Co-Designing Material-Robot Construction Behaviors

Teaching distributed robotic systems to leverage active bending for light-touch assembly of bamboo bundle structures

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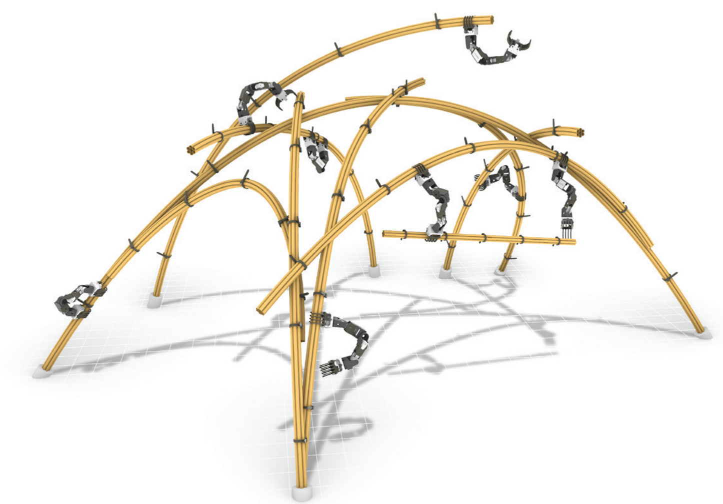

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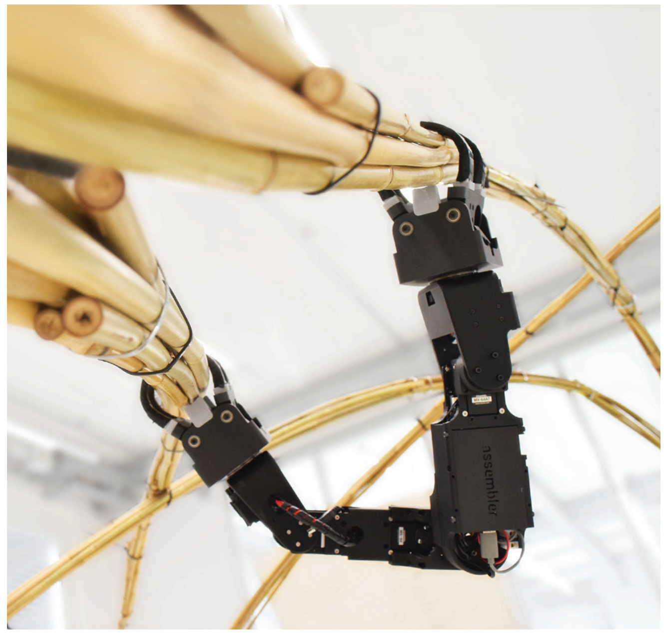

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ABSTRACT

This paper presents research on designing distributed, robotic construction systems in which robots are taught construction behaviors relative to the elastic bending of natural building materials. Using this behavioral relationship as a driver, the robotic system is developed to deal with the unpredictability of natural materials in construction and further to engage their dynamic characteristics as methods of locomotion and manipulation during the assembly of actively bent structures. Such an approach has the potential to unlock robotic building practice with rapid-renewable materials, whose short crop cycles and small carbon footprints make them particularly important inroads to sustainable construction. The research is conducted through an initial case study in which a mobile robot learns a control policy for elastically bending bamboo bundles into designed configurations using deep reinforcement learning algorithms. This policy is utilized in the process of designing relevant structures, and for the in situ assembly of these designs. These concepts are further investigated through the co-design and physical prototyping of a mobile robot and the construction of bundled bamboo structures. This research demonstrates a shift from an approach of absolute control and predictability to behavior-based methods of assembly. With this, materials and processes that are often considered too labor-intensive or unpredictable can be reintroduced. This reintroduction leads to new insights in architectural design and construction, where design outcome is uniquely tied to the building material and its assembly logic. This highly material-driven approach sets the stage for developing an effective, sustainable, light-touch method of building using natural materials.

1 Co-designed distributed material-robot construction system; speculative visualization of a lightweight bamboo bundle structure being assembled by the proposed team of bespoke mobile robots

2 Photo of the mobile robot prototype on the bamboo bundle structure; this robot was used in feasibility studies

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Methods of elastically bending wood to assemble structures:

3 Integration of active bending in plywood strips in a computationally designed lightweight structure bent into place onsite by humans, ICD/ITKE Research Pavilion 2010 (©ICD/ITKE, University of Stuttgart)

4 Precision elastic bending of glulam wood beams using an industrial robot in a prefabrication setup (©ICD/ITKE, University of Stuttgart)

INTRODUCTION: CO-DESIGNING MATERIAL-ROBOT CONSTRUCTION BEHAVIORS

Before the industrial revolution, humans relied on their experience and intuition of material behavior to build with low precision tools and lightly processed materials (Addis 2007). As the precision and automation of construction and fabrication methods grew, materials that are difficult to control and predict were discarded in favor of largely engineered, standardized, precise, and predictable building materials. However, recent research has demonstrated how natural materials, that are inherently heterogeneous and thus hard to handle and simulate, such as wood, can nowadays also be capitalized on to assemble structures that are economically, ecologically, and structurally performative (Menges 2011).

This research builds upon these examples and integrates material behaviors alongside a distributed, mobile robotic construction system within a single computational design process. By having the behavioral relationship between material and machine as the driver for co-design, the material behaviors, fabrication parameters and the procedural aspects of assembly all equally inform the computational process (Alvarez 2019). Such an approach takes a step towards unlocking robotic building with rapid-renewable materials, whose short crop cycles and smaller carbon footprints as compared to industrially produced materials make them a particularly important inroad to more sustainable construction (Ribeirinho et al. 2020; van der Lugt et al. 2006; Manandhar et al. 2019). One such material is bamboo, which has in the past been used as a building material in a range of applications and structures. Of specific interest is that bamboo used as raw rods exhibits excellent elastic bending characteristics making it ideal for structures utilizing active bending (Lorenzo et al. 2020; Bessai 2013).

The presented research proposes a newly invented mobile robot that learns a control policy for performing one of the identified assembly tasks: namely elastically bending bamboo bundles into designated configurations. Using deep reinforcement learning, the robot is taught to handle a range of mechanical properties and assembly scenarios, allowing it to operate in a more behavioral manner, not having absolute control over the material, but developing and using an understanding for how the material behaves (Figure 4). This allows it to be more responsive to the heterogeneity of the material as well as to other external disturbances during the assembly process, both of which are major challenges in the field of in situ robotic fabrication (Dörfler 2018). In future work, the intention is to introduce a team of these robots to collaboratively build full structures with a full range of assembly behaviors (Figures 1, 11). This research focuses on only one assembly behavior, that of bending bundles to designated positions. As such, this research:

- Challenges the linearity of conventional design in construction pipelines by proposing a workflow in which the architectural design and construction process emerges from the relationship between material and robotic behaviors.
- Leverages advances in reinforcement learning and sim-to-real methods to facilitate a return to more material informed building, enhancing existing practices of material independent robotic fabrication, and questioning the historical lineage of relying on excessive force and big machines and instead advocating for a light touch approach.
- Forges new avenues towards more sustainable construction by reintroducing the usage of non-standard natural building materials and materials with biological variability to the construction industry.

BACKGROUND

Collective Behavior-based Robotic Construction

By combining robotics, computer science, functional materials, and building design, collective robotic construction (CRC) is a rapidly growing field of research focused on the development of multi-robot systems tailored for architectural construction (Petersen et al. 2019). Successful projects have shown the assembly of both discrete building elements, such as bricks (Dörfler et al. 2016), and continuous materials, such as carbon fiber (Vasey et al. 2020). However, most examples rely on placeholder materials that are developed specifically for the respective research (Jenett et al. 2019). Furthermore, when materials are compliant, amorphous, or unpredictable, issues of mechanical tolerance, structural stability, and architectural design are discussed as major limitations (Thangavelu et al. 2020). Nevertheless, some research showcases a behavioral approach, based on sensor-actuator feedback between material and the robot, as a possible way to combat these limitations (Brugnaro et al. 2016). However, often the robot does not use the material's behaviors to its advantage and rather uses brute force of the machine to manipulate the material.

From the robotic platform perspective, off-the-shelf robots, including industrial robotic arms and UAVs (unmanned aerial vehicles), have been adapted with custom end-effectors for CRC (Vasey et al. 2020). The development of custom machines is a further trend within CRC, in which the robot system is created in direct relationship to the construction material and construction system. Such developments demonstrate how the co-design of material and machine leads to CRC systems with high precision, low cost, and structural efficiency (Jenett et al. 2019; Kayser et al. 2018; Leder et al. 2019; Yablonina et al. 2017). From the robotic platform perspective, off-the-shelf robots, including industrial robotic arms and UAVs, have been adapted with custom end-effectors for CRC (Vasey et al. 2020). The development of custom machines is a further trend within CRC, in which the robot system is created in direct relationship to the construction material and construction system. Such developments demonstrate how the co-design of material and machine leads to CRC systems with high precision, low cost, and structural efficiency (Jenett et al. 2019; Kayser et al. 2018; Leder et al. 2019; Yablonina et al. 2017).

Machine Learning

One common application of machine learning (ML) is the robotic learning of material manipulation (Zeng et al. 2019). Reinforcement learning (RL), specifically, is beginning to be used in the context of material manipulation for digital fabrication (Brugnaro et al. 2019; Apolinarska et al. 2021). This requires the learning of intelligent behaviors in complex dynamic environments that can then be transferred to robots in the real world. Robots are therefore able to quickly and effectively adapt to new tasks in real-time (Nagabandi et al. 2018). Adaptation is critical when designing robots expected to robustly perform autonomous tasks in chaotic environments, such as construction sites.

The adaptability enabled by RL is further emphasized by research on robots working with amorphous materials that have properties that are hard to predict (Zhang et al. 2020). However, examples of such research tend to be conducted only with simulation due to the complexity and cost of real-life training. In this paper, an approach is presented for training robots to perform construction tasks using materials with heterogeneous properties in the real world.

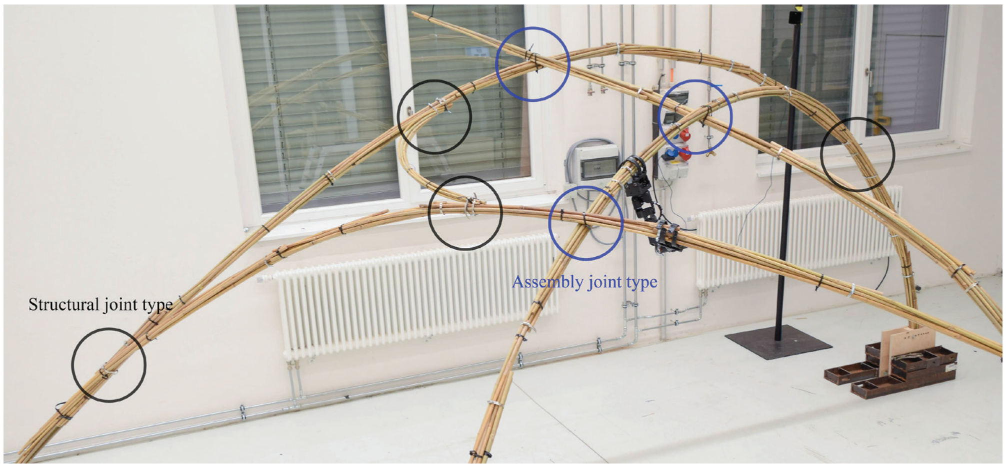
More specifically we focus on Deep Reinforcement Learning (DRL), a subset of machine learning methods adept at solving a wide range of nonlinear tasks that require learning intelligent behaviors in complex and dynamic environments. In contrast to supervised learning approaches, reinforcement learning algorithms learn from trial and error, making them a fitting method for the proposed context, due to the lack of rich and organized databases required for supervised learning.

REASEARCH METHODS

This research presents a distributed, mobile robotic construction system, capable of partially assembling bamboo structures using a control policy learned from interactions with the material. The system consists of bundled bamboo rods and custom mobile robots that assemble the bundles into architectural structures. Extensive training in a simulation environment teaches the robots to perform one assembly task, bending bundles, while dealing with unpredictable mechanical properties inherent to bamboo and varying geometric configurations as specified by the designer. Data collected from this training process could then be further utilized in designing bamboo structures, while the trained policy is used in simulations to determine the feasibility of assembling the design.

Construction System - Bamboo Bundles

The construction system is composed of bamboo bundles, metal zip-tie joints, and steel anchors. Bundles are created by zip-tying bamboo rods into assembly groups, while longer-length bundles are achieved by overlapping assembly groups, and further joining those together. The structural capacity and bending radius of each bundle can be adjusted by adding or removing bamboo rods, thus varying the cross-section along the length of the bundle.



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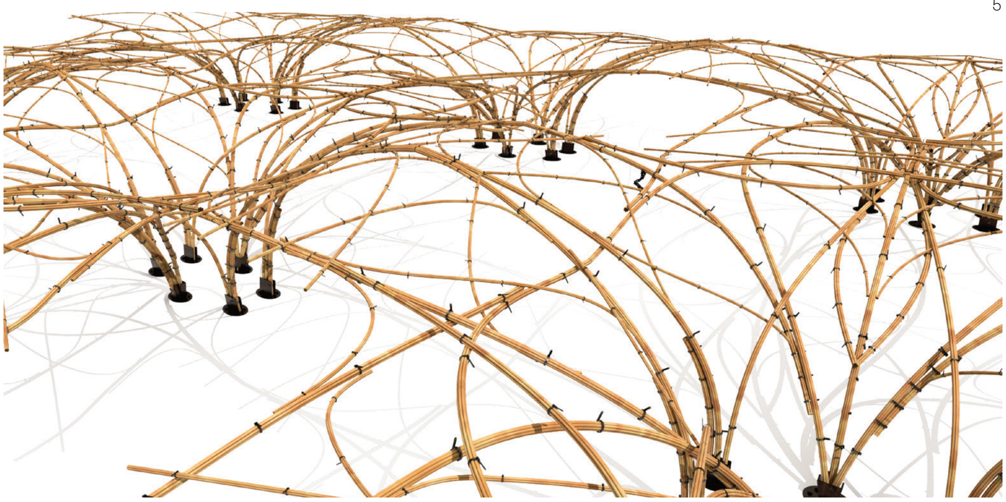

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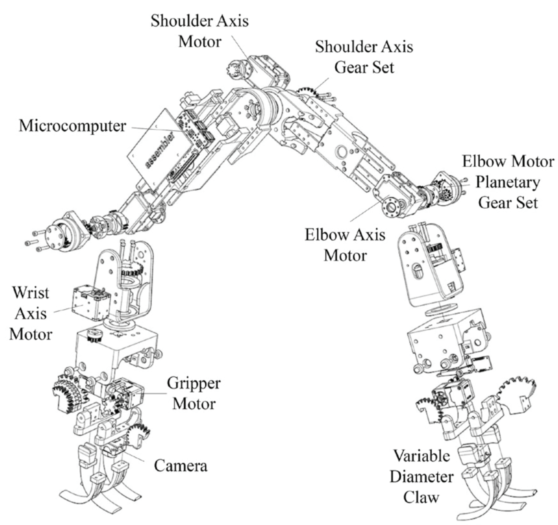
5 Joint types of the construction system: fixing joint labeled in black circles and assembly joint labeled in blue circles

6 Outlook for a speculative bamboo structure as enabled by the learned control policy and combination of the proposed joints

7 Exploded view of the mobile robot prototype featuring two grippers, 5 degrees of freedom, 40 cm height, and a weight of 2.3 kg; chassis parts were printed with Onyx and ABS plastics; prototype runs on a Raspberry Pi microcomputer and uses Dynamixel MX-64 and XL430 motors; approximated cost of 1,800 EUR

Furthermore, this flexibility allows for the typology of the structure to be adjusted during the building's lifetime or even serve as temporary scaffolding to be removed after assembly.

Bundles can be joined together with two types of joints: structural fixing joints, and non-structural assembly joints (Figure 5). In a fixing joint, the bundles are joined in parallel. Thus, a bundle interpolates its curvature with the other bundle it is connected to. In contrast, the assembly joint connects two bundles in non-parallel formations, and so the connected bundles keep their local curvature. The structural strength of the assembly joint is considerably smaller than the fixing joint and is, therefore, used to assist in the assembly process and for scaffolding purposes. Conversely, the fixing joints efficiently transfer loads between bundles and into the steel anchors. The combination of these two types of joints can be used in many variations to cover a wide range of scenarios and structural requirements (Figure 6).



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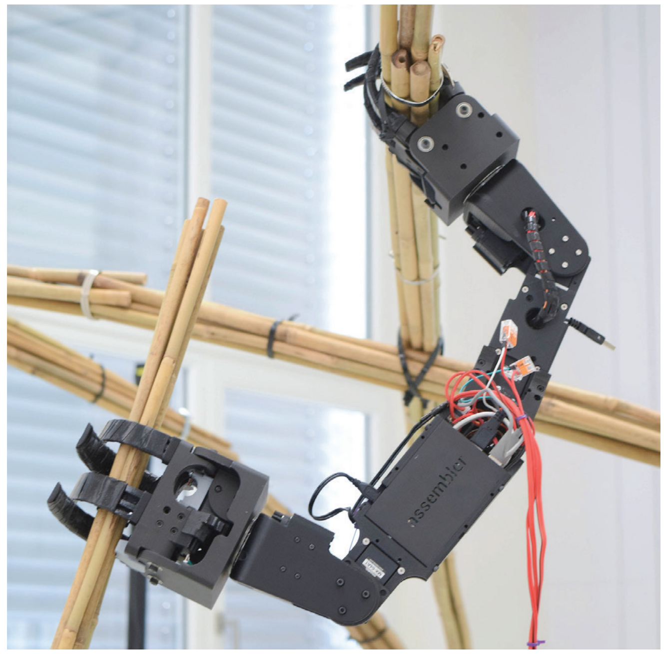
Mobile Robots

The mobile robots were designed with an articulated morphology comprised of 5 degrees of freedom in order to perform the various assembly tasks described in the next section (Figure 8). They are equipped with two variable diameter claws to grasp various bundle sizes and deal with the unpredictable arrangement of bamboo rods within each bundle. The robot is also equipped with various sensors that monitor and estimate both its state and changes in the environment (Figure 7). Localization is achieved with an external multi-camera tracking system, while more subtle and local corrections could be conducted via computer vision algorithms, by processing real-time images from the cameras embedded in each claw. Sensor fusion is conducted on accelerometer, gyroscope, and magnetometer readings to provide orientation and acceleration measurements during task execution.



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Material-Robot Behaviors

Material-Robot behaviors describe the relationship between the two core components of the construction system, bamboo, and mobile robot, and serve as the basis for the development of the computation design process.

Leveraging the Elastic Bending Behavior of Bamboo

Awareness of the benefits of bamboo, as material, and its bending behavior in modern construction is visible in the amount and architectural quality of new structures (Minke 2012). Bamboo is an elastic material and can undergo bending deformations in relation to the forces acting on it. This bending behavior can be further categorized as static bending and dynamic bending, both of which can be leveraged to assemble bending active structures from originally linear elements (Lienhard et al. 2013).

Static bending can be achieved by applying point loads in specific locations along the length of the material. The robot can achieve this by climbing to specified positions along the length of the bamboo bundle. This deformation can be calculated with force- or position-based models (Suzuki et al. 2018) and can be described by the elastica curve of the bundle, the robot's current location, self-weight, and gravity vector (Figure 9). Static bending as an assembly process, however, is geometrically restrictive, resulting only in forms expressive of the elastica curve.

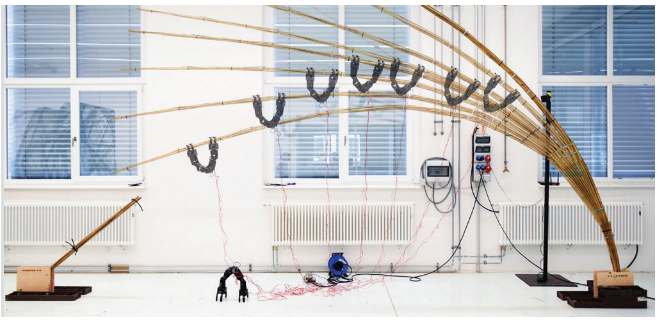
In contrast, dynamic bending allows for higher geometric freedom, which, in turn, enables more complex structures to be designed and built. This can be achieved when the forces applied to the bamboo are not aligned to the gravity vector (i.e. not self-weight), but instead align with the desired bending direction. The robot is capable of dynamic bending (Figure 10) by rhythmically swinging its appendages and thus introducing directed momentum to the system. However, such swinging requires an understanding of the natural frequency of the bundle, and cannot be pre-planned with trajectory optimization algorithms as this becomes a nonlinear and partially observable planning problem. Nonlinear problems involve solving for a goal with changing variables, some of which are unknown or unpredictable, such as the exact mechanical properties of specific bamboo pieces and the oscillation frequency of the bundled bamboo elements. Therefore, in order to perform such tasks, we train a neural network policy using deep reinforcement learning that controls the robot's axes in relation to the behavior exhibited by the bamboo bundle in real-time. This learning method is further elaborated in the Deep Reinforcement Learning section.

Manual Evaluation of Secondary Robotic Construction Tasks

Locomotion, material transportation, bundle extension, and joining are other assembly tasks (Figure 11) that require an understanding of the relationship between material and robot. Although these tasks have been identified and designed, they are linear problems largely unaffected by the varying mechanical properties and dynamics of bamboo and thus can be solved using existing methods for task and motion planning such as trajectory optimization algorithms. Validation of such behaviors is conducted through simulation and physical experiments and presented in the Results section.

Deep Reinforcement Learning: Learned Knowledge

Deep Reinforcement Learning is used to teach the robots how to operate relative to the bending behavior of the



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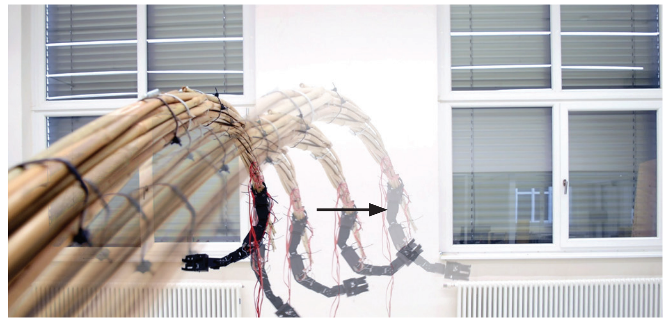

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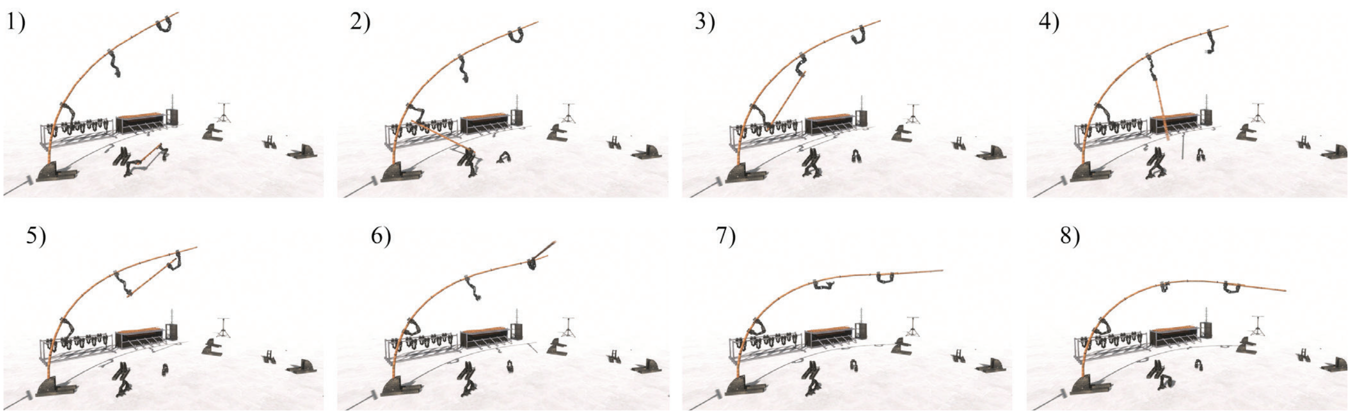

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8 Physical prototype of the mobile robotic builder

9 Behavioral experiment combining the elastic bending of the bamboo bundle and the dynamic positioning of the robot: the self-weight of the robot and its position along the bundle can cause static bending

10 Dynamic bending caused by the robot rhythmically swinging in the desired bending direction

11 Visualization of the bundle extension sequence: (1-2) robots transport material on ground; (3-6) robots transport material while on structure; (7-8) transported material is connected to extend the bundle

bamboo bundles. The knowledge gathered from this learning process is two-fold: first, the robot learns how to use its weight and movement to create and direct the required momentum to elastically bend a bundle. Specifically, the robot learns to match its motion with the natural frequency of the bundle and thus is capable of altering and amplifying the oscillation of said bundle in order to achieve goal configurations. This knowledge is used during the assembly process. Second, the robot learns how to determine what the material is capable of, or in other words, what geometric deformations it can undergo. This secondary knowledge is useful in the design process (Figure 11).

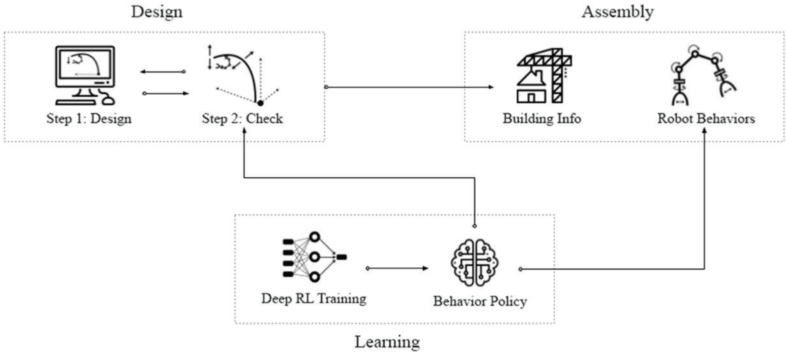
(PPO) Proximal Policy Optimization

More specifically, this research implements Proximal Policy Optimization (PPO) (Schulman et al. 2017). PPO is used to train a neural network to approximate the ideal function that maps an agent's observations (its state) to the best action an agent can take in a given state in pursuit of achieving a goal (i.e. assembly task). All policies are feed-forward networks with three layers of 128 units each, whose training is kept stable using asynchronous gradient descent.

The PPO algorithm consists of an agent, an environment, a set of states, actions, and a reward function (Figure 13). In this research, the environment consists of the robot dynamics and the bamboo physics simulation, which was approximated as a discrete chain of rigid-bodies connected by damped harmonic oscillators, where the motion of each spring depends on the balance of three forces: inertial force, restoring force, and a damping force. The state (i.e. observations) is the collection of inputs from the robot's sensors (specified as the robot's orientation in space, a vector between its end effector position and the goal's position, the motor joint angles, the angular velocity of the base link, and the linear velocity of the base link). The actions are the motor movements, resulting in a 5D action space, with each dimension relating to one of the axes). A reward is given when the virtual robot is able to bend the bundle and close its gripper around the goal location, while a penalty (negative reward) is given at each timestep in which the goal is not achieved in order to encourage exploration. The goal is to maximize the reward.

Design and Assembly Strategy

Existing form-finding methods for bending-active structures (Piker 2013; Suzuki et al. 2018) are not sufficient for



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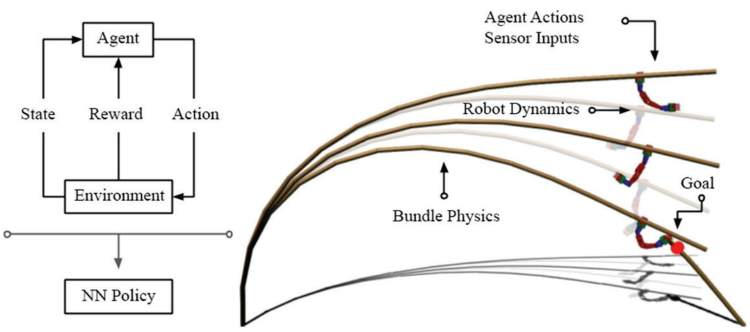

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12 Design and assembly workflow: machine learning enables: (1) the simulation of the assembly process of a bundle in a digital environment, which is in turn embedded in the design process; and (2) the use of material behavior knowledge during assembly of this structure on site

13 A screenshot from the simulation and learning process (right) as it relates to the abstracted reinforcevment learning algorithm (left)

14 The experimental setups utilized to validate the design and assembly workflow: (a-b) experiments within the training set; (c) experiment outside of the training set

the purposes of this research since they do not accommodate the integration of assembly-related constraints. The modeling workflow developed for the proposed construction system, on the other hand, allows for close interaction between the human designer and the digital twin of the robot. The role of the designer is to determine a bundle's shape and position in space by defining stiffness, starting position, length, and end position. Robots, in turn, utilize the knowledge gathered during the learning process (i.e. the trained policy) to assess the feasibility of the desired configuration through virtual bending choreographies. This serves as crucial feedback for designers, as it continuously informs their decision with material and assembly-related parameters.

Once the design satisfies structural, architectural, and robotic requirements, it is dispatched to the physical assembly system, which includes information on assembly order, joint types, and bundle positions as well as successful bending choreographies. This information, however, does not constitute a static blueprint but rather a rough set of instructions, given that the final geometry is highly contingent upon the dynamic relationship between material and robot.

RESULTS

For the demonstration and validation of the proposed system, a series of experiments were conducted that together resulted in the demonstrator structure. All bundles within the structure were made from 1.8 meter long *Arundinaria amabilis* bamboo rods, with diameters ranging from 1.0 to 1.8 cm. The cross-section of the bundles was designed in a gradient-like manner to control curvature distribution.

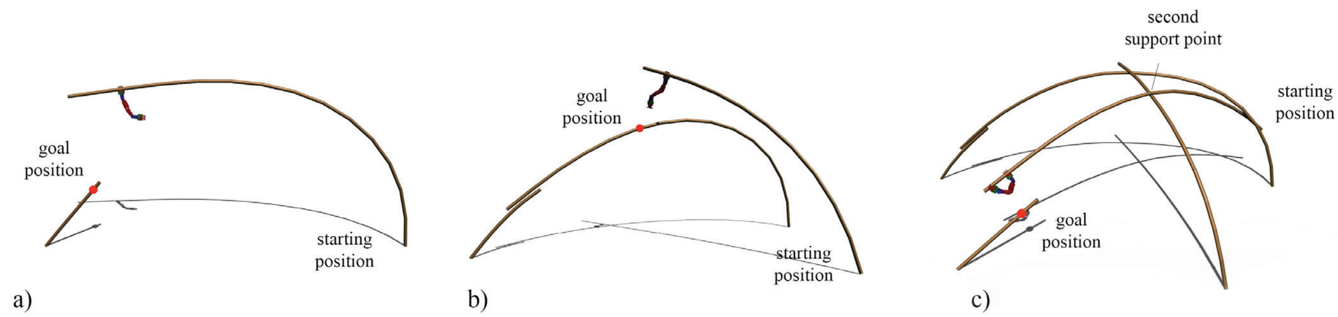
Demonstrator Structure (3 Experiments)

The demonstrator structure is the result of three assembly sequences, all of which were conducted as individual experiments (Figure 14).

The first experiment (Figure 14a) consisted of a 7.5-meter long bamboo bundle anchored vertically to the ground at one end and free at the other. The goal was to bend the initially free end of the bundle into a goal position near the ground in order for it to be anchored thus forming an arch.

During the second experiment (Figure 14b), the robot bent a shorter bundle, which was fixed at one end to the ground. In the final state, the other end connected halfway along the length of the bundle from experiment one.

Experiment three (Figure 14c) involved bending a bundle into an arch similar to that of the first experiment. However, in this experiment, the bundle is connected to the initial bundle of the first experiment with a fixing joint and must bend over the bundle placed in the second experiment.



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This scenario is unique in that the properties of multiple connected bundles affect the assembly process. As only the bending of a single bamboo bundle in isolation was initially trained for, this scenario is outside of the training data set and served to test the generalizability of training results.

Experimental Results

Five policies, trained with slightly different constraints, were tested in all of the above setups. The experiments were conducted both digitally (Sim-to-Sim), to test the trained policy in simulation during the design process, and physically (Sim-to-Real), to evaluate the transfer of knowledge from training to physical assembly.

In simulation, all results were successful, meaning that the robot was able to use its weight and momentum to bend an element into the desired position. During the Sim-to-Real tests, the best policy enabled the robot to find and match its momentum with the natural frequency of the bamboo bundle for each setup. The robot could adjust its swinging even when the bending response from the material was influenced through external means. However, the amplitude of the bending was much smaller than the one achieved in the simulation. In experiment three, the bending amplitude was even smaller than the previous two experiments due to the fact that the bundle from experiment two acts like a damper, which was not accounted for in the training. To overcome these deviations in the future, creating momentum from different positions along the length of the bamboo bundles was tested to understand its effects on the amplitude of bending for future training.

Evaluation of Secondary Behaviors

Physical experiments of the other tasks necessary for the assembly of structures built with the proposed construction system were also conducted. A hard-coded locomotion routine was tested, which allowed the robot to walk along the length of the bending bundle by repeating a loop of choreographed movements. Material transportation was tested by enabling the robot to grab, move, and release various bundle subsegments. And finally, the ability of the robot to connect bundles was validated by hard-coding a robot to grasp and then align a bamboo bundle to an already existing bundle in the structure.

DISCUSSION AND CONCLUSION

The presented research showcases the potentials and methodological implications of designing a construction system driven by a reciprocal relationship between material and robot behaviors. Here, designing is no longer conceived as an exercise in static material placement or isolated geometric exploration, but as an integrated and iterative workflow between simulating material behaviors and choreographing robot performances. In contrast to previous work in the field of Collective Robotic Construction, the presented system does not aim to automate construction processes tailored to human builders, nor does it rely on brute machine force enabled by large-scale construction equipment. Instead, it proposes an intelligent material-centered design-to-assembly process for robotically building structures made from natural materials.

Digital and physical experiments were conducted to validate this way of behavioral designing and building. To do so, a full-scale mobile robot was designed, built, and programmed. A neural network was trained in order to provide the robot with one of the skills necessary for assembling bamboo structures. Although this skill was successfully tested in both simulation and with physical experiments, one identified challenge was the ability of the algorithm to exploit the flaws of the physics simulation in order to reach its goals. As these sorts of flaws do not occur in reality, some of the policies with such tendency had to be discarded. Further research might investigate a more physically accurate physics engine in order to address this issue (Bousmalis and Levine 2017).

Despite the focus on bamboo structures, the methods proposed in this research are not meant to be limited to this construction system, but rather to lay the groundwork for further exploration of co-designing material-robot behaviors and their potential implementations in architecture and construction. With this approach, we intend to challenge the way in which building materials are currently used in architecture, by treating them as active drivers in the design, assembly, and lifetime of the construction process, rather than as static recipients of form (Menges 2015). New possibilities for sustainable architecture arise when natural, heterogeneous materials with high degrees of biological variation can be robotically assembled into large-scale structures.

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IMAGE CREDITS

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Figure 4: Loucka, ICD, University of Stuttgart, 2014
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