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The open rapid access of AI generative design tools (Text to 3D) to morphological expression of the cortical-trabecular hierarchical structure level for biomimetic bone-like design

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Abstract: Artificial Intelligence generative design tools are developing rapidly and revolutionizing their application in the design to fabrication processes. Especially, AI-Deep Learning Image generation models based on transformers, diffusion and convolution models which facilitate generating unlimited amount of rapid high-resolution, highly detailed and innovative visualizations from text either in static (text-to-image) or in animation (text-to-video). These played a crucial role in accelerating the design process especially in the conceptualization and rendering phases. However, it was limited in terms of possibility of direct fabrication since it necessitated the human intervention in digital and algorithmic modelling to turn the 2D image details and parameters to 3D object. Despite some recently developed DL-models of depth mapping and 2.5D prediction which required also human intervention to manipulate them. Currently text-to-3D AI-DL models are driving the unlimited capacity of computation of image recognition, diffusion, convolution and generation of novel patterns to direct fabrication. Where AI text-to-3D model generate editable meshes that can be directly 3D printed or customized for digital fabrication strategies. The current communication reports the manifestation of integrating AI-DL text-to-3D open-access free model (Luma AI) in generating biomimetic bone-like structures of chair designs, expressing the morphological characteristics of the cortical-trabecular hierarchical level in bone tissue. The results of the current work will highlight the possibility of integrating these AI text to 3D tools in biomimetic design and 3d printing of bone grafts as well as bone-like optimized structural design in architecture.

Keywords: AI generative design tools - Text to 3D - Bone hierarchical structural motifs - Cortical-trabecular level - Biomimetic design

[Resúmenes en inglés y portugués en las páginas 52-53]

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1. Introduction

Text-to-image diffusion models (Nichol *et al.*, 2021; Lin *et al.*, 2023) have revolutionized the design process in terms of high-resolution rapid visualizations of concept design phase and high-quality renders. Thanks to the large-scale datasets containing billions of annotated images scrapped from the Internet and immense computation capacity. The generation of high-resolution images by these models is realized by using a cascade of super-resolution models (Valsesia, *et al.*, 2020) or mapping from a lower-resolution latent space then upscale the decoded latent into high-resolution images. Despite advances in high-resolution image generation, using natural language to describe and customize 3D characteristics while maintaining a coherent fully defined 3D model remains a challenge. This resulted in the dependence on AI text-to-image 2D visualization more as a source of visualization, conceptualization or research precursor of innovative synthesized expression of diverse morphological characteristics that can be fused and reintroduced to offer innovative and unprecedented results in biomimetic design field (Abdallah and

Estévez, 2023). This novel DL-generated hybrids are of particular interest in biomimetic bone-like hierarchical structures design for application as realistic bone-like grafts or as an optimized structural design in architecture inspired from bone morphology and mechanics. However, despite the unlimited possibility of 2D image generation in high resolution through diffusion and/or convolution models, their role in the design process was limited to the conceptualization or rendering phases, while the possibility to translate them into 3D objects that can be directly fabricated through additive or subtractive digital fabrication techniques remained a challenge. Triggering the research in 3D object generation models (Chun *et al*., 2022; Gao *et al*., 2022; Zeng *et al*., 2022) which were still limited in terms of generalizability and creativity of the results due to shortage in diverse large-scale 3D datasets in comparison to image and video content, since a 3D object generative trained model is usually specialized in synthesizing single-class objects, despite some few recent attempts to scale to multiple classes as proposed by Zeng (*et al*., 2022). This problem has urged the research interest in different lines: one is based on predicting the 3rd dimension of these 2D images by depth mapping of a single shot image through combining metric and/or relative depth estimation models (Bhat *et al*., 2023). Another is based on 3D generative modelling through various architectures and models of 3D representations including 3D voxel grids (Kakillioglu *et al*., 2020), point clouds (Srivastava and Lall, 2019), meshes (Wei *et al*., 2021), or octree representations (Muzahid *et al*., 2020). The majority of these models train data in the form of 3D assets, which are hardly scalable. While another approach was inspired from Neural volume rendering (Zhang *et al*., 2021), in 3D-aware image synthesis, which can learn 3D generative models directly from images. However, volume rendering networks are deliberate resulting in long training time to achieve multi-view consistency, and they are limited to modelling objects within a single object category, lacking scalability or controllability of the 3D model creation.

Another line of research focused on generating 3D meshes that fits a specific text prompt by deforming the mesh attributes accordingly until reaching the specific description of a text prompt. A similar approach is utilizing pre-trained text-to-image diffusion model to optimize and synthesize these 3D mesh models. Augmenting the creativity, generalizability and resolution of these 3D generation models by exploiting the computational advantages of text-to-image generative models. One example is DreamFusion model (Poole *et al*, 2022) which uses pretrained text-to-image diffusion model to optimize Neural Radiance Fields (NeRF) (Mildenhall *et al*., 2022) to produce text-to-3D objects. This main DreamFusion components are a neural scene representation, and a pre-trained text-to-image diffusion-based generative model. The scene representation model is a parametric function $x = g(\theta)$, producing an image x at the desired camera pose. While g is the volumetric renderer, and θ is a coordinate-based MLP representing a 3D volume. On the other hand, the diffusion model ϕ is coupled with a learned denoising function $\epsilon\phi(xt; y, t)$ to predict the sampled noise ϵ of the noisy image xt, noise level t, and text embedding y, providing the gradient trajectory to update θ, to push all rendered images to the high probability density regions based on the text embedding under the diffusion prior.

However, in the process of text-to-3D object generation employing a pre-trained text-to-image diffusion model to optimize the 3D object characteristics and details representation; the optimization process ensures that rendered images from a 3D model, represented

by Neural Radiance Fields (NeRF) (Mildenhall *et al.*, 2020), align with the organization of photorealistic images across different viewpoints, given the input text prompt. However, models as DreamFusion operates on low-resolution images (64 × 64) which hinders synthesizing high-frequency and textured 3D geometries.
This is attributed to the used MLP models for the NeRF representation, which obstacles the feasibility of high-resolution synthesis due to increasing the computational and memory cost congruent with the resolution. Which necessitated a way to synthesize highly detailed 3D models from text prompts within a reduced computation time. To realize this, Magic3D model based on diffusion, developed a two-stage optimization framework by obtaining a roughly model through using multiple diffusion priors at different resolutions and accelerate it with a sparse 3D hash grid structure. Then optimizing it to a textured 3D mesh model with high-resolution and high detailed rendering by relating it to a high-resolution latent diffusion model, to produce high-resolution 3D mesh model with resolutions as high as 512 × 512 as proposed in Magic3D model, in limited computation time (Lin *et al.*, 2023).
This is possible thanks to the base diffusion model prior used to compute gradients of the scene model via a loss defined on rendered images at a low resolution 64 × 64. Followed by using a latent diffusion model (LDM) that allows backpropagating gradients into rendered images at a high resolution 512 × 512, which is the publicly available Stable Diffusion model used in Magic3D the employed software in the current work. Despite generating high-resolution images, the computation of LDM remains manageable because the diffusion prior acts on the latent zt with resolution 64 × 64. Another merit of the employed Magic3D model is that it employs use the hash grid encoding from Instant NGP enabling high frequency detailing of 3D geometry at low computational cost. This is mainly applied in the first optimization phase of creating the 3D geometry and its surfaces textures accommodating complex topological changes in the 3D geometry and depth uncertainties from the 2D supervision signals. Additionally, spatial data structure encoding scene occupancy and employing empty space skipping is used as well in this stage. Using the density-based voxel pruning approach from Instant NGP with an octree-based ray sampling and rendering algorithm. This text-to-3D diffusion-based model structure accelerates and accentuates significantly the optimization process of the 3D mesh geometry (Lin *et al.*, 2023).
Furthermore, the background is modelled via an environment map MLP, to predict RGB channels as a function of ray directions. Assisting learning the essence of an object by using the background environment map. The MLP environment map employed in the used model in the current study Magic3D, uses a tiny map of dimension size of 16 to reduce the learning rate to allow the model to focus more on the neural field geometry.
In the final rendering processes of the 3D created mesh by Magic3D, the focal length is increased to focus on the object details, to recover high-frequency details.
These generated 3D mesh objects are designer friendly in terms of their compatibility and consequent processability with wide array of 3D digital design and graphical rendering software. Giving the possibility of obtaining high-resolution renders of these models. Given that, in addition to Magic3D fast and high-quality text-to3D generation framework. The current work employed it in generating three different biomimetic design-to-fabrication chair models; each of which corresponds to a specific bone tissue morphological characteristics as explained in the following paragraphs.

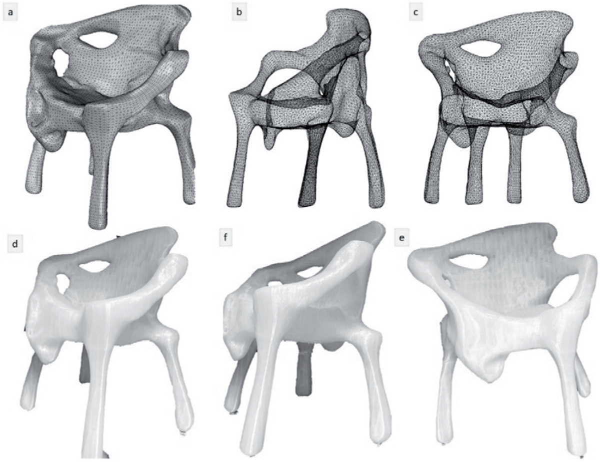
2. Hands on experimentation: Text-to-3D biomimetic bone-like morphologies to 3D printing

Based on previously published work reporting bone-inspired detailed biomimetic design approach (Abdallah and Estévez, 2023), and current advancement in the mentioned project by further analyses of the morphometric and mechanical properties of bone like structures and materials (Estévez and Abdallah, 2024), the current study aimed to explore the potential of the Magic3D text-to-3D DL-model, in expressing detailed morphometric characteristics of specific hierarchical structural motifs of the bone tissue in innovative hybrid biomimetic design approach of bone chairs. The tested hierarchical level morphometric characteristics in the current study in on the cortical and trabecular tissue level. Since they correspond to a wider scale-lengths margins from macro-to micro where the morphological characteristics of each tissue can be recognized with the unaided eye.

Thus, the design text-prompts were categorized to the following three separate prompts:

"Cortical Bone Tissue Chair; Cortical Bovine Distal Femur Chair".
"Trabecular Bone Tissue Chair; Trabecular Bovine Distal Femur Chair".
"Cortical-Trabecular Bone Tissue Chair".

Each of these prompts were tested three times separately using the Luma AI (https://lumalabs.ai/) open-access free platform to create 3D mesh-objects representing bone-like biomimetic chair design. No specific weights were added to the text prompt, since the imaginary capacity of the 3D-to-text model employed in the current study was the subject of testing. The author wanted to test the model limits of learning and differentiating the morphological characteristics of the described bone tissue hierarchical level as well as the possibility to formulate this understanding in a novel chair design. Moreover, in the current proposed hybrid combining the morphological characteristics of bone tissue either on cortical or trabecular level, with the functional requirements of a chair design, are equal in importance and this equilibrium was also subject of testing the capacity of the used model in achieving it.
The generated 3D mesh objects representing bone chair design in each case (each tested prompts) were 25 iterations per each prompt, each of which required 5 seconds in average to be generated. Each generation prompt-based process gives 4 different iterations, slightly differentiated in terms of their morphological characteristics, while each of these iterations had the possibility to be viewed singularly in a separate viewport where the user can hover around the 3D mesh model, upscale it, redefine its topologies, download the 3D mesh file in STL extension, or generate further variation of the same object in an unlimited open-end and rapid open-access process of text-to-3D generation.
Three main bone chair designs were selected based on their maximum representation of the morphological parameters of the hierarchical bone tissue level corresponding to their text prompts: Cortical, Trabecular, and Cortical-Trabecular. These three designs are exhibited in *Figures 1, 2*, and *3*.



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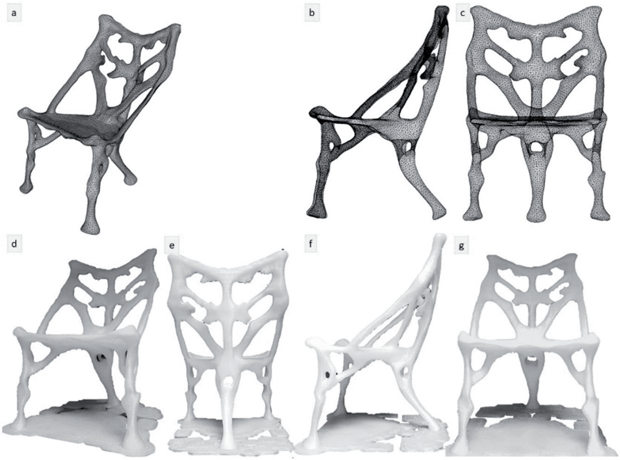

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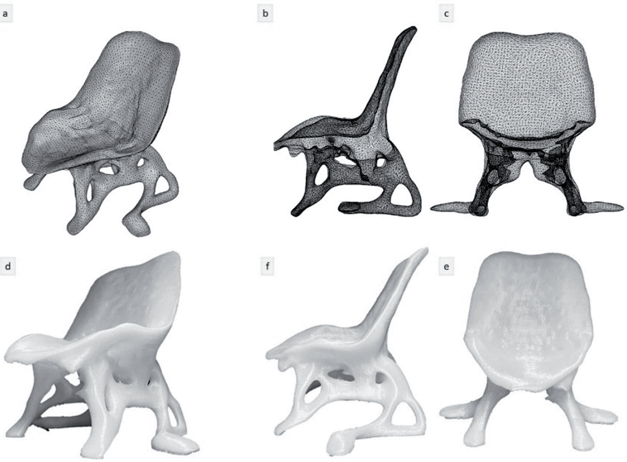

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Figure 1. The generated Cortical bone tissue biomimetic chair design, scale (1:10) generated from the text-to-3D model using Luma AI open-access platform. The upper row represents the 3D mesh file representation in different views downloaded from the platform directly without enhancement either while the text-to-3D generation process or after downloading the file in any 3D software (3D digital design Software Rhinoceros 3D and Blender 3D were only used to open the file and chick the 3D mesh smoothness). a) is the perspective view of the cortical bone tissue chair design. b) is the right-side view. c) is the front elevation view. While the lower row exhibits the different corresponding views of the cortical bone tissue chair, post-3D printing using Simplify 3D software for preparing the file to print and slicing, and Felix Tec 4 singular head printer to print the model with PLA Polylactic acid. d) is the 3d printed model perspective. f) is the 3D printed model right side view. e) is the front elevation view of the 3d printed model of the cortical bone chair.
Figure 2. The generated Trabecular bone tissue biomimetic chair design, scale (1:10) generated from the text-to-3D model using Luma AI open-access platform. The upper row represents the 3D mesh file representation in different views, downloaded from the platform directly without enhancement either in the text-to-3D generation process or after downloading the file in any 3D software (3D digital design Software Rhinoceros 3D and Blender 3D were only used to open the file and chick the 3D mesh smoothness). a) is the perspective view of the trabecular bone tissue chair design. b) is the right-side view. c) is the front elevation view. The lower row exhibits the different corresponding views of the Trabecular bone tissue chair, post-3D printing using Simplify 3D software for preparing the file for printing and slicing, and Felix Tec 4 singular head printer to print the model with PLA Polylactic acid. d) is the 3D printed model perspective. e) is the back view perspective. f) is the 3D printed model right side view. g) is the front elevation view of the 3d printed model of the Trabecular bone chair.
Figure 3. The generated Cortical-Trabecular bone tissue biomimetic chair design (scale 1:10) generated from the text-to-3D model using Luma AI open-access platform. The upper row represents the 3D mesh file representation in different views downloaded from the platform directly without enhancement; 3D digital design Software Rhinoceros 3D and Blender 3D were only used to open the file and chick the 3D mesh smoothness. a) is the perspective view of the cortical-trabecular bone tissue chair design. b) is the right-side view. c) is the front elevation view. The lower row exhibits the different corresponding views of the cortical-trabecular bone tissue chair, post-3D printing using Simplify 3D software for slicing, and Felix Tec 4 singular head printer to print the model with PLA Polylactic acid. d) is the 3D printed model perspective. f) is the 3D printed model right side view. g) is the front elevation view of the 3D printed model of the cortical-trabecular bone chair.

The results revealed that the file preparation for 3D printing process and slicing didn't require any specific requirement rather than the typical standard printing settings when using PLA filament as follows: printing head temperature 210ºC, bed platform temperature 60-70ºC, printing speed 100%, nozzle diameter 0.35 mm, extrusion multiplier 0.90 mm, extrusion width 0.40 mm, retraction distance 1 mm, primary layer high 0.2 mm, top solid layer 3, bottom solid layers 3, outline/perimeter shells 2, first layer high 100%. Additions were added to hold tight the deferential chair form tight on the printing bed while printing. These were as follows: skirt/brim layers 3, skirt offset part 0.1 mm, skirt outlines 10. In addition to using Raft top layers 3, and bottom layer 2, raft offset from part 1 mm, separation distance 0.15 mm, raft top fill 100%, above raft speed 30%. The infill percentage was reduced inspired by the trabecular bone tissue effect in resisting perpendicular load and long duration strains without collapsing, therefore the interior infill percentage was

15% following a fast honeycomb infill pattern and a rectilinear external fill pattern, the infill outline overlap was 15%, while the infill extrusion width was 100%, maximum infill length 5 mm, and infill was combined every 1 layer.
One limitation in printing the resulting 3D mesh files of the bone like chair designs was the wide span of overhangs higher than 45º. This is mainly attributed to the typical chair form design of having a wide span of 45 cm between the chair legs (between each two legs), to provide the space of seating. However, this can be considered a limitation of the text-to-3D used model as well, that wasn't able to provide more innovative and more bone-tissue like intricate structures, either on the cortical or trabecular level that might provide more than the typical standard four legs and cantilevered seat chair design. However, a clear decision about the used text-to-3D DL-model success in this specific point can't be concluded, since this specific criteria of reducing the cantilevered span of the seat by adding more legs to the chair wasn't conditioned clearly in the text prompt. However, it still signifies the limited creativity of the model in proposing novel and more biomimetic intricate designs. This limitation necessitated using supports specifically to support the wide seat span between the typical 4 legs of a chair, especially in design 1 and 2, while design 3 didn't need supports thanks to its intricate base with angles overhang less than 45º and limited openings. The supports generated for the 3D printing process of design 1: the cortical level, and design 2 the trabecular level followed these specifications: support infill percentage 10% to minimize the loss of the printing material as possible, combine support was performed every layer, dense infill percentage 70%, support type normal, maximum overhang angle 45º, horizontal offset from part 0.30 mm.
The printing duration and filament length varied between the three designs, the maximum printing duration was of 22 hours to print the third design of cortical-trabecular level despite printing without supports, while for printing the cortical bone chair design it required 18 hours and finally the fastest in printing was design 2 of the trabecular bone tissue chair printing in 7 hours. While the printing filaments varied as well between the three design however requiring in average 85000.00 mm filament length.
Al the 3D printed design models aligned typically with the 3D mesh STL files with all levels of details. Which proves the possibility of using such tool of text-to-3D model for direct 3D prototyping from design to fabrication process. Enabling AI generative design tools and specifically the AI text-to-3D diffusion-based models to entire the fabrication phase in the design process. However, as presented in *Figure 4*, a discrepancy between the high resolution generated upscales for each design which required from 15 to 40 minutes to generate them had further morphological volumetric details that weren't present in the med-resolution models which were 3D printed. This imposes a doubt about the computation, material, and time cost feasibility of 3D printing the high-resolution model as well, since it is obvious that it contains more spatial and volumetric information that should be expressed as well in their corresponding 3D printed model.
Furthermore, it is obvious the limited macrometric understanding of the cortical bone tissue hierarchical level in terms of representing the cortical bone tissue chairs with smooth, dense and closed surfaces and volumes which signifies that the search field of the training data of this text-to-3D model learned from the entire full bone scale of the outer cortical shell, despite that this aspect wasn't conditioned clearly in the used text prompt which

signifies the tendency to macro or meso scale understanding of the introduced biomimetic source of inspiration. This is pronounced as well in the trabecular bone tissue chair although it exhibited an effect of trabecular tissue porosity when judging it on the macro-meso scale as well. As well as on the cortical-trabecular bone tissue chair, where deferential effect of thin details wasn't obtainable using the employed text-to-3D diffusion-based model in the current study. In comparison to the finer tissue morphological characteristics represented in the previously generated bone tissue chair design by text-to-2D image diffusion model as exhibited in *Figure 4*, in addition to more gradients in color and in background shades which accentuates significantly the rendering of the resulting biomimetic bone-tissue inspired chair design. This might be attributed to that there are several 2D μ-CT, MRI and even histological 2D images describing the macro to nano multi scale lengths of the hierarchical structural motifs of the bone tissue in the red (internet), however 3D voxel or mesh 3D reconstructions that shows a section or a detail of the tissue by using the μ-CT and MRI 3D reconstruction algorithms aren't equally available which highlights the need for more 3d reconstructs of 3D details in 3d reconstructed models of the scanned bone tissues.