BAYESIAN IMAGE QUALITY TRANSFER

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Abstract

- **Image quality transfer (IQT)** [1] is a machine-learning based framework to enhance low quality images (e.g. clinical data) by learning and propagating rich information from rare high quality images from expensive scanners (e.g. HCP data).
- We propose a **Bayesian extension of IQT** and demonstrate in **super-resolution of dMRI.**
- Results show:
  1. our method **improves reconstruction accuracy**.
  2. our method provides a **robust uncertainty estimate**.
  3. the uncertainty measure can **highlight unfamiliar regions** not observed in training data e.g. pathology.

Background (IQT framework)

- **Super-resolution** as a **patch-wise regression** (Fig.1) as in [1].
- **Training data generation** (Fig.2): high quality images from HCP are downsampled to create matched pairs of high-res and low-res patches.

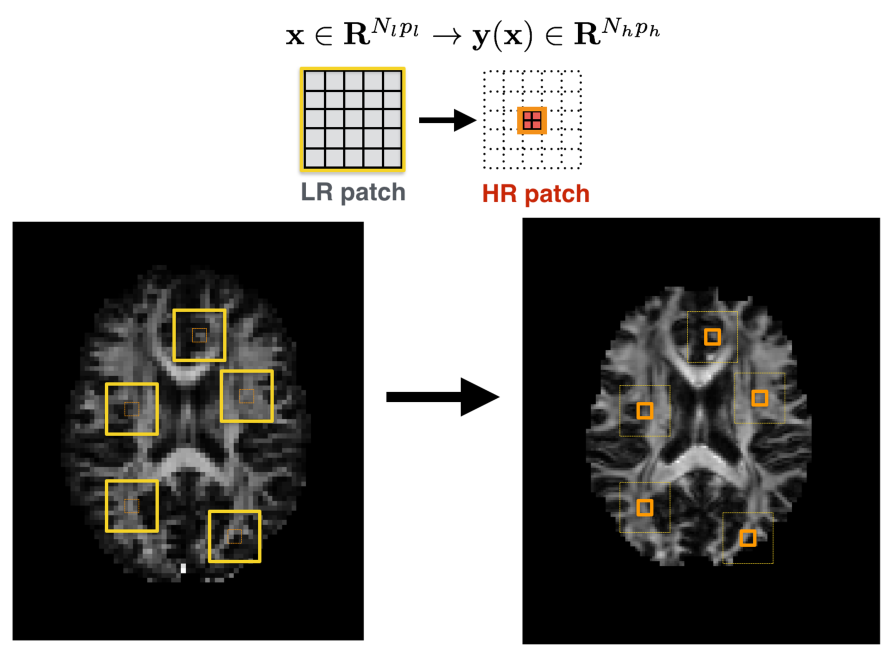


Fig.1 Patch-wise super-resolution

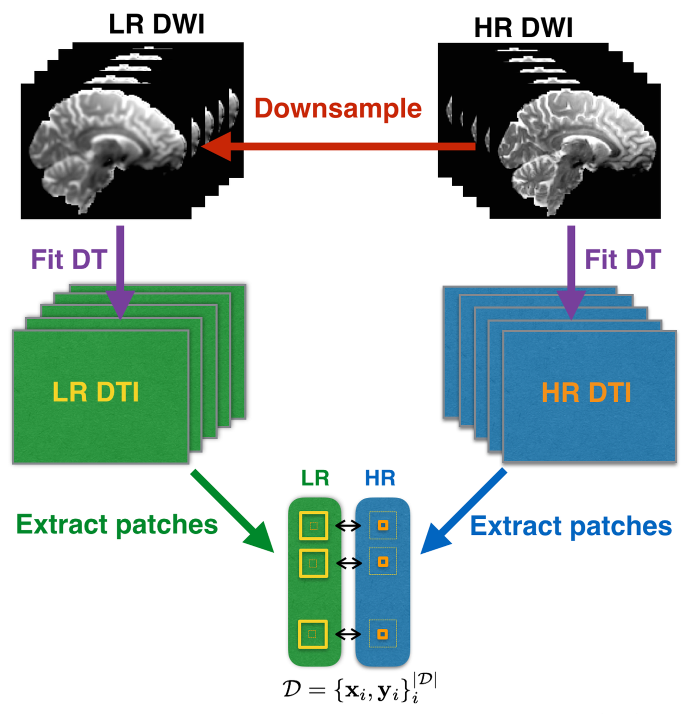


Fig.2 How to create $\mathcal{D} = \{\mathbf{x}_i, \mathbf{y}_i\}_i^{|\mathcal{D}|}$

Our solution (Bayesian IQT)

- **Node-wise Bayesian regression forest:** the Bayesian linear model is used to model the predictive distribution at **each leaf node** of each tree:

Model component

$$\mathbf{y} = \mathbf{W}\mathbf{x} + \boldsymbol{\eta}$$
$$\mathrm{P}(\boldsymbol{\eta}|\beta) = \mathcal{N}(\boldsymbol{\eta}|\mathbf{0}, \beta^{-1}\mathbf{I})$$
$$\mathrm{P}(\mathbf{W}_{|}|\alpha) = \mathcal{N}(\mathbf{W}_{|}|\mathbf{0}, \alpha^{-1}\mathbf{I})$$

Predictive distribution

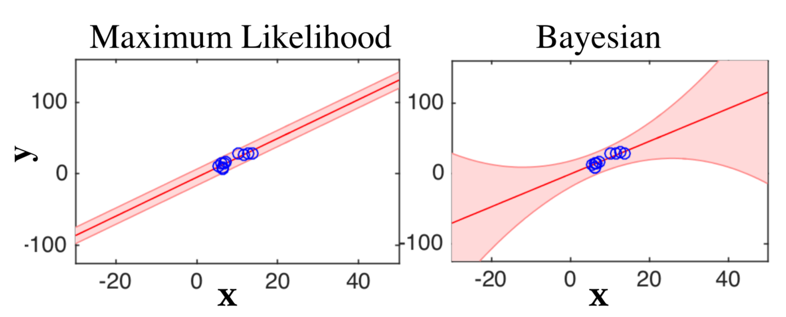
$$\mathrm{P}(\mathbf{y}|\mathbf{x}, \mathcal{D}, \alpha, \beta) = \mathcal{N}(\mathbf{y}|\, \mathbf{W}_{\text{Pred}}\mathbf{x},\, \sigma^2_{\text{Pred}}(\mathbf{x}) \cdot \mathbf{I})$$

- **Uncertainty quantification** by the variance at the assigned leaf node:

$$\sigma^2_{\text{Pred}}(\mathbf{x}^*) = \underbrace{\mathbf{x}^{*T}\mathbf{A}(\mathcal{D})\mathbf{x}^*}_{\text{Unfamiliarity}} + \underbrace{\beta^{-1}}_{\text{Noise}}$$

Unfamiliarity: distance from the training data

Noise: variability in the training data



Conclusions

Our method, **Bayesian IQT**:

- **provides an uncertainty measure** which *highly correlates with the reconstruction accuracy,* and is able to *highlight pathologies* not observed in the training data.
- **improves reconstruction accuracy** in super-resolution against the original IQT implementation and standard interpolation methods.
- **retains generality of IQT;** it can be applied to other modalities (e.g. structural MRI, CT) and different applications beyond super-resolution (e.g. image synthesis).

References

1. Alexander, D.C., et al.: Image quality transfer via random forest regression. In: MICCAI 2014.
2. Criminisi, A., Shotton, J.: Decision forests for computer vision and medical image analysis. Springer (2013)

Results

- **Uncertainty displays correspondence with reconstruction accuracy.**

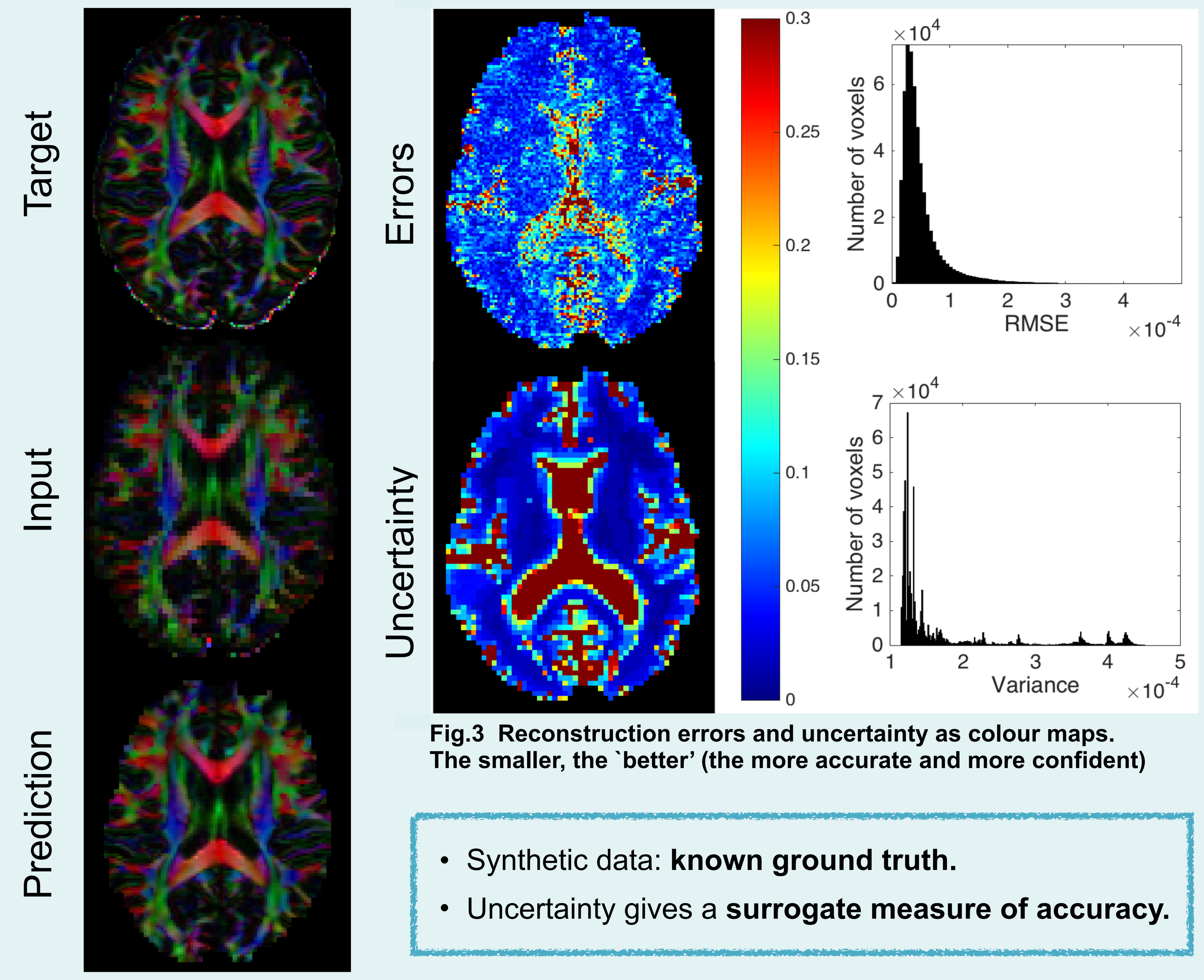


Fig.3 Reconstruction errors and uncertainty as colour maps. The smaller, the `better' (the more accurate and more confident)

- Synthetic data: **known ground truth.**
- Uncertainty gives a **surrogate measure of accuracy.**

- **Uncertainty highlights pathologies not present in training set by assigning higher uncertainty**

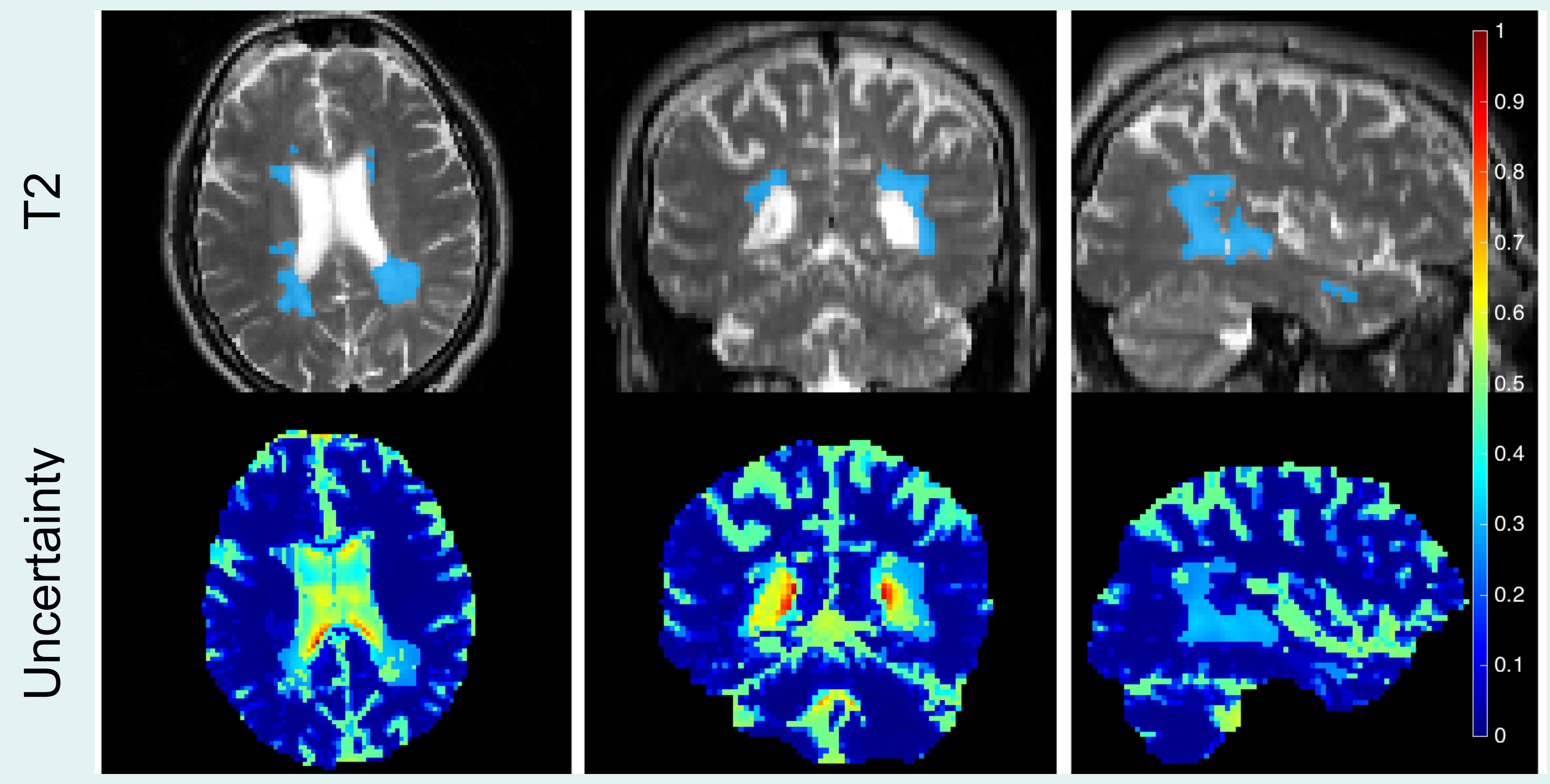
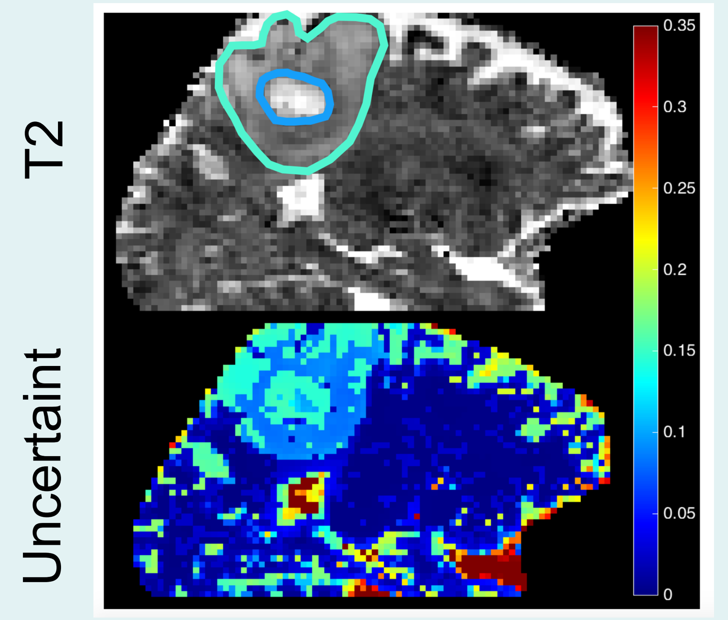


Fig.4 Uncertainty maps on super-resolved images of a Multiple Sclerosis patient. Top row shows the lesion labels from experts overlaid on T2.



- Clinical data: **unknown ground truth,** but one can look at the uncertainty map to judge the accuracy.
- **Super-resolved pathological brains** (MS + tumour) with random forests trained on healthy brains.
- **Uncertainty correlates with pathology.**

Fig.5 Uncertainty maps on images of a brain tumour patient (contours highlighted).

- **Outperforms in accuracy** the original IQT and standard interpolation techniques on three metrics in both healthy and pathological brains.

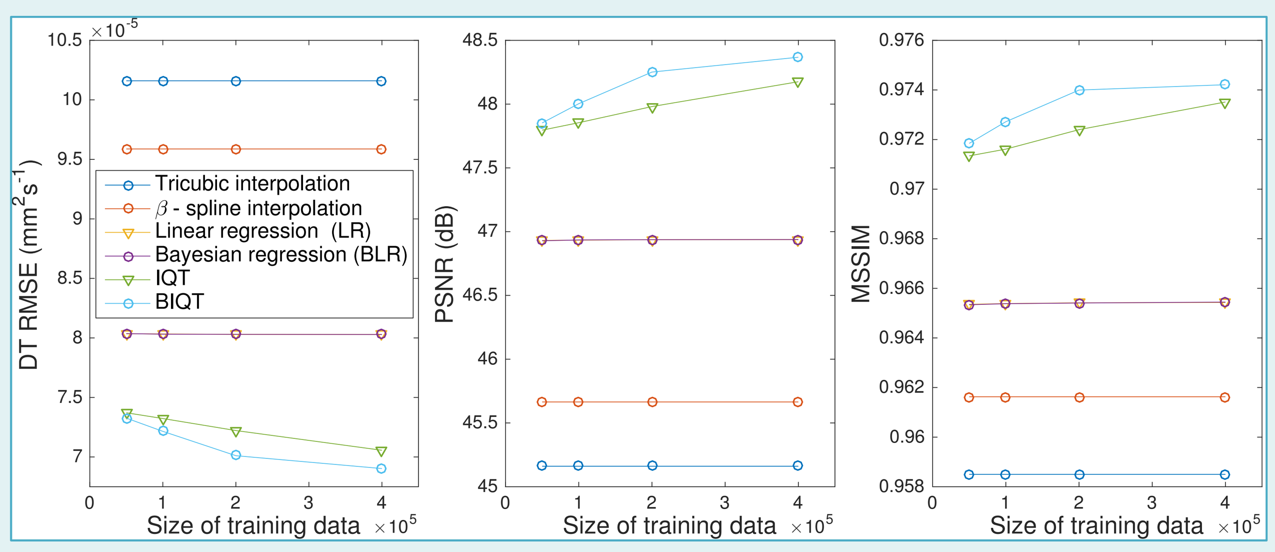


Fig.6 Reconstruction accuracy of various super-resolution methods on three reconstruction metrics; RMSE (left), PSNR (middle) and MSSIM (right). Artificially downsampled low-res images are super-resolved to recover the original resolution.

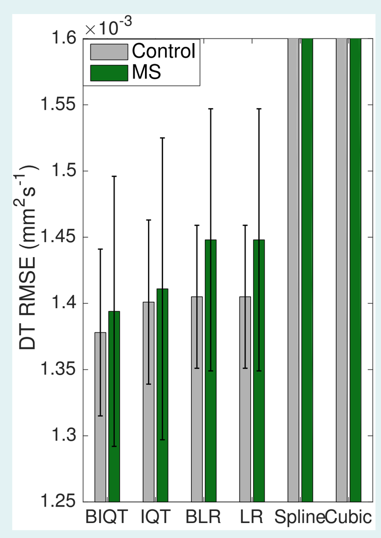


Fig.7 The average reconstruction errors for MS and control

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