PhD Fellowship on Few-Shot Generative Modelling for medical image synthesis

Thesis location : Laboratory of Medical Information Processing (LaTIM), French Institute of Health and Medical Research (INSERM UMR 1101), Brest, France,

Period : 3 years, starting on October 2020.

Context and objectives :

Among deep learning approaches, generative models (GMs) in particular based on GANs (Generative Adversarial Networks) are gaining a lot of interest in medical imaging.

One of the current limitations of GMs in a medical context lies in the large volume of images necessary for their training, as access to large clinical datasets is generally made challenging. For this reason, it is often necessary to resort to synthetic image generation methods, the objective of which is to reach the highest achievable level of realism. One way to produce realistic simulated image datasets is the use of Monte Carlo, particularly within the context of radiation based imaging (PET, SPECT, CT). However, these simulations are not suitable for all imaging methods (such as magnetic resonance imaging (MRI), or ultrasound imaging) and they require very long, sometimes prohibitive, computing times.

The objective of this thesis will be to develop an alternative approach for realistic medical image generation based on the concept of "few shot learning", an emerging idea in computer vision which consists in restricting the learning of generative models to a small number or even a single image. These promising methodological developments have so far not been exploited for pathological image generation in medical imaging. One of the objectives of the thesis will be the development of few-shot GAN models for PET, CT and MRI cancer image simulation. The realism of the generated images will be evaluated with scrutiny through comparison with highly realistic Monte Carlo simulations and real clinical images.

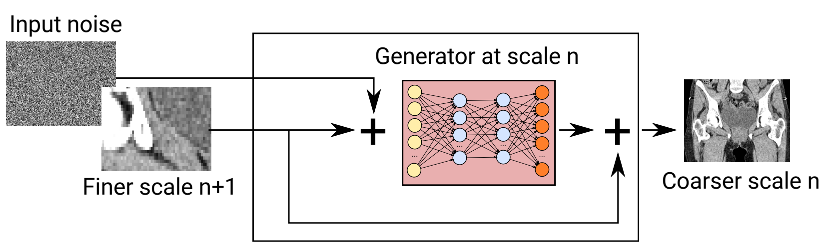

Fig. 1 : Example single-shot generative architecture in which a generative model is learned across the many scales of a pelvic computed tomography image.

Qualifications :

Education : The candidate must hold a Master's degree in one of these domains : physics, electrical/electronic engineering, computer science, applied mathematics.

Scientific interests : Good understanding of the physics of medical imaging and its challenges.

Programming skills : Fluent data processing using scripting langages (UNIX shell/python/Matlab).

Languages : English (complimentary), French (optional).

Contacts : Send before April 30th (in French or in English) CV, grades/marks (whatever currently available if you are actually on a Master), and a brief statement of interest by email to : Vincent Jaouen : vjaouen@gmail.com and Dimitris Visvikis (dimitris.visvikis@inserm.fr).

FR

Parmi les approches de deep learning, les modèles génératifs (MG) notamment basés sur les GAN (Generative Adversarial Networks) rencontrent un intérêt croissant en imagerie médicale.

Une des limites actuelles des MG dans un contexte médical réside dans le grand volume d'images nécessaires à leur entraînement, car l'accès à de grands jeux de données cliniques est généralement difficile. Il est ainsi souvent nécessaire de recourir à des méthodes de génération d'images synthétiques, dont l'objectif est d'atteindre le plus haut niveau de réalisme possible. Un des moyens pour produire des jeux de données simulées réalistes est la simulation Monte Carlo, en particulier pour les images de tomographie d'émission TEP/TEMP et de TDM (scanner). Cependant, ces simulations ne conviennent pas à toutes les modalités d'imagerie (comme l'imagerie par résonance magnétique (IRM) ou l'imagerie ultrasonore) et nécessitent des temps de calcul très longs, parfois prohibitifs.

L'objectif de cette thèse sera de développer une approche de génération d'images médicales réalistes alternative basée sur le concept de "few shot learning", un paradigme émergent qui consiste à restreindre l'apprentissage des modèles génératifs à un petit nombre, voire à une seule image. Ces développements méthodologiques prometteurs n'ont jusqu'à présent pas été exploités pour la synthèse d'images médicales. Un des objectifs sera notamment le développement de modèles GAN few shot pour la simulation d'images oncologiques en imagerie TEP, TDM et IRM. La plausibilité des images synthétisées sera évaluée scrupuleusement et comparée à des simulations Monte Carlo ultra réalistes et des images cliniques réelles.

EN

Among deep learning approaches, generative models (GMs) in particular based on GANs (Generative Adversarial Networks) are gaining a lot of interest in medical imaging.

One of the current limitations of GMs in a medical context lies in the large volume of images necessary for their training, as access to large clinical datasets is generally made challenging. For this reason, it is often necessary to resort to synthetic image generation methods, the objective of which is to reach the highest achievable level of realism. One way to produce realistic simulated image datasets is the use of Monte Carlo, particularly within the context of radiation based imaging (PET, SPECT, CT). However, these simulations are not suitable for all imaging methods (such as magnetic resonance imaging (MRI), or ultrasound imaging) and they require very long, sometimes prohibitive, computing times.

The objective of this thesis will be to develop an alternative approach for realistic medical image generation based on the concept of "few shot learning", an emerging idea in computer vision which consists in restricting the learning of generative models to a small number or even a single image. These promising methodological developments have so far not been exploited for medical image generation. One of the objectives of the thesis will be the development of few-shot GAN models for PET, CT and MRI cancer image simulation. The realism of the generated images will be evaluated with scrutiny through comparison with highly realistic Monte Carlo simulations and real clinical images.