PHD Proposal-3 years

Deep learning based PC-MRI imaging

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Scientific context

Phase Contrast Magnetic Resonance Imaging (PC-MRI) is a non-invasive quantitative imaging method where spatiotemporal blood velocity can be captured [1]. The principle of PC-MRI is to make use of the phase information of the complex MRI signal (also named k-space), to encode information on velocity. Consequently, one seeks to reconstruct complex images whose magnitude is proportional to the nuclear spin density ρ and whose phase difference $\Delta\phi$ is proportional to a velocity components. A minimum of d+1 sets of k-space signals are necessary to estimate a d-dimensional velocity field.

Despite providing relevant physiological information on blood flow in several cardiovascular pathologies, 4D PC-MRI is hardly used in clinical practice due to limitations in terms of complexity of planning and total acquisition time. A strategy that allows important reductions in acquisition time is measurement under-sampling. However, measurement under-sampling increases significantly the complexity of image reconstruction. Consequently, the reconstruction of the velocity field from an under-sampled k-space is a difficult non-linear inverse problem.

Resolution of this problem involves time consuming iterative approaches often resulting in sub-optimal image quality (in terms of SNR and sharpness) and velocity quantification (spatial and temporal smoothing of the velocity field). Magnitude image often has high-contrast features resembling a piecewise-constant function, which is sparse in the TV-transform domain, while the phase usually has smooth features since it encodes velocity information. Suitable regularizers have to be chosen for the magnitude and the phase [2]. Accurate velocity reconstruction from subsampled k-space signals remains a challenge.

Recently, several classical variational approaches have been developed to use some physical constraint to solve this problem. The governing equations are used as regularizers to reduce the search space velocity fields. The a priori knowledge for velocity regularization was used in the form of a Navier-Stokes boundary value problem in [3]. The aim is to use computational fluid dynamics in combination with 4D MRI to improve the resolution. The non-linear problem remains difficult to treat, however. On the other hand, recent research in inverse problems try to develop approaches that combine data-driven and model-based approaches. Many hybrid physics-deep learning frameworks have been studied, that integrate traditional physics-based modeling approaches with state-of-the-art machine learning or deep learning techniques [4,5]

Yet, there is very few studies for 4D MRI with deep learning methods. Some methods investigate super-resolution of the MRI images [6].

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Goal and tasks

Our goal for this project is to improve velocity field reconstruction from undersampled k-space data, both in terms of computation time, image quality, and velocity quantification. We intend to use deep learning for phase contrast magnetic resonance imaging and to propose novel approaches to increase the spatio-temporal resolution and decrease the calculation time. Our aim is to combine the knowledge of physical laws with deep learning approaches. In particular, we will investigate various deep learning inversion approaches based on physics-informed velocity regularization with some partial differential equation like the Navier-Stokes equations . We will also compare this type of methods with unrolling methods for nonlinear inverse problems which have been shown to improve the reconstruction results obtained with classical iterative methods. We will compare these deep learning strategies with classical variational approaches.

The main challenge is to find an appropriate deep learning strategy and some architectures to accurately solve the inverse problem even in the small data regime or with noisy data to leverage the data availability. Our aim is to integrate deep learning techniques with physically based regularization in order to capture the fluid patterns consistent with the physical laws and with the physics of PC-MRI and to overcome the ill-posedeness of the reconstruction problem.

The first approach considered will be to optimize a reconstruction network leveraging some partial differential equation constraint. We will investigate approaches where the PC-MRI signal can be reconstructed with a regularization method based on the Navier-Stokes equation. We will study several methods proposed recently in the literature for operator approximation and to solve inverse problem with pde constraint. The most efficient methods leverages model reduction with methods like proper orthogonal decomposition to mitigate the effects of the ill-posedness of the inverse problem. We thus intend to study coupling of POD model reduction to extract the modes of the Navier-Stokes equation with deep learning techniques. Starting from such model reduction, several neural networks architecture can be considered like PCA-Net or DeepOnet [7,8].

Recently, several unrolling approaches have been proposed using deep learning techniques that leverage the classical iterative approaches for inverse problems [9]. In the framework of these methods, some parts of the iterative algorithm are learned which improves the reconstruction results. These methods will be adapted to the inverse problem set by the PC-MRI problem [10]. We can also consider low rank plus sparsity penalization coupled with deep learning unrolling schemes [11].

Inspired by deep image priors (DIP) , we will try to use a convolutional neural networks (CNN) architecture as an implicit structural prior that constrains the search space of the optimization problem. In the framework of this type of approach, to learn the temporal dependencies of the dynamic measurements, we will have to impose a one dimensional manifold constraint [12]. We will also investigate the new methods to solve inverse problems based on Generative Adversarial Networks [13] for comparison.

The efficiency of the frameworks will be demonstrated with numerical examples with stationary and non-stationary velocity fields calculated with realistic simulations. We want also to test the methods on sparse and noisy k-space signals obtained with real data.

The training of networks will have to be addressed. The approaches will be trained on simulated 4D flow MR data obtained with the finite element software Fenics and consistent with the physics of MRI. We will also use experimental data. Deep learning methods will be implemented using TensorFlow, and specialised libraries in Python

Profile

Engineering or MSc degree in physics, applied mathematics, computer science or related disciplines.

Experience in image processing and programming in Python are required.

Experience in deep learning for image processing, programming and mathematics relevant to the problem strongly appreciated.

Language: English required, French optional

Period: 3 years

Contact

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References

[1] S.Crandon, MSM.Elbaz, JJM.Westenberg, RJ.Van der Gees, S.Plein, P.Garg, Clinical applications of intra-cardiac four dimensional flow cardiovascular magnetic resonance: a systematic review. Int J Cardiol. (2017) 249:486–93.

[2] M. Benning, L. Gladden, D. Holland, C. B. Schonlieb, and T. Valkonen, ¨ "Phase reconstruction from velocity-encoded MRI measurements - A survey of sparsity-promoting variational approaches," Journal of Magnetic Resonance. (2014) 238: 26–43.

[3] A.Kontogiannis, M.P. Juniper "Physics-informed compressed sensing for PC-MRI: an inverse Navier–Stokes problem", IEEE TIP (2023) 32:281-294.

[4] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature (2015) 521:436.

[5] S.Arridge, P.Maass, O.Oktem, and CB.Schonlieb "Solving inverse problems using data-driven models", Acta Numer. (2019) 28:1-174.

[6] E.Ferdian, A.Suinesiaputra, D.J.Dubowitz, D.Zhao, A.Wang, B.Cowan, A.A.Young "4DFlowNet:Super-resolution 4D flow MRI using deep learning and computational flow dynamics" Frontiers in Physics (2020) vol.8.

[7] K.Bhattacharya, B.Hosseini, NB.Kovachki and AM.Stuart "Model reduction and parametric pde" Journal of Computational mathematics (2017).

[8] L.Lu, P.Jin, G.Pang, Z.Zhang and GE.Karniadakis "Learning nonlinear operators via deeponet based on the universal approximation theorem of operators" (2021) Nature Machine Intelligence, (2021) 3:218-229.

[9] A.Hauptman, F.Lucka, M.Betcke, J.Adler, B.Cox, P.Beard, S.Ourselin, S.Arridge "Model based learning for accelerated, limited-view 3D photoacoustic tomography" IEEE Transactions on medical imaging (2018) 37:1382-1393.

[10] V.Vishnevskiy1, J.Walheim1, and S.Kozerke1 "Deep variational network for rapid 4D flow MRI reconstruction", Nature Machine Intelligence (2020)

[11] W. Huang, Z. Ke, Z.X. Cui, J. Cheng, Z. Qiu, S. Jia, L. Ying, Y. Zhu, and D. Liang, "Deep low-Rank plus sparse network for dynamic MR imaging," Medical Image Analysis, (2021) 73:102190.

[12] J.Yoo, KH. Jin, H.Gupta, J.Yerly, M.Stuber, and M.Unser "Time-Dependent Deep Image Prior for Dynamic MRI" IEEE Transactions on Medical Imaging, (2021) 40:3337-3348.

[13] J.T.Guibas, T.S.Virdi and P.S.Li "Synthetic medical images from dual generative adversarial networks", (2017) https://arxiv.org/abs/1708.01872.