Title:
Design for Additive Manufacturing of Porous Structures using Stochastic Point-Cloud: A Pragmatic Approach

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Introduction:
To utilize the fullest potential of the commercially available Additive Manufacturing (AM) processes (e.g., 3D printing, stereolithography, selective laser sintering, and alike), a concept called Design for Additive Manufacturing (DfAM) has been introduced [3]. One of the goals of DfAM is to create CAD models of relatively complex shapes so that an ordinary AM process can produce it in a sustainable manner. Here, "sustainable manner" means that all material, energy, and component efficiencies are achieved in a concurrent manner [10].

However, the shapes observed in the nature and biological organisms are by nature stochastic [1,6,7,11]. Sometimes, these shapes consist of Randomly Distributed Porous Structures (RDPS). Numerous authors have studied RDPS from the viewpoint of DfAM [2,4,5,8,12]. The methods developed so far are computationally heavily, and, thereby, require highly sophisticated soft/hardware facilities. As an alternative, this study describes a pragmatic approach to achieve DfAM for the shapes having RDPS. The main idea is to use a set of carefully generated stochastic point-clouds while creating RDPS. The following sections describes the main idea and the outcomes.

Main Idea:
This section describes the main idea of creating the RDPS. For the sake of better understanding, a cylindrically shaped object is considered.

First, consider a deterministic set of points as follows: $C_{Dj} = \{(x_i,y_i,z) \mid x_i = x_c + r\cos(\theta_i),\ y_i = y_c + r\sin(\theta_i),\ z \in \{h_1,...,h_m \mid h_j < h_{j+1},\ j = 1,...,m\text{-}1\},\ \theta_i = 2\pi i/n,\ i = 0,...,n\text{-}1\}$. The points in C_{Dj} are some deterministic points on the circumference of a circle at a height $z = h_j$ ($\exists j \in \{1,...,m\}$) or on x-y plane denoted as $z = h_j$. Here, $(x_i,y_i,z) \in \Re^3$, $\forall i \in \{i,...,n\}$. The radius of the circle is equal to $r \in \Re^+$ and the center of the circle is located at $(x_c,y_c,z = h_j)$. The size of the point-cloud is equal to n. One can generate m number of point-clouds for the heights $\{h_1,...,h_m\}$ denoted as $C_{D1},...,C_{Dm}$. These point-clouds collectively create a deterministic point-cloud denoted as C_D, i.e., $C_D = \{C_{D1},...,C_{Dm}\}$.

One can slightly modify C_{Dj} and create a set of stochastic points around it. Let this modified point-cloud be C_{Sj}. One of the definitions of C_{Sj} is as follows: $C_{Sj} = \{(x_i,y_i,z) \mid x_i = x_c + r_i\cos(\theta_i),\ y_i = y_c + r_i\sin(\theta_i),\ z \in \{h_1,...,h_m \mid h_j < h_{j+1},\ j = 1,...,m\text{-}1\},\ r_i \leftarrow SP,\ \theta_i = 2\pi i/n,\ i = 0,...,n\text{-}1\}$, i.e., C_{Sj} is a set of points generated at random around the circumference of a circle. The only difference between C_{Dj} and C_{Sj} is that for the case of C_{Sj}, a stochastic process denoted as SP determines the radius at random, i.e., it is no longer a constant value. As a result, $r_i \in \Re^+$, $\forall i \in \{1,...,n\}$, i.e., it is a positive real number generated at random using SP. For example, SP can a uniform distribution in the interval $[a,b]$, $(a > 0)$ [9]. Alternatively, SP can be a normally distributed variable denoted as $N(\mu,\sigma)$ where the mean is μ and standard deviation is σ, and so on [9]. One can generate m number of point-clouds denoted as $C_{S1},...,C_{Sm}$, all having the nature of C_{Sj}. These point-clouds collectively create a stochastic point-cloud denoted as C_S, i.e., $C_S = \{C_{S1},...,C_{Sm}\}$.

For example, Fig. 1 shows ten different instances of C_S where five of them correspond to a random number [20, 40], i.e., $r_i \in [a = 20, b = 40]$ and the other five correspond to a normally distributed variable $N(\mu = 30, \sigma = 5)$, i.e., $r_i = N(\mu = 30, \sigma = 5) > 0$. The other parameters are as follows: $x_c = 100$, $y_c = 100$, $z \in \{10, 20, \ldots, 100\}$, $n = 100$, and $m = 10$. The concave CAD models generated from the respective point-clouds in Fig. 1 using a commercially available software are also shown in Fig. 1. As seen from Fig. 1, all models consist of RDPS. The models corresponding to uniform distribution are likely to create more porosity. This mean that one can vary the stochastic process or the associated parameters to create a desired RDPS. However, until a physical model is being created using an ordinary AM process, it would be difficult to judge its (the point-cloud's) effectiveness. In this study, we are not interested in the general characteristics of C_S. We are rather interested in using it for physical models of RDPS.

SP is a uniform distribution　　　　*SP* is a normally distributed variable

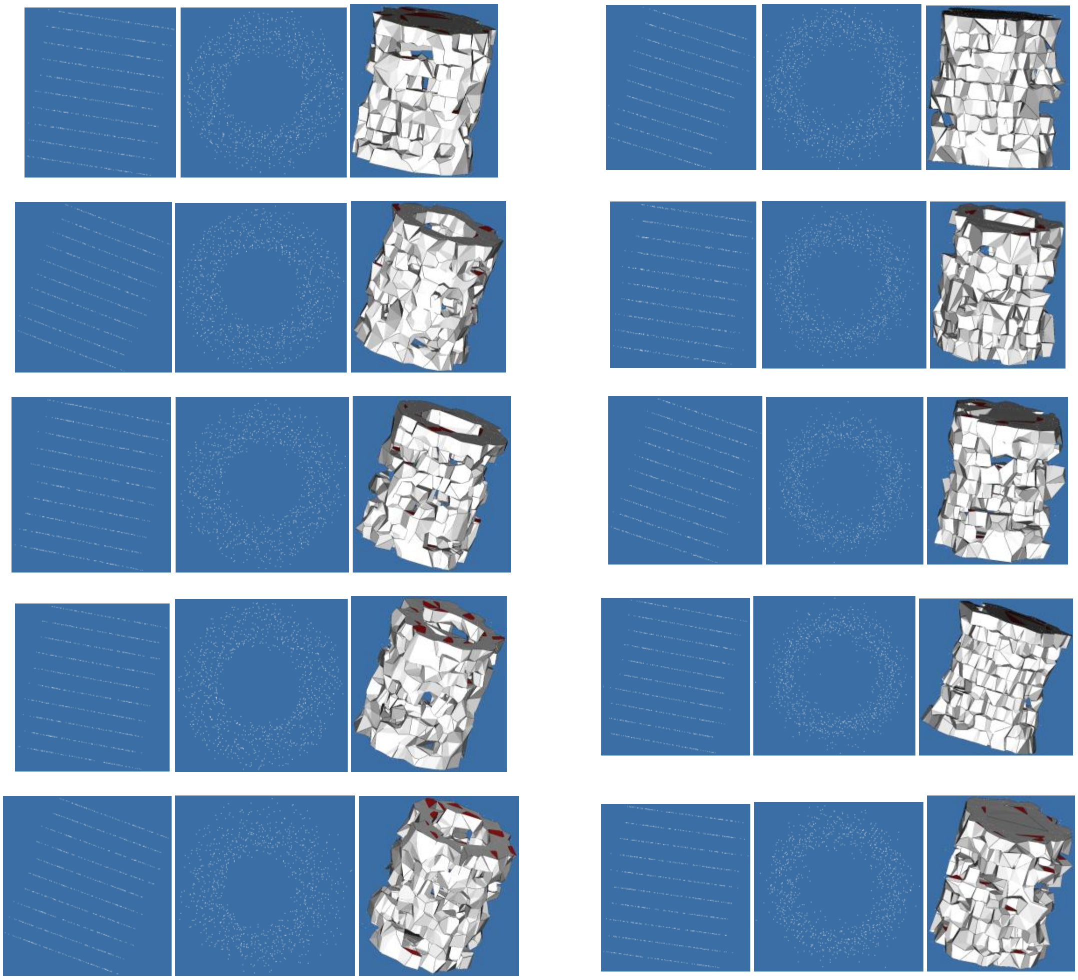


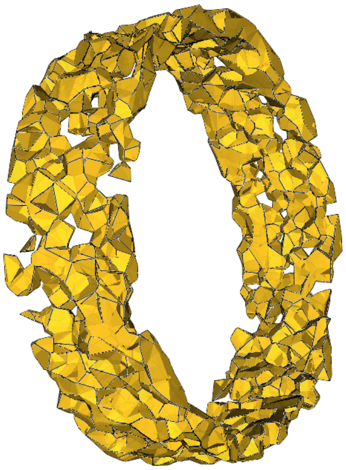
Fig. 1: Stochastic point-clouds and the resulting concave surface.

Nevertheless, the above description of C_D and the findings shown in Fig. 1 refer to an algorithm called Stochastic Point-cloud Generator (SPG), as follows:

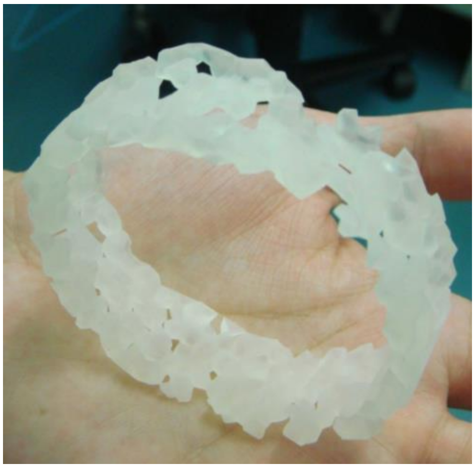
$$
\begin{aligned}
&define \quad SP, n, m, (h_1, \ldots, h_m), x_c, y_c \\
&\quad for \ \ j = 1, \ldots, m \\
&\qquad z = h_j \\
&\qquad\quad for \ i = 0, \ldots, n-1 \\
&\qquad\qquad r_i \leftarrow SP \\
&\qquad\qquad \theta_i = \frac{2\pi}{n} i \\
&\qquad\qquad x_i = x_c + r_i \cos(\theta_i) \\
&\qquad\qquad y_i = y_c + r_i \sin(\theta_i) \\
&\qquad\qquad (x_i, y_i, z) \\
&\qquad end \ \ for \\
&\qquad C_{Sj} \\
&\quad end \ \ for \\
&\quad C_S
\end{aligned}
\tag{1}
$$

To see the effectiveness of the proposed SPG in producing RDPS, several case studies have been carried out. Two of the case studies are reported below.

The first case study reported here deals with how to produce a thin-walled RDPS. The SPG for this case uses two nearby C_Ss generated by using two uniform distributions. The CAD and physical models are shown in Fig. 2. A commercially available CAD package and an AM machine are used to create the CAD and physical models as shown in Fig. 2. To avoid commerciality, the details of the packages are not mentioned here. The results shown in Fig. 2 shows that the proposed SPG is effective in producing CAD and physical models of RDPS.



(CAD model)



(physical model created by AM)

Fig. 2: Producing thin-walled RDPS.

The other case study reported here refers to cascaded modeling. The idea is to producing a RDPS by using a set of cascaded stochastic point-clouds. Figure 3 shows an example of cascaded modeling. For the case shown in Fig. 3, three cascaded point-clouds are used. The outer point-cloud is created by using the SPG where the radius refers to a uniform distribution in the interval [24, 20]. The middle point-cloud refers to a uniform distribution in the interval [20, 18], and the inner point-cloud refers to a uniform distribution in the interval [18, 16]. The heights are taken from set {10, 11, 12, 13, 14, 15}.

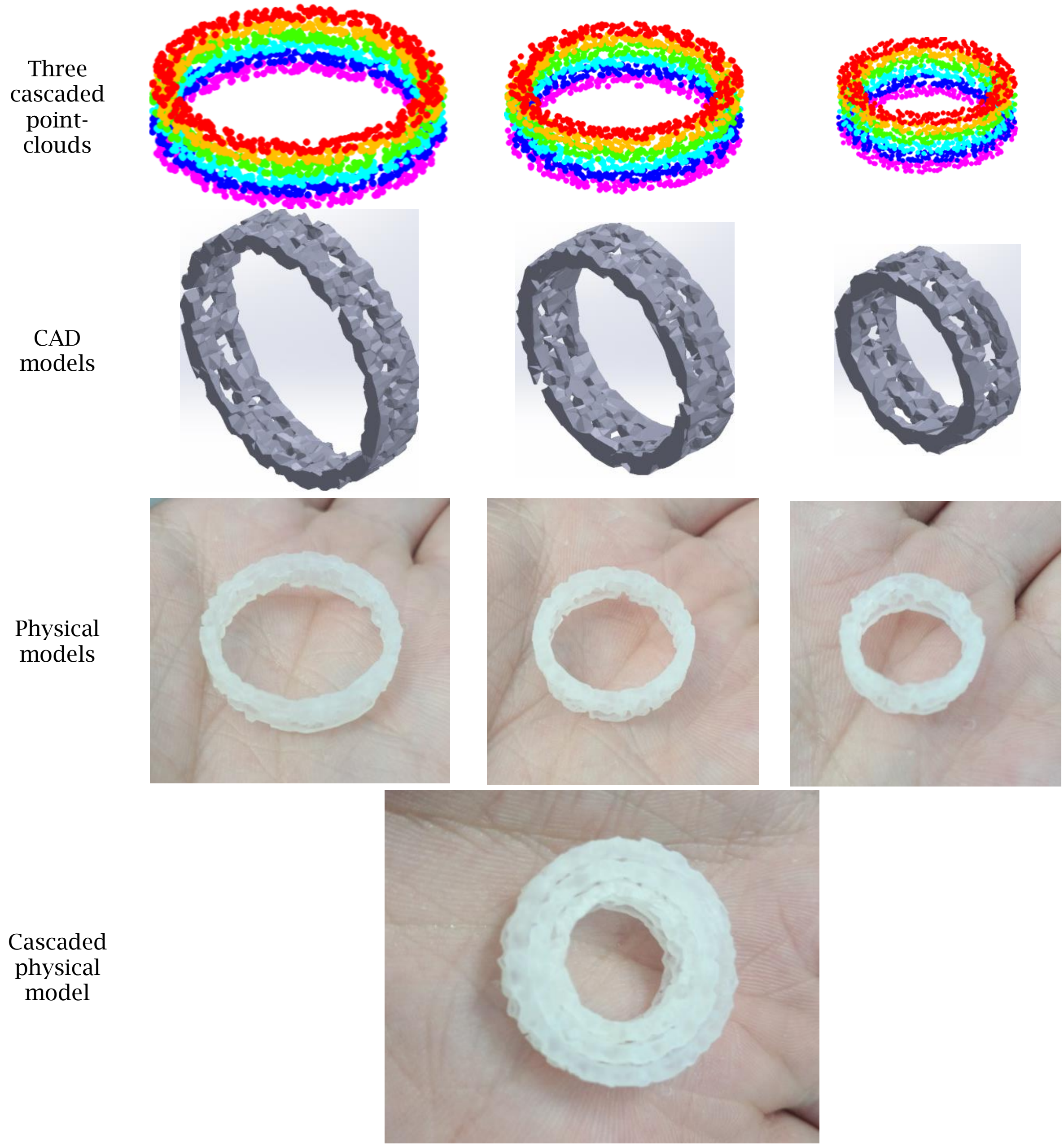


Fig. 3: Producing RDPS using cascaded stochastic point-cloud.

Three CAD models have been created using the respective point-clouds, as shown in Fig. 3. The respective physical models have also been created using commercially available AM machines. Finally, the three physical models are assembled to form cascaded RDPS.

Conclusions:

In this study, we have described a pragmatic approach for design for additive manufacturing of porous structures. The main idea is to use the a carefully generated stochastic point-clouds. The main idea is described by introducing an algorithm for generating stochastic point-clouds. Two case studies are also described showing the effectiveness of the proposed methodology. The first case-study deals with thin-walled porous structure and the other deals with cascaded modeling. In both cases, the CAD models consist of randomly distributed porous structures. The physical models are also created using the data of the CAD modeling using the ordinary additive manufacturing machines. The outcomes of this study enrich the field of design for additive manufacturing of complex shapes, in general, and shapes having randomly distributed porous structure.

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