

Hello folks,

Here is what's been going on in medical physics and related areas the last 24 hours. Here's what you might find interesting today.

Imaging Physics and Reconstruction

[Flow Matching-Based PET Image Reconstruction](#) (Hashimoto, Huang, Yokota, Gong)

This paper introduces flow matching as a generative prior for **PET image reconstruction**, moving beyond diffusion-based approaches that require many reverse sampling steps with interleaved data-consistency updates. The key insight is that flow matching can directly estimate clean images from intermediate states, decoupling data-consistency refinement from flow propagation. The authors build PET-FlowDPS by incorporating **Poisson likelihood guidance** with an EM-based preconditioner, and then formulate a model-based reconstruction method that interprets the flow-based prior, PET data refinement, and stochastic propagation within an **approximate Bayesian framework**. Results on [18F]FDG brain PET show improved bias-variance trade-offs across dose levels. This matters because it demonstrates a principled alternative to diffusion-based reconstruction with a cleaner separation of physics-based data fidelity from learned priors, which could simplify the design space for quantitative PET reconstruction pipelines.

Novel Architectures and Objectives for Imaging

[Coupled Optimal Transport with Landmark Constraints](#) (Gu, Sun, Xu)

This work proposes a **coupled optimal transport framework** that jointly optimizes a transport plan and a deformation field guided by sparse annotated landmarks, connected through a mutual-consistency constraint. The framework provides a principled bridge between **landmark-based registration** and **transport-based distribution matching**, enabling recovery of geometrically meaningful transport maps from sparse supervision. The authors establish well-definedness in a general variational setting and provide convergence analysis for their finite-element numerical scheme. While demonstrated on shape matching, the formulation is directly transferable to **image registration** problems where anatomical landmarks are available but dense correspondence is ill-posed, making it relevant to anyone working on physics-informed or geometry-aware registration in medical imaging.

[A Plug-in Interpretation of Conditioning in Score-Based Diffusion Models](#) (Chen, Ghosh, Deveney, Budd, Namboodiri)

The authors propose a conditioning mechanism for diffusion models based on **multi-speed joint diffusion** of the target and condition, learning an unconditional joint score network and enforcing conditioning at inference via a **plug-in correction term**. This separates the conditioning contribution from learned unconditional dynamics, offering a transparent view of how conditions steer generation. They derive explicit conditional reverse-time SDEs and approximate probability-flow ODEs, and introduce a **log-Fokker-Planck residual regularization** to reduce ODE-SDE discrepancy. This is relevant to **image reconstruction and synthesis** because the plug-in formulation could enable more principled and modular conditioning on imaging physics (e.g., forward operators, measurement data) within diffusion-based reconstruction frameworks, and the theoretical grounding makes the conditioning mechanism directly comparable across samplers.

Uncertainty Quantification and Likelihood-Free Inference

[Does Marginal Coverage Guarantee Class-Conditional Safety for Zero-Shot VLMs Under Shift?](#) (Sharma, Dutta)

This paper audits **split-conformal prediction** as an abstention layer for zero-shot vision-language models under deployment shift, revealing that marginal coverage can remain high while **class-conditional tail coverage collapses**. On ImageNet-Sketch, worst-class coverage falls to approximately zero despite marginal coverage of ~ 0.86 , with 10-12% of classes below a finite-sample null floor. The authors show that source-side Mondrian calibration does not transfer, and that clustered conformal and Conf-OT improve marginal metrics without recovering the worst-class tail. This matters for **calibrated uncertainty in diagnostic prediction** because it demonstrates that marginal conformal guarantees are insufficient safety mechanisms when deployed in clinical settings with class imbalance or distribution shift, motivating the need for class-conditional or group-conditional calibration strategies in medical imaging pipelines.

Back tomorrow with more!

P.S. In the most recent submission window: physics.med-ph: 2 papers cs.CV: 80 papers