Data-Driven Midsole

Performance-Oriented Midsole Design Using Computational Multi-Objective Optimization

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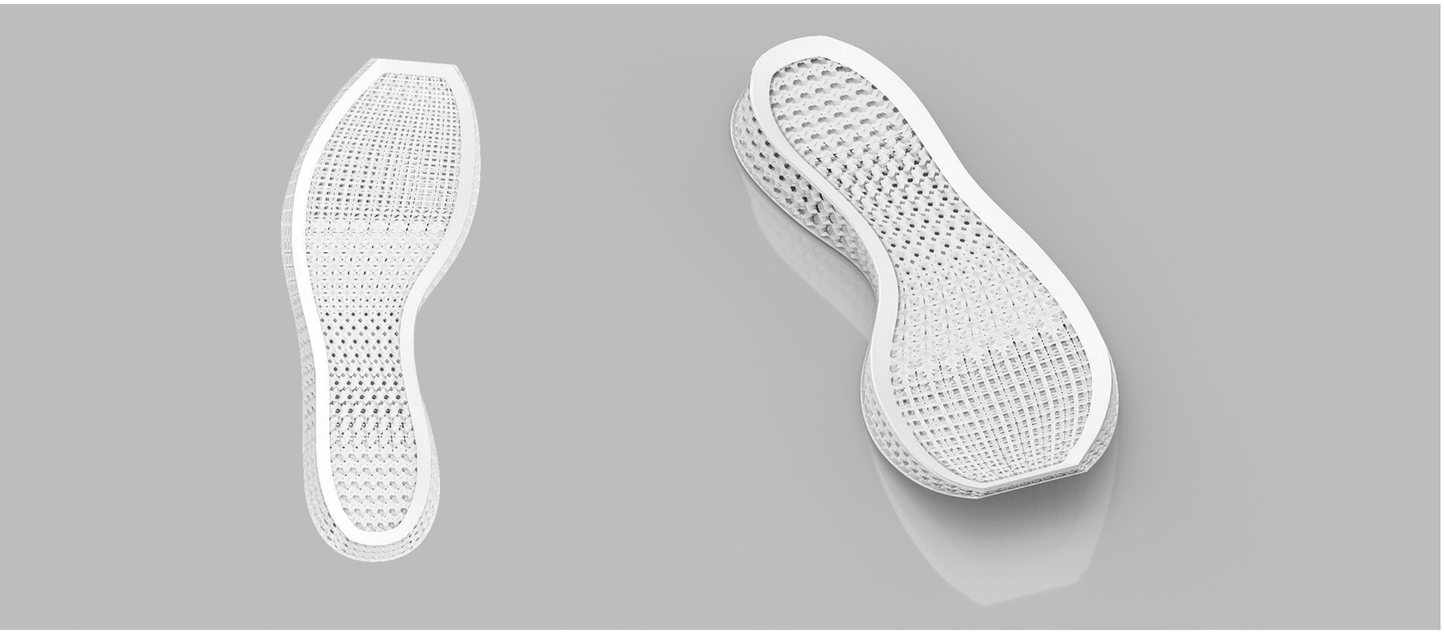

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1 Midsole design using deep temporal clustering and computational multi-objective optimization.

ABSTRACT

With the advancement of additive manufacturing, computational approaches are gaining popularity in midsole design. We develop an experimental understanding of the midsole as a field and develop designs that are informed by running data.

We streamline two data types, namely underfoot pressure and surface deformation, to generate designs. Unlike typical approaches in which certain types of lattices get distributed across the midsole according to average pressure data, we use ARAMIS data, reflecting the distinct surface deformation characteristics, as our primary design driver. We analyze both pressure and deformation data temporally, and temporal data patterns help us generate and explore a design space to search for optimal designs. First, we define multiple zones across the midsole space using ARAMIS data clustering.

Then we develop ways to blend and distribute auxetic and isosurface lattices across the midsole. We hybridize these two structures and blend data-determined zones to enhance visual continuity while applying FEA simulations to ensure structural integrity. This multi-objective optimization approach helps enhance the midsole's structural performance and visual coherence while introducing a novel approach to 3D-printed footwear design.

INTRODUCTION

3D printing has been broadly applied to product prototyping and fabrication. With the advancement of data science and volumetric modeling toolkits, there are opportunities in the footwear industry to employ computationally generated lattice systems in place of conventional components and materials to enhance performance with new design possibilities.

As a layer between the upper and the outsole, the midsole of a shoe performs as the main cushioning, stability and pronation control component. Midsole materials, subcomponents, and overall composition determine the quality of the running experience, and thus numerous running shoes end up featuring a broad range of midsole components and materials.

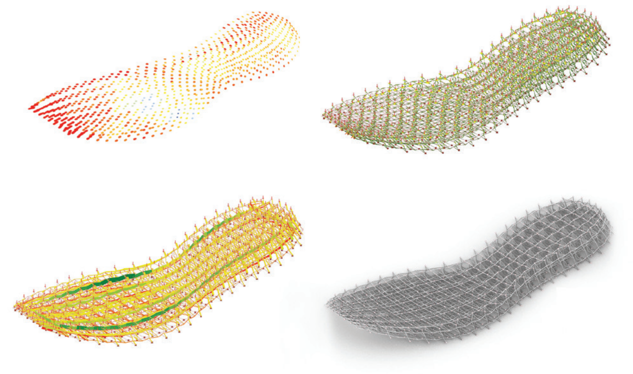
With the advancement of data science and volumetric modeling toolkits, we see an opportunity in the footwear industry to replace these components and materials through employing computationally generated lattice systems (Nazir et al. 2019) . We develop a data-driven design approach, utilizing multi-objective optimization and performance simulations.

In recent years, New Balance partnered with Nervous System to develop 3D-printed midsoles for performance running shoes in which 3D pressure data determined the 3D-printed lattice geometry.

The authors also experimented with traditional measures to design a midsole using a pressure-data-driven approach. In this case, we designed a midsole composed of lattice units whose structural unit angle and member diameter are proportionate to the underfoot pressure data in the midsole (Fig. 1).

Such approaches only take into consideration the instant or averaged sum of underfoot data. Nonetheless, typical midsole deformations are temporal processes such as running and jogging. The rich temporal information embedded in the change of external force across time is flattened and untapped. The ARAMIS data[1] is a set of midsole deformation data captured by stereo cameras during a unit duration of the running process on both sides of the midsole. During each frame, the strain and deformation for each lattice on the midsole were calculated (Fig. 5).

We see an opportunity to add to this data-driven approach by taking the temporal implications of running and ARAMIS dataset into consideration: various parts of the midsole come into effect during various human movement stages.



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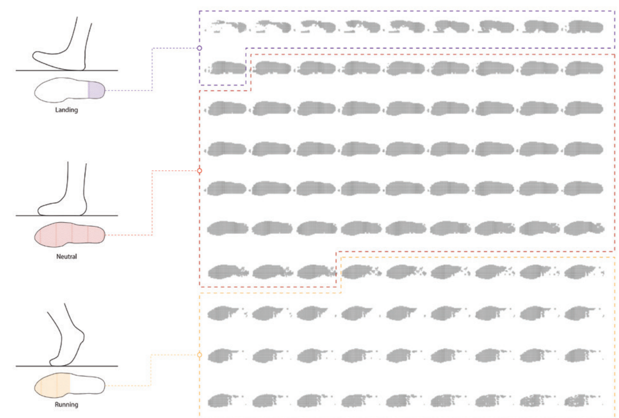

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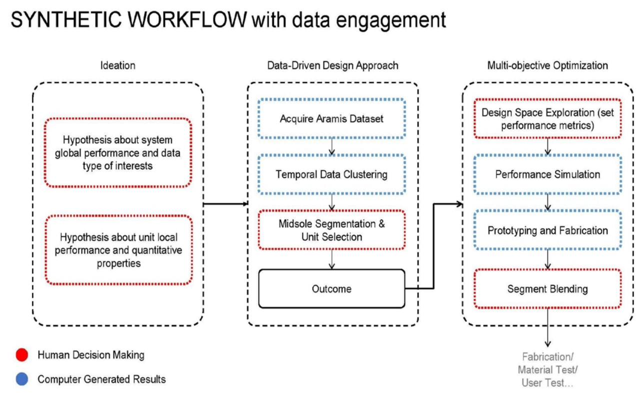
2 Pressure data-driven material distribution.

3 Visualization of sequential pressure data demonstrating running experience in three stages.

This can be used to inform lattice distribution and design (Fig. 2). This approach will augment the static pressure-data-driven approach and bring new opportunities and insights into computational midsole design.

METHODOLOGY: COMPUTATIONAL MULTI-OBJECTIVE OPTIMIZATION DESIGN

We develop a computational multi-objective optimization approach that takes both ARAMIS data and underfoot pressure data into design and evaluation processes. We apply a lattice system as a parametric design framework for the midsole design and determine the optimal lattice structure for each group of lattice units using deep-temporal clustering as a segmentation algorithm. We then evaluate the generated designs through performance-based computational simulations and determine each segment's optimal structure combination. We use underfoot pressure data to



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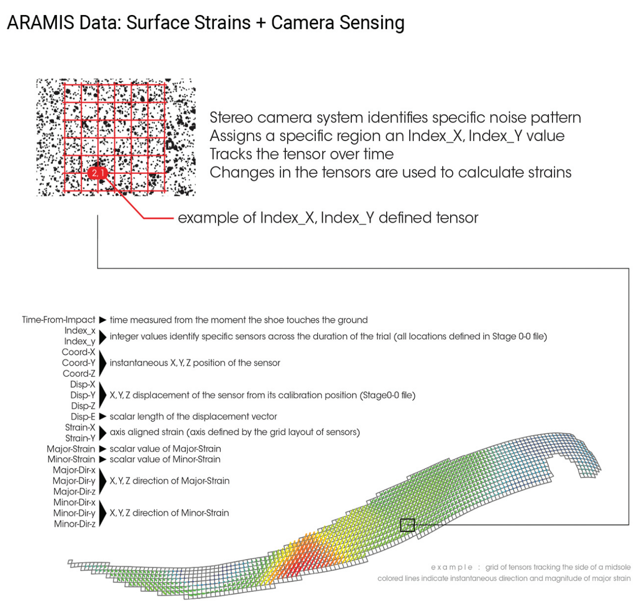

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4 Holistic computational multi-objective optimization workflow.

5 ARAMIS data overview.

determine the optimal form factor and material distribution for each lattice unit. Meanwhile, we research ways to implement aesthetic decisions into the design.

A holistic approach is critical in this method as we intend to unify and synthesize the performance and aesthetic goals and computation and human agency in the design process. The approach is composed of three steps: ideation, data-driven approach, and multi-objective optimization.

Ideation

The synthetic workflow starts with an ideation phase driven by human designers. In this phase, the designers define high-level shape grammars and hypotheses for performance space (Fig. 4).

The first hypothesis is the global-local hypothesis. It assumes that the global system performance corresponds to the case where each local segment's performance is optimal. Therefore, the midsole's optimal global performance of impact absorption is achieved where each segment deformation is at its local minima. Similarly, each segmentation archives its best performance metrics when each lattice unit resists its local temporal strain effect to its best.

The second hypothesis proposes a blending hypothesis. In this case, the designer assumes that the strain is interpolated along the major axis of midsole and that the aesthetics metric is optimal when the lattice units between the center of two segments are smooth volumetric interpolation of lattice units on the two poles.

Data-Driven Approach

The performance-based midsole design starts with ideating how available data types affect the running experience.

There are two types of footwear data available in this project: the under-foot pressure data[2] and ARAMIS data. Both are sequential, making it possible to track the midsole's behavior over a specific period.

The under-foot pressure data reflects the load distribution of midsole upper surface in the running process, but it cannot be used for temporal analysis due to its limited frame counts.

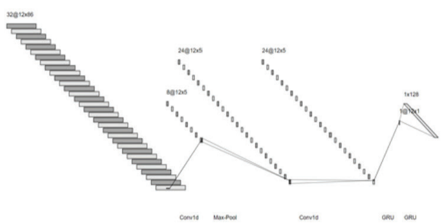
There have been many explorations of using under-foot pressure data as a primary form factor for additive manufacturing (Brennan-Craddock, Wildman, and Hague 2012) and midsole designs (Dong, Tessier, and Zhao 2019). The approach we present challenged this conventional footwear data usage by proposing a new design agenda that treats ARAMIS data as the primary factor and pressure data as the secondary factor.

The ARAMIS data set (Fig. 5) includes measurements of the surface deformation of the inner and outer side-surface for midsole, and is created by New Balance Inc. using digital-image-correlation (DIC) systems (Chu et al. 1985). The data set includes more than 200 instantaneous frames of optically measured position data and surface strains for midsole deformations. We used the midsole side surface data, which is composed of a grid of 152 × 18 data points. Each data point in the data set contains the unique x and y index for the point, the coordinate of the point on that frame, the displacement of the point in x and y direction compared to the calibration status, the strain in x, y, and z direction,

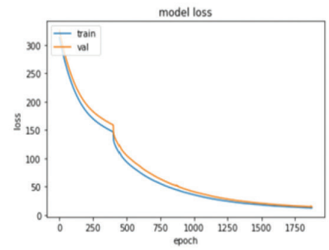
	TIME-FROM-IMPACT	INDEX_X	INDE-Z	DISP-X	DISP-Y	DISP-Z	RAIN-Y	MINOR-STRAIN	MAJOR-DIR-X	MAJOR-DIR-Y	MAJOR-DIR-Z	MINOR-DIR-X	MINOR-DI Y
0	0.2	17	144	39.77452	121.0083	-21.8903	1.33741	0.51291	-0.93437	0.307481	-0.18748	-0.37157	-0.81124
1	0.2	18	144	39.75324	120.1739	-21.9601	1.31835	0.45842	-0.30454	0.841156	-0.45419	-0.9579	-0.26649
2	0.2	19	142	39.37608	118.9675	-22.0656	1.31615	0.51291	-0.26445	0.869291	-0.42283	-0.96716	-0.2336
3	0.2	20	148	38.97893	117.7658	-22.1595	1.31918	0.51797	-0.71256	0.655539	-0.25018	-0.70497	-0.64315
4	0.2	21	148	38.57319	116.5678	-22.2199	1.44937	0.51814	-0.82937	0.535644	-0.16114	-0.56125	-0.75946
5	0.2	22	146	38.18861	115.3623	-22.3428	1.47966	0.52383	-0.8369	0.528042	-0.14506	-0.54848	-0.77002

130 frames of inside of midsole ARAMIS data

features = ['Disp-X','Disp-Y','Disp-Z','Disp-E','Major-Strain','Minor-Strain','Major-Dir-x',
'Major-Dir-y','Major-Dir-z','Minor-Dir-x','Minor-Dir-y','Minor-Dir-z']



Deep Temporal Clustering with Recurrent Neural Network Autoencoder



Training Result

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6 ARAMIS data sample and deep temporal clustering algorithm.

and the x, y, and z directions of minor and major strain. Here we use the primary strain vector and the displacement vector as major features for temporal clustering.

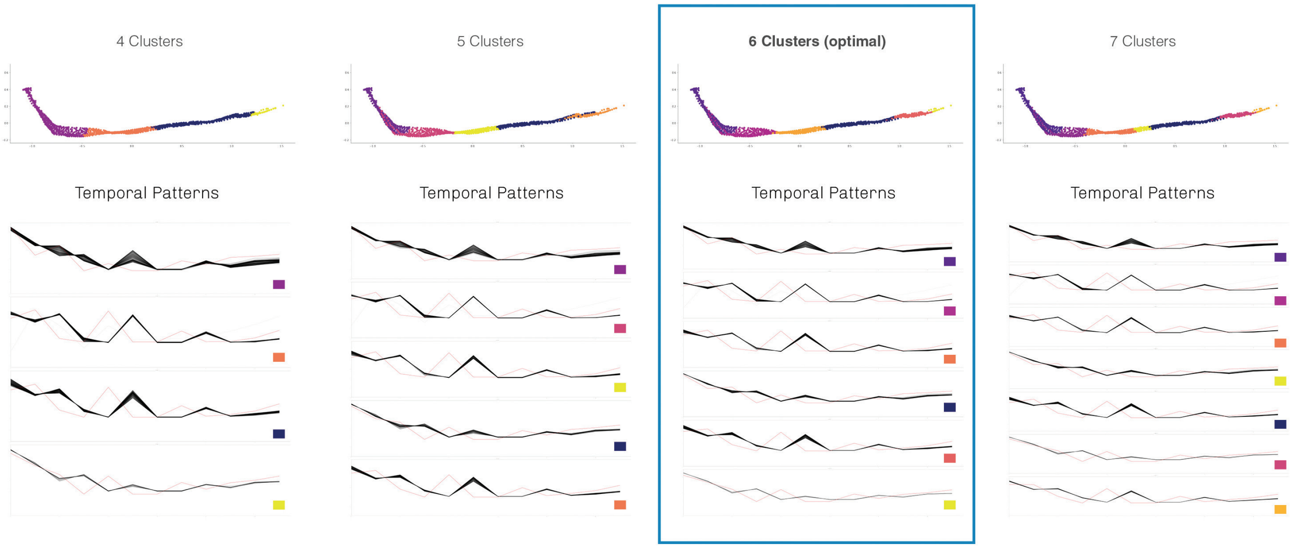
Data clustering allows us to understand different zones of the midsole's behavior and come up with different data interpretations to inform various types of designs. Applying the deep temporal clustering (Madiraju et al. 2018) and K-Shape clustering (Paparrizos and Gravano 2015) algorithms to the ARAMIS data, we can discover a reasonable range of segments with the available frames of displacement and strains.

- Deep temporal autoencoder: We first extract time series data for each data point in the ARAMIS data set based on the deformation pattern for the strain and displacement. Then we use a long-short term memory (LSTM) (Hochreiter and Jürgen 1997) autoencoder composed of multiple LSTM layers to learn a latent representation of the temporal data for all data points in the data set. The strain data and displacement data are concatenated as input vectors to the neural network. We minimize the mean-squared error (MSE) and Kullback–Leibler (KL) divergence as the loss function of the autoencoder. With the LSTM autoencoder, we reduce the dimensionality of input data from a high-dimensional signal to a one-dimensional signal, which allows us to further use the K-shape algorithm for further clustering the temporal pattern (Fig. 6).
- K-shape clustering: Then we use the K-shape algorithm for clustering the latent time series for each data point in the ARAMIS data set. K-shape uses a normalized version of the cross-correlation measure algorithm that compares the time series's shape (Paparrizos and Gravano 2015).
- Obtain optimal segmentation: In the deep temporal clustering approach above, we have a hyperparameter—cluster number—that we need to determine using validation. We first select a reasonable range of cluster numbers (between 4 and 8) that do not convey too overwhelming visual variation while maintaining the design's shape diversity (Paparrizos and Gravano 2015). We select the optimal clustering number with validation where the number of clusters is maximum while all segments maintain a reasonable number of data points. We maximize the number of segments in the midsole to obtain a diversity of unit structures to reflect the midsole deformation process's temporal pattern.

Then we segment the whole midsole into optimal zones with optimal lattice units to be distributed in each segment. The pressure data is then utilized to affect material distribution in terms of the lattice units' member diameter.

Computational Optimization Approach

Predefined and tested metrics help evaluate design iterations across design spaces in computational optimizations (Ma, Wu, and Matusik 2020). In this project, we set up two optimization goals for lattice units. The primary goal is to create a rigid and protective structure to resist the load (Alderson et al. 2019). We achieve this by selecting lattice units with a smaller vertical displacement under



7

pressure in proportion to the overall unit height (shifting ratio). The secondary goal is to achieve a smaller overall material-to-volume ratio, which yields lighter solutions for similarly performing designs.

- Design space exploration: We make iterations with selected design variables for design space exploration (Gün 2010). We control the lattice system's form factors and focus on the performance of the lattice unit with two variables as the internal form factor: the scale ratio for compactness and the member diameter for manufacturing feasibility.
- Performance simulation: We set up multiple optimization objectives and search for optimal unit cell design. The simulation results are then evaluated according to two metrics: the shifting ratio (reflecting rigidity to deformation) and the volume ratio (reflecting material efficiency). Finite element analysis (FEA), which subdivides a large complex system into smaller, simpler solvable parts through discretization in the space dimensions, is implemented here to quantify the displacement of members of the lattice units when being applied to the same load by treating auxetic units as beam-like structures (Wang 2018) and gyroid units as shell-like structures (Yang et al. 2019).
- Prototyping and fabrication: We made a 1:1 partial prototype with resin 3D printing thanks to New Balance Sports Research Lab. This experiment helped understand the actual material performance and behavior through physical impressions and simple material tests to understand how the segments respond to pressure and deformation.
- Segment blending: Segment blending creates a smooth transition between segments by tuning material density and blending the unit cell structure. The blending factors are associated with the characteristics of adjacent segments. Parameters of lattice unit structure in adjacent segments are tuned to achieve coherent aesthetics through gradient transition.

RESULTS AND DISCUSSION

A Performance-Based Midsole Design Using Computational Multi-Objective Optimization

The authors designed and prototyped a midsole that functioned as part of the sneaker with a lattice system as a experiment for the proposed workflow.[3]

A multi-objective optimization system was designed to evaluate the performance of designs. First, a family of unit structures was selected based on heuristic speculations. Within this family, each unit was tested with simulation in accordance with each temporal cluster. The unit with optimal performance was matched to the respective cluster.

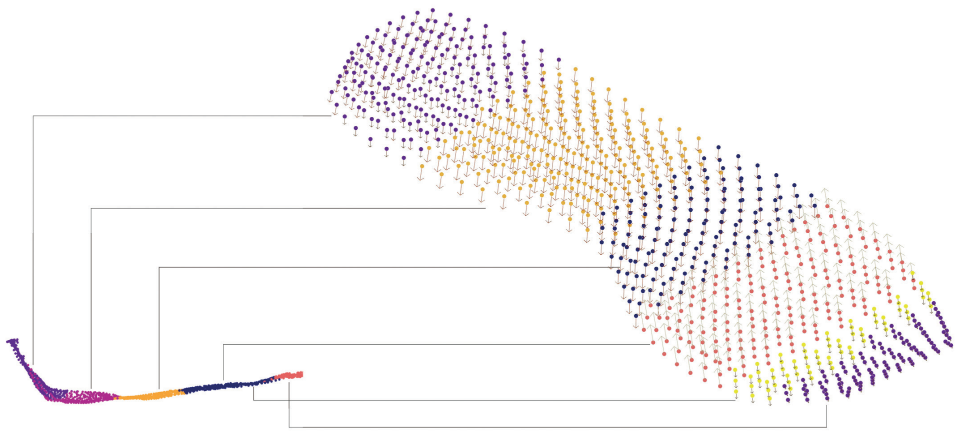
Lattice System Design

The midsole design used a lattice system as a flexible structure, as this system could be easily deformed and remapped. We tested various lattice units, starting from an auxetic structure that provides cushioning and bouncing to a solid minimal surface structure that provides resistance in the pronation process (Wang 2018).

We apply a uniformly distributed lattice system of 18 × 20 × 6 in x, y, and z dimensions. The lattice system's size is

7 Principle component analysis visualization of the latent space of temporal data clustering and K-shape analysis.

8 Lattice unit segmentation based on deep temporal clustering.



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constrained by the fabrication precision and the consistency with the data grid size in the ARAMIS data.

Temporal Clustering and Midsole Segmentation

Our deep temporal clustering network comprises a mixture of one-dimensional convolutional layers, max-pooling layers, and multiple gated recurring unit (GRU) layers. The decoder is composed of a similar structure of deconvolutional layers, unspooling layers, and GRU layers.

Then we train the deep temporal autoencoder on the feature-engineered ARAMIS data set with MSE and KL divergence. The training process converged after 2,000 epochs on both the training set and validation set to prevent overfitting.

We obtain a low-dimensional latent representation that captures each data point's essential temporal pattern with the deep temporal clustering. Then we use the K-shape clustering to further visualize the temporal pattern for the latent signal representation for each data point across all time stamps (Fig. 7).

We experiment with cluster numbers 4–8 to observe the result for temporal clustering. Then we visualize the clustering result for various cluster numbers in the latent space with principal component analysis. All cluster numbers seemed reasonable.

From this visualization, we observe that cluster number 5 does not differentiate temporal patterns between clusters, underfitting the clustering task, and in the case of cluster number 7, two clusters have temporal patterns that are too similar, therefore overfitting the clustering task. Therefore, we determined that cluster number 6 would be used as the optimal hyperparameter (Fig. 8).

Design Space Exploration of Unit Structure

A multi-objective optimization system was designed to evaluate the performance of the designs. First, a family of unit structures was selected to test metamaterial properties. Within this family, each unit was tested via simulation in accordance with each temporal cluster. The unit with optimal performance was matched to the respective cluster.

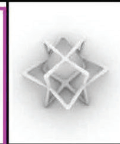
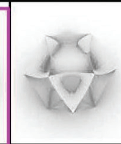
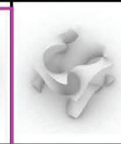
With controlled form factors of the lattice system, we generated lattice unit iterations for performance simulations focusing on two internal unit form factors as input variables: the scale ratio for compactness and member diameter for material manufacturability.

The form factor was further determined with a pressure data set about the material grading. The structure performance was then validated with simulation for testing.

After six iterations of design and performance simulation, we concluded that Schoen Gyroid surfaces, shell-based Schoen Gyroid surfaces, Schwarz P surfaces, and Schoen I-WP surfaces would produce reasonable shape blending effects as well as balanced deformation characteristics of minimal surface structures (Fig. 9).

Multi-Objective Optimization of Cluster Performance

Various lattice units were tested, starting from an auxetic structure that provides cushioning (Wang 2018)

Unit Cell Type	Auxetic			Hybrid Isosurfaces			Struct-based Gyroid		
Form Factor	scale factor			Octo + IWP			density factor		
	0.3	0.6	0.9	20%+80%	50%+50%	80%+20%	0.3	0.6	0.9
Visualization									
Shifting Ratio (%) [Rigidity]	7	13	17	9	9	7	9	6	4
Volume Ratio [Material Efficiency]	0.09	0.25	0.38	0.24	0.27	0.34	0.13	0.22	0.3

9 Finite element analysis (FEA) performance simulation of lattice units.

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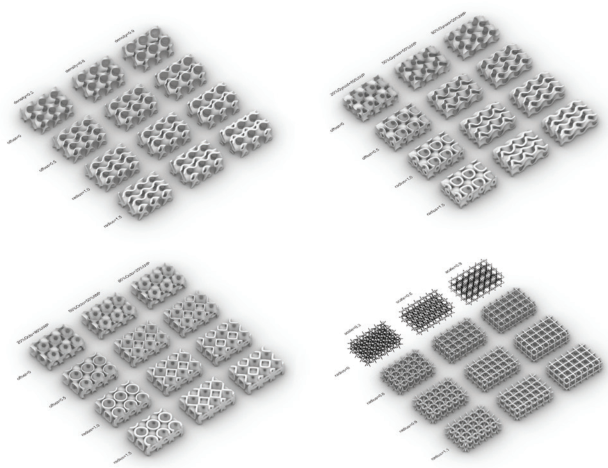

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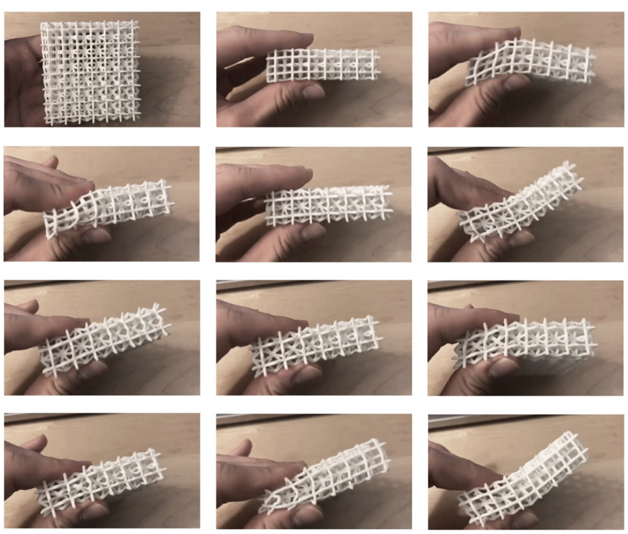

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10 Design space exploration with lattice unit clusters.

11 Partial prototype and deformation experiments with thermoplastic powders via SLS printing.

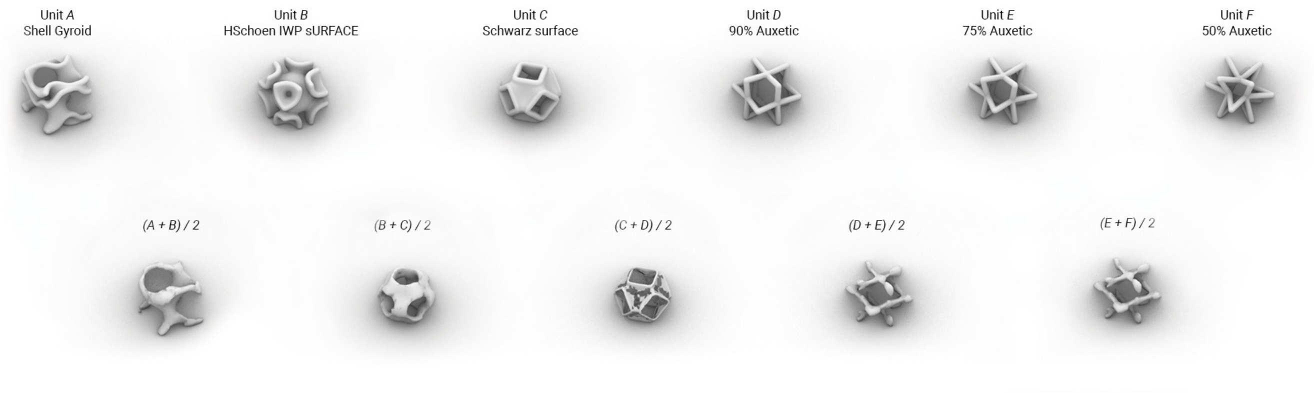
and bouncing, to a solid minimal surface structure that provides resistance in the pronation process (Yang et al. 2019).

According to two metrics, the simulation results are evaluated: the shifting ratio (reflecting rigidity to deformation) and the volume ratio (reflecting material efficiency). The shifting ratio is the vertical displacement in proportion to the overall unit height responding to the same vertical load applied to the unit surface area. It reflects the rigidity of the unit to deformation by measuring how geometry responds to the same load. The volume ratio is the lattice unit's material volume in proportion to the uniform unit cell volume. It reflects the material efficiency of the lattice unit in the additive manufacturing process. We aim to select unit cells with a lower shifting ratio (higher rigidity) and lower volume ratio (higher material efficiency) and hybridize them into segments responding to optimal ARAMIS data segmentation through iterative performance simulations (Fig. 10).

Finite element analysis (FEA) conducted with Kiwi!3D (str.ucture 2020), a plugin for Rhino and Grasshopper enabling the integration of isogeometric analysis (IGA) into the CAD environment, is implemented to quantify the displacement of members of the lattice units when applied to the same load on the unit surface area. Auxetic units are treated as beam-like structures (Wang 2018), and gyroid units are treated as shell-like structures (Yang et al. 2019) in the simulations. Material properties of additive manufacturing are also applied in the simulation.

Prototyping and Fabrication

Partial prototypes of the segment samples were 3D printed with photopolymer/rebound resin powder by a selective laser sintering (SLS) printer to test physical properties and material performance (Fig. 11). Further material testing in a rigorous lab environment would be an ideal next step.[4]



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12 Volumetric blending of lattice units and resulting lattice structure.

Volumetric Blending and Optimal Selection

With the blending hypothesis, we decided to interpolate the lattice units volumetrically in adjacent segments to create a midsole design that could reflect a delicate balance of local and global temporal strain patterns. We tested with various lattice unit structure set choices and discovered the optimal unit set that allows reasonable material density after the blending process.

We implemented the blending algorithm using the Dendro for Rhinoceros 3D Library. Dendro is a volumetric modeling library for Rhino/Grasshopper built on top of the OpenVDB library (ecrlabs 2020). We perform a trilinear volumetric interpolation between the optimal structural units to populate the lattice units between structure segment centers. This blending process serves both aesthetic and functional purposes (Fig. 12).

Various lattice units were tested both individually and hybrid to search for the optimal midsole design. We tested with six combinations of the same primitive lattice units and selected the optimal design based on both the evaluation metrics derived by computational optimization and the form density evaluation metrics that influence aesthetic quality (Fig. 13).

CONCLUSION

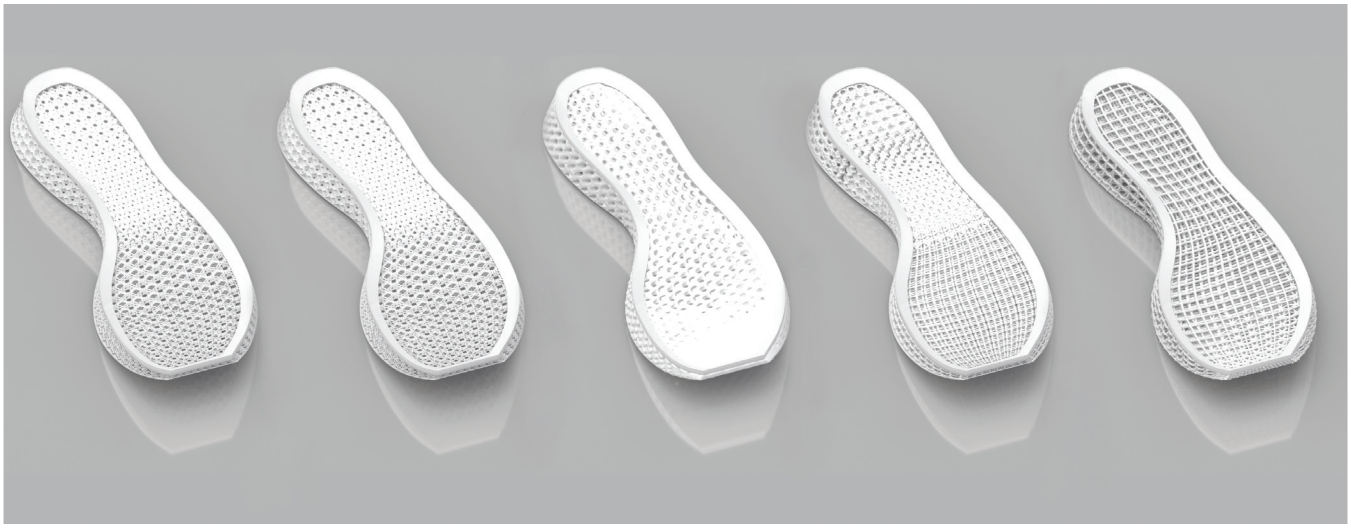
Unlike the standard approach in which certain types of lattices get distributed across the midsole according to an averaged pressure data, in this project we use ARAMIS data reflecting the distinct surface deformation characteristics as our primary design driver (instead of averaged pressure data). We proposed a data-driven workflow for midsole design.

Our approach demonstrated how to use deep temporal clustering to analyze the sequential pattern of running experience and segmentation of midsole areas. We developed a multi-objective computational system for midsole design optimization. Furthermore, we employed computational simulations to make informed decisions to iterate our designs. We developed a method for blending lattice units with different topological configurations.

As computational optimization tools become central in decision-making processes, human interventions become even more crucial for setting and running such systems efficiently and intuitively.

Our holistic approach could be applied to a scenario in which the design resides in a context with an explicit temporal pattern. The shape-blending approach reveals the material response to external force and strain and will serve as a generic aesthetic quality that could be used in various scenarios in performance optimization.

Computational optimization requires quantitative metrics to run, and thus, subjective decision-making, such as visual choices, cannot easily be quantified (Gün 2017). However, such decisions remain significant for design space exploration. While computational optimization tools remain central in decision-making processes, human interaction becomes even more crucial for setting and running such systems in efficient and intuitive ways. Revisiting the challenges of blending visual and performative design goals in this project, we aim to develop systems to enhance human input into our optimization system through more holistic computational design approaches in the future.



13 Various iterations of midsole designs.

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NOTES

1. The ARAMIS data set is proprietary information created by New Balance Inc.
2. Data source available through New Balance Sports Research Lab.
3. We developed the proposed workflow in a computational design class 4.s56 Special Subject: Shape Grammars — Superseding Parts, Computing Wholes, taught by Onur Yüce Gün PhD at Massachusetts Institute of Technology in 2020. The course's objective was to "employ computational design with a critical inquiry of conventional part-to-whole relationships."
4. This experiment has been postponed due to COVID-19. Future research will incorporate more physical prototype testing.

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IMAGE CREDITS

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