Doctor of Engineering (EngD) Project Proposal

Optimisation of Aggregate Porous Materials using Generative Adversarial Networks

Luke K. Rose, BSc
psylr5@nottingham.ac.uk

Interdisciplinary Research - Schools of Engineering and Computer Science

Supervisors
Primary Alvaro Garcia Hernandez, *School of Engineering* [Alvaro.Garcia@nottingham.ac.uk]
Secondary Isaac Triguero, *School of Computer Science* [Isaac.Triguero@nottingham.ac.uk]

1 Background

Generative Adversarial Networks (**GAN**)[2] are a relatively new concept [2014] that are growing in popularity across many fields in Computer Science. They utilise a form of Turing Learning[6] in order to train a *Generative* Neural Network, which produces synthetic objects **y'**, labelled *0*, and a *Discriminative* Neural Network that predicts whether a given object originates from the ground-truth training set **y** (*1* label) or has been synthesised by the *Generator* (*0* label). The aim is to *trick* the discriminator into classifying synthesised objects **y'** as ground-truth images with label *1*, allowing for the creation of novel graphical representations of information in various applications. The final generator network can then be used to synthesise novel objects which *could* be found in some training set such that **y'** $\in$ **y** . The two networks play a *'Zero-Sum game'*, hence *Adversarial*, by minimising the generator error and maximising the discriminator error, until the output of the generator is deemed to be of satisfactory quality.

The necessity of utilising GANs in this context is based in the expense involved in retrieving large-scale CT images; training such a network on more manageable samples will reduce the space, time and financial costs involved with imaging various materials. This network can then be used to produce scaled-up synthetic X-Ray CT images virtually, without requiring laboratory/imaging equipment.

The majority of GAN research considers *Two-Dimensional* image training and synthesis [4][9], however more recently *Three-Dimensional* applications are being implemented, considering voxel-based data rather than pixel-based, allowing for the unsupervised creation of realistic 3D object models. These models can then be optimised based on their application, with many uses throughout *Engineering*, *Computer Science*, *Medical Science* at al. Whilst such potential applications may have yet to be realised, within Engineering GANs are becoming more prominent in the production of optimally configured composite mixtures, attracting both academic and industrial interest. Application of GANs to products such as *concrete* and *asphalt* used in paths and roads will result in an improved, safer product, reducing the frequency and severity of damages that may occur. Pairing such a product with other cutting-edge research in the field such as *self-healing*[8] via capsules, induction heating and microwave heating, will bring us closer to the production of a *perfect* paving material.

2 Overview

Based on the research paper *'Reconstruction of Three-Dimensional Porous Media using Generative Adversarial Neural Networks'*[7], which considers only the aggregate material in products such as *concrete* and *asphalt*, this research will consider the introduction of *mastic* or *bitumen* based components. Whilst existing research has successfully simulated the activity of asphalt in a virtual environment, using tools such as Unity3D[1], they fail to include considerations of intermediary ingredients which ultimately will affect the effectiveness and geometry of the material's final composition when considering the impact of air bubbles and compactness of aggregates in the mixture.

Furthermore, existing research using solutions such as Simulated Annealing and other methods of *AI-based optimisation* are infeasible due to their excessive runtime requirements. Even the work of *Mosser*[7] can still require tens of hours to train, but the resulting network can be stored and produce suitable models within a fraction of the time without the need for retraining.

Given the properties and quantities of aggregates and bitumen, the proposed system shall produce a synthesised X-Ray CT (*Computer Tomography*) scan using a GAN, which can then be passed to multiphysics software (considering kinetics, fluid/molecular dynamics and other mechanics imposed on the product) to measure air void content, hydraulic/thermal conductivities and mechanical properties. The GAN will allow the inference of the resultant shape of any mastic introduced into the mixture and how it will interact with aggregates having dimensions ranging from microns ($1\text{x}10^{-6}$m) up to centimetres ($1\text{x}10^{-2}$m) and varying levels of porosity. All calculations and models will be simulated in a virtual environment, allowing for an accelerated time-frame and reduced-cost testing environment.

3 Problems

Whilst GANs can be very powerful tools, the process of training is often unstable and slow, sometimes failing to ever converge or produce usable results. Very recent works attempt to fix this issue, such as the *Wasserstein Generative Adversarial Network* (**WGAN**)[1], which improves the training process but still does not guarantee convergence or optimal results. Further improvements of WGANs have been made by replacing inter-node weight clipping with a gradient-based penalty, resulting in faster training and better output quality[3]. Based on these proceedings, the efficiency of any networks used within this research must be carefully considered and optimised where possible, based on GAN improvement proposals published during, and indeed after, the scope of the project. The work of *Mosser* currently utilises the introduction of *Gaussian noise* and *one-sided label smoothing* to stabilise training on volumetric data[7] and so the process may benefit from such architectures as *Improved WGANs* in addition, or as an alternative, to noise inclusion and label smoothing.

4 Research Questions

Using Generative Adversarial Networks, is it computationally feasible to produce synthesised CT images of porous materials involving both aggregates and bitumen/mastic?

Whilst reducing the cost of requiring laboratory equipment, can such a system produce suitably comparable and usable images?

[1]https://unity3d.com/

5 Preliminary Aims and Objectives

- Literature review of latest GAN research, applying careful consideration to suitability of this application; research of porous material measurement techniques and resultant data collected.
- Collection of X-Ray CT Scan data for training GANs.
- Data pre-processing of CT Scan data (dimensionality reduction, cross-fold segmentation of training set).
- Development of GANs and delegation of computation to Graphical Processing Unit (**GPU**) cluster or High-Performance Computing (**HPC**) unit.
- Training of GANs, hyper-parameter tuning, consideration of alternate activation functions, network topology and size etc.
- Runtime efficiency improvement of GANs during training, using methods such as Adam optimisation[5].
- Output quality improvement of GANs e.g. by further training or optimising the networks based on recent research (WGAN, Improved WGAN etc.).

References

[1] Arjovsky, M., Chintala, S., and Bottou, L. Wasserstein Generative Adversarial Networks. In *International Conference on Machine Learning* (2017), pp. 214–223.

[2] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. Generative Adversarial Networks. In *Advances in neural information processing systems* (2014), pp. 2672–2680.

[3] Gulrajani, I., Ahmed, F., Arjovsky, M., Dumoulin, V., and Courville, A. C. Improved Training of Wasserstein GANs. In *Advances in Neural Information Processing Systems 30*, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds. Curran Associates, Inc., 2017, pp. 5767–5777.

[4] Isola, P., Zhu, J.-Y., Zhou, T., and Efros, A. A. Image-to-image Translation with Conditional Adversarial Networks, 2016.

[5] Kingma, D. P., and Ba, J. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014).

[6] Li, W., Gauci, M., and Gross, R. Turing Learning: a metric-free approach to inferring behavior and its application to swarms. *Swarm Intelligence 10*, 3 (2016), 211–243.

[7] Mosser, L., Dubrule, O., and Blunt, M. J. Reconstruction of Three-Dimensional Porous Media using Generative Adversarial Neural Networks. *CoRR abs/1704.03225* (2017).

[8] Tabakovic, A., and Schlangen, E. Self-Healing Technology for Asphalt Pavements. *Self-healing Materials 273* (2016), 285–306.

[9] Zhu, J.-Y., Park, T., Isola, P., and Efros, A. A. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. *arXiv preprint* (2017).