Abstract #1130

From Registration Uncertainty to Segmentation Uncertainty

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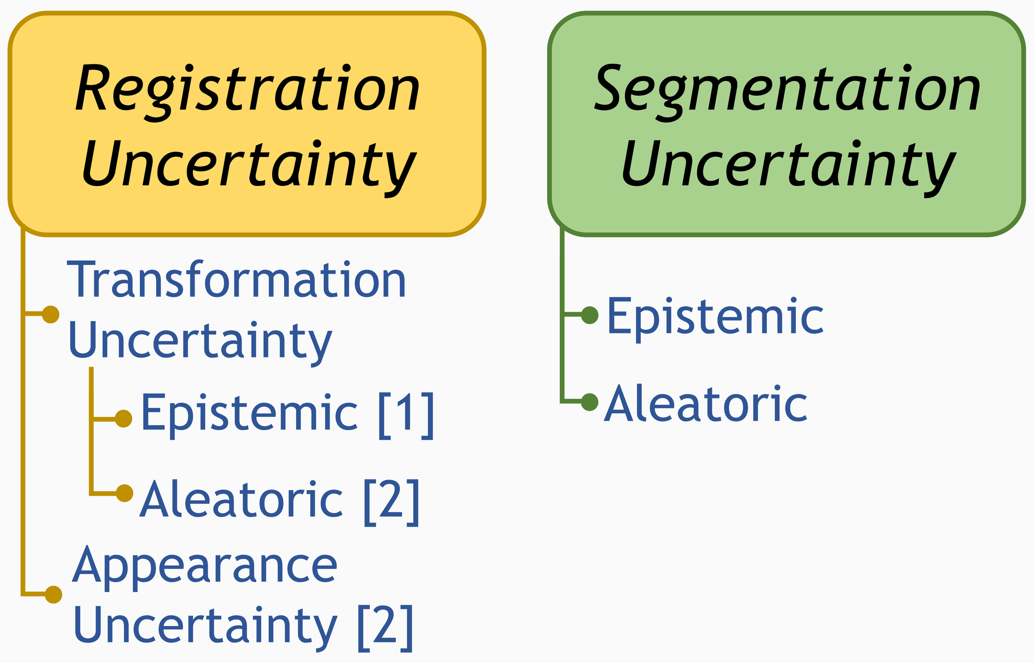
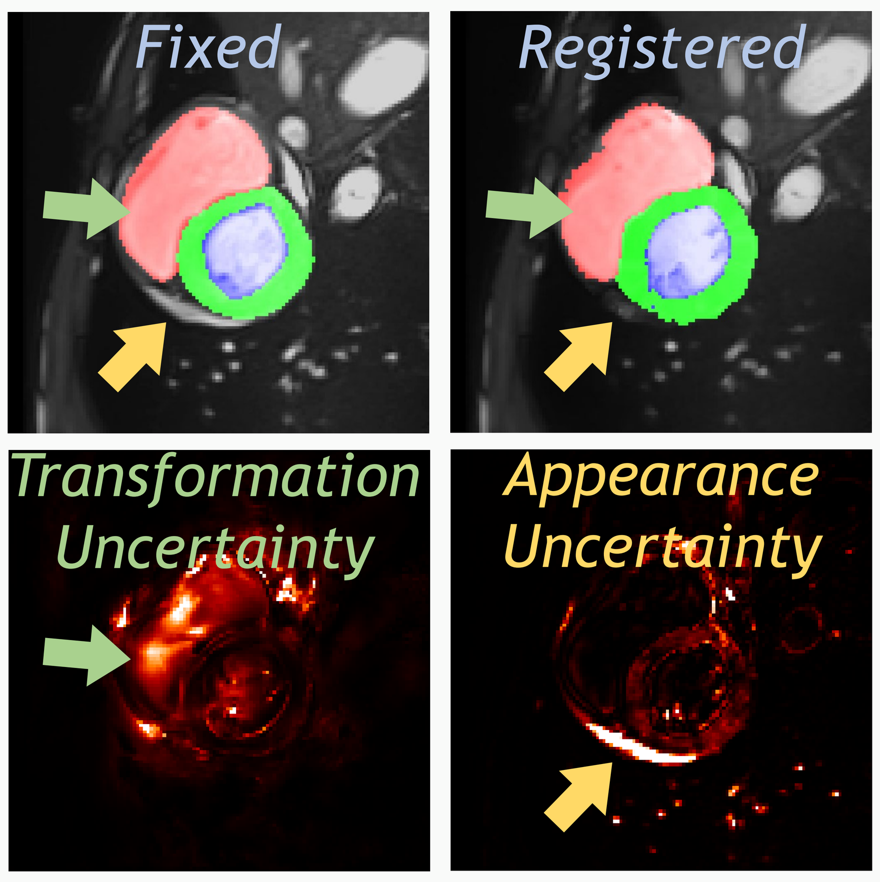
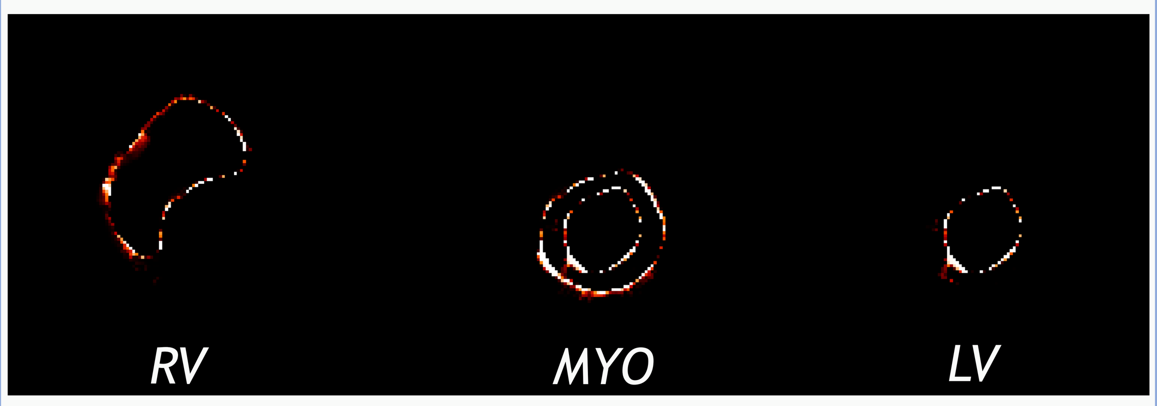
Introduction



- ***Epistemic uncertainty:*** Quantifies uncertainty in the model.
- ***Aleatoric uncertainty:*** Quantifies uncertainty in the data.
- ***Registration Uncertainty Breakdown:***
  - *Transformation Uncertainty:*
    - Quantifies ambiguity in deformation.
    - Large in areas with piece-wise constant intensity.
  - *Appearance Uncertainty:*
    - Quantifies uncertainty in image similarity matching.
    - Large during mismatches in image appearance.



However, neither the transformation nor the appearance uncertainty reliably indicates **segmentation errors** when using the registration model for label propagation.



Squared Label Errors for three different classes: right ventricular (RV), myocardium (MYO), and left ventricular (LV).

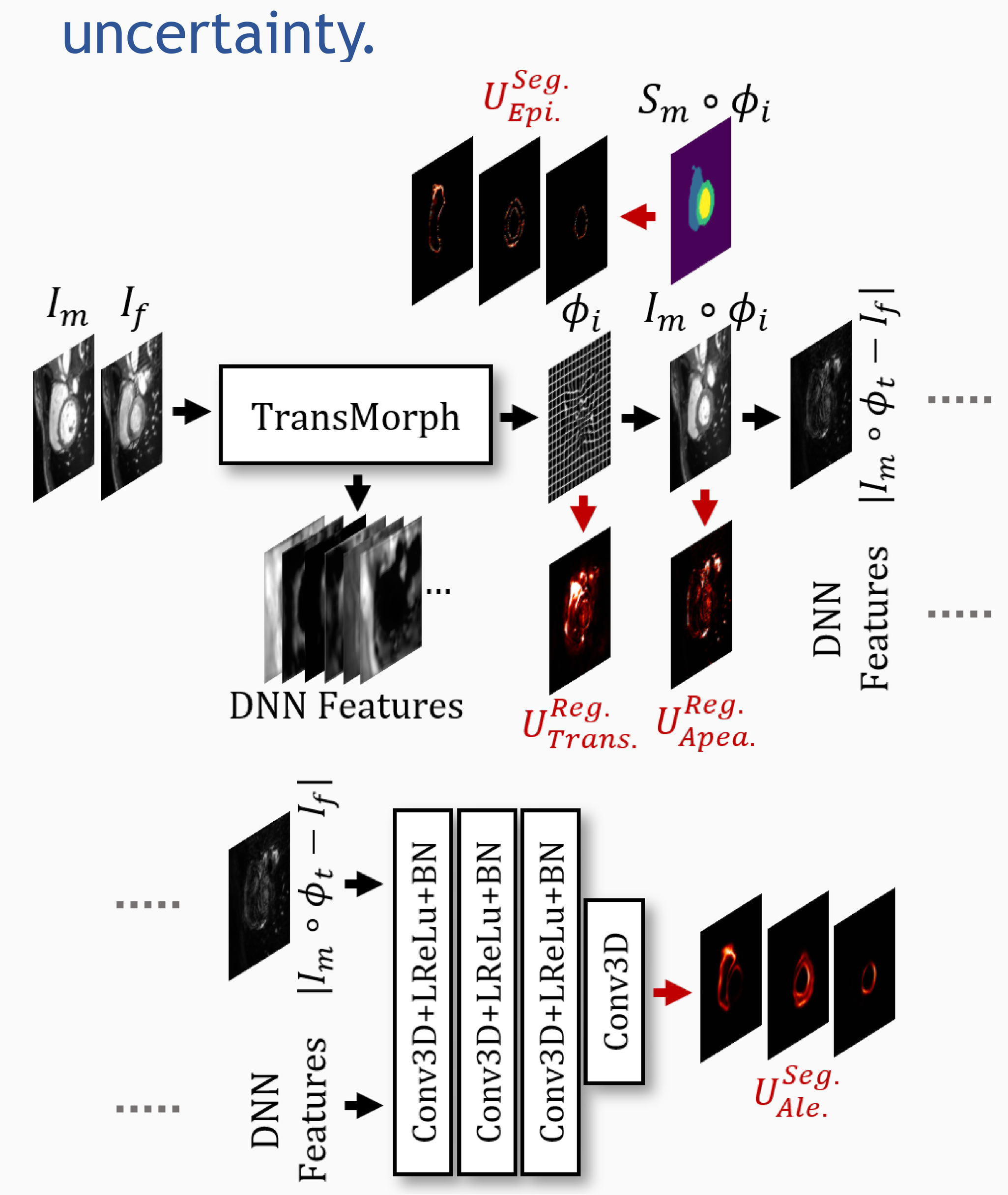
Our contribution:

- We bridge registration and segmentation uncertainty by developing a compact DNN that can be integrated with existing registration networks to estimate **segmentation uncertainty for image registration**.

Methods

Overall framework:

- *Registration network*:
  - Uses a Monte-Carlo Dropout-based network to generate T deformation fields via Monte-Carlo sampling.
- *Compact DNN*:
  - ***Input***: High-level features from the registration network as input.
  - ***Conditioning***: Based on the appearance difference.
  - ***Output***: Aleatoric segmentation uncertainty.



- I_m, I_f: Moving and fixed images
- S_m, S_f: Label maps for I_m, I_f
- ϕ: Deformation field

Warping function:

- Warping operations for both images and associated label maps use **linear interpolation**.
- For label maps, the operation is defined as: $S_m = \operatorname{argmax}_C(\boldsymbol{S}_m^C \circ \phi)$

Transformation Uncertainty:

- Computed as the variance of T deformation fields:
  - $U^{Reg.}_{Trans.} = \frac{1}{T}\Sigma_i^T\left(\phi_i - \frac{1}{T}\Sigma_i^T\phi_i\right)^2$

Appearance Uncertainty:

- Computed as the variance of T registered images:
  - $U^{Reg.}_{Apea.} = \frac{1}{T}\Sigma_i^T(I_m \circ \phi_i - I_f)^2$

Epistemic Segmentation Uncertainty:

- **Requires** label maps of the moving image to be available during testing.
- Voxel-wise entropy is calculated as:
  - $U^{Seg.}_{Epi.} = -\sum_{c\in C}\left(\frac{1}{T}\Sigma_i^T S_m^c \circ \phi_i\right)\log\left(\frac{1}{T}\Sigma_i^T S_m^c \circ \phi_i\right)$

Aleatoric Segmentation Uncertainty:

- **Does not require** label maps during testing.
- $U^{Seg.}_{Ale.}$ is the variance, σ^2, of the negative log-Gaussian likelihood [3]:
  - $\mathcal{L} = \frac{1}{\Omega}\sum_{p\in\Omega}[\sigma^2(p)](\frac{1}{2}\sigma^{-2}(p)\|S_m(p) - S_f(p)\|^2 + \frac{1}{2}\sigma^2(p))$

Experimental Setup

Dataset:

- *3D cardiac MRI datasets*: the ACDC [4] and the M&Ms [5] challenges.
- *Registration task*: Registration between the ED and ES stages.

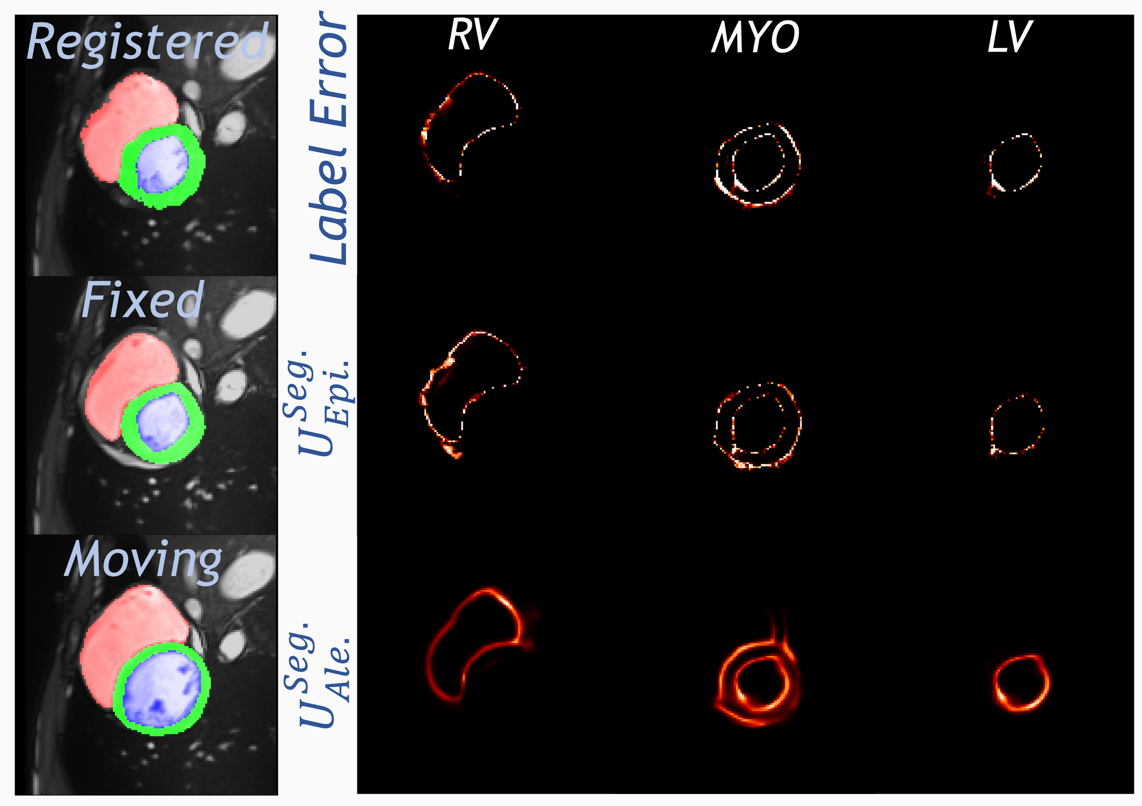
Metrics:

- *Deformation*: Dice + Non-positive Jacobian Determinants (%$|\boldsymbol{J}|\leq 0$) + Non-diffeomorphic Volumes (%NDV)
- *Uncertainty*: Pearson's correlation ($\boldsymbol{r}$) to quantify the correlation between the segmentation uncertainty estimates with the squared label errors

Source code is available at:

Results & Discussion

Qualitative Results:



Quantitative Results:

Method	LV Dice ↑	RV Dice ↑	MYO Dice ↑	Mean Dice ↑	%$\lvert J\rvert \leq 0$ ↓	%NDV ↓
Initial	0.595±0.162	0.608±0.114	0.445±0.144	0.549±0.112	-	-
SyN	0.691±0.157	0.634±0.134	0.687±0.099	0.670±0.110	0.000±0.001	0.000±0.000
SYMNet	0.766±0.111	0.797±0.102	0.765±0.060	0.776±0.068	1.735±1.417	1.627±1.544
VoxelMorph	0.836±0.094	0.788±0.097	0.786±0.058	0.803±0.063	0.808±0.792	0.293±0.328
TransMorph	0.859±0.088	0.824±0.093	0.832±0.046	0.838±0.057	1.216±0.990	0.230±0.187
Proposed	**0.861±0.089**	**0.824±0.092**	**0.834±0.045**	**0.839±0.058**	1.297±1.011	0.268±0.206
	LV r ↑	RV r ↑	MYO r ↑	Mean r ↑		
Transformation	0.078±0.044	0.107±0.047	0.080±0.040	0.088±0.030		
Appearance	0.053±0.047	0.080±0.065	0.048±0.029	0.060±0.031		
Epistemic	0.531±0.091	0.579±0.086	0.546±0.046	0.552±0.056		
Aleatoric	0.376±0.084	0.371±0.075	0.399±0.060	0.382±0.059		
Epi.+Ale.	**0.567±0.073**	**0.603±0.077**	**0.579±0.035**	**0.583±0.045**		

Introduction of auxiliary DNN:

- We have implemented a compact DNN that estimates aleatoric segmentation uncertainty during label propagation in image registration, eliminating the need for label maps at test time.

Insights into registration process:

- By combining entropy to represent epistemic segmentation uncertainty, the method offers a comprehensive estimation of uncertainties for both image warping and label propagation.

Reference

1. Dalca, Adrian V., et al. "Unsupervised learning of probabilistic diffeomorphic registration for images and surfaces." Medical image analysis 57 (2019): 226-236.
2. Chen, Junyu, et al. "Transmorph: Transformer for unsupervised medical image registration." Medical image analysis 82 (2022): 102615.
3. Seitzer, Maximilian, et al. "On the Pitfalls of Heteroscedastic Uncertainty Estimation with Probabilistic Neural Networks." International Conference on Learning Representations. 2021.
4. Bernard, Olivier, et al. "Deep learning techniques for automatic MRI cardiac multi-structures segmentation and diagnosis: is the problem solved?." IEEE transactions on medical imaging 37.11 (2018): 2514-2525.
5. Campello, Victor M., et al. "Multi-centre, multi-vendor and multi-disease cardiac segmentation: the M&Ms challenge." IEEE Transactions on Medical Imaging 40.12 (2021): 3543-3554.