Approximating the full-field temperature evolution in 3D electronic systems from randomized "Minecraft" systems

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Thermal simulations are a time-consuming part in the design of electronic systems. In this work, we apply a convolutional neural network (CNN) to obtain a fast approximation of the transient heat distribution in electronic systems. The major contributions are:

- We investigate three-dimensional electronic systems with complex geometries consisting of different materials (see Fig. 1, right). The material properties span a wide range (e.g. copper, epoxy). The full-field temperature distribution is predicted.
- Instead of training directly on electronic systems, we exploit the fact that a fully convolutional network is used. We designed "Minecraft" systems consisting of randomly located blocks of randomly selected materials (see Fig. 1, left). The network trains only on these random systems but generalizes well to the electronic systems. The electronic systems are four times as large as the training systems. Thus, it would not be possible to train directly on the electronic systems.

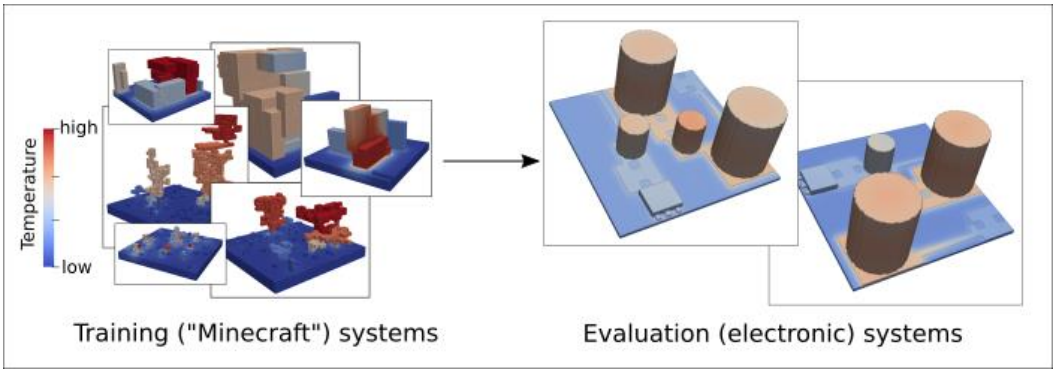

Figure 1: Training is performed on the Minecraft systems (left). The network generalizes well to electronic systems (right).

Supervised learning is applied using the relative L_1 loss and a physics-informed loss based on a discretized transient heat equation, inspired by [1]. The CNN architecture employs parallel branches with different dilations to enable the aggregation of far-field features [2].

For the Minecraft systems the network obtained an average L_1 relative loss of 0.08% for the one-time-step prediction. Good generalization to the electronic systems was observed (0.7% average L_1 loss) even though they are four times as large as the training systems.

REFERENCES

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