Stripe Segmentation for Branching Shell Structures

A Data Set Development as a Learning Process for Fabrication Efficiency and Structural Performance

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This article explains the evolution towards the subject of digital fabrication of thin shell structures, searching for the computational design techniques which allow to implement biological pattern mechanisms for efficient fabrication procedures. The method produces data sets in order to analyse and evaluate parallel alternatives of branching topologies, segmentation patterns, material usage, weight and deflection values as a user learning process. The importance here is given to the selection of the appropriate attributes, referring to which specific geometric characteristics of the parametric model are affecting each other and with what impact. The outcomes are utilized to train an Artificial Neural Network to predict new building information based on new combinations of desired parameters so that the user can decide and adjust the design based on the new information.

Keywords: *Digital Fabrication, Shell Structures, Segmentation, Machine Learning, Branching Topologies, Bio-inspired*

INTRODUCTION

According to the line of previous research, conducted during courses and workshops, it has been examined how the evolution of architectural generative design processes aim to apply similar physical and geometrical principles of biological processes and to translate them to fabrication processes (Giannopoulou et al. 2019a);(Giannopoulou et al. 2019b). The theoretical framework speculated processes which implement manufacturing knowledge inside a computational design system. Inspired by the effects on pigmentation patterns of shell growth (Figure 1) and biological pattern prediction of reaction-diffusion mechanism (Turing 1952), the logic of stripe has been tested as a construction system in several different prototypes (Figure 2). As Stach (2010) said, instead of post-rationalizing complex geometrical structures the goal is to "pre-rationalize" the design method. The logic of stripes was used as a pre-rationalization construction system.

Relaxation processes (Piker 2013) and weighted graphs representations (Nejur and Steinfeld 2016)

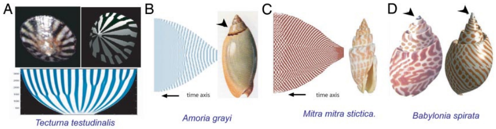

Figure 1
The effects on patterns of shell growth and perturbations. As the shell grows, the width of the pattern domain increases leading to changes in the pattern (Boettiger et al. 2009).

have been employed parallel as design tools for the development of structural rigid skin and pattern, made of flexible sheets of material (polypropylene). The spring system, which allowed to arrive close to minimal surfaces was linked with the segmentation process, which divided the mesh into stripes, which was linked with the fabrication process, that integrated material properties, tolerances, constraints, machine limitations and interactivity. The desired effect was manifested in one unified system in equilibrium, merging three design methods, three materials and three corresponding fabrication techniques (CNC, Laser cutting, 3D printing). The dual graph concept implemented as a data object was capable of generating a vast amount of interconnected complex networks of stripe configurations to choose from with possible structural characteristics.

However, a discussion has been raised upon the stripes topology (if they are closed rings, or open), their direction (if they are vertical or horizontal), in relation with the branching topology of the shell structure and its performance. Also, from the structural analysis with a very fast linear analysis of shell elements in 3D [1], a relevance has been observed between stress lines (curves that at each point are tangent to one of the principal stress directions), and the deflected areas. Those lines could not guarantee usable structural patterns (Tam and Mueller 2015). This has led to the study of an intelligent design processes for developing a creative design methodology of decision making based partly on the intuition, designer skills and experience and partly on the prediction capabilities of machine intelligence (Giannopoulou et al. in press a)

Further development is proposing a machine learning approach, using the already established parametric design workflow, as a method of expanding the design space of segmented thin shell structures. The extracted data sets serve as a first filter of visualising those attributes that are affected and/or mostly affecting each other. The goal is to achieve better understanding of which control parameters that define the geometric characteristic of the shell, influence mostly the structural performance, material usage and number of segmented pieces and to adjust the design based on the new information. The graphs demonstrate a relation between the periodic or non periodic pattern changes of the input and output attributes. Finally, a vital benefit of creating the database is to be utilised to train an Artificial Neural Network to be able to give approximations of new building information based on some desired parameters and to save computational time (Giannopoulou et al. in press b).

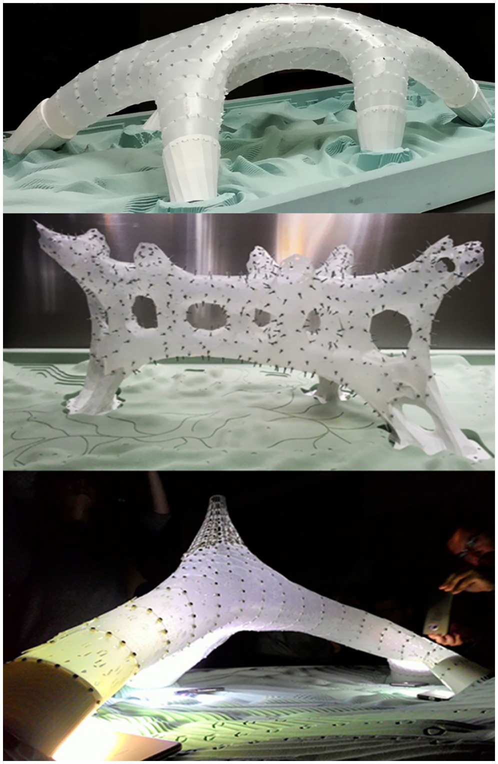

Figure 2
Biodigital Fabrication Studio Series 2017/2018/2019, University Master in Biodigital Architecture, ESARQ-UIC Barcelona, (bottom) open branching network with three legs, (center) cantilever with four anchors, open topology (top) cantilever with six anchors, closed topology. (Image by authors).

BACKGROUND METHODOLOGY

Based on Sennett (2009), that in the learning process,"technique -considered as a cultural issue rather than as a mindless procedure" and it's applications, both come hand to hand, then, apprentice is in fact a learning by doing process. So, if the method gives the possibility of trial and error, then is implementing intuition inside the design procedure. On the other hand, Hanna and Mahdavi (2007) state that "for several centuries the mathematical tools for explicit analysis have been dominant, but the vast majority of design decisions throughout history have been based on experience of precedents. In a similar way, once a machine learning algorithm is trained, the advantage is the same advantage as the human builder's training and experience". But the problem has to be simple and well defined.

Examining the intersections between machine learning and simulation could enable a practice of structural intuition. The integration of simulation into computational design workflows give rise to a performance-based design methodology. Using parametric as well as generative design tools with structural, energetic or other simulation tools is today state-of-the-art practice. While experienced practitioners rely in these situations on intuition, machine learning can act similarly and predict simulation results out of precedent, how new systems would behave (Tamke et al. 2018). In addition, "solution spaces are always multi-objective bringing together divergent criteria that don't map to a single optima. As a result, solutions are assessed not absolutely as true or false, but rather qualitatively as better or worse. To employ machine learning strategies in architecture therefore necessitate methods by which results can be evaluated holistically" (Tamke and Thomsen 2018).

Apart from examining the available simulation models and computational tools employed in other domains, as have been briefly described in previous papers by the authors, the ability to integrate intelligent design systems that can analyse, process and transform design, could expand the ability to work across knowledge domains and explore potential for innovating existing practice. What Tamke & Thomsen (2018) refer to as extending design intuition, is that "the model becomes a creative-analytical engine into which external data can be ported and analysed or internally generated to create the basis for intelligent design practices".

Nowadays, apart from standard topological, shape, size, structural optimisation methods, that give standard results without allowing creativity or the user participation, it is difficult to find an alternative method, oriented to fabrication that could enable the designer to intervene. Also, during a generative process with evolutionary algorithms, the system allows you to see only the final optimised option, it is time consuming, computationally demanding, requiring repeated iterations and is subject to error due to local optima in the search space (Hanna and Mahdavi 2007).

Also, coming from the field of statistical studies, there are some techniques (as subdividing, prioritising, tracking impact of sensitive variables) to process the larger design spaces produced by taking advantage of the constantly growing computational power. Using simulation models for analysis the designer could be seen as an analyst who must assume that only few factors of the simulation are really important (Kleijnen 1997), because of the computational time required and the learning goals. Linear growth of variables or ranges, as parametric modelling, triggers an exponential growth of the resulting design space, but mainly produce geometric variations with limitations in terms of topological transformations during the exploratory design tasks (Bernal 2016).

Under this context, the case study is examining the feasibility of a machine learning approach which will enhance the design space by predicting new results. The first step, described in this paper, is to automatically generate a database of 1890 possible alternatives, which could be evaluated with reference to the whole and partially based on the experience of the user and intuition. A series of images and statistical charts will allow to visually compare parallel results, rather than one optimised option and to analyse and have insights, relating numerical values for the purpose of gaining experience and knowledge. This learning process, directed especially for fabrication, can also lead to a better decision making and inform the design. When there are many criteria involved and multi-objectivity, such as structural performance, less material waste, less stripes, less connectivity, surface continuity this method consequently, it will make the fabrication and assembly process more efficient.

CASE STUDY

Owing to the limitations of parametric modelling, the design methodology has an obvious obligation to follow into the footsteps of its predecessors and pursue a generative model that can iterate several design solutions with manageable inputs and outputs. Moreover, considering the challenges offered by fabrication, the design methodology is compelled to accommodate constraints related to material, fabrication tools and methods, assembly processes and the general structural-aesthetic integrity. The objective at this stage is to establish a parameterized design workflow that revolves around actualising the amalgamation of branching structures and thin shell structures.

Unbranching Skeleton and Shell

Branching structures are based on geometric systems that expand through bifurcation without returning to form closed cells. In this sense, branching structures resemble the structure of trees that branch continually outward (von Buelow 2007), following their phototropic trajectories while maintaining a dynamic structural equilibrium. Thus, branching patterns generated traditionally, for example following an L-System will have its origins in an Axiom. This means it will have more points at a certain iteration than it had at its origin. In our case, the design of the branching pattern needs to follow an opposite process, if the thin shell structure needs to be mounted on the base. Which means that each iteration must have less points than its origin, or to move from outwards towards inwards. This significant parameter further dictates the design methodology to perform a virtual unbranching of origin points into an eventual nodal iteration (Figure 3). Thus, an unbranching algorithm is generated following an inwardly growing progression that is programmed to start from 4, 6, 8, 10 and 12 random points to end in 1 single point that refers to the average point location between 2 or 3 points.

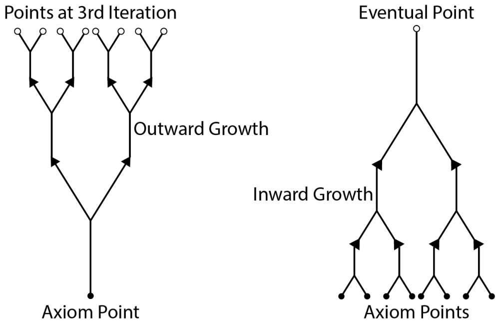

Figure 3
Branching/Unbranching, (left) a typical Lindenmeyer system with an outward growth of branching, (right) the adopted inward growth of unbranching.

The shell structure is achieved by considering the initial unbranching structure as a skeletal shape, in which each point is a branch node. The skeletal system, used as medial axes, is converted into a network of tubular quadrilateral meshes. To generate the right sizes of branch nodes, a proximity algorithm is generated so that a relation between the thickness of the node is established with its distance from the eventual pinnacle node. This relation is very essential in a generating a smooth, minimal, non-self-intersecting mesh with equidistant subdivisions throughout its topology.

Learning Goals

The goal is to experiment the structurality of thin shells with branching topologies so that they would self-support and might withstand an additional weight apart from the material itself, taking in count at the same time the material usage. In contrary to a previous design methodology of static inputs, the

Table 1
Explains the quantity of total iterations based on all combinations of input attributes and the total computed, where the process stopped for unknown reason.

Number of Anchor Points	Spring Strength	Vertical force	Divisions	Min.# KStripe Faces	Seeds	Total	Total computed
4,6,8,10, 12	300, 350, 400, 450, 500. 550, 600	14000, 16000, 18000	0,1	8,16,32	6, 12,18	1890	1150

approach allows the generation of a dynamic input geometry which permits the selection between various outcomes that fit best the criteria. General reference/criteria are defined as: deflexion, material usage, configuration and number of stripes, connectivity and surface continuity. The learning goals to examine are: How topology and spring strength affect the number of stripes, how topology affect material usage, and how topology affects structurality. The learning process suggests that the combination of some attributes indicating an efficient fabrication process which is balancing assemble time, number of sheets and extra weight due to the connecting elements and is up to the user to decide.

Database Preparation

The branching shell structure was geometrically constructed to iterate. The database was based on the selected input and outputs parameters as attributes of the structure. Modifications, extensions and clustering operations are applied to the initial model in order to extract the appropriate data sets in the format of CSV data and corresponding images. As a matter of fact, the most interesting part of this process is to determine, based on intuition and by experimentation, those sets of attributes/features/behaviours that influence most, inside the design workflow and which ultimately will train the model to predict.

The input attribute introduced in the initial design phase is the *Number of Anchor Points* creating a branching network of connected lines, the foundation of a skeletal shape, second, third and fourth input attribute are introduced, the *Spring Strength* of the spring system, the loading vertical force -*Strength* and the mesh triangular subdivision parameter -*Division*, after the relaxation. A segmentation parameter, the minimum amount of faces per stripe-*Kmin*, is introduced as input as well. A *Seed* also acted as a modification factor, giving new anchor point locations. The output attributes are chosen based on structural and fabrication criteria: *Number of Stripes and Sheets* of Material, *Cutting length* in mm, *Waste* of Material in sq. mm, *Height* in mm, *Deflection* in meters and *Weight* in kilos.

Table 2
Sample of the training data.

in: Anchors	in: Strength	in: Seed	in: Force	in: Divs	in: KMinF	out: stripes	out: CutLen	out: Sheets	out: Waste	out: height	out: DEF	out: Weight
4	300	6	14000	0	8	28	23093	3	0.477388	496	9.57E-06	5.977882
4	350	6	14000	0	8	27	22029	3	0.519702	444	9.79E-06	5.493882
4	400	6	14000	0	8	25	20934	3	0.552054	402	0.000011	5.123816
4	450	6	14000	0	8	27	20606	3	0.57782	368	0.000012	4.829098
4	500	6	14000	0	8	27	19977	3	0.598992	340	0.000014	4.586918
4	550	6	14000	0	8	30	20348	3	0.616832	316	0.000015	4.382856
4	600	6	14000	0	8	25	18849	3	0.632141	296	0.000016	4.207748
6	300	6	14000	0	8	45	38257	5	0.488319	498	0.000018	9.754748
6	350	6	14000	0	8	41	35747	5	0.528155	447	0.000015	8.995323
6	400	6	14000	0	8	44	35332	5	0.558601	407	0.000013	8.414893
6	450	6	14000	0	8	45	34778	5	0.582795	375	0.000012	7.953647
6	500	6	14000	0	8	45	33849	4	0.503264	348	0.000012	7.575876

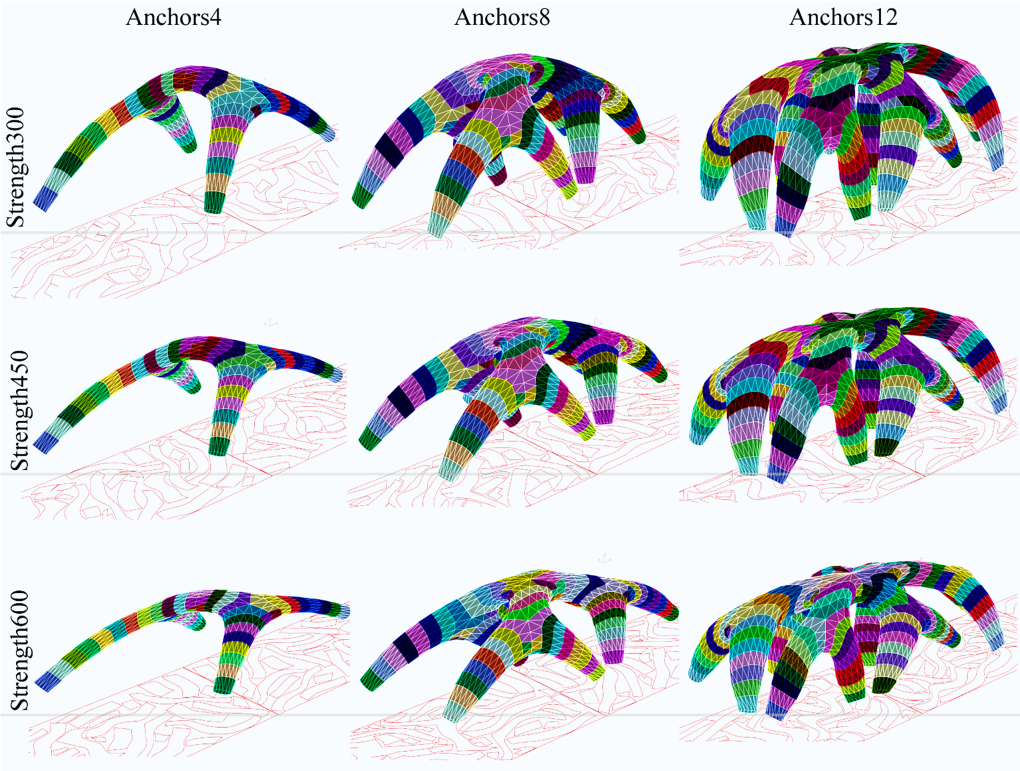

Figure 4
Sample of the images, in a table organization.

RESULTS AND ANALYSIS

Based on the above input and output attributes, the database (Table 2) was generated, computationally extensive, performing all possible combinations in an excel sheet, including the image for each alternative (Figure 4). Table 1 explains the quantity of total iterations. As a result, different types of graphs were tested to visualise which combinations of attributes are giving a clear image of the relationship.

Charts with Vectorial Data

The real values of each attribute were converted to vector values from 0 to 1, using the remapping component and finding the minimums and maximums bounds of each in all the database to be used as a source. The same process happened for all the inputs and outputs values.

The vectorial analysis demonstrate how attributes behave, throughout the timeline. We observe that the *Cutting Length* and *Number of Stripes* do not affect *Deflection* (orange bars) (Figure 5). From the analysis of the *Height*, shown in blue bars, (Figure 6) we observe that it is affected, hierarchically, mostly by the amount of anchors (grey line), second by the *Strength* (higher values in the middle of every 35 iterations, that could mean that some specific point locations are generating higher structures), third, is following the *Seed* pattern and forth is affected by the

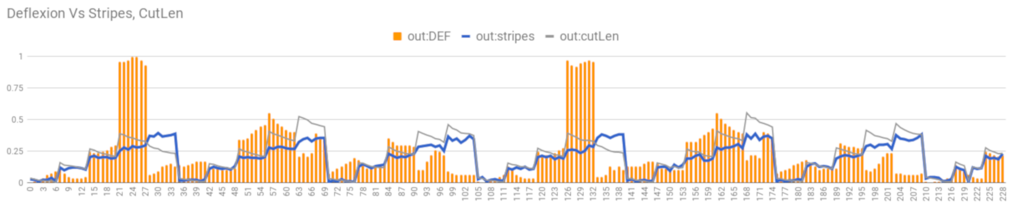

Figure 5
Chart of 230 iterations. Showing the Deflection pattern (orange bars) how it coincides with the Seed (red line, figure 6), every time it restarts its loop.

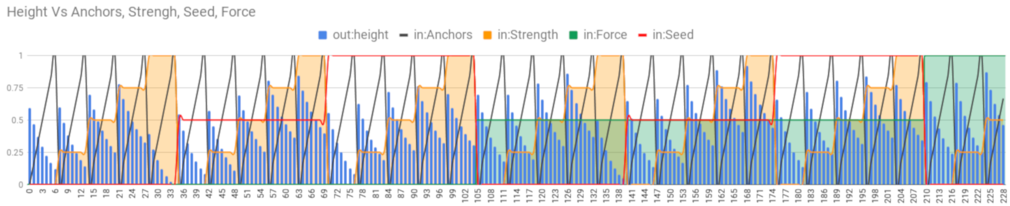

Figure 6
Chart of first 230 iterations. Showing the Height (blue line) attribute pattern that coincides with the Anchors and Strength loop dramatically.

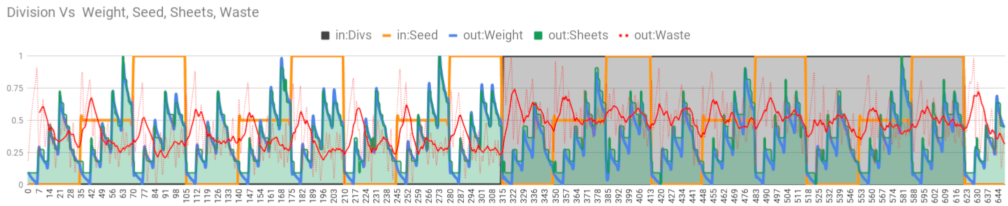

Figure 7
Chart of 650 iterations with vectorial data. A periodic pattern of Seed, Weight, Sheets, Waste, remains quite constant, in all iterations, even when Division attribute (grey area) is changed. The Waste of Material (red line) gets slight modification.

Force.

In the vectorial data analysis (Figure 7), it is possible to compare and see the patterns of change for each attribute. More *Subdivisions* do not affect *Weight*, *Number of Sheets*, *Waste of Material*.

CONCLUSION

The proposed research examined a design workflow that allows to produce sets of segmented shell topologies. This generative method gives the user the possibility to learn, analyse and balance priorities between alternatives that respond to various needs and to adjust the design based on the new information. The vital benefit of creating such database is to be utilized specifically to train an ANN to be able to predict new models information based on a new combination of desired input parameters (Giannopoulou et al. in press).

According to Wujec [3], machine learning drastically affects the field of design and architecture through its direct link to computational design, however its applications are still in an experimental stage. Although biological skin patterns (Kondo 2002) and segmentation in fabrication open a new field for interdisciplinary investigation and architectural applications, a machine learning approach to solve the complexities of such integration need to be further developed. Under the framework of Ito's extended intelligence (Ito 2018), "the convergence of cyber, physical and biological systems of production" (Sousa et al. 2019), requires not only new tools, methods and ways of understanding, but to question the purpose as observers and designers of a machine-based system of thinking to help developing sustainable and safe societies.

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