

PhysOM: *Physarum polycephalum* Oriented Microstructures

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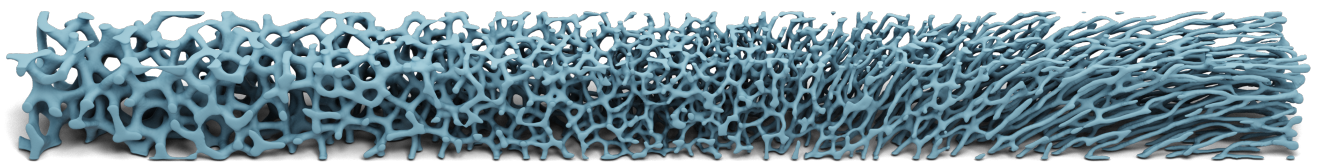


Figure 1: Our parameterized 3D anisotropic *Physarum polycephalum* model is able to generate foam-like cells and filaments ranging from coarse to dense cells (left side), to varying orientation and elongation magnitude (right side).

Abstract

Biological shapes possess fascinating properties and behaviors that are the result of emergent mechanisms: they can evolve over time, dynamically adapt to changes in their environment, while also exhibiting interesting mechanical properties and aesthetic appeal. In this work, we bring and extend an existing biological-inspired model of the *Physarum polycephalum*, aka the blob, to the field of computer graphics, in order to design porous organic-like microstructures that resemble natural foam-like cells or filament-like patterns with variable local properties. In contrast to approaches based on static global optimization that provides only limited expressivity over the result, our method allows precise control over the local orientation of 3D patterns, relative cell extension, and precise infill of shapes with well defined boundaries. To this end, we extend the classical agent-based model for *Physarum* to fill an arbitrary domain with local anisotropic behavior. We further provide a detailed analysis of the model parameters, contributing to the understanding of the system behavior. The method is fast, parallelizable and scalable to large volumes, and compatible with user interaction, allowing a designer to guide the structure, erase parts, and observe its evolution in real-time. Overall, our method provides a versatile and efficient means of generating intricate organic microstructures that have potential applications in fields such as additive manufacturing, design, or biological representation and engineering.

CCS Concepts

• Computing methodologies → Shape modeling;

1. Introduction

Microstructure-made synthetic materials, which refer to small-scale structures filling the interior domain of a larger shape, have become increasingly popular in shape design. These materials offer desirable mechanical properties, including local stiffness, lightness, and porosity [WWG21], that can be tailored by varying the type of infill patterns. Furthermore, these microstructures exhibit visually compelling appearances, mimicking complex organic materials that may interest art-based design [MSDL17]. In this work, we focus on microstructure exhibiting foam-looking patterns made of oriented foam-like cells, or long filament organizations (see Fig. 1) and relate their parameters to mechanical and visually appealing characteristics.

In recent years, the study of complex shapes filled with mi-

crostructures has gained significant attention due to the efficiency of additive manufacturing to build them, in particular along the so-called topological optimization methods. However, designing these materials still presents several challenges. Firstly, creating intricate and delicate micro-structures that occupy relatively large volumes can result in laborious modeling, massive data structures, and prohibitively high computational costs associated with global optimization. Secondly, microstructure shapes can be highly diverse, which adds significant complexity to the design process and requires meticulous tailoring and parameterization for each object to achieve the expected behavior and appearance.

Through this work, we wish to highlight the power of adapted bioinspired morphogenesis approach to tackle such challenges. Indeed, real biological systems have evolved to optimize their struc-

tures and functions through a variety of mechanisms, including self-assembly, growth, and adaptation. Morphogenesis models inspired by biological systems typically rely on local rules from which global characteristics emerge from an iterative process, possibly representing time evolution. A key interest of such a local and time-evolving process relies upon its inherent adaptation to local conditions and its ability to generate organic-like microstructures that follow a general pattern while exhibiting irregular local variations. One may note that disordered porous structures found in nature are neither fully random nor perfectly ordered. Interestingly this structural disorder in organic architected cellular materials has been found to be beneficial for their damage tolerance [vEYC*21]. These remarks led to our main motivation for exploring biological-inspired microstructure generation. Instead of aiming at a globally optimized shape model that would be hard to control, we rather target locally adaptable behaviors that can give rise to a global emerging structure, which remains controllable by the end user at any time of the evolution, and provide a visual appealing organic-looking disorder that enhances strength.

In this work, we show that the biological system designated as *Physarum polycephalum*, also known as *the blob* [How31] can be adapted to model our target microstructure for 3D shapes in a controllable way. This slime mold is a unicellular organism that has gained attention in recent years as it has been found to exhibit remarkable capabilities for optimizing transport networks, and adapting to changing environments. The *Physarum polycephalum* can be represented by an agent-based models [Jon09] simulating various aspects of the organism behavior including its growth, foraging, and decision-making processes. Existing simulations of this model already showed the natural emergence of global structures in 2D [Jon10] and in 3D [Jon15, EBPf20a, EBPf22] but were never explored for oriented microstructures generation. We describe several adaptations and/or simplifications to the existing models to extend it to oriented organic-foam-looking emerging microstructure, and provide insights into the choice of the model and simulation parameters to converge toward the expected shape characteristics effectively. Our technical contributions are twofolds. First, we extend the existing agent-based *physarum* models toward anisotropic emerging infilled-pattern generation, and describe its efficient implementation. Second, we provide a comprehensive study on the effect of the parameters in such an anisotropic context with a specific focus on providing explicit control over the averaged size and elongation of microstructure cells. We demonstrate the applicability of our approach to various shape-design applications such as mechanical design and biology. Overall, we hope that such an approach simulating the emergence of natural forms will help and inspire designers from various domains in their process of creating more complex and organic-looking shapes.

The rest of the article is organized as follows. We start with a review of the related work (Sect. 2) and background on the particle-based model of the *Physarum* (Sect. 3). Section 4 presents an overview of our generative method, followed by our technical contributions for 3D oriented emerging patterns (Sect. 5) and parameter analysis (Sect. 6). We then present our results (Sect. 7) before concluding.

2. Related Work

In Section 2.1, we delve into the topic of microstructure infill for material design, as our method is closely tied to this field, particularly in terms of efficient fabrication using Additive Manufacturing. Furthermore, in Section 2.2, we address Bio-inspired Modeling and specifically focus on the *Physarum polycephalum* as a compelling model for our intended purpose.

2.1. Microstructures and shape infill for AM

The importance of internal fill patterns in additive manufacturing has a long research history in mechanical engineering [AAD98]. By avoiding dense interior fills, both printing time and material usage can be significantly reduced. As a result, the initial infill patterns were developed with the primary goal of reducing material density while also being quick to generate and effective in production.

Topology optimization, allowing the optimization of the distribution of material within a given domain subject to a set of constraints, has been successfully used in a large range of applications as described in these reviews [BS03, WSG21]. Porous material generation [WAWS18, SPG19] can, in particular, benefit from high resolution topology optimization [AALS17], but remain computationally prohibitive. Additional flexibility in the generated pattern has been proposed by the use of post-process applied on top of topology optimization result, such as the use of procedural functions [PT08, AGDP19], or reaction-diffusion [GSR22].

Periodic structures, originally proposed by Sigmund [Sig95], have also been widely explored to generate complex structures featuring, for instance, targeted rigidity [ZSCM17], deformation [TTZ*20], or balance [WWZW16]. Gradation of microstructure design can be achieved via the use of different tiles [PZM*15, GKW*19], or regularized deformation [GDAP20]. Although periodic microstructures are highly efficient, they depend on underlying regular grids, which make them challenging to apply to microstructure with spatially varying orientation and curved boundaries. Moreover, graded or oriented periodic microstructures seldom produce patterns with smooth connectivity at the interface between neighboring cells. This connectivity must thus be enforced by introducing additional geometrical constraints onto the generated patterns.

Close to our approach, stochastic processes provide design flexibility and progressive gradation since they are not restricted by a grid or subdivision rule. They have been recently used for foam-like microstructures [MDL16], and extended toward anisotropic [MSDL17] shapes, polyhedral cells [MHSL18], or lamellar structures [KTZK20]. Compared to fully periodic microstructures, the lack of a perfectly symmetric structure of stochastic process has been reported to exhibit greater resistance to fabrication imperfections [PVK*20, vEYC*21]. While 2D Voronoi cells [LS03, LCL*21] can relate to *physarum* cell look, the direct use of 3D Voronoi cells results in surfaces, generating membranes instead of filaments as observed in our case. Voronoi cell edges have been employed for foam modeling in previous works by Martinez et al. [MDL16, MSDL17], but we emphasize that these ap-

proaches exhibit polygonal structures with straight edges, lacking the organic, curved shapes that our method generates natively.

Our approach can be described as a stochastic morphogenetic process and relies on the local emergence of non-periodic microstructures spatially graded by orientation and density fields. Compared to other stochastic approaches, it has the advantage of relying only on local computation, thus avoiding computationally expensive global optimization steps. In addition, the underlying emerging process allows for generating flexible patterns that align well with curved boundaries and can dynamically adapt to local user modifications.

2.2. Bio-Inspired Modeling and *Physarum polycephalum*

Multi-scale structures are abundant in nature and can be observed in various plant and animal organisms [Lak93, FW07]. Despite the fact that their underlying conception processes are not always completely understood, they typically possess remarkable mechanical properties. This has recently given rise to a new field known as "Bio-Inspired Modeling" or "Bio-Inspired Design," which is commonly employed in the context of structural design for Additive Manufacturing [DPBY*19, PMNWW19, ZWZ*20]. In contrast to mathematical optimization, *Bio-Inspired Modeling* has its origins in the field of morphogenesis and seeks to employ natural processes to create optimized designs. Due to its interdisciplinary nature, it is challenging to consider it as a singular design process. Rather, it comprises various approaches that use different representations and operate at different scales [CHK*05].

The "many-headed" slime mold, known as *Physarum polycephalum* or "blob", was initially misclassified as a fungus, but is actually a giant unicellular protist with multiple nuclei. First described by [How31], this organism has been extensively studied in various fields including cell biology, biochemistry, genetics, and more recently, physics. In recent years, it has gained interest due to its remarkable properties. Hence, despite lacking a brain, the unicellular organism is capable of decision-making and spatial memory of its environment [RLDB12, BL15]. Furthermore, akin to other self-organizing systems, the slime mold exhibits self-repairing abilities [Ada13]. A seminal experiment conducted by Japanese researcher Toshiyuki Nakagaki [NYT00] demonstrated that the slime mold can find the shortest route through a maze. Since then, many studies have investigated its maze-solving capability [NYT01, Nak01, ZZD11, NVSA17], and it has even been shown to solve the Towers of Hanoi problem [RB13]. Its ability to solve the Steiner tree problem [TNT*10] and thus to reproduce real-world infrastructure networks [TTS*10] has also been explored.

While several models have been proposed to explain the *Physarum* behavior such as mathematical equations on flux [TKN07] or Cellular Automaton [TS12], we direct our attention to a particle-based model introduced by Jeff Jones [Jon09, Jon10], described more precisely in Section 3, due to its ability to generate intricate organic-looking structures. To the best of our knowledge, only a few works extended this concept to three dimensions. Jones [Jon15] himself described a brief exploration of three-dimensional environments, followed by applications toward design

and architectures [MX17, DMM18], as well as for artistic application in the *BioArt* concepts [Sch13, Que20, Bar09, Seb23]. These approaches, however, provide only limited analysis of their model's parameters. Additionally, this early 3D variant [Jon15] relies on five samples for directional sensing (1 central, and 4 peripherals) which leads to artifacts when applied to the anisotropic case, as explained in Sect. 5.1.

The most recent extension of Jones' model in 3D, the so-called *Monte Carlo Physarum Machine (MCPM)*, tailored for reconstructing and visualizing the cosmic web [BET*20, EBPf20a, EBPf20b, EBPf22], introduces stochastic updates helping to produce highly connected networks that align with cosmological data. This probabilistic model offers an elegant and robust formalization, and contains the deterministic Jones' model (called Max-PM by the authors, and relying on 1 central and 8 peripheral sensing directions) as its limit case. As stated in [EBPf22], Max-PM yields a clean, well-defined structure, which however does not consistently cover all the input cosmological data compared to the MCPM variant. Yet in our case, the property of providing clean and well-defined structure is very well suited for shape modeling, in contrast with the parameterized fuzziness introduced by the MCPM variant. Nonetheless, we note that Ehrlich et al. [Ehr21, EHE22] have proposed an application to additive fabrication based on the MCPM model. If [Ehr21] limits the emergence of the pattern to a guiding mesh's surface, [EHE22] demonstrates the infilling of a 3D helmet, close to our volume-based pattern generation, but without the possibility to control the local orientation. We propose to build on the simple Max-PM model, with the addition of (i) rotation-invariant particles' sensor sampling for a fully 3D consistent model; (ii) a more comprehensive control over the local infill structure using anisotropic diffusion weights for precise oriented propagation behavior; (iii) associated to a pattern cells size analysis, suitable for both aesthetic application and additive manufacturing.

3. Background on *Physarum* Agent Based Model

Our methodology relies on an agent-based model of *Physarum polycephalum*, originally proposed by [Jon10] for 2D simulation. For the sake of clarity, we describe this existing model in this section.

As illustrated in Figure 2, the model represents the *Physarum* as a collection of agents $\mathcal{A} = \{a_k\}_{k \in \llbracket 1, N \rrbracket}$ that interact with a density grid $\mathcal{T}$ through a deposit/sensory behavior. Each agent a_k possesses a location p_k , a heading direction u_k , and three front sensors, each positioned at a distance r (Sensor Offset, denoted SO in the original paper) from the particle. The front sensor is oriented in the heading direction, and the positions of the left and right sensors are obtained through a rotation of $\pm\phi$ (Sensor Angle or SA) around p_k . $\mathcal{T}$ is stored as a 2D array of scalar values representing the marker (in biological contexts usually referred to as chemoattractant) emitted by the agents and is called the *trail map* as the density will evolve toward showing the trajectory trails of the agents through the simulation. By using its sensors, each agent can read the trail map $\mathcal{T}$ and adjust its movement accordingly. The simulated evolution of the model is obtained via discrete-time iterations, where both $\mathcal{A}$ and $\mathcal{T}$ are updated according to a six-step rule (see Fig. 2):

1. **Sense.** Each agent starts by reading the density in the cells of



2. **Rotate.** In case of change of direction, the heading vector of the agent is then rotated from an angle α (Rotation Angle or *RA*). Note that in general $\alpha \neq \varphi$.
3. **Move.** The agent moves along its updated heading direction of a distance h (Step Size or *SS*).
4. **Deposit.** The agent located in p_k adds a small amount of density δ in the corresponding grid square of $\mathcal{T}$.

6. **Decay.** A temporal decay is modeled by damping the diffusing values of $\mathcal{T}$ by μ (typically 0.1) : $\mathcal{T} \rightarrow (1 - \mu)\mathcal{T}$.

Jones's original paper includes a collision detection step that guarantees the presence of at most one particle within each grid square. Measures of space availability (growth of the population of agents) and overcrowding (adaptation by population reduction) are also introduced later [Jon15]. These steps are essential for faithfully emulating the behavior of *Physarum polycephalum*, yet they do not crucially affect the patterns produced and we don't implement them in our approach. Additionally, avoiding this collision detection conveniently eliminates any sequential dependence, enabling enhanced computational parallelism. In practice, starting from a random distribution of agents, the emergence of patterns is observed after about a few hundred steps and leads to a relatively stable configuration around a few hundred steps. An exhaustive study of the effect of the different parameters (r , h , α , ϕ , agents population size s , decay value μ ,...) on the pattern formation can be found in the founding paper [Jon10]. According to Jones, the transition from 2D to 3D sensors can be conceptualized as a shift from a flat anchor shape to a three-dimensional "grappling hook" shapes with four hooks. In our work, we expand upon this concept by adopting a 3D grappling hook shape with more hooks. Furthermore, we introduce the capability to confine pattern formation within a specific area and modify the diffusion equation to account for anisotropy. This modification enables the generation of oriented microstructures.

Given a set of initial parameters (Fig. 3-left), the agent-based simulation updates the set of particles $\mathcal{A} = \{a_k\} = \{p_k, u_k\}$, where p_k represents their positions and u_k denotes their heading directions. Each particle can move and deposit a small amount of material density on the trail map $\mathcal{T}$, creating a network of patterns over time (Fig. 3-middle). The final shape surface is obtained by computing an isovalue of the *trail* $\mathcal{T}$ (Fig. 3-right), typically using techniques such as marching cubes or dual contouring when a triangular mesh is required for visualization and manufacturing purposes.

In order to generate oriented microstructures that infill a guiding shape defined as a boundary surface $\mathcal{B}$, we introduce three specific input fields defined on a rectangular domain $\Omega \subset \mathbb{R}^3$, namely, an infill space field $\mathcal{I}$, a tensor field $\mathbf{D}$, and a guiding trail $\mathcal{T}^*$.

Infill Space Field $\mathcal{I}$. The scalar field $\mathcal{I}(\mathbf{x} \in \Omega)$ is used to implicitly define the space where the microstructures grow as $\mathcal{D}_{\mathcal{I}} = \{\mathbf{x} \in \Omega \mid \mathcal{I}(\mathbf{x}) > 0\}$. In practice, we consider $\mathcal{I}$ to be a simple binary field (1 inside and 0 outside) or a signed distance function to the boundary surface.

Tensor field $\mathbf{D}$. The tensor field $\mathbf{D}(\mathbf{x} \in \Omega)$ indicates the desired local orientation and local anisotropy of the microstructures. It can be derived from specific data available to mechanical engineering such as desired stress, or from a direct user's defined orientation field. $\mathbf{D}$ is used as a diffusion tensor in the **Diffuse** step and tends to align the cell-like and filament-like patterns with its principal direction, and its parameterization will be described in Sect. 6.1.

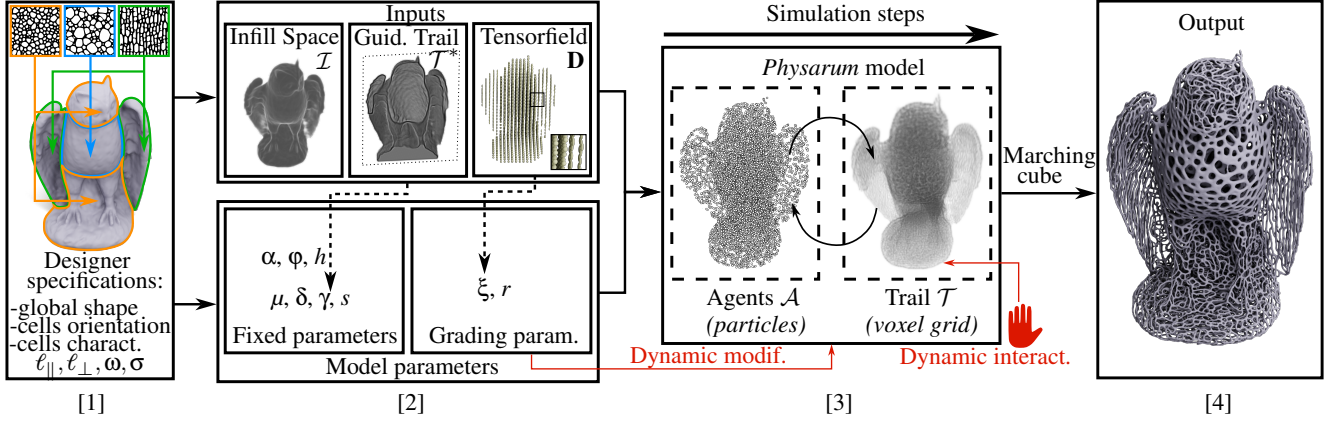


Figure 3: Overview of our approach. [1] User defined constraints: Global shape domain with cell’s local orientation and characteristics. [2] Expression of the constraints as models parameters: Infill domain ($\mathcal{I}$), anisotropic behavior ($\mathbf{D}$), and boundary conditions ($\mathcal{T}^*$), that can be associated to spatially varying parameters to generate different local pattern aspects. Other simulation parameters are fixed. [3] The physarum simulation evolves through iterations leading to the emergence of microstructure patterns on the output Trail map $\mathcal{T}$ stored in a grid structure. Interactive modifications from the user can be applied at any time, either via the change of the model parameters, or on the evolving Trail map. [4] A final mesh surface representing a porous structure can be extracted from the trail map using marching cube. Grid size for the Trail map $\mathcal{T}$: $370 \times 306 \times 534$.

Guiding Trail $\mathcal{T}^*$. The scalar field $\mathcal{T}^*(\mathbf{x}) \in [0, 1]$ is used to enforce the pattern formation in specific areas. The *guiding trail* operates during the **Sense** step, we set the sensors to read an *effective density field*

$$\mathcal{T}^\gamma = (1 - \gamma) \mathcal{T}^0 + \gamma \mathcal{T}^*, \quad (1)$$

given as a linear interpolation between the normalized trail $\mathcal{T}^0 = \frac{\mathcal{T} - \min \mathcal{T}}{\max \mathcal{T} - \min \mathcal{T}}$ in $[0, 1]$, and $\mathcal{T}^*$. The weight γ is a fixed value chosen in $[0, 1]$ which controls the influence of $\mathcal{T}^*$. Because of their sensing behaviour, the agents are sensible to the local variations of the *trail*, which means that attractive areas of $\mathcal{T}^*$ are indicated by its gradient toward its high value. Note that unlike $\mathcal{T}$, the *guiding trail* $\mathcal{T}^*$ does not evolve during the simulation, therefore facilitating consistent pattern formation in specific areas. While we can not give a general formulation for $\mathcal{T}^*$ since it is provided by the user as input, we can define it within a specific use case. A common use of $\mathcal{T}^*$ is the creation of an outer shell of thickness ϵ encouraging pattern formation along the curved boundary. Let us call $d(\mathbf{x}, \mathcal{B})$ the closest Euclidian distance between $\mathbf{x}$ to the boundary $\mathcal{B}$, in that case $\mathcal{T}^*$ can typically be defined as a characteristic function

$$\mathcal{T}^*(\mathbf{x}) = \mathbb{1}_{\{\mathbf{x}, d(\mathbf{x}, \mathcal{B}) < \epsilon\}} \quad (2)$$

which creates a gradient of trail toward this area, illustrated Fig. 4.

While we call these three fields inputs, other parameters involved in the model (sensor values, guiding influence, decay factor, etc) can also vary spatially. We will call them *grading parameters* and

provide a guideline in Sect. 6 to set their values depending on the expected pattern appearance.

5. Efficient 3D oriented Physarum Model

We describe in the following the specific modification we apply in the Physarum model in order to efficiently simulate its emergence in a 3D spatial environment in the anisotropic case.

5.1. Spatial sensing

The first essential element for 3D Physarum growth is to extend the agents’ sensors into a 3D structure. Figure 5 showcases different possible layout for this. A natural extension consists in adding sensors associated with the rotation of the 2D basic layout around its heading direction. This leads to these n -legs grappling hook-looking shapes with 1 central sensor and n peripheral, that we call $\{1 + n\}$ layout. Fig. 5 shows that n has to be sufficiently high (typically ≥ 8) to consistently sample the circle produced with the sensors and avoid any artifacts in the anisotropic case. Increasing n beyond 10 has no real impact on the generated structures. Previous early attempts on 3D Physarum models [Jon15, MX17] (respectively $\{1 + 4\}$, $\{1 + 4 \times 2\}$ layouts Fig. 5) used only four sampling directions which leads to directional artifacts in anisotropic representations due to the lack of angular sampling. Uniform sampling on a hemisphere could also be considered, but comparing the results given by the $\{1 + 8\}$ and the Unif. $\{9\}$ layouts shows that uniform distribution does not generate better aligned and clean cells. Moreover when the number of uniformly distributed sensors increases (Unif. $\{40\}$ Fig. 5), the model changes of behavior and tend to always keep their heading direction aligned with the anisotropy direction leading to filament structures. As a result, the non-continuous sampling offset allows to form stable oriented

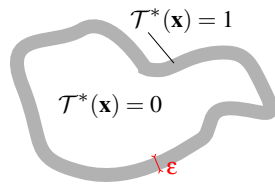


Figure 4: Typical $\mathcal{T}^*$.

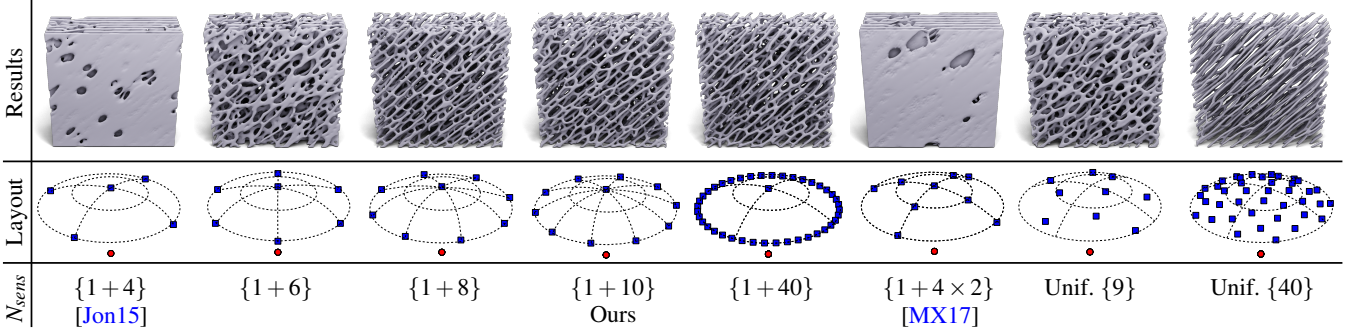


Figure 5: Resulting anisotropic structures for different 3D sensors layout, with parameters $r = 3$ and $\xi = 4$ (parameter introduced Section 6.1) generated on a $200 \times 200 \times 70$ grid. From left to right, the five first layouts $\{1+n\}$ are n -legs grappling hook-looking shape with increasing n , $n = 4$ being the layout proposed by [Jon15]. $\{1+4 \times 2\}$ layout comes from [MX17]. In the last two layouts Unif. $\{n\}$, n sensors are uniformly distributed on the hemisphere using the Fibonacci Sphere.

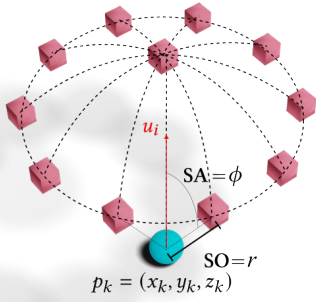


Figure 6: Agent and its sensors in 3D.

foam-cell structures, which is also why we do not rely on continuous probabilistic distribution sampling such as in [EBPF20a]. In all our examples we used the $\{1+10\}$ layout showed Figure 6.

5.2. Infill Space Restriction

To confine the pattern generation within a 3D shape described by the infill space $\mathcal{D}_{\mathcal{I}}$, we add a positional constraint after the step **Move**. In practice, we check at each frame the value of $\mathcal{I}(p_k)$ for each agent's position p_k . If $\mathcal{I}(p_k) \leq 0$, the position is outside of the shape, then we project it back along its backward heading direction $p_k - u_k \Delta t$, where Δt is the simulation time step. This yet simple approach proved to be sufficient to deal with boundaries without accumulation as the trail is diffused and is mixed with the guide $\mathcal{T}^*$ near the border $\mathcal{B}$.

5.3. Anisotropic patterns

The local pattern orientation can be controlled by the anisotropic tensor $\mathbf{D}$ given as input. In the **Diffuse** step, the trail is diffused according to the anisotropic diffusion equation

$$\frac{\partial \mathcal{T}}{\partial t} = \nabla \cdot (\mathbf{D} \nabla \mathcal{T}). \quad (3)$$

This modified equation results in patterns that align with the input tensor field. Specifically, the cells/filaments tend to follow the direction indicated by the eigenvector of $\mathbf{D}$ corresponding to the highest eigenvalue.

Care has to be taken when integrating anisotropic diffusion using discrete finite differences. Indeed, the use of the classical centered differences on a regular grid has greater accuracy along the main directions. While hardly visible for isotropic diffusion, this leads to strong artifacts when oriented patterns need to be generated in non-axis-aligned directions. To address this issue, we propose a solution by generating at each frame a 3D rotation R randomly oriented on the unit sphere, and applied to both the trail map and the tensor field $\mathbf{D}$ before computing the **Diffuse** step. Once computed, the updated trail map is transformed back in applying the inverse rotation R^{-1} . By doing so, we can effectively handle any direction in a consistent manner while still utilizing the simplicity of a regular grid. It is important to note that this approach does not aim at improving numerical accuracy for the diffusion process but provides an orientation-invariant one, which is sufficient for our purpose.

5.4. Local block-based synthesis

Generating microstructures on a large-scale domain at once can be memory intensive. To avoid memory shortage in such case, we propose a per-block synthesis approach leveraging the local behavior of the physarum coupled with the guiding-trail input $\mathcal{T}^*$. As illustrated in Fig. 7, the global domain Ω can be split into blocks Ω_i with small overlapping areas on their boundary. The interior of the blocks is filled independently, one after the other, while ensuring a coherent boundary condition. This condition is ensured by copying the value of the trail of the filled neighbors block (Ω_1 in Fig. 7) on the overlapping domain into the guiding trail map $\mathcal{T}^*$ of the block to be filled (Ω_2 in Fig. 7). This technique can scale to an arbitrary range and level of subdivision as long as the block size is sufficiently large compared to the typical length of a cell pattern. Therefore physarum structures can be generated on grids of any size using this approach. As shown Fig. 8, visual artifacts introduced by this process are minor if non-existent, as long as the

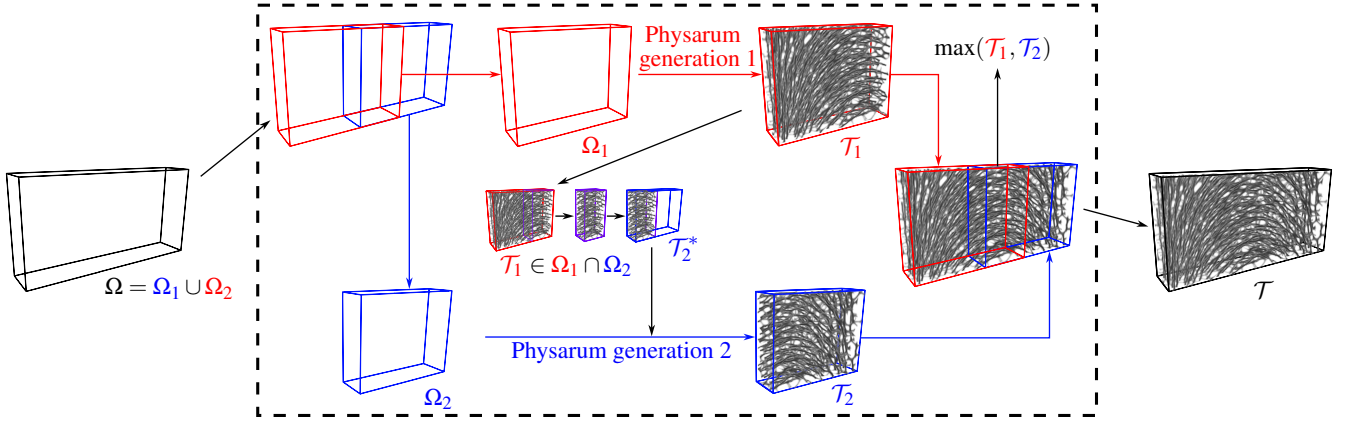


Figure 7: Per-block synthesis allows locally synthesizing a physarum structure and coupling it to nearby blocks via their common boundary.

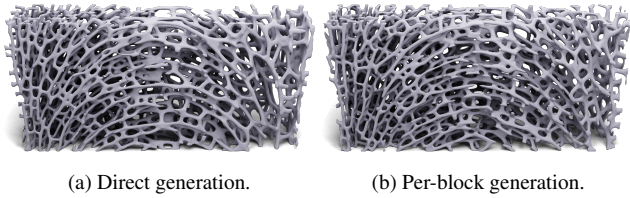


Figure 8: Physarum structure generated directly on the whole grid (a) and using the local block approach shown Fig. 7 (b). Grid size : $400 \times 200 \times 70$.

fields vary continuously and infill structures are small compared to the size of the blocks.

6. Parameters Study

Emerging morphogenesis models, similarly to Cellular Automata or Reaction/Diffusion systems, often require a laborious process of parameter selection in order to observe effective pattern formation. This section proposes a comprehensive guideline describing how to choose the main parameters depending on the expected pattern formation. While we refer the reader to Jones [Jon10] for a general study of the main behaviors generated using such Physarum simulation, we concentrate our analysis on the Anisotropic-Voronoi-like behavior, which is more suitable for Additive Manufacturing. It is worth noting that the introduction of anisotropy in the physarum simulation increases its sensitivity to the parameters, resulting in a narrower range of values where the patterns are consistently generated. Additionally, a distinct behavior emerges with significant relative anisotropy, as the microstructure patterns transition from Voronoi-like cells to elongated filaments.

We focus on defining the parameter domain where cell or filament patterns can be expected. And, for cell-like structure, to be able to control their appearance via a notion of averaged cell elongation ω , and a notion of cell area (2D) or cell volume (3D) σ (measured in pixel/voxel) using an adapted parameterization of the inputs. We define these average cell characteristics as:

$$\omega = \frac{\ell_{\parallel}}{\ell_{\perp}}, \quad \sigma = \ell_{\parallel} \ell_{\perp}^{d-1}, \quad (4)$$

with $d = 2$ or 3 according to the dimension, and where $\ell_{\parallel}$ and $\ell_{\perp}$ are the averaged cell lengths in the most elongated, and least elongated directions.

While $\ell_{\parallel}$ and $\ell_{\perp}$, and thus of ω and σ , can be directly computed by direct minimal and maximal length measurement over closed cells in 2D, their computation is not straightforward in 3D as the cells are not associated to bounded sub-domains. We propose a common computation methodology that can be applied to both two-dimensional and three-dimensional structures in relying on the apparent frequencies of the trail map.

Let us call

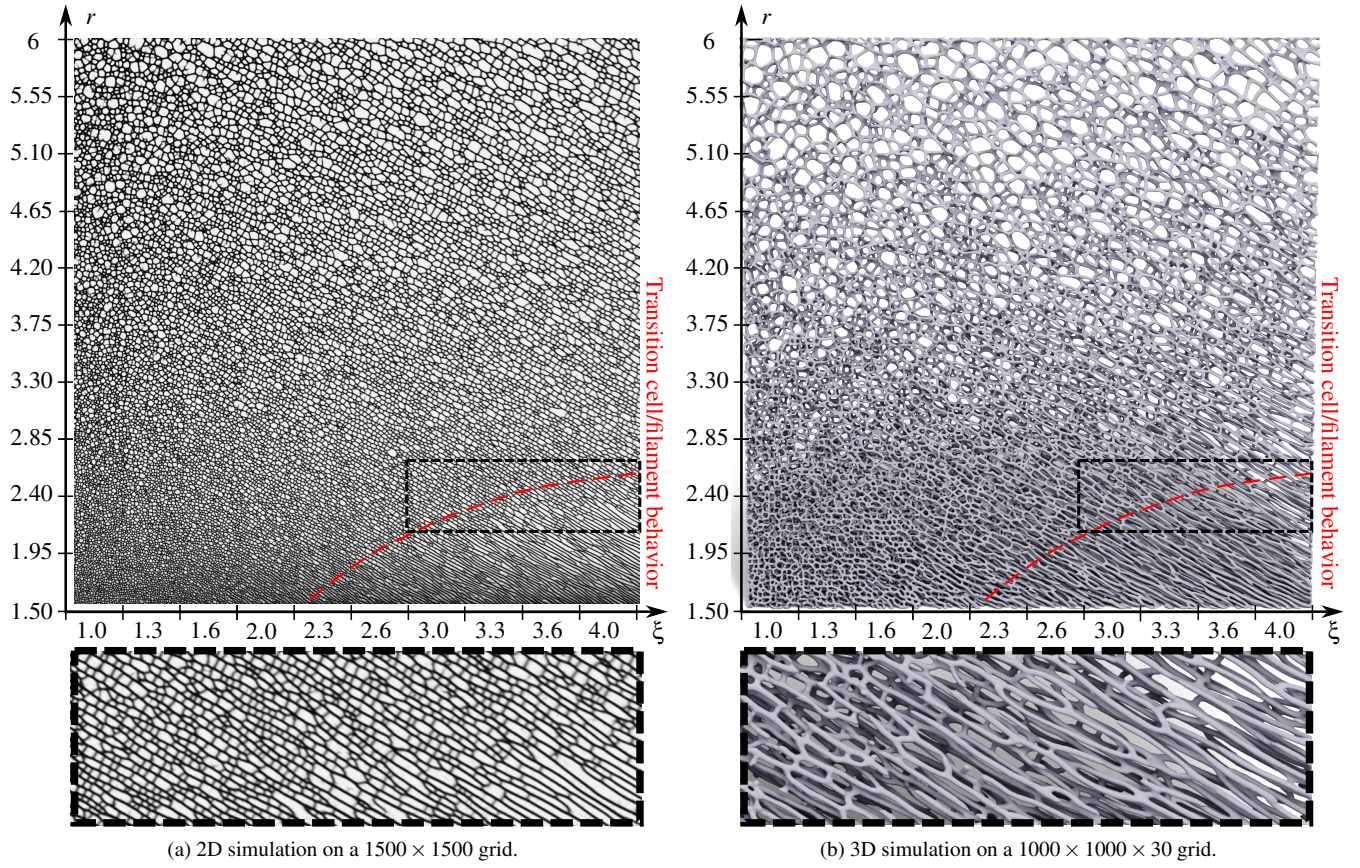
$$f_{\parallel} = \frac{L}{\ell_{\parallel}}, \text{ and } f_{\perp} = \frac{L}{\ell_{\perp}}, \quad (5)$$

the frequencies corresponding to the averaged cell length in the respective most and least elongated directions. Here, L designates the total length of the square/cubic domain. These two frequencies are the most apparent and, therefore, correspond to local peaks of magnitude in the spectrum of the trail map. To compute $f_{\parallel}$ and $f_{\perp}$, we perform a Fast Fourier Transform on the output trail and consider a frequency as being locally dominant if its magnitude in the Fourier spectrum is higher than a certain percentage p of the local maximum magnitude. For values of p chosen between 25% and 75%, values of $f_{\parallel}$ and $f_{\perp}$ are translated by a similar offset, but their behavior remains the same. In all of our experiments, we chose $p = 37\%$ as this value gives elongation values that match a direct elongation computation in the 2D case for closed cells.

In the following, all numerical values are obtained using the parameters provided in the summary Table 1.

6.1. Diffusion ratio ξ and tensor parameterization

The diffusion tensor field $\mathbf{D}$ can be defined from specific data provided by the designer, such as desired mechanical properties, ori-

Figure 9: Patterns obtained for varying values of ξ and r .

Param.	Designation	Pattern affect	Values
ξ	Diffusion ratio	Elongation ω Fil. behavior ($r \leq 2.5$)	[1, 2.5] [2.5, 4]
r	Sensor Offset	(ω, σ) Fil. behavior ($\xi \geq 2.5$)	[2.5, 6] [1.5, 2.5]
φ	Sensor Angle	Pattern aspect	27°
α	Rotation Angle	Pattern aspect	70°
h	Step Size	Pattern formation	1
μ	Decay	Scaling, edge thickn.	0.1
δ	Deposit	Trail scaling	0.01
γ	Guid. influence	Influence of $\mathcal{T}^*$	[0, 1]
s	Pop. size	Pattern formation	[2, 4]

Table 1: Summary of the Physarum parameters, respective influence, and typical values. The values of r and h are given in pixel/voxel.

a diffusion ratio $\xi(\mathbf{x}), \mathbf{x} \in \Omega$, guiding how much the cells should be elongated along this principle direction. In the following, we will assume that we restrict our model to elongated cells in a single direction in space, while assuming a transversal isotropy in the two remaining orthogonal directions

The 3×3 diffusion tensor matrix $\mathbf{D}$ can be decomposed at any position $\mathbf{x} \in \Omega$ as

$$\mathbf{D}(\mathbf{x}) = \mathbf{R}_o^T(\mathbf{x}) \mathbf{\Lambda}_\xi^T(\mathbf{x}) \mathbf{\Lambda}_\xi(\mathbf{x}) \mathbf{R}_o(\mathbf{x}), \quad (6)$$

where $\mathbf{R}_o(\mathbf{x})$ is a rotation matrix defining a local orientation frame for the diffusion, and $\mathbf{\Lambda}_\xi(\mathbf{x})$ is a diagonal matrix whose entries are the eigenvalues of $\mathbf{D}(\mathbf{x})$. The matrix $\mathbf{R}_o(\mathbf{x})$ can be defined from the directional vector $o(\mathbf{x})$ as $\mathbf{R}_o(\mathbf{x}) = (o(\mathbf{x}), o_1^\perp(\mathbf{x}), o_2^\perp(\mathbf{x}))$, where $(o_1^\perp, o_2^\perp)$ can be arbitrarily oriented as long as they form an orthonormal frame. The matrix $\mathbf{\Lambda}_\xi(\mathbf{x})$ can be defined as

$$\mathbf{\Lambda}_\xi(\mathbf{x}) = d_0 \text{diag}(\xi(\mathbf{x}), 1, 1), \quad (7)$$

where $d_0 \in \mathbb{R}$ is a diffusion magnitude, and $\xi(\mathbf{x}) \geq 1$ is the diffusion ratio.

ξ has a direct influence on ω as increasing the diffusion ratio leads to longer cells in the principal direction provided by o . Both ξ and o are then considered as input parameters to control the result of the simulation. The value d_0 has a direct influence over the cell size

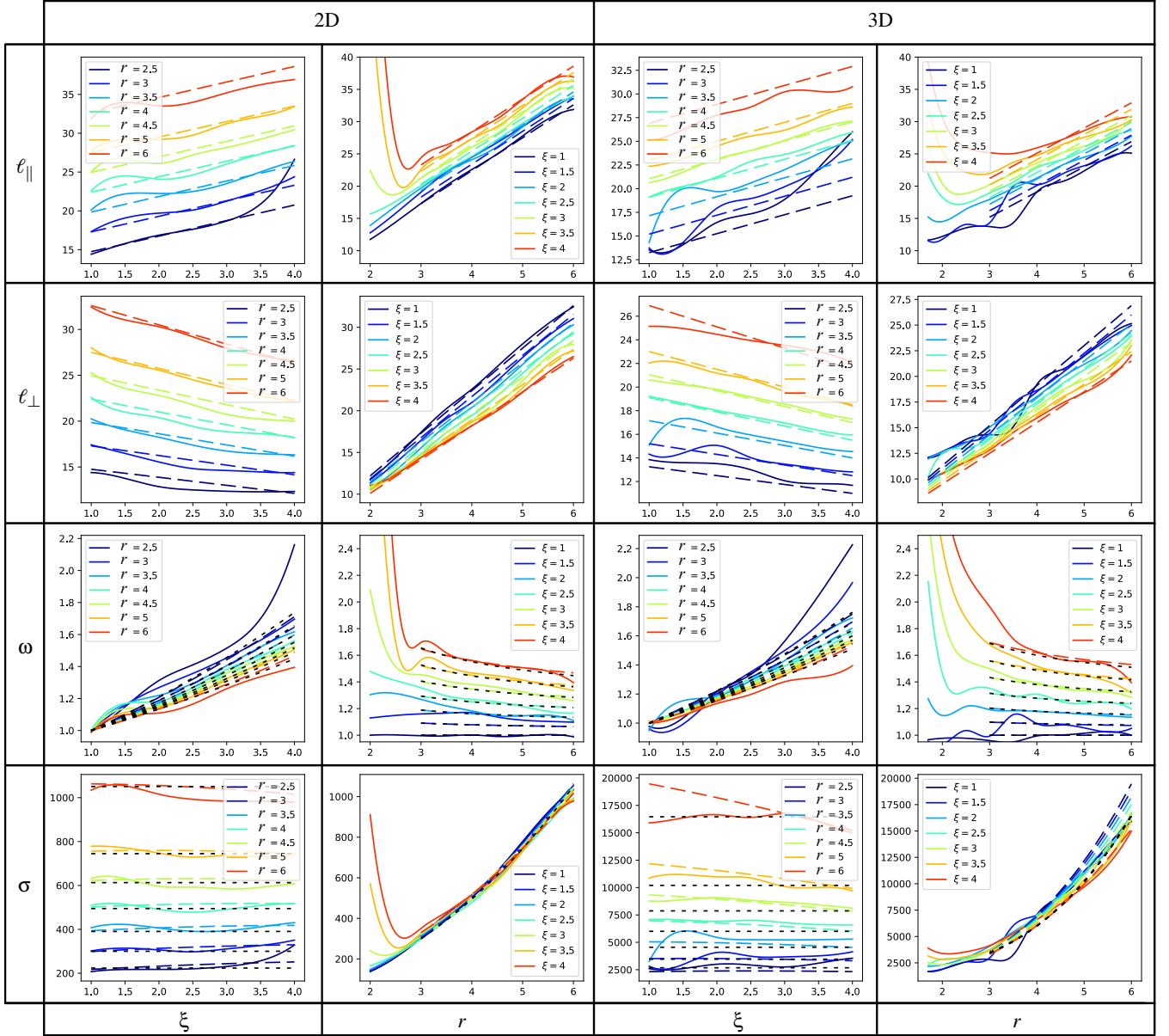


Figure 10: Plots of $(\ell_{\parallel}, \ell_{\perp}, \omega, \sigma)$ as a function of (ξ, r) , in 2D and in 3D. Dashed color curves are the fitting curves for $\ell_{\parallel}$ and $\ell_{\perp}$, and the resulting ones for ω and σ , at the extreme values where our proposed numerical model is valid for cells patterns (i.e. where $\ell_{\parallel}$ is defined, for $\xi \in [1, 4]$, $r \in [3, 6]$). Values outside these intervals (darker blue curve of columns 1 and 3, leftmost part of columns 2 and 4) represent filament patterns. Black dotted curves for ω and σ are fitting curves with a more simple model provided equation 16.

since a large diffusivity leads to larger cells. However, the range of possible values of d_0 is limited by the stability of the numerical scheme to solve Eq. (3). Using an explicit scheme and a maximal diffusion ratio $\xi \simeq 4$ leads to a value d_0 that cannot exceed 0.2 (assuming a discrete time step and spatial discretization set to 1). Based on this limitation, we consider d_0 to be a constant and set it to 0.1375.

6.2. Controlling cells characteristics

The second parameter to influence the cell size is the sensor offset r . At the opposite of d_0 , r is not restricted by numerical stability condition, and we therefore use it as a varying input variable. In the following, we analyze the influence of the two inputs (ξ, r) toward the cell characteristics $(\ell_{\parallel}, \ell_{\perp}, \omega, \sigma)$.

We first illustrate in Fig. 9 the typical patterns obtained for varying values of ξ and r . While ξ acts primarily on the elongation of the patterns, r directly controls their global size. The dotted red line

delimits the two domains with different behaviors: the filament-like pattern in the bottom-right, and foam-like patterns. The foam-like patterns are obtained for moderate anisotropy relative to the cell size. In this configuration, the cells are characterized by long edges oriented along the main direction that increase with ξ , and a few orthogonal edges which lead to this typical foam-cell appearance. When the anisotropy becomes large ($\xi \geq 2.5$) while keeping a narrow cell ($r \leq 2.5$), the edges orthogonal to the main anisotropic direction are not able to emerge persistently anymore. As a result, the generated patterns are then dominated by long edges propagating along the principal direction that doesn't appear to be made of cells but look like long filaments instead.

In Fig. 10, we provide a finer analysis of the relation between $(\ell_{\parallel}, \ell_{\perp}, \omega, \sigma)$ plotted as functions of (r, ξ) . These curves can be used as an abacus to finely set a prescribed cell size and elongation. Let us first consider the parametric subdomain where $r \in [3, 6]$, $\xi \in [1, 4]$. This domain corresponds to foam-cell patterns where the characteristic cell lengths can be well predicted by our inputs using simple model. As we can see on the first line of the plots Fig. 10, at the first order, the elongation length $\ell_{\parallel}$ can be approximated by having a linear dependence to ξ and to r independently. The transverse length $\ell_{\perp}$ can be approximated by having a linear dependence to r , with a slope value that linearly decreases with ξ . We propose the following numerical model that approximate this behavior as

$$\begin{cases} \ell_{\parallel}(\xi, r) &= a_{\parallel} \xi + b_{\parallel} r + c_{\parallel} \\ \ell_{\perp}(\xi, r) &= a_{\perp} \xi r + b_{\perp} r + c_{\perp}, \end{cases} \quad (8)$$

with an additional condition on the elongation:

$$\forall r, \quad \omega(1, r) = \frac{\ell_{\parallel}(1, r)}{\ell_{\perp}(1, r)} = 1, \quad (9)$$

describing the fact that the cells are not elongated in the isotropic case. This gives a relation between the previous coefficients:

$$\begin{cases} a_{\parallel} + c_{\parallel} = c_{\perp} \\ b_{\parallel} = a_{\perp} + b_{\perp}, \end{cases} \quad (10)$$

which allows to eliminate two coefficients to re-write the expressions under the form:

$$\begin{cases} \ell_{\parallel}(\xi, r) &= a_0 \xi + (a_1 + a_2) r + a_3 \\ \ell_{\perp}(\xi, r) &= (a_1 \xi + a_2) r + (a_0 + a_3). \end{cases} \quad (11)$$

with values fitted using simple regression, for the 2D and the 3D cases,

$$\begin{cases} 2D : a_0 = 2.0, a_1 = -0.35, a_2 = 5.4, a_3 = 0 \\ 3D : a_0 = 2.0, a_1 = -0.30, a_2 = 4.2, a_3 = 1.5 \end{cases} \quad (12)$$

The behavior is similar in 2D and 3D but the fitting coefficients slightly differs between the dimension. Still, they remain close enough to assimilate these numerical differences to the fact that 2D cells and 3D cells are not completely comparable as they define slightly different structures and the 3D case exhibits wider degree of freedom to measure $\ell_{\parallel}$ and $\ell_{\perp}$.

Overall, characteristic lengths of foam cells behave in the same way in 2D and 3D. $\ell_{\parallel}$ increases with ξ ($a_0 > 0$) and with r ($a_1 + a_2 > 0$) which is to be expected. $\ell_{\perp}$ also increases with r ($a_1 \xi + a_2 > 0$) but it decreases with ξ ($a_1 < 0$) meaning the anisotropy tends to bring the pattern closer in the transverse direction. For $r \leq$

3 and $\xi \geq 2.5$, the behavior changes to filament-like patterns. This change of behavior is also visualized on the plots, with a sudden increase of $\ell_{\parallel}$ values. Our model is still valid for $\ell_{\perp}$ because this length is still well defined in the filament behavior. These simple linear models are only first order approximation, and we may note for instance consistent local maxima for low ξ values (for $\ell_{\parallel}$), that we neglect in such fitting.

ω and σ can also be well approximated using our proposed model for $\ell_{\parallel}$ and $\ell_{\perp}$ (dashed color curves Fig. 10). To really understand how ξ and r influence these characteristics, we re-write their expressions differently:

$$\omega(\xi, r) = 1 + \frac{\xi - 1}{r} f(\xi, r), \quad (13)$$

with

$$f(\xi, r) = \frac{a_0 - a_1 r}{a_1 \xi + a_2 + \frac{a_0 + a_3}{r}}, \quad (14)$$

and

$$\sigma(\xi, r) = (a_1 + a_2) a_2^{d-1} r^d + g(\xi, r), \quad (15)$$

with $g(\xi, r)$ a rational polynomial that we do not fully develop and $d \in \{2, 3\}$ corresponding to the dimension (2D or 3D).

In practice we observe that we can approximate $f(\xi, r)$ to be linearly varying with ξ and with r independently, and that $g(\xi, r)$ can be approximated by a constant σ_0 as its variation is negligible in front of $(a_1 + a_2) a_2^{d-1} r^d$. Finally the cell elongation and area/volume can be approximated by:

$$\begin{cases} \omega(\xi, r) &= 1 + \frac{\xi - 1}{r} (\alpha_0 \xi + \alpha_1 r + \alpha_2) \\ \sigma(\xi, r) &= (a_1 + a_2) a_2^{d-1} r^d + \sigma_0, \end{cases} \quad (16)$$

with values fitted using simple regression, for the 2D and the 3D cases,

$$\begin{cases} 2D : \alpha_0 = 0.045, \alpha_1 = 0.08, \alpha_2 = 0.24, \sigma_0 = 50 \\ 3D : \alpha_0 = 0.040, \alpha_1 = 0.11, \alpha_2 = 0.20, \sigma_0 = 1600 \end{cases} \quad (17)$$

This corresponds to the plots of the black dotted curves for ω and σ Fig. 10. Under this form, this shows clearly that the elongation can be approximated by having a quadratic relation to ξ , which can be linked to the square of ξ found in the expression of $\mathbf{D}(\mathbf{x})$. The influence of ξ tends to diminish while r increases, as the invert of r appears in the expression, with the other coefficients being positive. This is also to be expected because as r increases, the size of pattern increases, but not the radius of diffusion, therefore anisotropic diffusion is less likely to affect larger patterns. The cell area/volume is governed by the quadratic/cubic term r^d in σ , which is also coherent with the expected influence of r .

6.3. Fixed parameters for patterns formation

Beyond ξ and r used as *grading parameters*, other simulation parameters may influence how well patterns are defined. We briefly review in the following the influence of these additional parameters and propose the appropriate values we have been considering in addition to their summary in Table 1.

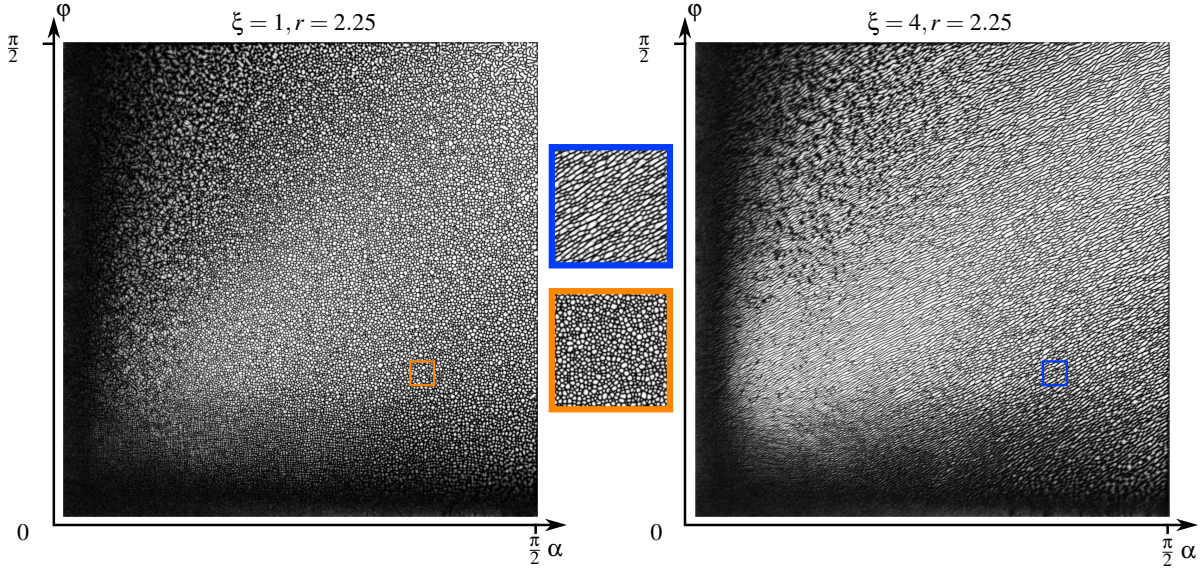


Figure 11: *Physarum* 2D pattern with α continuously varying along the x axis and ϕ continuously varying along the y axis, for isotropic (left) and anisotropic cases (right).

Rotation angle α and Sensor Angle ϕ have a significant influence on the appearance and formation of patterns. Jones [Jon10] proposed the general rule of $\alpha = 2\phi$, with typical value $\alpha = 45^\circ$, $\phi = 22.5^\circ$. We, however, note that the region where the foam-cell pattern appears consistently is narrower in the anisotropic case, and can lead to a mix of filament patterns when using $\alpha = 2\phi$. This behavior can be seen in Fig. 11 illustrating the patterns obtained along a continuous variation of ϕ and α between $[0, \pi/2]$ in both isotropic ($\xi = 1$, left), and anisotropic case ($\xi = 4$, right). The square illustrates the typical area providing foam-cells generation with consistent density in isotropic and anisotropic cases. This area corresponds to the ratio $\alpha = 2.6\phi$ and the typical considered values in our case are respectively $\alpha = 70^\circ$, $\phi = 27^\circ$.

Pattern formation: Agent population, Step Size. In all our simulation, the agents are initially uniformly distributed. The number of agents as well as the step size both impact the possibility of the microstructure being generated. Too low or high-value results in either non-connected structure or dense infill. We note that the sensibility of the simulation is higher when using large anisotropy, and normalized them as follows. First, the total agent population N is normalized by the ratio $s = N/V$, where V is the volume of the infill space. We found that values between $s = 2$ and $s = 4$ give satisfying results in all our cases. In fact, in 3D, satisfying results can be obtained with lower values i.e. for $s \geq 0.5$, which is very convenient from a computational cost. We assume that s does not need to be as high in 3D than in 2D because 3D shapes are much more porous than 2D shapes, while similarly connected. Second, the Step Size h is set to 1 pixel of the trail map image $\mathcal{T}$.

Scaling factors: Decay μ , Deposit δ . These two parameters do not change the type of pattern, but only act as scaling factors. While deposit δ simply scale the trail density value $\mathcal{T}$ uniformly, the decay μ slightly change at the extreme values near 0 and 1 the thickness

of the edges on the trail map. We consider in all our experiment $\mu = 0.1$ and $\delta = 0.01$.

Grid size. As parameters such as r , h and the diffusion radius are defined in pixels or voxels, the resolution of the underlying grid used for $\mathcal{T}$ has a significant impact on the result. For a same set of parameters, if L designates the maximum length of the domain space Ω measured in pixel/voxel i.e. the resolution of the grid, the characteristic lengths of microstructures are equal to $\frac{\ell_{\parallel}}{L}$ and $\frac{\ell_{\perp}}{L}$. Hence a grid of higher resolution λL will return smaller microstructures by a factor $1/\lambda$, because the characteristics lengths do not vary in pixel/voxel.

Structure thickness. The thickness of cell edges/filaments can be slightly controlled in the final structure mesh by slightly shifting the isosurface used for the Marching Cube algorithm.

7. Results and Applications

We present the results of our pattern generation method using PhysOM. All the models are generated on a PC workstation with an Intel Xeon Gold 6148 CPU running at 2.40GHz, 128GB RAM and a GPU Nvidia Quadro RTX6000 with 24 GB memory. Our implementation is based on CuPy library in Python to store the 2D and 3D grids with operations performed in parallel on the GPU. The dimension of the voxel grid and the computational time associated with the full generation of our 3D examples are reported in Table 2. At the exception of Fig. 8, the examples were created from a single grid structure without the per-block optimization. The total time reported corresponds to the simulation for 200 steps. The core of the method relies on uncoupled particle simulation, where each particle update (steps Sense, Rotate, Move, Deposit) is "embarrassingly parallel". The diffusion step and the handling of the 3D texture and its rotation are implemented using trivial and non-optimal

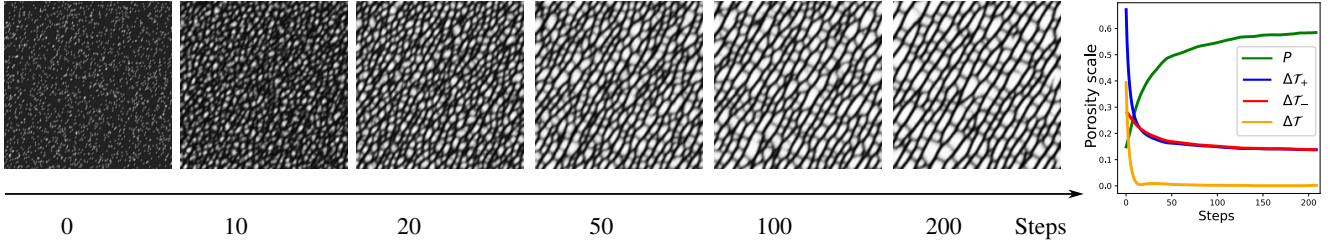


Figure 12: Physarum 2D pattern on a 200×200 grid at several steps on a simulation with the associated curves of porosity P , amount added ΔT_+ , amount removed ΔT_- and variation ΔT . These last three quantities are scaled by a factor that allows them to be visualized on a single plot.

algorithms in our case. A very detailed breakdown and fine comparison of timings with other approaches would not be relevant. For instance, [EBPF22] reported measures implemented in C++ with compute shader, while our 3D implementation uses Python. The timings are indeed very different, and our approach could be highly optimized with dedicated developments that are beyond the scope of the current contribution. However, we have developed a real-time 2D prototype relying on WebGL for the entire simulation. This 2D version is obtained as an extension of a standard physarum implementation proposed by Ghassaei [Gha22]. Please refer to the attached video for a visual demonstration of the animated outcomes.

	Grid size (voxels)	Total time
Teaser (Fig. 1)	$64 \times 64 \times 768$ (3M)	2 min
Owl (Fig. 3)	$369 \times 306 \times 534$ (60M)	20 min
Eiffel Tow. (Fig. 17a)	$666 \times 247 \times 247$ (40M)	15 min
Chair (Fig. 17b)	$256 \times 256 \times 256$ (16M)	6 min
Femur (Fig. 17c)	$400 \times 210 \times 265$ (22M)	8 min

Table 2: Grid dimension and timings of our 3D examples, for 200 steps of simulation.

7.1. Simulation convergence

The physarum simulation remains in permanent evolution over the simulation steps which allows a designer to interact with the structure by modifying the grading parameters locally or modifying the trail map by erasing/adding some parts and letting the system adapt at any time. However, for structure generation purposes, we may consider that the system has reached a stable state when the general type of patterns remains consistent over time. We defined this state when the average density of the trail map reaches a stable state. Let us call ΔT_+ the total amount of density added from Step 3 to Step 4, and ΔT_- removed by the decay process from Step 4 to Step 6. We call $\Delta T = |\Delta T_+ - \Delta T_-|$, the net change of density. We consider that the simulation has converged when the relative variation of $\Delta T/V_\Omega$ remains below a threshold during several steps. The evolution of these parameters along the simulation steps are illustrated in Fig. 12-right.

7.2. Structural Design for Additive Manufacturing

A classical application of microstructure infill is the generation of porous material that can be 3D printed. We show in the following that our approach allows designing materials with varying stiffness and density/porosity in adapting the anisotropy, orientation, and cell area.

We introduce the material porosity P , i.e. the reverse of its averaged density, as

$$P = 1 - \frac{1}{V_{\mathcal{T}}} \sum_{\mathbf{x} \in \Omega} \mathcal{T}(\mathbf{x}), \quad (18)$$

where $V_{\mathcal{T}}$ is the volume of the infill shape domain $\mathcal{D}_{\mathcal{T}}$. The porosity tends to converge towards a constant value, as depicted in Figure 12-right, also confirming the attainment of a stable state.

To confirm the suitability of our generated structure for material design, we propose a study of its anisotropy-dependence deformation using the methodology used in density-based topology optimization [ACS*11]. We apply a continuous vertical compressive stress on generated structure, then simulate and measure the displacement of the global structure using an isotropic linear constitutive stress-strain relation. Each element of the grid $\mathbf{x} \in \Omega$ is associated to a Young's modulus:

$$E(\mathbf{x}) = E_{\min} + \mathcal{T}^0(\mathbf{x})(E_0 - E_{\min}). \quad (19)$$

Here, E_0 represents the material's stiffness, and $E_{\min}$ is a small stiffness assigned to void regions to prevent the stiffness matrix from becoming singular. $\mathcal{T}^0$ is the normalized trail in $[0, 1]$. The global stiffness matrix is denoted as $\mathbf{K} = (E(\mathbf{x})\mathbf{k}_0)_{\mathbf{x} \in \Omega}$, where $\mathbf{k}_0$ corresponds to the stiffness matrix for an element with a unit Young's modulus. The global displacement and force vectors at the grid nodes are represented by $\mathbf{U}$ and $\mathbf{F}$, respectively. Computing the resulting displacement $\mathbf{U}$ caused by an applied force $\mathbf{F}$ involves solving the equation $\mathbf{KU} = \mathbf{F}$, which can be expressed as $\mathbf{U} = \mathbf{K}^{-1}\mathbf{F}$.

Figure 13-a illustrates the results obtained in applying such constraint while varying the direction and magnitude of the anisotropy. From the isotropic case in the center, we increase the anisotropy, respectively, in the vertical direction on the left-side, and in the horizontal direction on the right-side. This experiment is performed at constant porosity value by selecting tailored values for (ξ, r) . To achieve this, the porosity is computed on small grid samples (200×200) for varying combinations of (ξ, r) , resulting in a density grid representation $P(\xi, r)$. By selecting an iso value of P , the

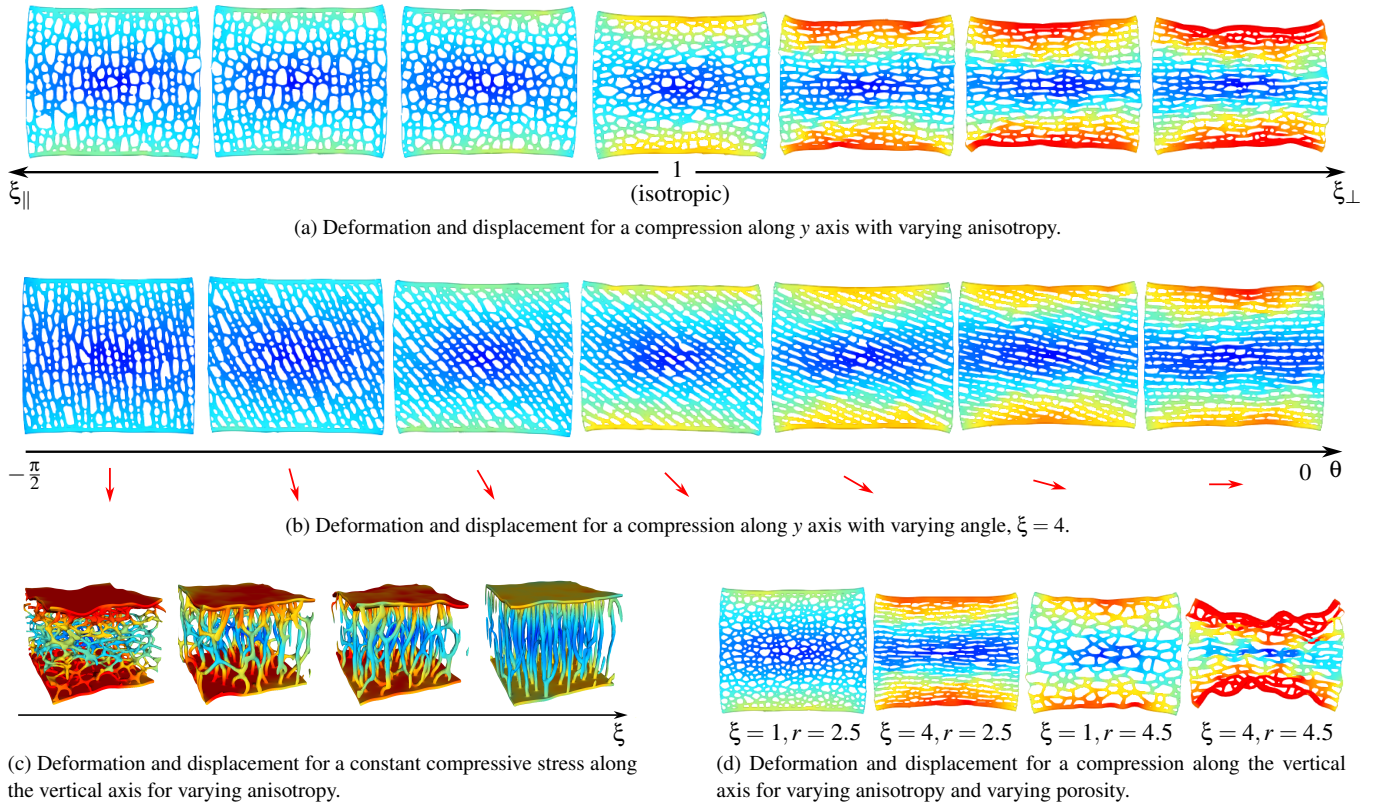


Figure 13: Structural simulations.

desired values for (ξ, r) can be obtained. As expected, an increase of anisotropy in the vertical direction provides stiffer material resistance, while a horizontal one will lead to a more deformable structure. A similar test is conducted in 3D, as shown in Figure 13-c, using a cubic infill that demonstrates the same property. In Figure 13-b, the anisotropy is held constant while progressively changing the angle from vertical to horizontal, once again reinforcing the same conclusion. Finally, Figure 13-d illustrates the significant influence of material porosity on the resulting displacement. Note that our simulations on 2D quad-meshes and 3D hex-meshes did not consider material nonlinearities, and the large displacement factor in visualization is deliberate. We found these simplifications acceptable for the purpose of validating the effects of the porosity and anisotropy parameters. Indeed, to truly capture such large deformations, a simulation would need to consider geometrical nonlinearities (e.g. buckling), material nonlinearities (e.g. plasticity), as well as internal contacts.

Being able to link the parameters of the *Physarum* to the local porosity and anisotropy of the microstructures generated allows for tailored design for deformable shapes. A more in-depth study could allow to map these parameters to material properties or mechanical parameters such as the Young's modulus, similarly to [MSDL17]. More generally, the effective constitutive law for any set of *Physarum* parameters could be evaluated through homoge-

nization, thus compiling a reverse mapping from desired mechanical properties to their appropriate generation parameters.

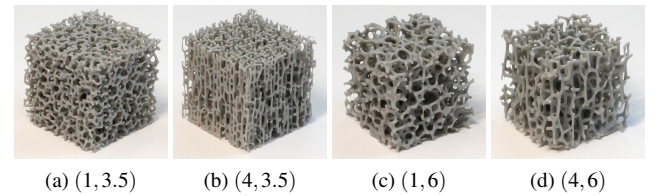
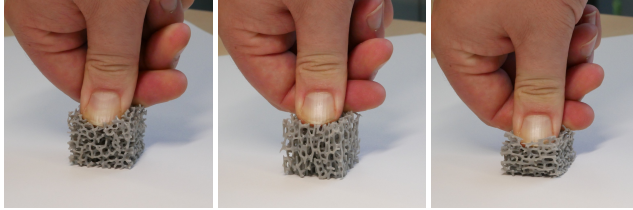


Figure 14: Printed cubic samples with respective varying (ξ, r) values. The numerical models were generated on a $200 \times 200 \times 200$ grid.

Based on these observations, our approach is particularly well-suited for printing deformable structures. Figure 14 shows real pictures of printed cubic samples of 3D structures, illustrating both isotropic and anisotropic cases with various r values. These models, along with those showcased in Fig. 17, were generated using the most affordable SLA 3D printer available (Geeetech Alkaid) at the time of writing this paper, demonstrating the printability of such structures.

Using a flexible material, Fig. 15 demonstrates that the deformation of the structure is highly influenced by its anisotropy and the

alignment of the applied force. For a comparable applied pressure, an anisotropic structure aligned with the force experiences less deformation than its isotropic counterpart. Additionally, the isotropic structure deforms less than the anisotropic structure perpendicular to the applied force direction, aligning with our numerical simulations.



(a) Isotropic (b) Anisotropic, $F_{\parallel}$ (c) Anisotropic, $F_{\perp}$

Figure 15: Pressure applied on cubic samples ($r = 6$) for (a) the isotropic case, (b) the anisotropic case with anisotropy direction aligned with pressure direction, (c) the anisotropic case with anisotropy direction orthogonal to pressure direction.

In Figure 16, we showcase a comparison of chairs where the top-left chair is generated from Martinez et al. [MSDL17], designed using orthotropic k-nearest foams and inspired by the designs of Lilian van Daal [vD14]. The top-right chair in Figure 16 is obtained through our PhysOM approach in 2D, employing a similar underlying orientation field. Note that our approach provides aesthetically pleasing homogeneous organic features and well-defined borders thanks to the use of the guiding trail $\mathcal{T}^*$. In Figure 16 (bottom row) we show pictures of a 3D-printed model with deformation behavior also similar to the one shown in [MSDL17]. These models were printed using an inexpensive FDM printer (Creality CR-10).

7.3. Art and Design

Our approach can also find relevant applications in art, design, and animation. The natural and organic aesthetic of the shapes produced by PhysOM can be of interest to creative designers and artists. Figure 17a and 17b showcase our version of the Eiffel Tower and the biomimicry chair inspired by Lilian van Daal [vD14]. The resulting prints are presented Fig. 17e and 17f. It is worth noting that these structures are dynamic and "alive" as long as the simulation is running. This characteristic opens up various possibilities, such as animation or the creation of unique designs. Two structures extracted from the same simulation but at slightly different time steps will appear very similar yet distinct, offering opportunities for producing diverse and individualized designs.

7.4. Biological representation

The organic pattern generated by our method can also be desirable for representing biological structures. It can be utilized to design organic textures in 2D, as demonstrated by the dragonfly wing showcased in Figure 18. Designers can sketch inputs such as the infill space field or the orientation, specifying labeled areas for anisotropy. Our method then automatically generates a coherent,

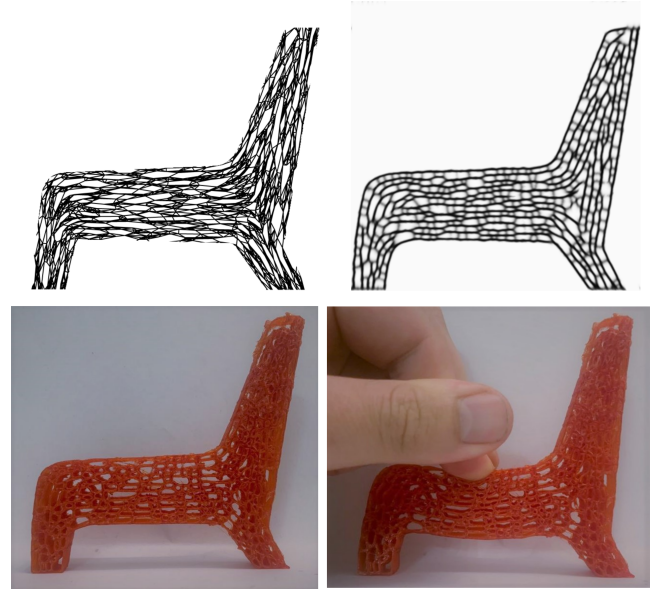


Figure 16: **Top-left:** Chair from Martinez et al. [MSDL17]. **Top-right:** chair designed by PhysOM. **Bottom** Real 3D printed structure. Finger pressure is applied to the chair similarly to [MSDL17].

biologically-inspired texture that accurately represents the desired design.

This process can also be applied to 3D application, where, for instance, the patterns formed by *Physarum* organisms bear resemblance to the intricate network of trabeculae found in spongy bones, as illustrated in Figure 17c and Figure 17d.

8. Conclusion and Future Work

In this work, we have presented a novel approach for generating intricate organic microstructures inspired by the behavior of the *Physarum polycephalum* slime mold. By extending the classical agent-based model of *Physarum* to a 3D domain with local anisotropic behavior, we have enabled the design of porous organic-like microstructures that resemble natural foam-like cells or filament-like patterns with variable local properties. Our method offers precise control over the local orientation of 3D patterns, relative cell extension and size (in 2D), and precise infill of 3D forms, all with well-defined boundaries.

The versatility and efficiency of our method make it suitable for a wide range of applications, including additive manufacturing, design, and biological representation and engineering. These microstructures, with their locally stiff or elastic, lighter, and porous properties, provide interesting mechanical characteristics that can be adjusted by varying the type of infill patterns. By leveraging the local rules and time-evolving processes inherent in biological systems, we have achieved locally adaptable behaviors that give rise to global emerging structures. This approach allows the end user to retain control over the evolution of the structure, ensuring a controllable and visually appealing organic-looking disorder that enhances strength. This visually appealing appearance of these mi-



Figure 17: Examples of PhysOM model (first line), with their associated prints (second line).

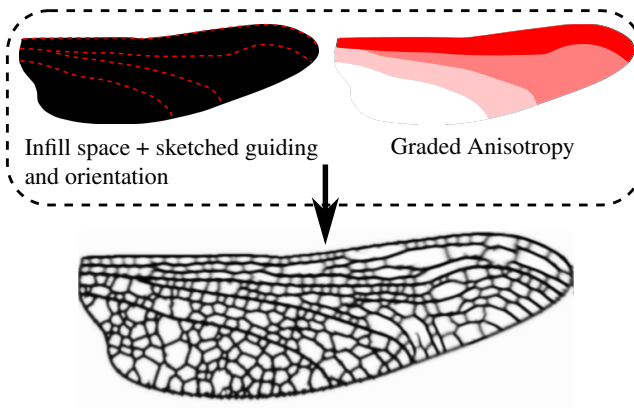


Figure 18: Synthesis of a Dragonfly wing patterns using our approach.

tures using the Physarum polycephalum-inspired model shows promising results, there are certain limitations that should be acknowledged. Firstly, the current implementation focuses on infilling 3D domains with local anisotropic behavior, but it does not take into account external constraints or specific material properties. Future work could explore the integration of mechanical and material considerations to optimize the microstructures for specific applications. Additionally, the computational costs associated with simulating large-scale volumes and complex shapes could be a limitation, especially when real-time interactivity is desired. Developing more efficient algorithms or exploring parallel computing techniques could help address this issue. Furthermore, while our approach provides control over the evolving structure, there is still room for improvement in terms of providing intuitive and user-friendly design interfaces. Future research could investigate interactive design tools that enable users to manipulate and guide the evolution of the microstructures more effectively.

crostructures, mimicking complex organic materials, offer potential for art-based design. We believe that our approach will inspire and assist designers across diverse domains in their pursuit of creating more complex and visually appealing shapes. Future research directions may involve exploring additional biological systems and further refining the control mechanisms to enhance the capabilities and versatility of our method.

While our approach for generating intricate organic microstructures

Conflict of Interest

None of the authors have a conflict of interest to disclose.

Data Availability

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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