VISUAL CHARACTER ANALYSIS WITHIN ALGORITHMIC DESIGN

Quantifying Aesthetics Relative to Structural and Geometric Design Criteria

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Abstract. Buildings are responsible for 40% of world C02 emissions and 40% of the world's raw material consumption. Designing buildings with a reduced material volume is essential to securing a post-carbon built environment and supports a more affordable, accessible architecture. Architecture's material efficiency is correlated to structural efficiency however, buildings are seldom optimal structures. Architects must resolve several conflicting design criteria that can take precedence over structural concerns, while material-optimization is also impacted from limited means to quantitatively assess aesthetic decisions. Flexible design methods are required that can adapt to diverse constraints and generate filagree material arrangements, currently infeasible to explicitly model. A novel approach to generative topological design is proposed employing a custom multi-agent method that is adaptive to diverse structural conditions and incorporates quantitative analysis of visual formal character. Computer vision methods Gabor filtering, Canny Contouring and others are utilized to evaluate the visual appearance of designs and encode these within quantitative metrics. A matrix of design outcomes for a pavilion are developed to test adaptation to different spatial arrangements. Results are evaluated against visual character, structural, and geometric methods of analysis and demonstrate a limited set of aesthetic design criteria can be correlated with structural and geometric data in a quantitative metric.

Keywords. Generative/Algorithmic Design; Computer Vision; Environmental Performance; Multi-Agent Systems; Visual Character Analysis; SDG 10; SDG 11; SDG 9; SDG 12; SDG 13.

1. Introduction

Buildings are responsible for 40% of world C02 emissions and 40% of the world's raw material consumption (Bergman, 2013, pp. 24–25). Reducing material volume in building designs is an essential step towards a post-carbon built environment that can support a more equitable, affordable and sustainable future. Recent developments in

POST-CARBON, Proceedings of the 27th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2022, Volume 1, 131-140.

large format Additive Manufacturing (AM) potentially enable the fabrication of more materially efficient buildings. AM methods encompass a wide range of material and manufacturing constraints, yet typically allow substantial formal and topological complexity. Although these can support greater material efficiency and design expression, design methods that can generate and evaluate both criteria concurrently are relatively nascent. Architecture's material efficiency is correlated to structural efficiency; however, buildings are seldom optimal structures. Architects must resolve several conflicting design criteria that can take precedence over structural concerns. Examples include planning or site-related constraints, that might impose variations in column or wall spacings. Additionally, formal, or aesthetic criteria might undermine optimization of material volume. Flexible design methods are required that can adapt to diverse planning conditions while minimising material usage. The utility of such methods is contingent on their ability to provide materially quantitative feedback to the designer relative to their aesthetic design concerns. While optimisation methods can be integrated within generative architectural design processes (E.g., reinforcement-learning or evolutionary solvers (Mitchell, 2019)), these require fitness data to be obtained from design iterations. To integrate visual aesthetic criteria is challenging, as it requires a quantitative means of assessing qualitative formal character. Material volume offers one means to assess environmental and cost impacts of an architect's spatial, formal, or ornamental design propositions. Large-scale design decisions (E.g., floor planning, 3D massing or structural grids) are often constrained by programmatic or structural parameters that require explicit design input. Fortunately, AM architecture can support these constraints while enabling design expression and material optimization at smaller scales, traditionally considered to be the preserve of ornament. However, explicitly modelling such high-definition designs is prohibitively laborious, necessitating algorithmic or software-automated approaches.

2. State of the Art

Increases in a design's topological complexity can support greater material and structural efficiencies, as can be seen in the use of Topological Structural optimization (TSO) for the design of slabs, pavilion canopies, and large-span halls (Jipa et al., 2016; Sasaki et al., 2007). However, TSO operates primarily as a design-rationalization method with limited potential to directly inform aesthetic variability. Several algorithmic design approaches that encode a formal-aesthetic condition in addition to structural parameters have been developed for AM architectural elements such as columns and floor slabs (Anton et al., 2020). These have primarily focused on the design and manufacture of individual elements with limited demonstration of adaptation to variable spatial-structural conditions and no investigation into the relationship between their visual formal character and material volume. Multi-Agent design methods are particularly well suited to resolving spatial-formal problems and have already been utilized for architectural design (Snooks & Stuart-Smith, 2012). To date, multi-agent methods for AM architecture have not been developed that are adaptive to the varied structural conditions found in many buildings' structural layouts. Algorithmic methods also encode a designer's formal intentions to a large degree. Programmers/designers engage in subjective aesthetic decision-making when writing algorithms, and by assigning values to variables within code. During this process, a designer has limited means to reflect or quantify visual character's impact on material efficiency. As algorithmic design and optimization methods operate on quantitative data, it is difficult to correlate qualitative concerns such as aesthetics. In the field of computer science, computer vision research has produced image processing methods that enable the quantification of visual features. Methods for pixel filtering, contouring, or clustering are critical to several data collection and machine learning algorithms (Davies, 2017). Recent research into the programming of aesthetics principles within deep learning approaches(Shaji, n.d.) suggests aesthetics can be engaged within algorithmic design. While architectural researchers recognise algorithmic processes may generate new aesthetics (Rehm, 2020), little research has been conducted into how evaluation of such aesthetics might inform optimisation processes, or impact a design's carbon footprint. Although clustering techniques have been used to classify architectural precedent buildings (Alymani et al., 2020), such methods have not been employed to evaluate visual formal character in algorithmically generated designs.

3. Algorithmic Design with Visual Formal Character Analysis

This research proposes a novel approach to topological design through a custom Multi-Agent Design (MAD) method that is adaptive to spatial and structural inputs, and incorporates Visual Character Analysis (VCA) together with Structural Analysis (SA) and Geometric Analysis (GA). GA also supports estimation of Embodied Carbon (ECO2). Computer vision methods such as Gabor filtering, Hough Line, and Canny Contouring (OpenCV, 2021) are utilised to evaluate and encode the visual appearance of designs within quantitative metrics in addition to SA deflection and principal stress, and GA metrics for volume and surface area. The term 'visual character' can be used to describe a wide range of visible attributes. Within this research, a narrow set of visual characteristics were selected that were deemed relatively easy to quantify and aesthetically related to the design method's ability to produce increased topological complexity, including heterogeneity, intricacy, continuity, and recesses. Proposed visual characteristics and corresponding analytical criteria offer an extremely limited form of aesthetic evaluation. As a first foray into the quantification of visual character, these categories are utilised to establish a proof of concept, sufficiently general to be of relevance to a broad number of manufacturing methods and design approaches. No optimisation routines are undertaken within the research, instead, novel research into design and analysis methods is presented that could be utilised in conjunction with optimisation methods. A matrix of design outcomes for a pavilion was developed to test the method's adaptability to different spatial and structural arrangements. Outcomes are tested against visual character, structural, and geometric methods of analysis, to evaluate whether a limited set of aesthetic design criteria can be correlated with structural and material volumetric efficiency as a quantitative metric.

4. Methods

A Multi-Agent Design method (MAD) (Figure 1) was developed that included quantitative analytical methods to provide SA, GA, and VCA metrics (Figure 2). Using the method, a matrix of design outcomes (Figure 3) was produced to evaluate the effectiveness of the approach, and its suitability to support optimisation processes.

4.1. MULTI-AGENT DESIGN METHOD (MAD)

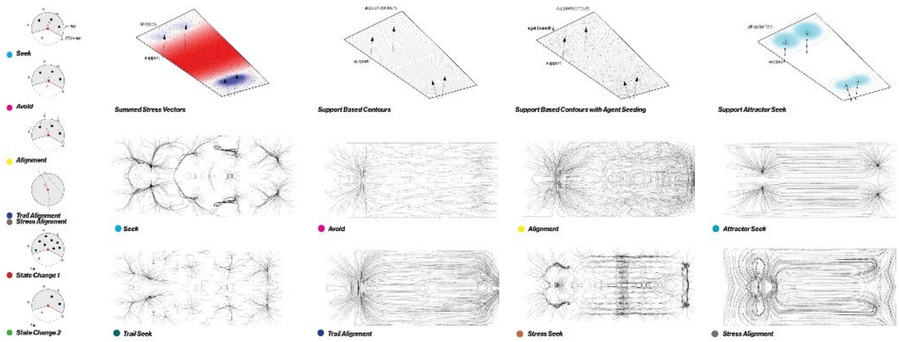

Figure 1. MAD Method: a)Agent rules b)Set-Out data and agent seeding. c) rule trajectories

A custom multi-agent design algorithm was developed to enable geometrically integrated ceilings, slabs and column/wall designs to be developed from a flexible, user-specified spatial set out of vertical supports, adapting designs to different planning and structural constraints within the Rhino3D software environment (Figure 3). A ceiling/slab mesh model with user-specified column and wall support locations is first structurally analysed in Karamba3D™, with resulting principal stress and deflection data stored in Python lists. A custom Python agent class inspired by Craig Reynolds Boids algorithm (Reynolds, 1987) was written that governs the motion of particles over simulated time. The ceiling mesh surface is populated with instances of the agent class, that seek and align to high stress areas, and attempt to travel down support locations. Agent motion trajectory curves are interpolated as a single mesh topology.

To ensure each simulation's initial set-out is consistent across diverse permutations of user-specified structural support conditions, a method was developed that provides a variable density distribution of agents relative to structural stress and surface area. A contour field is generated by uniformly offsetting curves that radiate out from each support position and Boolean-Unioned where they overlap. Seed points are randomly distributed between each contour curve relative to surface area between the contours at a probability of 0. $0.0157/M^2$, and further culled relative to local principal stress values at a rate of: 0.700. This results in a variable density of agents relative to surface area and structural stress distributions, seeding more agents in high deflection areas.

Each instance of the agent class contains an (x,y,z) coordinate for current position, (x,y,z) vectors for velocity and acceleration, and an integer for its current ‘state’. Each timeframe an agent sums an acceleration vector with its current velocity and adds this vector to its current position to move in space-time. Position and velocity vectors are constrained to the ceiling mesh by finding their closest points on the mesh. The acceleration vector is calculated each frame by summing results from a series of behavioural methods (Figure 1) that includes: agent-to-agent methods (seek, avoid, align), agent-to-agent trail methods (seek trail, align to trail), agent-to-structural data methods (seek local highest stress values, align to local stress vectors), and agent-to-vertical supports methods (seek top of support, align to support). Each method calculates the distance to neighbours of a specified type (agent, trail, structural data or vertical support) within a specified radius (R) and field of view (FOV). For each method, vectors are calculated only relative to neighbours located inside of the agent's R and FOV. Seek methods calculate a vector pointing towards the average position of neighbours while avoid methods calculate an inverse vector. Align methods average the orientation of neighbours. All methods determine a steering vector that is the difference between their calculated vector and the agent's velocity vector, resulting in a vector that causes the agent to turn towards or away from each influence. All methods return a single vector which is then unitized to ensure they can be proportionally scaled relative to one another to influence an agent's behaviour. Agents operate under two states which utilise different weightings of the above method calculations, commencing as state "1", and changing to state '2" when in range of a vertical support to prioritize seeking and aligning to vertical supports (Figure 1).

Each agent's motion trajectory over 100 timeframes is translated to a Nurbs curve. As agents were constrained to the ceiling mesh, a method was created to adjust the z-height of each agent trajectory curve knot below the ceiling, relative to adjacent agent curves and structural stress. The displacement vector is calculated as the difference in position (pos) to neighbouring agents (a.pos) scaled by the closest principal stress value divided by the number of agents in range (n) and weighted by a constant (C):

$$\mathrm{pos.z} = \mathrm{pos.z} - \left(\frac{\sum(distance(a.pos\ to\ pos)) * \mathrm{stress}}{n} * \mathrm{C}\right)$$

A continuous mesh geometry is generated around the adjusted curves by first creating polysurfaces from a single rail sweep from cross-section curve profiles arrayed along each curve. Polysurfaces are then converted to a mesh and imported into Zbrush™ and merged into a single mesh using Zbrush's dynamesh and smooth commands. This method was selected over more accessible methods in Rhino3D™ such as isosurfacing due to its benefits in enabling greater control over cross-sectional geometry.

4.2. STRUCTURAL, GEOMETRIC & EMBODIED CARBON ANALYSIS

Design outcomes were geometrically analysed (GA) for surface area and volume, and structurally analysed (SA) for deflection and principal stress. GA metrics were obtained using built-in Rhino3D™ methods for mesh analysis. Although SA can be performed on meshes using a shell analysis, it would be computationally prohibitive if integrated within high-iteration optimization routines. As such, a frame analysis was performed using Karamba3D™ that was computable in a fraction of time. To prepare a structural model for frame analysis, each agent trajectory curve was converted to a polyline and exploded into several line elements. A series of connective lines between trajectories was generated between nodes in proximity to one another at a range equivalent to mesh cross-section profiles, producing a network with connectivity comparable to the mesh result. This was then used for SA. To estimate embodied carbon, a high-strength steel re-enforced concrete (RC40/50) with 100kg/m3 steel reinforcement and 30% fly ash was specified with an embodied carbon (ECO2) value of 330 kgCO2/m3 (MPA The Concrete Centre, 2020). By utilising volumetric data obtained in GA, an embodied carbon value is estimated for design outcomes.

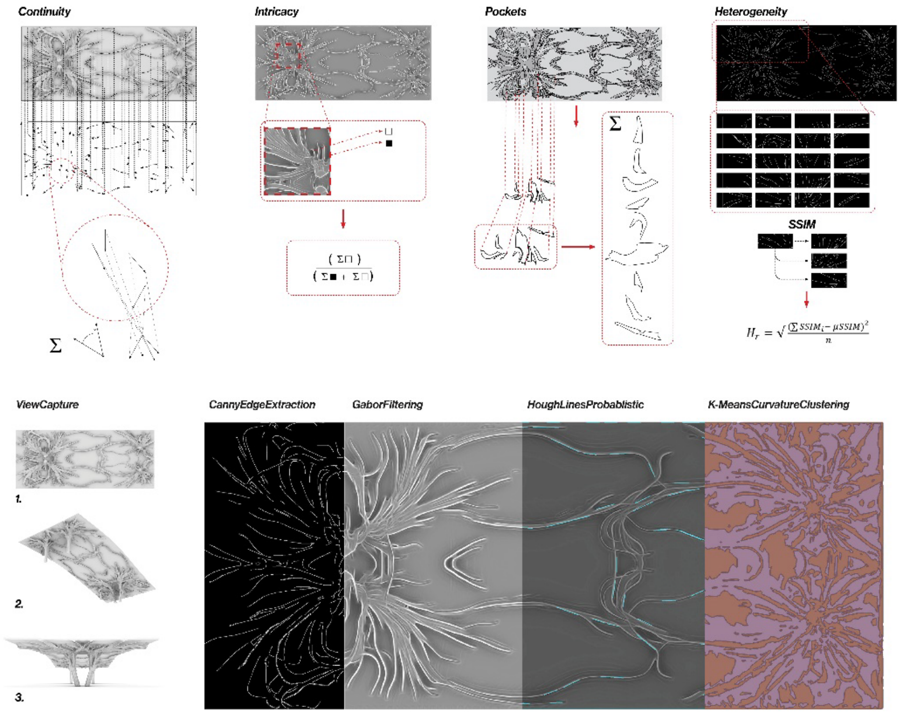

Figure 2. VCA. a) quantitative methods b) image processing methods applied to three camera views

4.3. DESIGN VISUAL CHARACTER ANALYSIS (VCA)

To assess the visual character of design outcomes a methodology for image analysis was developed that involved viewport capture and image processing in Rhino3D™. For each design outcome, Images at 1920x1080 resolution were captured using three specified camera views and Rhino3D's 'Arctic' display style. The computer vision framework OpenCV™(OpenCV, 2021) was made accessible within Rhino3D by using GHPythonRemote™ to enable Python to be executable within Rhino3D's IronPython 2.7 GHPython components. A series of visual characteristics (including *intricacy, heterogeneity, continuity,* and *surface recesses* were established. To quantify these, specific OpenCV methods were selected that could generate new images that corresponded to each characteristic, and methods developed to extract and quantify data from each OpenCV image outcome. The specific methodologies are illustrated in Figure 2 and summarised below:

- *Intricacy:* greater amounts of geometrical definition. A method was established to quantify edges in an image. A linear filter used for texture analysis, Gabor Filtering was selected due to its ability to highlight edges by identifying areas of highest difference in pixel value which are representative of edge curvature (OpenCV, 2021). In greyscale images, these are visualised as white pixels, whose quantity relative to total pixels in the image was quantified to describe a degree of intricacy.

- *Heterogeneity:* greater degrees of difference between different regions within an image. The Canny edge detection method was utilised to first identify features in the geometry due to its ability to produce an image that depicts continuous edges in white on a black background through a multistep process that leverages spatial-frequency filtering and hysteresis thresholding (Davies, 2017, p. 136). A Structural Similarity Index (SSIM) Image Difference Comparison is then performed on the Canny image to evaluate the similarity between different tiled regions within the image (OpenCV, 2021). This returns a float for the standard deviation of SSIM distance evaluation between the image tiles and used as a value of Heterogeneity.

- *Continuity:* degree of alignment between edges in areas of high curvature. OpenCV's Probabilistic Hough Lines Transform method was utilised to create a series of line segments that approximate continuous edges within an image (OpenCV, 2021). As the Hough Transform is more effective if edge detection pre-processing is performed beforehand, a Canny Edge image was created and used as the input image. An average angle between Hough Line segments within proximity of Height/6 pixels to each other was calculated and averaged for all lines within the image to provide a metric for continuity.
- *Surface Recesses:* degree to which a surface geometry is separated into regions of varying depth. In lieu of the artic render, a coloured image was produced through the development of a custom Rhino3D Python script that coloured mesh vertexes relative to local mesh curvature. Pockets are identified by segmenting the image into regions of different colour, thus segmenting by local minima/maxima of curvature in the surface. K Means Clustering of the image is used to categorise pixels of similar colour as a cluster (OpenCV, 2021). OpenCV contouring of pixel clusters enables the quantity of clusters to be identified as a metric for pockets.

4.4. DESIGN MATRIX AND COMPARATIVE ANALYSIS

A matrix of pavilion designs was developed for four different spatial set-outs (A,B,C,D) that varied the number and spacing of columns, walls, and slab dimensions including an 8x8m 4-column grid, a 30x12m rectangular grid with symmetrical and asymmetrical column supports, and an option combining walls and columns. The MAD method was tested with three variations in ruleset values (labelled 1,2,3), together with an additional base condition (0) for each set-out that was explicitly modelled to have regular rectangular columns similar to Le Corbusier's Maison Domino (Figure 3c). VCA, GA, and SA metrics were developed for each design outcome. Metrics were re-mapped to a value between 0 and 1 and graphed (Figure 4) to support comparative analysis and to establish whether the method could be used to describe a multi-objective design fitness value.

5. Results and Discussion

The MAD method demonstrated successful adaptation to diverse spatial and structural conditions (Figure 3a). Minor differences in the rulesets had significant impact on outcomes, illustrating an expansive design space with varying degrees of geometric alignment and density. SA and GA results for all three rulesets performed similarly well in symmetrical spatial set outs A and B yet evidenced greater variability in asymmetrical set outs C and D, indicating potential improvements could be achieved by inclusion of an optimization routine. While MAD and SA/GA methods were

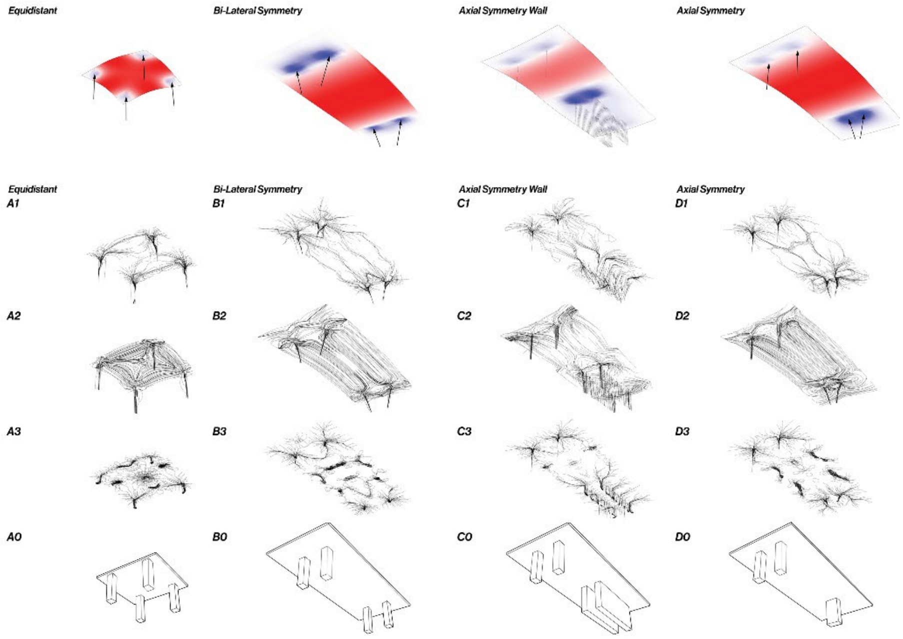

Figure 3. Matrix of design outcomes relative to user-specified column/wall and slab spatial organizations. a) structural loading conditions, b) agent trajectories, c) explicit base condition

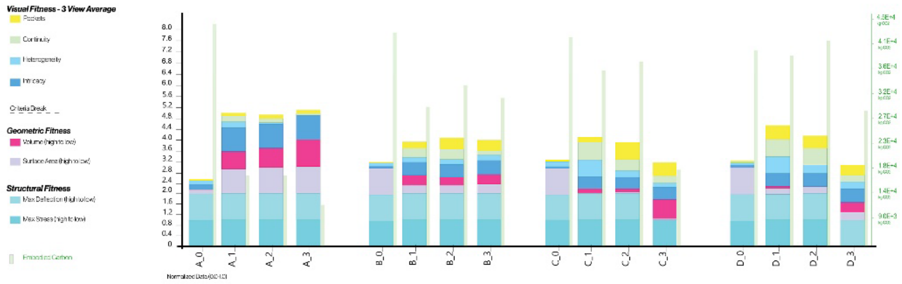

Figure 4. Comparative analysis of design matrix results

materially agnostic (with calibration to specific materials and performance requirements in future work), embodied CO2 (EC02) was estimated using a high-strength reinforced concrete. ECO2 calculations derived from GA volumetric data demonstrated ruleset #1-3 MAD efficiency gains of 4-39% over base conditions. For set-out #A, a 23% reduction is equivalent to a saving of 4400 kgCO2.

As anticipated, all MAD rulesets scored substantially higher in VCA than base conditions. Evaluating VCA methods, Heterogeneity was validated by high-value results in asymmetrical set outs C and D, and ruleset #1's high values reflected a greater organisational diversity in its design outcomes. MAD results also demonstrated more *intricacy* than base conditions yet remained relatively constant across all rulesets. This suggests that the quantification of Gabor filter images was not effective at describing *intricacy* of design outcomes, or, that all MAD rulesets generated similar levels of intricacy despite ruleset #3 consolidating detail in smaller clusters. *Continuity* was greatest in ruleset #1 and extremely low in base conditions as expected. K-Means Clustering was not as successful for evaluating recesses. Values were similar across all MAD rulesets, with the most heterogeneous results scoring lower than more homogenous outcomes. The number of clusters did not adequately describe the significance of features. As MAD Ruleset #1 outcomes have more distinguishable recesses at a range of scales compared to other rulesets, scale should be incorporated into the recesses evaluation method.

While MAD rulesets #1 and #2 scored higher in SA, ruleset #3 had superior GA results demonstrating the need for SA and GA feedback within an iterative optimisation process. The authors found MAD ruleset #1 exhibited preferable design outcomes that were formally continuous and heterogeneous (Figure 4). MAD ruleset #3 was least preferable due to a lack of heterogeneity resulting from dense clusters around supports. Results validate that selected visual character rules aligned to the author's aesthetic intentions yet highlight a conflict between author (or any user) preference, material, and structural optimisation. This demonstrates the importance of quantitative evaluation of visual characteristics to ensure that some aesthetic properties can be developed in relation to optimisation approaches. In assessment of the matrix of results, a suitable fitness function for a design optimization process might enhance intricacy(I), heterogeneity(H) and continuity(C) while reducing material volume (V) and structural deflection (D) and stress (S). This might be paraphrased as:

$$fitness = \frac{w_1\mathrm{I} + w_2\mathrm{H} + w_3\mathrm{C}}{w_4\mathrm{V} + w_5\mathrm{D} + w_6\mathrm{S}}$$

Whereby w_1 through w_6 are constants assigned by any user/designer to weight the influence of each parameter and could be adjusted to any designer's preferences.

Figure 5. a) MAD outcomes adapt to structural and spatial constraints, while producing visual character that is quantitively evaluated using b) VCA computer vision methods.

6. Conclusion

The research demonstrates a MAD method that integrates VCA methods together with SA, GA and, EC02 estimation. The MAD method demonstrated successful adaptation to diverse user-specified spatial and structural set-out conditions, while the use of computer vision image processing techniques supported quantification of visual character alongside more readily quantifiable performance metrics for structural and material efficiency. Results illustrate the utility of the research but also highlight the necessity for inclusion of an optimization routine such as reinforcement learning to achieve results suited to material, and structural performance requirements. Given the challenges of establishing VCA methods and the limited criteria developed in this research, more work expanding VCA to encompass a broader set of generalisable aesthetic conditions would provide greater utility outside of this proof of concept. A survey paper of image-processing methods would be a good next step. Further development of the research will involve expansion of broader spatial/formal user design input, and incorporation of MEP and environmental performance considerations. AM architecture holds immense potential to reduce the material and environmental impact of building, while offering exciting opportunities for geometric design freedom. This research provides a means to develop topologically complex designs suited to AM methods together with feedback from structural, volumetric, and visual character metrics, providing a novel design approach that can be integrated with optimisation routines. It is hoped the research fosters a more holistic approach to design, correlating aesthetics with the material and structural efficiency of buildings, and thereby facilitating a reduction in the carbon footprint of architectural designs.

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