

PHD Proposal-3 years

Model-based image reconstruction dedicated to Phase Contrast MRI for improved velocity quantification from highly under-sampled acquisitions

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IIMR 5720



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Background:

Unlike anatomical imaging where MRI encodes only tissue contrast, phase-contrast MRI (PC-MRI) takes advantage of the fact that moving spins accumulate a phase shift that is proportional to their velocity. By carefully designing velocity-encoding gradients, one can extract quantitative maps of blood flow throughout the cardiac cycle. The velocity encoding is tuned through a parameter called VENC, which sets the maximum velocity measurable without phase wrapping. Noise of the measured velocity is directly proportional to VENC. Consequently, use of a high VENC reduces sensitivity to slow flows, which become buried in noise. Conversely, use of a low VENC leads to velocity aliasing for fast flows. Simultaneous acquisitions using a low and a high VENC value (dual-VENC) enable a high dynamic range for fast flow and good sensitivity for slow flow. However, these acquisitions require a nearly doubled acquisition time compared to standard single-VENC. High data under-sampling significantly reduces acquisition time and allows dual and multi-VENC measurements to be performed in a time comparable to single-VENC measurements [[1], [2]].

Conventional reconstruction in PC-MRI relies on a two-step pipeline: first, complex images are reconstructed independently for each velocity encoding, and then the velocity maps are derived from the phase differences. This separation makes the method sensitive to noise and artifacts, since errors in the image reconstruction stage propagate into the velocity estimation. It also becomes increasingly challenging when trying to accelerate acquisitions, because undersampling introduces phase wraps and ghosting that degrade the accuracy of the velocity maps.

Model-based reconstruction provides an alternative: instead of reconstructing complex images first and then extracting velocity, it directly estimates both the underlying anatomy and the velocity field from the k-space data. A forward model describes the full acquisition process, including coil sensitivities, Fourier encoding, undersampling, and the velocity-encoding gradients that introduce phase shifts proportional to velocity. The reconstruction then becomes a joint inverse problem, where the task is to find the anatomy and flow that best explain the acquired data, while allowing the introduction of additional constraints or prior knowledge. This approach has proven highly advantageous. By estimating velocity and anatomy simultaneously, it improves SNR, reduces phase errors, and suppresses artifacts such as wraps and ghosting. It also naturally accommodates undersampled data, enabling the use of compressed sensing, parallel imaging, and non-Cartesian trajectories. For example, state-of-the-art studies have shown that combining model-based reconstruction with radial sampling allows real-time 2D phase-contrast MRI, offering higher temporal resolution and more accurate flow measurements than the standard pipeline [3], [4].

Very recent deep learning approaches can also be used for comparison with these model-based reconstruction methods and they can be useful to improve them. The principle of these approaches based on autoencoders is to build a regularization term for the velocity field that is learned with some velocity data set. It constrains the reconstructed velocity on some velocity manifolds parametrized by a low dimensional latent variable [5].

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Objectives:

The goal of this PhD project is to build on these advances and extend them to more complex but clinically relevant scenarios. The first objective is to generalize model-based reconstruction from 2D real-time radial acquisitions to full 3D radial sampling with velocity encoding in multiple directions. This will make it possible to capture volumetric flow information with higher spatial and temporal resolution, but also requires new reconstruction strategies to cope with the larger datasets and the coupling between multiple encoding directions.

The second objective is to develop model-based reconstructions for dual- and multi-VENC acquisitions. In conventional single-VENC imaging, there is always a compromise: a high VENC is needed to capture fast jets without phase wrapping, but this makes slower velocities difficult to detect; conversely, a low VENC improves sensitivity to slow flow but causes aliasing for fast velocities. Multi-VENC acquisition strategies solve this at the data level, but integrating them into a model-based framework allows joint exploitation of the redundancies across encodings. This could provide more accurate velocity estimation across the entire dynamic range and improve robustness to noise and artifacts.

Overall, the project aims to advance the methodology of model-based flow MRI, bringing it from successful demonstrations in 2D towards robust applications in 3D and in dual-/multi-VENC imaging. An extensive comparison with new deep learning methods based on autoencoders will be also developed. This will require innovations in inverse problem formulation, optimization algorithms, and the incorporation of regularization strategies — potentially including physics-informed priors such as incompressibility or smoothness of blood flow. Ultimately, the vision is to make model-based reconstruction a practical and powerful tool for high-resolution, accelerated 4D flow MRI with clinical impact.

Methodology:

The reconstruction strategy will build on **state-of-the-art model-based methods** with a specific focus on **3D radial (free-running) acquisitions**, which are implemented by the team. It is important to emphasize that while several recent methods incorporate physics-informed constraints in phase-contrast MRI, not all of them are **true model-based reconstructions**. In most physics-informed approaches, the algorithms operate on pre-reconstructed velocity fields or phase images, enforcing physical laws such as incompressibility or Navier–Stokes consistency to denoise or refine the flow. In contrast, model-based reconstruction directly formulates an inverse problem from the raw k-space data, jointly estimating both the complex anatomy and the velocity fields using a forward model of the MRI acquisition, including coil sensitivities, Fourier encoding, and velocity-encoding gradients.

In this project, we aim to combine the advantages of both strategies. We will start from a true model-based reconstruction framework for 3D radial free-running acquisitions and extend it by incorporating physics-informed regularization. This allows the reconstruction to remain fully consistent with the MRI signal while benefiting from prior knowledge about flow, such as smoothness, incompressibility, or CFD-derived constraints. By embedding these priors directly into the joint inverse problem, the method is expected to improve robustness against undersampling, phase wraps, and noise, particularly for dual- and multi-VENC acquisitions.

To extend model-based reconstruction to **dual- and multi-VENC acquisitions**, the forward model will explicitly account for the phase dependence on each velocity encoding. For each VENC, the MR signal is modeled as the complex anatomy multiplied by a velocity-dependent phase term proportional to the underlying flow. By including all VENC encodings simultaneously in the forward operator, the reconstruction becomes a **joint inverse problem**, where a single velocity field is estimated consistently across low and high VENC data. This formulation naturally handles phase wrapping: low-VENC measurements provide high sensitivity to slow flows, while high-VENC measurements constrain fast flows, and the physics-informed regularization ensures smoothness, incompressibility, or CFD-derived flow patterns are respected across all encodings. Solving this joint problem directly from k-space allows full exploitation of the redundancy across VENCs, improves robustness to noise and undersampling, and avoids errors introduced by traditional post-hoc unwrapping methods.

To explore and validate these reconstruction strategies, **the project will combine both synthetic data and real MRI acquisitions**. On the simulation side, we have computational fluid dynamics (CFD) data generated in an idealized vascular geometry designed to produce complex flow patterns similar to those encountered in vivo. This dataset provides a valuable ground truth: from the CFD velocity fields we can synthesize realistic MRI signals and generate k-space data, with different levels of undersampling, noise, and encoding strategies. In this way, new reconstruction algorithms can be systematically tested against a known reference, providing quantitative benchmarks of accuracy and robustness.

Complementing this, we also have **experimental flow phantom acquisitions** performed in a physical model with the exact same geometry as the CFD simulations. These measurements bridge the gap between in-silico and in-vivo experiments: they allow us to assess reconstruction performance on real MR acquisitions, while still providing a controlled environment where the geometry and flow are well characterized.

By combining synthetic k-space from CFD with phantom MRI data, the student will have a unique framework to iteratively design, test, and refine reconstruction methods. This dual strategy ensures that methodological advances are not only validated against perfect ground truth, but also shown to be robust when applied to real-world MRI acquisitions — an essential step before translation to clinical data.

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

References

[1] M. Aristova *et al.*, “Accelerated dual-vent 4D flow MRI with variable high-vent spatial resolution for neurovascular applications,” *Magn. Reson. Med.*, vol. 88, no. 4, pp. 1643–1658, 2022, doi: 10.1002/mrm.29306.

[2] O. Kilinc *et al.*, “Aortic Hemodynamics with Accelerated Dual-Venc 4D Flow MRI in Type B Aortic Dissection,” *Appl. Sci.*, vol. 13, no. 10, Art. no. 10, Jan. 2023, doi: 10.3390/app13106202.

[3] Z. Tan *et al.*, “Model-based reconstruction for real-time phase-contrast flow MRI: Improved spatiotemporal accuracy,” *Magn. Reson. Med.*, vol. 77, no. 3, pp. 1082–1093, 2017, doi: 10.1002/mrm.26192.

[4] J. M. Kollmeier, O. Kalentev, J. Klosowski, D. Voit, and J. Frahm, “Velocity vector reconstruction for real-time phase-contrast MRI with radial Maxwell correction,” *Magn. Reson. Med.*, vol. 87, no. 4, pp. 1863–1875, 2022, doi: 10.1002/mrm.29108.

[5] H. Csala, S. Dawson, A. Amirhossein, “Comparing different nonlinear dimensionality reduction techniques for data-driven unsteady fluid flow modeling,” *Phys Fluids*. 2022; 34:443–482.

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