodynamic planning approach for an icosahedron robot.[129] They used an informed asymptotically optimal sampling-based approach to generate collision-free sequences of kinematic rolling primitives to navigate along a desired path through cluttered environments. Doney *et al.* used a quality diversity algorithm running a model-free physical tensegrity to autonomously generate a collection of motion primitives.[130]

Grand Challenges

Tensegrity robots have many advantages compared to traditional autonomous ground vehicles: robustness to impacts, low weight, novel locomotion modes, and modularity. However, no work to date has demonstrated a fully autonomous, untethered tensegrity robot navigating through unstructured terrain. Many roadblocks to this goal remain unsolved across the domains of design, locomotion, sensing, and control. In this study, we discuss key challenges and potential solutions, providing a roadmap for future research.

Automated system design

Building a tensegrity currently requires significant domain knowledge to balance trade-offs between competing performance objectives. Various authors have emphasized different objectives in the form of quantitative metrics, as we discuss later in this section. As an initial example, the performance objectives for a locomoting tensegrity could include high locomotion speed, low mass, and minimized cost of transport. Even when a tensegrity robot is designed for one specific task—locomotion, manipulation, or load bearing—understanding the interplay of topology, materials, and function is crucial to realizing an effective system. Across all tensegrity applications, future research must prioritize a codesign of materials and topology, rather than treating them as independent of one another. An emerging example of such codesign is incorporation of variable stiffness material struts, which have been shown to enhance deployability and modulate the mechanics of a tensegrity *in situ*.[131] Another example are interconnections in a tensegrity robot arm that can be adjusted to change the tensegrity's topology and adjust stiffness during operation.[28]

Simulators can serve as a practical tool to evaluate thousands of different topology-material arrangements in the context of a prescribed function. Yet, finding an appropriate compromise between design parameters while ensuring that the corresponding robot is physically realizable is challenging. There is not currently an established rigorous way to prescreen designs for their feasibility as physical hardware. Complicating this issue is the fact that simulators contain many parameters that contribute to a gap between simulated and actual performance. The parameters describing system geometry—such as the length, radius, mass, and system topology—are easy to obtain. These parameters could be measured on a physical robot and hard coded into the simulation. However, the parameters for the actuation dynamics and contact forces—such as restitution, friction coefficient, and actuator speed—are more difficult to measure and model.

Simplifying cable mechanics and soft material contacts in simulation reduces the number of parameters to tune, but simultaneously enlarges the sim2real gap. For example, the simplification of non-Coulombic friction in cable elements leads to design outputs that would only be possible with motors with torques and angular velocities beyond what is commercially available. Reducing the sim2real gap, or at least estimating this gap to allow informed prototyping and hypothesis testing, would allow faster transfer from simulation to physical hardware. Possible solutions include injecting noise into the simulator[132] and generating a function to estimate the reality gap.[33,133] As other promising options, sensor feedback[57] and a pretrained classifier from sensors[134] have been used to improve sim2real for tensegrity robots. In contrast to manually measuring the robot parameters, data-driven methods such as these may reduce the human labor requirements in the iterative identification process.

Other ways to decrease the sim2real gap include improving and expanding the tools available for manufacturing tensegrity robots. Ideal designs would boast strong lightweight materials, low power consumption, lightweight, rapid, and strong actuators, high-density power packs, and high-resolution sensors for state reconstruction and environmental sensing. Numerous hardware challenges remain, precluding a simple scale-invariant design and manufacturing strategy.

One significant challenge is the ''curse of dimensionality,'' whereby the complexity of both design and assembly increases exponentially with increased numbers of struts and cables, in addition to the complexities of designing robots at various length scales. For example, the power density of various actuator choices varies significantly at different scales. Winch and cable actuators have an excellent power density in large (e.g., meter-scale) tensegrities, but are obstructive in centimeter scale tensegrities. Conversely, shape memory alloy actuators have excellent power density at all scales, but are inefficient relative to rotary motors and slower at large size scales due to slower heat transfer between the actuator and the environment. Another important factor can be that material properties do not scale with system mass, affecting the level of engineering required. For example, in small, low-mass tensegrities, the material choice for the endcaps of the struts is trivial. In contrast, for heavier meter scale tensegrities, the endcaps experience higher impact loads and abrasive wear.

Furthermore, tensegrities are notoriously difficult to assemble and poorly disposed to automated assembly due to their complex spatial connections. Recently proposed modular lattices[31,41] and vibration-driven struts with integrated motors[19] reduce assembly times, but much remains toward developing a streamlined tensegrity robot manufacturing process with integrated sensing and actuation. For example, the number of struts in a given design has a profound impact on assembly complexity, which is one of the reasons it is rare to see rolling tensegrities with more struts than the canonical six-bar arrangement or crawling tensegrities with more than three or four bars in their arrangements. There are several ways that this challenge may be addressed in the future. One important step toward reducing the complexity of design and assembly is the reduction of custom designs for each tensegrity robot or making a greater number of the components digitally manufactured and/or assembled.

State estimation and environmental sensing

In addition to mechanical design challenges, current tensegrity robots are limited by state estimation inaccuracies on the order of several percent of the tensegrities' strut length.[25,26] Such noisy sensing resolution makes closed-loop control difficult, driving a need for improved sensor fusion algorithms and more stable onboard sensors. For example, low-noise strain sensors[135] could be integrated into the sensor cables or a 3D camera[136] or ranging sensors[25] could be attached to strategic locations for tracking node positions. Furthermore, estimating the state of modular tensegrities has been unexplored. Once improved sensor suites are developed, there are likely optimal ways to fuse sensor data to obtain a full state estimate and then use that to produce and control efficient locomotion gaits. Finally, environmental perception is a largely unexplored domain of tensegrity robotics research, yet presents immense scientific potential for exploring extraterrestrial environments. While the compliant structure of a tensegrity provides a safe internal space for placing environmental sensors, scant work has dedicated that space to house scientific payloads. Many open questions thus remain, including how to maintain sensor orientation during rolling and how to mitigate the occlusions caused by the tensegrity struts.

Autonomous navigation

To date, tensegrity locomotion has largely been confined to laboratories—simplified environments that are but approximations of real-world scenarios. However, navigating unstructured environments autonomously will be essential for future robotic missions. Improved state estimation could potentially be used in a closed-loop control policy and integrated into higher level task planning. For example, one possible hierarchical control scheme would combine advances in polyhedral path planning, real-time adjustment of found paths, and machine learning-based dynamic control frameworks to create a robust tiered autonomous controller.

Tensegrity planning algorithms could take advantage of many environmental features that prove catastrophic to conventional wheeled or legged robots. Discontinuities, such as cliffs and ridges, require traditional robots to search for a new safer path. In contrast, a tensegrity robot could take a shortcut—simply rolling off the edge. Such an unconventional planning framework could save mission-critical resources like time and fuel. Recent work has begun to explore ways to efficiently locomote between arbitrary waypoints using symmetry-reduced RL on the rough terrain and steep slope,[64,134] but further research is needed to minimize power consumption. Overall, with appropriately dense and accurate state information and planning algorithms that embrace discontinuities rather than avoid them, the next generation of tensegrities could complete missions rapidly at lower risk.

Standardized reporting of performance metrics

In the course of preparing this review article, we found that few articles reported the same sets of system-wide performance metrics beyond locomotion speed (in addition to measurements like rod length and robot mass), with many instead only presenting measurements directly related to the study's novel claims. Without standardized metrics for tensegrity robotics, it will be difficult for the field to measure progress in an objective manner. While adoption of metrics is ultimately up to the research community and warrants further debate and standardization, here we outline a few that we believe are particularly relevant to tensegrity robots. This list is not exhaustive and is meant as a concise starting point for the field to build and improve upon. Some metrics can be obtained on a static robot, while for others the robot must be dynamic during measurement. For example, potential ''static'' hardware metrics include:

- Robot density (kg/m^3)—the mass of the tensegrity robot divided by its volume, where the volume is defined as the convex hull of the robot when the robot occupies its maximum volume.
- Characteristic rod length (*m*)—the length of a tensegrity strut. Since compressive elements in tensegrities can vary widely, we define the characteristic length based on one of several cases as: the minimum or rest length of actuated rods, the average distance between the geometric center and the element's multiple ends for compressive elements with more than two end nodes (e.g., a tetrahedral element in a tensegrity spine), or the average strut length in tensegrities that have struts of different lengths. Having characteristic rod length as a reported metric is especially important for comparing the costs of transport of tensegrity robots at very different scales.
- Maximum bending, buckling, and crushing loads (*N*)—the load at which a rod experiences plastic deformation in any of these three load configurations, typically in impact scenarios.

These metrics seek to provide a quantitative depiction of how lightweight, large, and strong the robot is, while enabling comparison between robots as different as the six-bar icosahedron and spine-like robots. Beyond these static, structurally-oriented metrics, we present potential locomotion performance metrics, including:

- Cost of transport (unitless)—typically defined as $CoT = mgv/P_{in}$, where m is the system mass, g is the gravitational constant, v is the average velocity, and P_{in} is the average power input to the robot. Alternatively, it can be defined as $CoT = mgx/E_{in}$, where x is the distance traveled and E_{in} the energy input. Cost of transport gives the ratio of energy used in productive motion to that input to the system. Here, we propose measuring the cost of transport while traveling over flat ground without obstacles at standard atmospheric conditions. Since it is unitless, cost of transport is an effective way to make comparisons between disparate tensegrity designs, as well as other robots.
- Characteristic velocity (BL/s)—the robot's velocity divided by longest length of the robot body. In many cases, the longest length of the body will be approximately the characteristic rod length.
- Maximum climbable incline (*degrees*)—the maximum angle a locomoting robot can climb in its intended environment.

Conclusions

Leveraging their lightweight resilient bodies, tensegrity robots have shown great potential to explore extreme environments. Tensegrities can engage in numerous locomotion modes, including crawling, rolling, and hopping. Such operational flexibility enables them to adapt to changing demands, navigate novel terrain, and operate even after experiencing significant damage. Continued development of tensegrities could one day allow us to explore locations inaccessible with existing technology, such as lava tubes on extraterrestrial environments.

Beyond the field of robotics, tensegrity structures have provided simplified models to test biomechanical theories. Progressing the field of tensegrity robotics presents a unique opportunity to build controllable analogs for testing theories of legged locomotion, the spine's role in animals' dynamic stability, the role of passive stabilization mechanisms in cellular behavior, and the stresses experienced throughout the human body's bone-muscle system.[4] Illuminating these dynamics will lead to more targeted physical therapy, ergonomic exosuits, and informed biological models. Indeed, by studying the tensegrity, roboticists have the chance to increase our knowledge of ourselves and improve human life.

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