Three-Dimensional Deep Learning Experiments using an Octree-based Approach

Xu Zhang, Ivan Voutchkov, Andy Keane
UTC for Computational Engineering, University of Southampton

The employment of Artificial Intelligence (AI) and Machine Learning (ML) techniques including Convolutional Neural Network (CNN), and conditional Generative Adversarial Network (cGAN) has been proven to be powerful and efficient to generate feasible solutions to the aerofoil design problem. As shown in Figure 1 (a), our UTC in-house trained cGAN models can easily generate the pressure field around aerofoil shapes with embedded design parameters by specifying the MOloss targets within a certain range. The design variables could then be decoded from the images for manipulating the baseline geometry to get new designs.

Although cGAN has shown its advantages for feature extraction and geometry generation using 2D images, it is a non-trivial task to adapt a cGAN designed for regularly sampled 2D images to irregular-shaped 3D models. Since the memory and computation costs grow cubically as the voxel resolution increases, these methods become prohibitively expensive for high-resolution voxels, which makes the voxel not ideal for complex models.

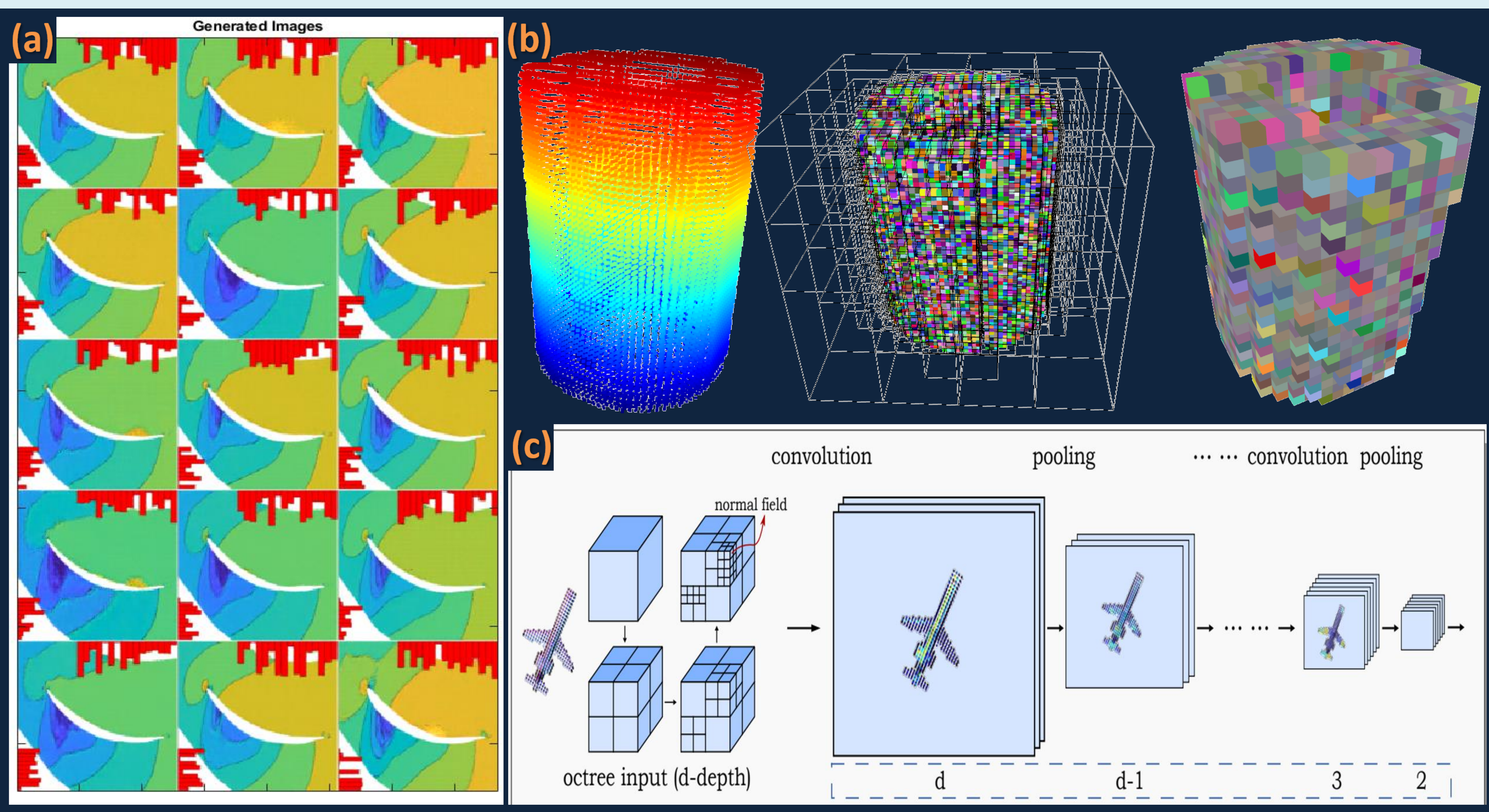

Figure 1: (a) cGAN generated aerofoil shapes with embedded design variables; (b) From left to right: point cloud, octree subdivision, and voxel model; (c) The octree-based convolutional neural network for 3D model classification

This research tries to explore possible approaches to applying AI/ML techniques to 3D geometries so that realistic 3D CAD models can be generated directly from trained neural networks. 3D Octree-based cGAN (3D OcGAN) has its advantages over the full voxel-based method.

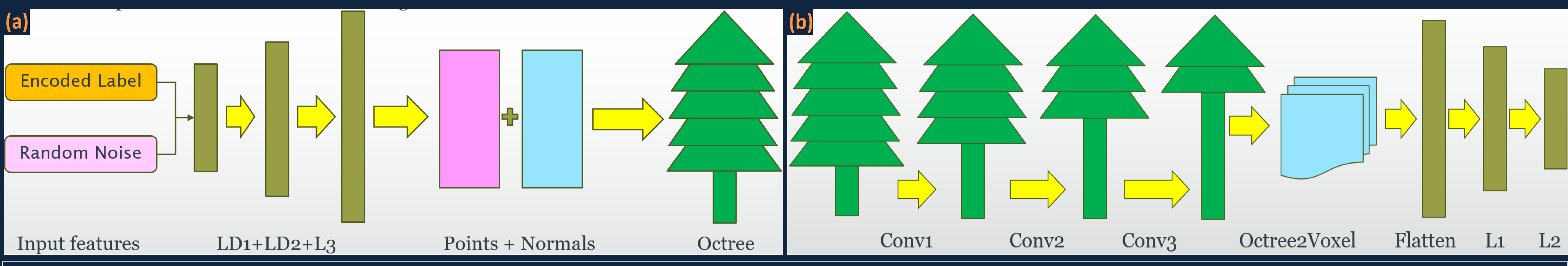

Figure 2: (a) the generator of a 3D OcGAN (5-layer); (b) the discriminator of a 3D OcGAN (5-layer)

Advantages of octree-based method over full voxel-based method:

- CNN operations applied to sparse octants only
- No interaction with empty regions in 3D space
- Lower memory and computation cost:
  - Octree-based method: $O(n^2)$
  - Voxel-based method: $O(n^3)$
- Octants are saved continuously in memory
  - High performance GPU computation
  - Store neighbour information by a hash table for fast access

As shown in Figure 2, the structure of 3D OcGAN includes both a generator (a) and a discriminator (b). For the generator, it accepts one label (class) and random noise vectors as the input. The data then flows through two linear and dropout layers (LD) before going through the last linear layer (L3). The output from L3 is split into two sets that represent the point cloud and the associated normals at each point, where they are used to build an octree with a given layer. The octree will be passed to the discriminator for verification. The discriminator of 3D OcGAN is very similar to a normal cGAN's discriminator, except the convolutional operations only apply to the sparse octants rather than the whole point cloud. After passing 3 convolutional layers, the octree will be flattened at the 2nd-depth layer, where all octrees for training are forced to have the full octants for aligning the features. The output will be given by the discriminator after several linear layers at the end.

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Southampton UTC contact email: xu.zhang@soton.ac.uk; Rolls Royce liaison – Marco.Nunez@Rolls-Royce.com
Computational Engineering & Design Group, University of Southampton, SO16 7QF, UK