**BAYESIAN UNSUPERVISED DISENTANGLEMENT FOR GROUPWISE IMAGE REGISTRATION**

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## Abstract

Deep learning–based image registration has significantly advanced medical image analysis by enabling automated alignment of anatomical structures across subjects. However, most existing approaches focus on pairwise registration and often entangle anatomical appearance with geometric deformation, limiting interpretability, robustness, and uncertainty modeling. This work presents a Bayesian unsupervised framework for disentangling anatomy and geometry in deep groupwise image registration. The proposed model separates anatomical content (what the structure is) from geometric transformation (how it is spatially deformed), enabling consistent template learning across a population without requiring ground-truth deformation fields.The framework employs dual latent variable encoders within a variational inference setting. An anatomy encoder learns a probabilistic latent representation capturing shared structural appearance across images, while a geometry encoder models subject-specific deformation through a displacement field generator. Both latent spaces are regularized using Kullback–Leibler divergence to enforce Bayesian priors, allowing principled uncertainty estimation. A differentiable spatial transformer module warps the decoded anatomical representation using the predicted geometric deformation, reconstructing the observed image. Training is performed in a fully unsupervised manner using similarity measures such as normalized cross-correlation, smoothness regularization of deformation fields, and groupwise anatomical consistency constraints.By disentangling structure from deformation, the model learns a shared anatomical template that remains stable across the dataset while capturing individual geometric variations separately. This separation enhances interpretability and enables robust groupwise alignment without explicit supervision. Moreover, the Bayesian formulation provides uncertainty-aware representations, improving reliability in clinical scenarios where ambiguous or noisy data may exist.Experimental validation on synthetic image datasets demonstrates that the proposed approach successfully reconstructs anatomically consistent templates while generating smooth and realistic deformation fields. The architecture supports scalable groupwise registration and can be extended to multi-resolution, diffeomorphic transformations, or uncertainty-aware medical imaging applications. Overall, the proposed Bayesian disentanglement framework advances deep unsupervised groupwise image registration by integrating probabilistic modeling, representation learning, and spatial transformation into a unified end-to-end system.