Implicit Neural Representations for Physically Based Simulations of Fluids.

(Masters or last year Engineering internship)

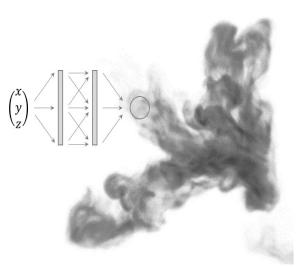
Guillaume Cordonnier, GRAPHDECO, Inria Sophia Antipolis (France) <u>http://team.inria.fr/graphdeco</u>

<u>Guillaume.Cordonnier@inria.fr</u> <u>http://www-sop.inria.fr/members/Guillaume.Cordonnier/</u>

Context and goal

Fluid simulations (liquid, smoke, ...) have many uses in virtual environments, from VFX and games to advertisement and commercial applications; and the gap between visual experiments and engineering applications is thinning. However, the computation, storage, and display of the 4D (3D+time) simulations are still a bottleneck for several applications [1].

Recent advances in Implicit Neural Representations are promising because of their ability to approximate multidimensional functions, with applications for image or object representation [2], and image-based scene reconstruction [3]. We propose to explore the use of neural representations to store, compute and edit fluid simulations.



Approach

In the first part of the internship, we will study the ability of a neural network to compress a fluid simulation. Following previous work on implicit shape representation [2], we will use a multi-layer perceptron that takes as input a 4D vector (position and time) and output the fluid density. Trained on a pre-computed fluid, the purpose of this task is to find the optimal architecture that faithfully represents the animation, while minimizing the memory and computation cost.

A seminal work on implicit representations advocated for the use of sine activation functions [4]. This idea has several advantages, and in particular, the n-th order derivatives with respect to the input are readily available, a key component that enables us to include the physical equation directly in the loss function. We will first consider this loss as a regularization for improving the compression efficiency, and then we will study the ability of the network to recover the simulation only from the equation and boundary conditions, inspired by recent work in physics [5]

As a final task, we will study how the simulation can be controlled, for instance with latent codes corresponding to obstacles, forces, or fluid parameters [6].

Work environment and requirements

The internship will take place at Inria Sophia Antipolis in the GRAPHDECO group (<u>http://team.inria.fr/graphdeco</u>). Inria will provide a monthly stipend of around 1100 euros for EU citizens in their final year of masters, and ~600 euros for other candidates.

Candidates should have strong programming and mathematical skills as well as knowledge in computer graphics, geometry processing and machine learning, with experience in C++, OpenGL and GLSL on the graphics side, and tensorflow/pytorch for learning. Knowledge in physics and physically-based simulation is a plus.

References

[1] Learning three-dimensional flow for interactive aerodynamic design, Nobuyuki Umetani, Bernd Bickel, ACM Transactions on Graphics (Proc. SIGGRAPH 2018) http://visualcomputing.ist.ac.at/publications/2018/LearningFlow/

[2] DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, Steven Lovegrove, *The IEEE Conference on Computer Vision and Pattern Recognition (Proc. CVPR 2019)* https://github.com/facebookresearch/DeepSDF

[3] NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis, Mildenhall Ben, Pratul P. Srinivasan, Matthew Tancik, Jonathan T. Barron, Ravi Ramamoorthi, Ren Ng, *European Conference on Computer Vision (Proc. ECCV 2020)*

https://www.matthewtancik.com/nerf

[4] Implicit Neural Representations with Periodic Activation Functions, Vincent Sitzmann, Julien N.P. Martel, Alexander W. Bergman, David B. Lindell, Gordon Wetzstein, *Neural Information Processing Systems (Proc. NeurIPS 2020)*

https://vsitzmann.github.io/siren/

[5] Physics-informed neural networks (PINNs) for fluid mechanics: A review, Shengze Cai, Zhiping Mao, Zhicheng Wang, Minglang Yin, George Karniadakis, *arXiv preprint*, 2021 <u>https://arxiv.org/pdf/2105.09506.pdf</u>

[6] Deep Fluids: A Generative Network for Parameterized Fluid Simulations, Byungsoo Kim, Vinicius C. Azevedo, Nils Thuerey, Theodore Kim, Markus Gross, Barbara Solenthaler, *Computer Graphics Forum (Proc. Eurographics 2019)*

https://cgl.ethz.ch/publications/papers/paperKim19a.php