A TOOL FOR SEARCHING ACTIVE BENDING BAMBOO STRIPS IN CONSTRUCTION VIA DEEP LEARNING

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Abstract. As an alternative material for construction, the structural use of bamboo in architecture is commonly associated with active bending. However, as natural material, the deformation of unprocessed bamboo strips is affected by the distribution of nodes, whose impact on deformation is difficult to precisely programme for each individual case and thus often causes discrepancies between generic digital simulation and construction. This research proposes a tool for searching active bending bamboo strips via deep leaning based on a multi-task neural network. The tool is able to predict both the number and locations of nodes suggested on bamboo strips according to a target curve as tool input. By approximating the prediction, users can find a strip that is most likely to deform into the desired geometry.

Keywords. Neural network; active bending; neural architecture search (NAS); bamboo; material behaviour.

1. Introduction

1.1. BAMBOO AS AN ALTERNATIVE BUILDING MATERIAL

As well known, bamboo, with a simple and fast production process, is a sustainable, economic and structurally efficient material (Van der Lugt et al., 2006). As an alternative building material, bamboo construction consumes far less energy when compared to the use of conventional building materials such as concrete or steel of the same size (Janssen, 1988) .

Earlier life cycle assessment studies show that among different types of bamboo-based construction, the use of raw bamboo including bamboo poles and strips has the lowest environmental impact (Escamilla and Habert, 2014; Escamilla et al., 2018). In traditional architectural practices, structural use of raw bamboo is commonly associated with systematic choreography of active bending (Dunkelberg, 1985; Lienhard et al., 2013).

1.2. DIGITAL SIMULATION OF ACTIVE BENDING

Bending-active structures are often formed by rod elements that deform in bending, and are usually light-weight and resilient, due to the fact that elastic bending in

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the material allows for flexing instead of breaking and buckling (Cuvilliers et al., 2018). The lightness and adaptability of bending-active structures have been of spatial and technical interest to architects such as Frei Otto (Nerdinger and Barthel, 2005).

The deformation of material in bending-active structures can usually be described by analytic geometry following the rules of the elastica (Lienhard, 2014), which offers a mathematical basis for its form-finding regardless of materiality. In the digital age, form-finding simulation methods are actively developed to accommodate architectural designers' interest in bending-active structures in the design stage (Bauer et al., 2018). For instance, by reducing the degree of freedom of a spatial node from 6 to 3 (Adriaenssens and Barnes, 2001), Kangaroo Physics, a plug-in for the digital modeling software Rhinoceros, applies dynamic relaxation method to simulate bending-active behavior of an elastic rod (Piker, 2013; Cuvilliers et al., 2018).

1.3. INACCURATE SIMULATION OF NATURAL MATERIALS

Despite the wide adoption of digital simulation solutions for bending-active structures, it has been difficult to accurately design and construct bending-active bamboo structures in the contemporary digital design context. One major reason has to do with the inaccuracy of commonly adopted digital form-finding process when applied to natural materials such as bamboo, thus creating a gap between the design and subsequent construction.

Two major reasons cause the difficulty to accurately simulate and construct the designed form of bamboo strip structures. First, the structural performance of bamboo strip bending displays non-linear characteristics due to its foam-fibre composite structure (Obataya et al., 2007; Zhou et al., 2012), which renders the form-finding process of bending bamboo strips rather difficult through commonly used design software. Also, the compression and tensile modulus of the material are different from each other, causing more complex material behaviour (Dongsheng et al., 2013). Second, the distribution of bamboo nodes has a complicated impact on compression during the bending process and therefore impact the deformation (Meng and Sun, 2018). Due to the uniqueness of unprocessed bamboo strips, it is much laborious to precisely programme the impact on deformation for each individual case.

The inaccuracy of digital simulation for material behaviour of bending raw bamboo strips is particularly pronounced when node distribution is involved in real world, as shown in an earlier study (Chen and Hou, 2016). In a preliminary one to one scale simulation-construction test (Figure 1) conducted by the authors in the early stage of this research, extra lateral supports had to be added to the bending-active structure in order to respond to the obvious deviation from the simulated geometry caused by unpredictable distribution of nodes, thus effectively rendering the load condition different from the intended design.

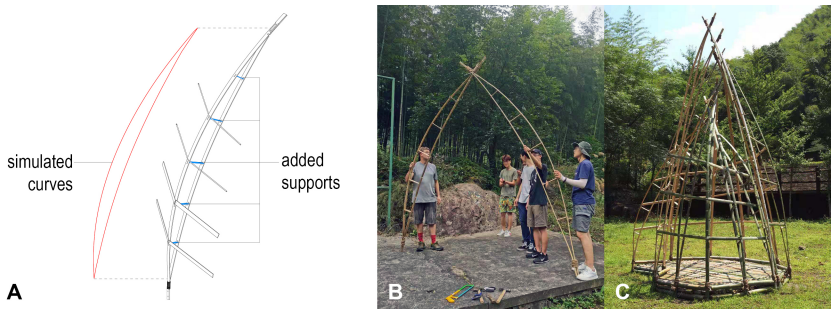

Figure 1. The preliminary one to one scale simulation-construction test. A: extra lateral supports added to respond to the deviation from simulation; B: construction process; C: final outcome .

1.4. MACHINE LEARNING'S RECENT DEVELOPMENT IN ARCHITECTURE

In the recent years, enabled by the rapid growth of computational power, machine learning techniques emerge quickly and have been globally implemented in many disciplines such as autonomous driving, biological diagnose, privacy protection and so on. It has also been increasingly deployed in architectural studies to solve various problems including material behaviour prediction (Luo et al., 2018; Chen et al., 2019; Wu et al., 2019) that were previously difficult to approach through conventional structural modelling. One important advantage of machine learning in solving material behaviour problems is that it is data-driven instead of computing the outcomes following structural formulas, which paradoxically have difficulties in describing the behaviour of natural materials as introduced in section 1.3.

Among all machine learning subfields, neural network (NN) makes up the backbone of deep learning. Early NNs can date back to the 1960s or even earlier and gained their popularity in the new millennium (Schmidhuber, 2015). Usually, a neural network takes numerical input, and can be used for regression and classification problems.

1.5. PROPOSED SOLUTION

This research proposes a handy tool which could predict a specific number and locations of nodes required on a bamboo strip in order to better deform the bamboo strip into a desired shape in construction via deep learning. Architects or builders can search for such a bamboo strip by approximating the prediction. This tool closes the gap between digital simulation and subsequent construction of a design. It also helps designers avoid confronting simulation software with structural knowledge as the tool bypasses programming structural rules by using machine learning techniques.

A neural network model is chosen to build up the tool because of its powerful nonlinear fitting ability, and the model is trained and tested with a dataset collected by the authors.

2. Methods

2.1. DATA COLLECTING

In this research, a series of bamboo strip bending experiments are conducted. A set of original data is collected from the experiments and processed automatically with the help of computer vision algorithms.

2.1.1. Preparation of Bamboo Strips

A batch of 40 bamboo strips of the same species purchased from the same supplier are used for the experiments to minimise the impact of unmeasured parameters such as fibre quality or node structure. Each bamboo strip is about 4,000 mm in length, 50 mm in width measured from the bottom end and 10 mm in thickness. Due to the nature of the species chosen, the strips are rather even in width and thickness distribution. Because each node occupies a tiny visual proportion in the environment, to enhance the apparentness of nodes, each node on the bamboo strips is marked with bright red elastic tapes before the bending experiments. The experiments are finished within two weeks in order to minimise the potential material behaviour change caused by bamboo dehydration and preservation conditions.

2.1.2. Bending Platform and Environment Setup

A pair of two Kuka KR120 R2500 six-axis industrial robots placed 3,200 mm apart from each other measured from the canter points of the base are used to form the bending platform. The bending platform is placed in an indoor lab with ample artificial lighting. However, the lab has a few large skylights that cannot be blocked, creating a changing lighting environment throughout the day. Due to the limited experiment time window, a few bending and video shooting sessions have to be executed during the day. A large piece of black fabric, along with a few pieces of black PVC boards have to be placed behind and around the bending platform to reduce the impact of the natural light. However, the lighting environment change is still visible from the videos taken.

The end effectors of the bending platform are designed to freely rotate in order to minimise torque from the holding positions. A pair of QT-120 steel ball lock tool quick change system are used as its base, and an NSK sliding bearing are placed as its core. The position of the bearing is locked onto the flange by four M10 bolts, and the journal of the bearing is subsequently connected to a round stainless-steel platform on top of which two adjustable rubber clamps are mounted. The rubber clamps are marked with blue paint for segmenting the holding positions through computer vision method.

2.1.3. Bending Experiments

The free-rotation setup of the end effectors allows the operation of only one robotic arm. A fixed route-following algorithm generated in Grasshopper is used on different bamboo strips for half of the bending and video shooting sessions. To add to the randomness of the data sample, for the other half, the robotic arm is

manually operated through the teach pendant. In both cases, as demonstrated in Figure 2, the end effectors are placed in a surface perpendicular to the camera direction. An iPhone XS placed 5000 mm from the center-to-center line of the bases of the industrial robots and 1250 mm above floor level is used for shooting videos. Subsequently, the movement of the end effector is controlled to be around the same height and refrained in the same plane 4000 mm from the camera. During the bending experiment, most bamboo strips are held at three different positions to allow for different node distribution patterns, and for each position, the robot arm moves along at least two route settings to obtain different bending curves. Along each route, three to five distinguishable bending curves are saved by extracting frames from the videos. Finally, a total number of 1100 images are collected with 40 bamboo strips.

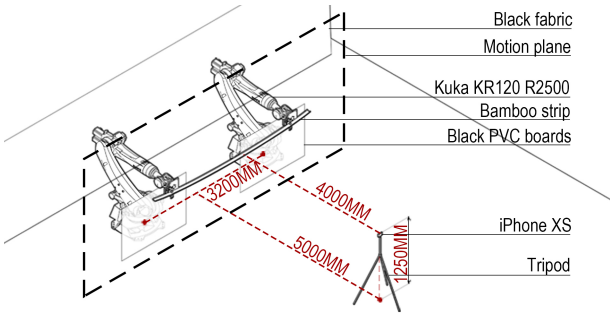

Figure 2. The bending experiment .

2.1.4. Computer Vision Processing of Images

Because of the visible light changes across images, in order to guarantee a uniform quality of the images and obtain a more accurate colour segmentation result, each bamboo node is marked again in Adobe Photoshop before processing with a computer vision algorithm. However, this extra marking step can be avoided by recording the videos in a fully light-controlled condition.

The computer vision algorithm separates bamboo strips and nodes from the background. In details, for every input image, pixels of the bamboo strip are segmented and converted into a curve lying in the centre of the bamboo strip in a Cartesian coordinate system. Then the curve is discrete into 1000 points so that each point can be assigned a probability of being a node. Secondly, the X and Y values of the node centroids in the coordinate system are computed. Thirdly, the Euclidean distance between each node centroid and its adjacent points on the curve is calculated. Probabilities of being a bamboo node for the 1000 points are assigned according to this distance and are normally distributed around the node centroids. Compared to labelling a few specific points as bamboo nodes, assigning points with node probabilities is more feasible for training the neural network introduced in later sections. Finally, a 1002-line text file is generated. The first 1000 lines document the coordinate values of each point on the curve and their corresponding probabilities of being a node. The last two document the total number of nodes

and the indexes of them respectively. With the 1100 images mentioned in section 2.1.3, a same number of such files are generated. Figure 3 demonstrates an original image and the output of the computer vision algorithm.

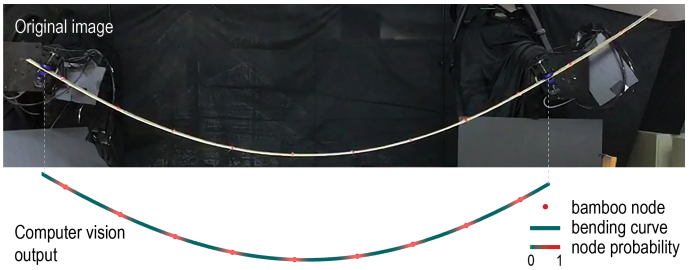

Figure 3. An original image and the computer vision output.

2.2. THE NEURAL NETWORK

This tool is established based on an artificial neural network. In construction, to better achieve a particular form through bamboo strip active bending, one can input the designed curve to the neural network model, which can then predict the node distribution of a bamboo strip that can most probably deform into the designed curve.

2.2.1. Dataset

The dataset contains 1100 files introduced in section 2.1.4, representing different combinations of bamboo strip node distribution and bending curve. Regardless of the actual length of the curves in reality, the coordinate values are all normalised to the range between 0 and 1. Among the files, randomly 1000 are used for training the neural network, and the rest 100 are used for testing.

2.2.2. Basic Neural Network Architecture

The neural network has a multi-task learning architecture consisted of an input layer, backbone, node number branch and node location branch as Figure 4 shows.

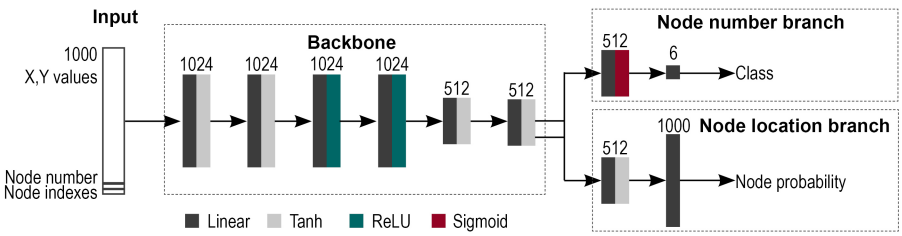

Figure 4. Architecture of the neural network.

The backbone plays the role of extracting features shared by the node number branch and node location branch. It contains 6 layers: the first 4 layers have 1024

channels, and the width of the last 2 layers is 512. This particular architecture is chosen via automatic neural architecture search which will be introduced in section 2.2.3. In this research, predicting the number of nodes is considered as a classification problem where each type of node number is seen as one class. As in the current dataset the number of nodes ranges from 6 to 11, there are 6 classes in total. Accordingly, the node number branch outputs 6 classification probabilities. The node location branch contains 1000 output units. Each unit outputs the node probability of a curve point.

The neural network was originally designed as one single branch predicting the probabilities of the 1000 points being a node. Consequentially, the number of nodes is calculated according to the number of probability peaks. However, this method could not provide accurate result because it is very complicated to denoise the probabilities without knowing the exact number of nodes. Since it is necessary to obtain both the number of nodes and the 1000 probabilities, it is then considered as a multi-task learning problem. The performance of the neural network dramatically improves when the architecture is modified to consist the truncated node number branch and node location branch.

2.2.3. Neural Architecture Search

As manually developing the architecture of neural networks can be time-consuming and inefficient, automatic neural architecture search (NAS) (Elsken et al., 2019) is increasingly deployed in various machine learning tasks. This research uses the Neural Network Intelligence (NNI) v1.9, a toolkit developed by Microsoft to automatically search the backbone architecture of the neural network that could best perform the tasks.

There are three major parameters in the search space, namely, depth of the neural network, types of activation functions, and number of channels in each hidden layer. Specifically, the depth of the network can range from 2 to 6, and every linear layer is followed by an activation function of Tanh, Sigmoid or ReLU. The channel of each layer can vary among 256, 512 and 1024. In a prediction, if the number of nodes does not match the ground truth, this prediction is considered as an error. The total number of errors is reported to the NNI tuner to be minimised.

Within the allowance of computational power and research period, 1020 different backbone architectures are tested in the search space. Figure 5 displays the search trials where the backbone architecture introduced in section 2.2.2 is chosen from.

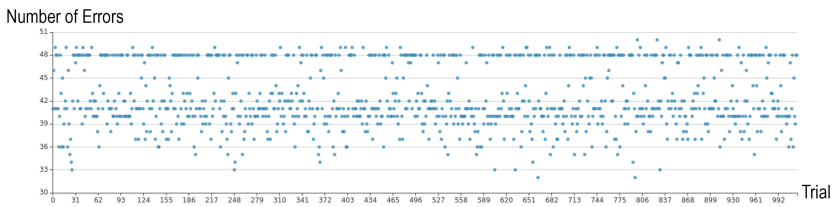

Figure 5. Neural architecture search trials.

2.2.4. Training

To train the neural network model, an initial learning rate of 1e-3 is adopted with a Cosine learning rate decay limited to 1e-8 as minimum. An Adagrad optimiser (Duchi et al., 2011) is used. There are two different types of loss functions applied to the number of nodes and the locations of them. For the number of nodes, it uses cross entropy loss, while for the locations of nodes, mean squared error loss is adopted. The total loss equals to the location loss summed with a dynamically weighted node number loss whose weight increases from 0.1 to 0.3 from the first epoch to the last. The total epochs are 1500 when training the network whereas to accelerate the NAS, the number of epochs is set to only 360 during the search. The batch size is 16.

3. Result

Through testing, 74% of the node number predictions are accurate, within which the average discrepancy of node locations equals to only 3.66% of the length of a bamboo strip. Among the inaccurate predictions of node numbers, the average discrepancy is only 1.2 nodes. This is considered as just acceptable as having one node different would not affect the deformation dramatically. The result demonstrates a decent accuracy of the tool in both node number and location prediction tasks. Figure 6 demonstrates some of the prediction results.

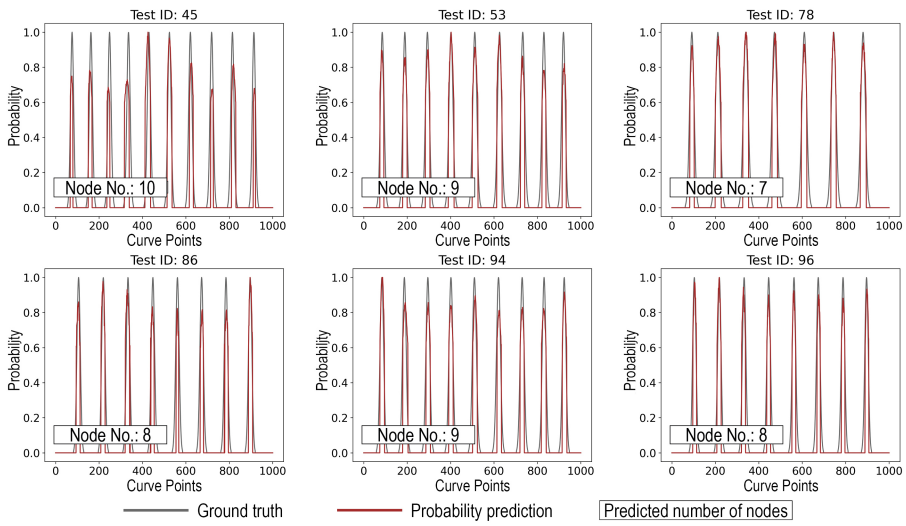

Figure 6. Predictions of the neural network compared with ground truths .

4. Future Line of Research

The current dataset contains a small number of samples. For the following two reasons, it is critical to expand the dataset to improve the performance of the tool and obtain more useful applications. First, as the deformation of bamboo strips is

affected by many other factors than nodes, it can be valuable to develop a much larger dataset of bamboo strips to involve factors such as species, humidity, age and so on, and use them all as machine learning features. In this way, the model can be extended to practical use under varied conditions. Second, a larger dataset with more evenly distributed number of nodes can help achieve a higher overall accuracy, since the current dataset has a very biased amount of data in each class.

The current computer vision algorithm uses colour segmentation to extract node locations. This makes it very prone to light conditions when the images are taken and is very likely to be affected by other contents within the image. However, using object detection to detect nodes could avoid these disadvantages.

As of applying the findings in this research to actual construction, future exploration should also include how an integrated workflow can be setup from establishing a digital material database to design and subsequent material allocation. Due to the dynamic nature of bending-active structure construction, real-time feedback of the construction with technologies such as augmented reality should also be considered.

5. Conclusion

This research is a primary study of utilising machine learning techniques to predict natural material behaviours which are difficult to simulate with conventional architectural design software. A dataset of bamboo node distribution patterns and bending curves is created, based on which a tool for users to search bamboo strips that can better deformed into the desired shape is developed via multi-task learning method. It achieves a very promising accuracy when applied to the range similar to the current dataset. However, it needs to be further developed to suit a wider range of applications.

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