Thesis Proposal: Conditioning of DDPMs on Accelerated MRI

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Start	18.09.2023
End	25.12.2023
Supervision	**Prof. Dr. Ender Konukoglu**
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Advisors	Georg Brunner & Emiljo Mehillaj

Contents

1 Background

Data acquisition in magnetic resonance imaging (MRI) takes a long time and reducing this acquisition time has been a long standing research problem for the following reasons:

1. MRI machines could perform more scans, driving down the cost per patient, and opening up diagnosis with MRI for a larger number of patients.

2. Better performance on dynamic imaging, since the temporal resolution could be increased.

3. Higher patient comfort and less unsuccessful scans due to patient motion.

Recently, methods using undersampling of Fourier space have received much attention and with the rise of generative deep learning [4, 2, 3] it is now possible to use highly sophisticated learned priors when solving this ill-posed inverse problem.

2 Thesis Project

2.1 Implementation of State-of-the-Art Reconstruction using DDPMs

The final goal of the thesis is to reach reconstruction performance comparable to the state-of-the art [12], using denoising diffusion probabilistic models (DDPMs), conditioned on the undersampling pattern of the measurement space and other measurement parameters.

As a first step, unconditioned DDPMs have to be understood and implemented. This includes experiments with different noise schedules (e.g., linear scheduling, cosine scheduling, . . .) [3, 7] and different neural network backbones (e.g., U-Net and variants) [9]. To understand conditioning, this can be extended to inverse problems such as inpainting, trainable on publicly available datasets like ImageNet [1] or FashionMNIST [11]. This is thought to be a simpler problem, due to better interpretability of the measurement space in normal images compared to MRI.

In a second step, the created models should be adapted to the context of accelerated MRI. This includes the creation of a forward model, that allows creating articial acquisitions of undersampled and multi-coil MRI using publicly available MRI datasets. [10] The forward model will vastly increase the amount of available data for training. Further, a study of the current state-of-the-art [12] and strongly performing foundation models outside the medical context [8] should provide ideas for enhancing the conditioning and the neural network backbone, and those enhancements should be implemented.

The last step should focus on improving training and evaluation. Specifically this includes performance comparison to the current state-of-the-art, using the same evaluation metrics, as well making use of novel training strategies that the student is interested in [5, 6].

2.2 Theoretical View on Generative Machine Learning

As part of the written thesis, an overview over the history and the existing methods of generative modeling and machine learning should be provided. This part should also provide a Bayesian perspective on the training objectives when optimizing/training these models.

2.3 Focus on Code Reuseability

The research output of the thesis project should have long-lasting value to the research group and the research community as a whole. The produced code should therefore focus on reuseability, by following the principles:

1. Trackable version history and open-source accessibility through git and GitHub.
2. Extensive useage of PyTorch interfaces for easy interoperability and scalability with other PyTorch-based components.
3. Automated code documentation and instructions for stable set up of the build/run environment.

The repository for the project has been set up as `https://github.com/liopeer/diffusionmodels` and the corresponding documentation is published on a dedicated webpage `https://liopeer.github.io/diffusionmodels/index.html`.

2.4 Further Ideas

The documentation homepage maintains an idea corner (Diffusion Models - Idea Corner) for collecting ideas on publicly available datasets, training strategies, related research papers, theoretical views on generative machine learning and more. The idea corner should not only be populated by the student, but also the supervisor/advisors, and certain points from this idea corner should be included in the code implementation after discussion with the supervisor/advisors.

3 Project Schedule

September/October	Implementation of basic conditioning outside the medical imaging context.
November	Completion of the forward model, adaptation of datasets for the stated purpose & implementation of sophisticated conditioning.
December	Evaluation, training strategies and finalizing the written thesis.

4 Supervision and Support

The student will be given computing resources to fulfill the task and will have the possibility to discuss issues with the advisors and the supervisor. A large part of the thesis work should be conducted on-site to enhance collaboration between the team members.

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Prof. Dr. Ender Konukoglu

Advisor
Emiljo Mehillaj

Advisor
Georg Brunner

Student
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References

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[11] Han Xiao, Kashif Rasul, and Roland Vollgraf. *Fashion-MNIST: a Novel Image Dataset for Benchmarking Machine Learning Algorithms.* 2017. arXiv: `1708.07747 [cs.LG]`.

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