Vascular Morphogenesis Controller: A Generative Model For Developing Morphology of Artificial Structures

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ABSTRACT

Morphology of an artificial structure can be designed beforehand or it can be developed over time via interactions between different parts of the structure. Since structures are supposed to sustain and act in their surrounding environments, a successful generative process needs to consider both the global and local effects of environment during morphogenesis. As in their biological counterparts, many morphogenesis models are distributed over the growing structure. In this paper, a novel distributed model, called Vascular Morphogenesis Controller (VMC), is introduced by being inspired from branching mechanisms in plants where every branch of a plant acts as an autonomous agent competing with the other agents for a larger share of the resources for growth. To the best of our knowledge, this is the first explicit use of distribution of limited resources in morphogenesis process of artificial structures. The model is implemented for growing a simulated modular robot that is designed based on a physical robot. The parameters of model are successfully evolved to direct the growth of robots in different environmental condition, i.e., in harsh and calm environments, in various light conditions, and in a layered environment. The results demonstrate usability of the model despite simplicity of its logic.

KEYWORDS

Generative models, developmental models, morphogenesis, modular robots, swarm systems, evolutionary computation

1 INTRODUCTION

Growth is a ubiquitous phenomenon in nature. Living organisms grow and develop their morphologies based on their genetic information, conditions of their environment, and the rules of physics

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and chemistry governing the dynamics of their world [12]. Morphology of biological systems develops over time in a process of growth changing their body and nervous system. In biological studies, evolutionary developmental biology (EvoDevo) [16, 28] is the approach towards investigation of self-organized processes of growth by looking into embryogenetic development and differentiation of cells. Growth and morphogenesis is also a topic of interest in artificial and robotic systems, i.e., in evolutionary robotics [2] and modular robotics [19]. In such artificial systems, as in their natural counterparts, patterns and structures are a result of self-organization. The different components interact with each other and with the environment leading to high diversity and adaptivity [4, 12, 31]. Self-organizing morphogenesis is usually implemented by using indirect encodings where the encoded parameters are subject to evolutionary algorithms for optimization. The body of the robot or the controller structure develop over time based on a set of parameters encoded in the genotype, a set of rules determining how those parameters drive the development, and the inputs to the system resulting from the interactions between the system and its environment (e.g., [8, 22, 29]).

While most of the work in robotic morphogenesis is done in simulation, a number of attempts exist towards real physical hardware [3, 10]. Many morphogenesis approaches are strongly inspired from the concepts of real cell development, for example by implementing variants of gene regulatory networks and the concepts of cell division and migration [1, 5]. Other methods (e.g., [14, 22]) use the more abstract generative encodings, such as different variances of L-systems [18]. Generative encodings start with a basic unit (a seed) and a set of context-free developmental rules driving the development of morphology. In [26] the L-system is extended by adding a swarm of interacting agents and a swarm grammar defining their dynamics. Another swarm-based morphogenesis model is the embryomorphic model [6] that implements the concepts of gradient diffusion for positional information, gene regulatory networks for transformation of cell types, and cell division. The model draws a separation between the physical level and the information level of the growing system in order to keep the generality. In [17] a morphogenesis system based on Cellular Automata (CA) is defined with different types of cells including transport, barrier, and normal cells where the transport cells stay connected with each other to serve the normal cells during growth. Several different morphogenesis approaches are reviewed in [7]. The morphogenesis methods of structure development have also been applied to the field of computer networks. For example, in [23], a self-organized peer-to-peer overlay network develops in a computer network by using an

algorithm inspired from fungal growth that maintains communication between nodes and demonstrates robustness against network failures.

In the context of the EU-funded project *flora robotica* [9, 13], structures are developed to act as a robotic part of a bio-hybrid system consisting of plants and robots [27]. The bio-hybrid self-organizes into architectural artefacts that support their own growth and resource balancing. The plant side of the bio-hybrid grows and influences the robotic structure. In turn, the structure develops into different shapes and influences the growth of the plant side in a dynamic environment in interaction with humans.

In this paper, we are interested in the growth of robotic structures in a distributed and balanced way. Here, a robotic structure is a modular robot where new modules can be added on demand in the process of growth. A distributed morphogenesis control algorithm runs independently in every module of the robot. The local controllers self-organize the process of growth based on local interactions with each other and with their environment, deciding how the growth should continue such that the global objectives are met.

Our morphogenesis approach for robotic structures is based on inspiration from the mechanisms of branching and branch competition in plants. Various branches of the same plant act as agents exploring their local environments and finding preferable regions and resources (i.e., light). Plants grow and extend their branches and develop new ones. Different branches compete for common global resources (i.e. water) and winning is biased towards the branches that find better local resources (i.e., light) [11]. The information collected by the branches are used to find preferable regions of the environment leading to new shapes of the organism that facilitates access to more resources in a cascading way. In a more abstract view, branches are seen as members of a swarm competing for limited shared resources and it leads to new formations of the swarm that result in more overall resources for the system as a whole. Water, nutrients, and sugars are transported to different parts of a plant through the plant's vascular system. Evidence suggests that the vascular system not only transports materials needed for survival of the plant, but it is also a long-range communication channel that enables the plant to adapt to changes [20].

There are several biological models of plants, e.g., modelling transportation of materials via vascular systems incorporated in growth models [32]. While the models developed in the field of plant science are mostly complex, focusing on details of particular plants, here we are interested in a simple decentralized model that captures the general concepts of growth such that it can be easily implemented in a limited robotic system. A preliminary version of the current work has been shortly introduced in [30]. In this work, we are inspired from development of vascular systems in plants and their effects in the growth of different competing branches in an abstract level. We propose a novel controller called "Vascular Morphogenesis Controller (VMC)" for guiding the morphology of structures based on competition and resource balancing. The method differentiates between the information level (algorithmic logics of growth) and physical level (actual structure) in order to keep generality and broad scope of usability for the morphogenesis algorithm. The actual morphology of a structure being developed by this method is the result of parameters of the algorithm, and

the resource sharing and competition mechanisms, as well as the physical realization of the system, and their interactions with the environment on both informational and physical levels leading to diverse possibilities of dynamic forms.

The main contribution of the paper is to introduce VMC as a novel distributed generative model for self-organized growth of structures and evolution of its parameters in a set of example implementations. For the physical realization of a system growing by VMC, we have used a growing simulated modular robotic structure based on a physical modular robot. The structure is subject to physical forces such as gravity, elasticity, and environmental disturbances. The parameters of the VMC controllers are evolved for different objectives and the effects of various parameters of the algorithm are investigated based on the evolved controllers.

2 PLANTS: COMPETITION FOR VESSELS

Vascular strands transport water and minerals from roots, and sugars produced at the leaves to all over a plant. The vascular structure of a plant is dynamic as the vessels in different branches are reinforced or degenerated over time based on their status. Research in plant physiology [21, 24] suggests that different branches of a plant compete for more vessels. For example, experiments [21] with two-shoot pea seedlings, demonstrate that casting shadow on previously equally-placed shoots, e.g., with equal access to light, causes the decrease and finally stopping of the shaded shoot while the other shoot grows faster and becomes dominant (see Fig. 1). This dominance can be reversed by restraining the dominant shoot that is located in light.

A hormone called auxin is produced at the tips of plants and flows via plant vessels towards the roots. Auxin production is influenced by local conditions at the tips (e.g., light access). One effect of auxin is to make the bundles of unspecialized stem cells, called cambium cells, which are located near the vascular tissues to transform into vessels. This is especially interesting considering the fact that limited common resources (e.g., water) need to be distributed between different branches of a plant via their vessels. More flow of auxin at a branch leads to more vessels, and thus more transportation of the common resources to the branch. More resource means more growth and perhaps positioning of the branch's tip at even better locations making a positive feedback loop. On the other hand, as common resources are limited for a plant, the distribution of limited resource between all branches creates a negative feedback pushing towards homeostasis of the plant.

3 THE ALGORITHM: VASCULAR MORPHOGENESIS CONTROLLER

By taking inspiration from the competition between branches of a plant for more vessels and consequently more resources, the Vascular Morphogenesis Controller (VMC) algorithm is designed. The idea is to let the growable parts of a structure compete for a common resource of growth via a network of pathways that are dynamic based on interactions and local conditions of the branches. For that, VMC is defined as an acyclic directed graph (tree) that is distributed over the physical growing structure (see Fig. 2). Initially, the graph consists of a root node and a number of potentially growable nodes attached to the root making the initial leaves of the
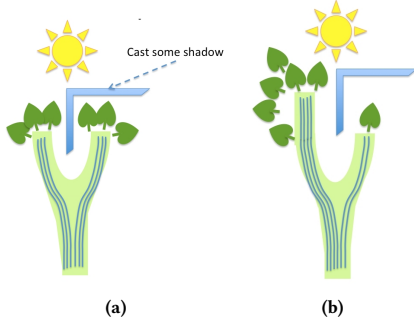
Figure 1: If one of the two equal branches (a) is in a comparatively preferable environmental conditions (e.g., gets more light), it develops more vascular tissues and grows more vigorously (b).

graph. Growth can only happen at the leaves of the graph. Each leaf assesses local conditions and accordingly produces a value, namely Successin (S) in analogy to auxin in plants. The Successin produced at the leaves flows back to the root and on its way, it regulates the vascular pathways of resource (V) - in analogy to plant vessels. The pathways are then used to distribute a limited resource (R) between the leaves. The limited resource is initiated at the root and flows towards the leaves being split at every branching point according to the thickness of the vascular pathways. The leaves that gain more share of the resource are more motivated to grow. When a leaf grows, new leaves are generated as its children, and hence the old leaf turns into an internal node of the graph.

A VMC includes a set of parameters that influence its dynamics. At the leaves, a set of parameters along with the sensor values determine the rate of Successin production. The amount of Successins can be altered in their way from the leaves to the root, based on a set of parameters and the sensor values at the internal nodes. The regulation of the vascular pathways at the nodes is based on the value of Successin passing the node as well as a set of parameters. The parameters of the algorithm are identical for all the nodes and can be subject to optimization (e.g., evolutionary algorithms as in here) in respect to given objectives for the growing structure.

Every node of VMC runs independently and updates its state variables in parallel to other nodes. The dynamics of the variables, i.e., the production of Successin at the leaves and the Successin flow at the internal nodes, the thickness regulation of the vascular pathways, and the distribution of the common limited resource are summarized in Fig. 3.

Successin S_i is produced at a leaf i based on the local sensor values and parameters of the algorithm as follows:

$$S_i := \omega_{const} + \sum_{s \in sensors} \omega_s \cdot I_s \qquad (1)$$

where ω_{const} is a parameter representing the production rate of Successin at the leaf independent of the sensor inputs. I_s is the input from sensor s and ω_s is a parameter determining the weight associated with the input s.

The Successin flows towards the root. The value of S at the internal node i is updated based on the sum of the Successin values arriving from all the children of the node, local sensors, and constant parameters:

$$S_i := g(\rho_{const} + \sum_{s \in sensors} \rho_s \cdot I_s) \cdot \sum_{b \in branches} S_b \qquad (2)$$

where in the current implementation $g(x)$ is a sigmoid function mapping the input to the range of $(0, 1)$. The ρ_{const} and ρ_s are transfer rates influencing the rate of reduction in the Successin flow passing a node. ρ_{const} is an independent rate and ρ_s is the rate associated with a sensor input s. The values of the parameters in this equation contribute to the effect of the distance from the root to the share of the resource reaching the leaves (recall that the values of S passing the nodes adjust the thickness of vessels (V) and consequently influence the distribution of the limited resource between the leaves).

The following equation represents how a vascular pathway V_i is adjusted every time step based on the current value of the Successin passing through it:

$$V_i := \begin{cases} min(S_i, (1-c) \cdot V_i + \beta + \alpha \cdot (S_i - V_i)) & \text{if } S_i \geq V_i \\ max(S_i, (1-c) \cdot V_i) & \text{if } S_i < V_i \end{cases} \qquad (3)$$

where c is a constant decay rate of the vessels, β is the constant addition rate, and α is the factor of adjustment. The equation states that if the current value of S_i is more than the V_i, V_i is likely to increase (depending on the values of the parameters c, β, and α) up to the value of S_i. Otherwise, V_i decreases by a constant decay rate down to the value of S_i. Note that the parameter values in this equation influence the competition between branches by changing the significance of difference in S of different branches.

Finally, the limited common resource initiates at the root node and flows towards the leaves. The value is constant at the root. The resource reaching a node m (R_m) is simply divided between its children based on the current value of their vessels:

$$R_i := R_m \cdot \frac{V_i}{\sum_{b \in children} V_b} \qquad (4)$$

where R_i is the resource value at the child i of the node m, and *children* is the set of all children of the node (See Fig. 3 for a summary).

4 A MODULAR ROBOTIC IMPLEMENTATION OF VMC

As mentioned in the previous section, growth happens at the leaves of the VMC graph. When a leaf grows, it turns into an internal node with new leaves attached to it as its children. The new leaves then compete for the resource with all the other leaves in the VMC in order to get their chance to grow. In a physical system, for example, in a growable modular robot that is controlled by VMC, a leaf node is associated with every extension point of every module where new modules can potentially be added. When a particular leaf is supposed to grow, a new module is attached to the extension point associated with that leaf. The new module brings its own extension points and hence new leaves are added to the graph as the children of the previous leaf that now has become an internal node. The number of the new leaves is a feature of the modules. For example, in a homogenous modular robot with two extension points, adding a new module to the structure means adding two
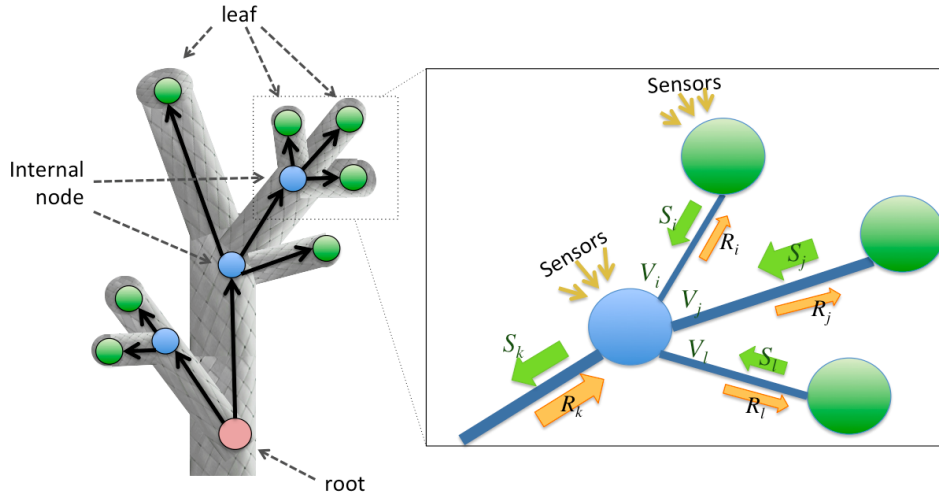
Figure 2: A VMC as a whole is an acyclic directed graph that is distributed on the physical growing structure. The leaves of the graph are the potential places for growth. The leaves produce Successin (S) that flows back towards the root and on its way regulates the thickness of the vessels (V). The vessels are pathways that transport the limited resource (R) from the root to the leaves. The more a leaf gets the resource, the more it is motivated to grow. Sensors and constant parameters of the algorithm contribute to the production and flow of the Ss and regulation of the Vs at every node.

a) Updating Successin (S)

GENERATED AT A TIP:

$$S_{tip} := w_{const} + \sum_{s \in sensors} w_s \cdot I_s$$

MODIFIED AT A JUNCTION:

$$S_{junction} := g(\rho_{const} + \sum_{s \in sensors} \rho_s \cdot I_s) \cdot \sum_{b \in branches} S_b$$

b) Updating vessels (V)

$$if\,(S_i > V_i)$$
$$V_i := \min(S_i, (1-c) \cdot V_i + \beta + \alpha.(S_i - V_i))$$
$$else \quad V_i := \max(S_i, (1-c) \cdot V_i)$$

c) Distributing resource (R)

$$R_{branch} := R_{main} \frac{V_{branch}}{\sum_{b \in branches} V_b}$$

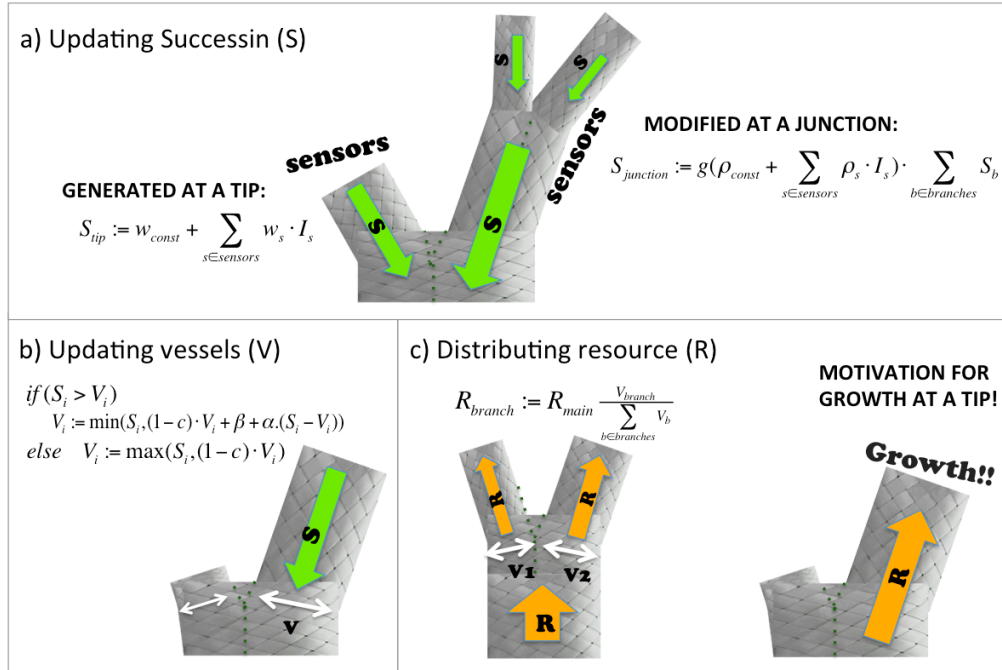**MOTIVATION FOR GROWTH AT A TIP!**

Growth!!

Figure 3: Dynamics of Successin flows, vessel thickness, and resource flows.

more leaves (each associated to one of the extension points) to the graph as the children of a previous leaf.

Here we are interested to use VMC to drive the morphology of a growing structure in presence of some physical effects such as gravity and elasticity. For that, we have built a simple modular robot where extending its morphology is possible during run time.

Unlike a biological organism, our modular robot cannot grow autonomously and the growth process is sequential (one module at a time). The growth is achieved by the help of a human operator who follows the suggestions of the distributed controller running on the modules of the structure.

4.1 Design of the Modular Robot

The designed modular robot is built based on a small mobile robot called Thymio [15] that is available off-the-shelf (Fig. 4a). We have connected several Thymios to each other to build the single modules of our modular robot (Fig. 5). The Thymios are connected in a way that their local communication is still possible. The built modules are to some extent flexible and elastic due to the usage of rubber bands and zip-ties for keeping together the rigid parts of the modules which are basically the Thymios (please see the attached video for an impression of the physical modules[1]). Two types of modules are built: non-branching and branching modules. Fig. 5 represents a module of each type both in physical and in simulated versions. The elasticity of the modules and their bent shapes makes the structure building more challenging and closer to real world. Fig. 4b shows an example structure built out of non-branching modules growing against gravity. In a branching module, the two upper Thymios can communicate with the bottom robot (and vice versa) via Infra-Red (IR) sensors. Each Thymio robot contains an accelerometer that is used for sensing the orientation of the module against the vector of gravity.

In this work, we have mainly used the branching modules in simulation. A simplified physics-based 2-dimensional simulation is designed based on the physical robot and considers gravity and elasticity of the modules due to the use of rubber bands. It allows the modules to bend to some extent and the structure is prone to collapse when the center of gravity is sufficiently far from the base. The local communication between the modules is constrained in the simulation in order to emulate the constraints in the physical robot. The simulation is developed in the Processing framework[2] with Box2D physics engine[3].
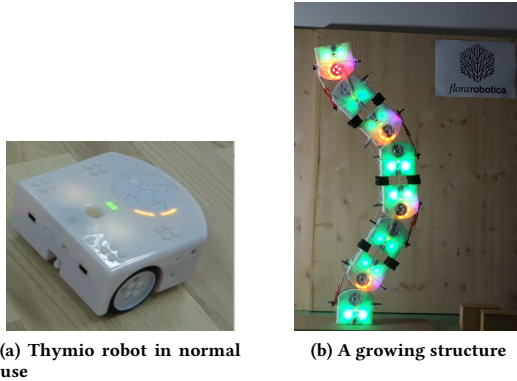

(a) Thymio robot in normal use

(b) A growing structure

Figure 4: A Thymio robot and an example of a growing structure made out of non-branching modules

4.2 Implementation of VMC in the Robot

The growth of the robot starts from a base module that is a non-branching module fixed to the ground making a tilted flexible starting point for the growing structure. All the other modules of the

[1]https://youtu.be/tAj_uHk9oNg
[2]https://processing.org
[3]http://box2d.org/

(a) A simulated and a physical non-branching module

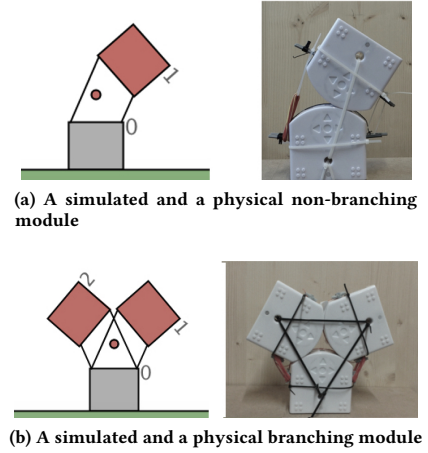(b) A simulated and a physical branching module

Figure 5: Single modules

robot are branching modules. Growth in this structure means attaching a new branching module to a potential extension point. Every branching module has two extension points (two Thymios on the upper part of the module) and a point of attachment (Thymio on the bottom).

As the base is non-branching, the VMC of this structure initially contains a root and its single child (a leaf). The root constantly produces a fixed resource value of 1 unit that is distributed between the leaves via the connections. At every time step, the modules that contain the leaves show to human operator, an indication of their share of resource. The human attaches a new module to the leaf that indicates the highest resource. In simulation, the process of adding a new module is done automatically and regularly at every 150 time steps.

The accelerometers at the leaves are used to perceive the vector of gravity relative to the nodes. The magnitude of this vector is used as the local sensor input at the leaves and is available for influencing the production of Successin. In addition to the vector of gravity, the modules can perceive the light intensity. No sensors are used to perceive the presence of obstacles (e.g., other modules or the ground) by the modules. Hence, the VMC leaves are not aware of the presence of other leaves or the ground even if they are facing them. If the robot intends to grow at a leaf and fails due to the presence of obstacles, the failing leaf goes to a non-growable mode and will not produce Successin anymore for the rest of the experiment.

4.3 Evolving the parameters

VMC is implemented here to grow a modular robot in different setups and objectives. To evolve the VMC parameters for each setup, a genetic algorithm is used. The population size of the genetic algorithm in all the experiments is 20 and the populations are evolved for 24 generations. The experiments are repeated for 20 independent runs in every setup. Elitism of one genome and a crossover rate of 20% is implemented. All the genomes (except the elite) are mutated with a *stepsize* $\sim \mathcal{N}(0, 0.2)$. A genome is a set of VMC parameters. The length of the genome depends on the

number of the sensor types used for the VMC in every particular setup. By using the light sensor in both leaves and the internal nodes, and using the accelerometer of the modules (for sensing the angle of gravity) at the leaves, the genome would look like: $(\omega_{const}, \omega_{acc}, \omega_{light}, \rho_{const}, \rho_{light}, c, \alpha, \beta)$ (see Section 3 for the description of the parameters). The genomes are randomly initialized between $[-1, 1)$ for the sensor-related parameters and between $[0, 1)$ for the others.

For evaluating the fitness, each genome is used to parameterize VMC to grow a structure in a given setup. At the end of a run, the structure is evaluated based on the given objective function according to the setup. Since the setups are noisy due to the physics and the additional randomly imposed force to the structures in some of the experiments, each genome is evaluated in three independent runs and the fitness is the minimum of the three evaluations.

5 EXPERIMENTS: GROWING IN DIFFERENT CONDITIONS

In the first set of experiments, VMC is used to grow a robot with 10 modules to become as tall as possible against gravity. An impulse force is imposed to the base module randomly from the left or the right side of the module. Considering the flexibility of the modules and the effect of gravity, the structures might collapse during the growth ending up to (even long) structures which are fallen onto the ground and therefore are not considered tall against gravity, thus not meeting the objective of experiment. We evolved the system in two different setups: a low impulse force and a high impulse force. The strength of impulse in the latter setup is three times as large as in the former setup and thus the structures in the latter setup are more prone to collapse. In this experiment, the accelerometer sensors at the leaves are used. The fitness is computed as the height of the highest module of the robot at the end of the experiment. Fig. 6a and 6b show the structures developed by the best genomes evolved in each setup (see a video here: https://youtu.be/xBEIwFixtJs). As shown in the figure, the morphologies are different in each setup. To investigate the difference, we developed two robots each in one of the two environments and positioned them both in the harsher environment (high impulse setup) for a while without any further growth. The result was the collapse of the robot developed in the calmer setup, while the robot from the harsher setup stayed upright until the end of the experiment, showing a higher stability. Fig. 7a and 7b show the fitness trajectory of the best genomes accumulated from all 20 evolutionary runs.

In the second experiment, we evolved VMC for growing a bushy robot. For that, the fitness is computed as the number of modules with no children (i.e., both extension points of the module are free). Fig. 6c shows the resulted morphology in this setup. The grey leaf in the figure indicates that the robot has tried to grow at that leaf but it has failed due to the collision with ground. Finding the VMC parameters for this setup seems to be easy for evolution (many possible solutions) such that the solution is found already in the first couple of generations (not shown).

In order to get a better understanding of the effect of each of the VMC parameters in the final morphology of the robot, the parameter sets with the highest fitness in the three above setups are collected

from the several runs and represented in Fig. 8. The value range of parameter α (adjustment factor of V), and parameter c (decay rate of V) are narrow for all the setups. The highest variation between different setups can be seen in the values of ω_s and ω_{const} that deal with production of S at the leaves (respectively, regarding and regardless of the sensor inputs), and also ρ which is related to the transfer rate of S from a node to its parent. The ω_{const} for a bushy morphology is narrow and close to zero, and ω_s for the same morphology is always negative leading to no production of flow at the leaves. The range of the parameter ω_{const} is broad for both of the tall morphologies. The value of the parameter ρ is very close to 1 for the tall morphology in the low impulse environment, meaning that (almost) all of the S is transferred from each node to its parent which implicitly increases the effect of the S generated at the leaves.

Based on the evolved parameters in the previous experiments and our gained understanding of the effects of different parameters, we manually parameterized the VMC for a special setup. In this setup, in addition to the accelerometer and light sensors at the leaves, the light sensors are also used at the junctions. The aim here is to use the same set of parameters in environments with different light conditions and the robot is supposed to grow bushy in high intensity of light, and to grow tall in low intensity of light (shadow). For that, we set a ρ_{light} to a negative value such that the high intensity of light reduces the transfer rate of S between the modules, thus more bushy structures emerge in light. On the other hand, we set the ω_{light} higher than ω_{acc} such that the S production is more sensitive to light than to the angle of gravity. Thus, the parts of the structure that are placed in light are more likely to grow than the parts in shadow. The parameters are chosen as follows: ($\omega_{const} = 0.01, \omega_{acc} = 0.6, \omega_{light} = 1, \rho_{const} = 0.9, \rho_{light} = -0.5, \alpha = 1, c = 0.25, \beta = 0.2$). Fig. 6d shows the result of growing a robot controlled by the same parameters in light, shadow, and half-shadow environments.

In the final experiment, we evolved VMC parameters with the aim of growing a robot in a layered environment such that the structure gets the highest levels of light. The environment consists of several obstacles in different layers. The highest layer has the maximum intensity of light (say 1 unit). With every layer down, and below every obstacle, the light intensity decreases by 0.1 units. The intensity of light is constant all over each block and the nodes are only capable of sensing the local light (not direction). Fig. 6e shows the environment and the robot developed by the best evolved VMC in this environment (see a video here: https://youtu.be/dSkjohr5Nqs). The leaves use both the accelerometer and the light sensors. In order to evaluate the fitness, the robot is developed up to 80 modules and the fitness is computed as the total sum of the light intensity sensed by all the nodes. Fig. 7c shows the fitness trajectory of the best genomes accumulated from all the runs.

6 CONCLUSION

In this paper a novel distributed morphogenesis controller, called Vascular Morphogenesis Controller (VMC), is proposed. The controller is inspired from the vessel dynamics and branch competition in plants and is used for driving the morphology of artificial structures. The algorithm is successfully implemented in a growing

(a) growing tall in a calm environment

(b) growing tall in a harsh environment

(c) growing bushy

(d) identical parameter set grows the structure differently in different light setups

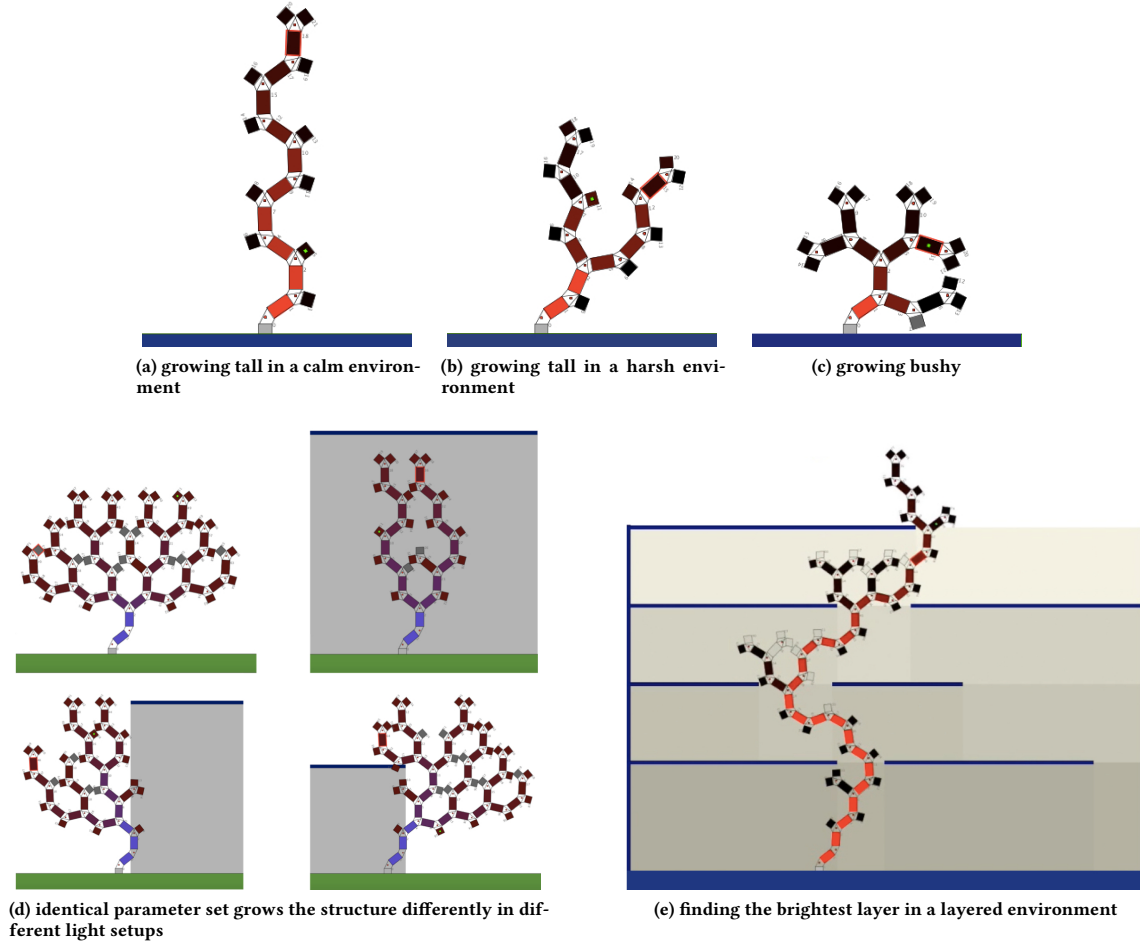(e) finding the brightest layer in a layered environment

Figure 6: Growing the structure in different setups. The gradients of red/violet to black indicate the resource passing modules.

modular robot in different setups and the evolved parameters are investigated regarding the effects of each parameter on the morphology of developed structures.

The VMC works based on the distribution of a limited common resource between competing growable parts of a developing structure. The morphology of the structure is guided by the negative and positive feedback loops in the dynamic system determining the amount of resource that reaches every growable part. In turn, the feedback loops change due to the changes in morphology yielding a morphogenetic cascade of growth. The concept of dissipating quantities through a system, that is utilized in VMC, is comparatively similar to Turing's reaction-diffusion models [25, 31] since both models use (more or less) conserved quantities. Yet, the dissipation in reaction-diffusion models is isotropic while it is vascular in VMC and the vessels are dynamic. This allows for more complex structuring within the system and higher adaptivity in response to sensory inputs and externally imposed changes to physical body.

The VMC does not make assumptions about the physical host where the actual development of the morphology occurs. This separation between the information and physical levels makes the controller usable for various types of systems. For example, it can be implemented in heterogeneous modular robots, loosely connected structures, or even swarms of autonomous robots. In the future, VMC can be extended for using several roots providing the growth resource, spatially heterogeneous parametrization of the controller and online adaptation of parameters in the structure.

7 ACKNOWLEDGMENTS

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(a) Growing tall against gravity in a calm environment

(b) Growing tall against gravity in a harsh environment
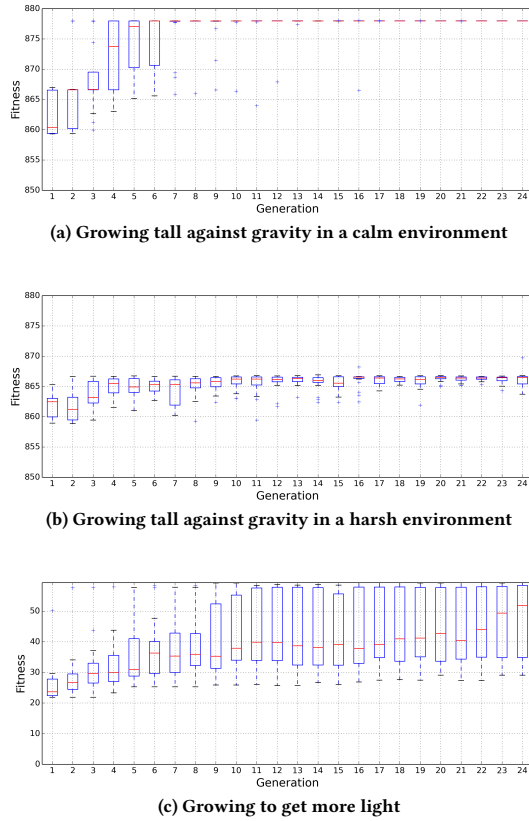

(c) Growing to get more light

Figure 7: Fitness trajectory of the best genomes over generations collected from all the independent runs. Box-plots indicate medians and quartiles, + signs indicate outliers.
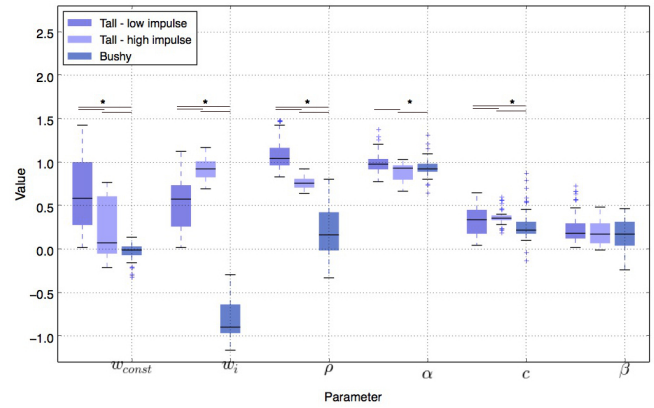

Figure 8: Comparison of parameter values of controllers evolved for growing tall in low and high impulse setups, and growing bushy. The parameters are collected from the best controllers of the runs. The horizontal lines with the asterisks indicate statistically significant differences (Mann-Whitney U test, $p < 0.05$)

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