MANCHESTER 1824

The University of Manchester

A Generic Method for Evaluating Appearance Models and Assessing the Accuracy of NRR

Roy Schestowitz, Carole Twining, Tim Cootes, Vlad Petrovic, Chris Taylor and Bill Crum

Overview

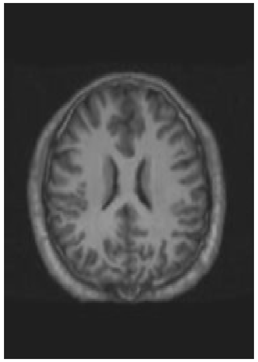
- Motivation
- Assessment methods
  - overlap-based
  - model-based
- Experiments
  - validation
  - comparison of methods
  - practical application
- Conclusions

Motivation for Assessment

- Different methods for NRR
  - representation of warp (including regularisation)
  - similarity measure
  - optimisation
  - pair-wise vs group-wise
- Limitations of current methods of assessment
  - artificial warps (algorithm testing, but not QA)
  - overlap measures (need for ground truth)

Overlap-based Assessment

Original image



Warp

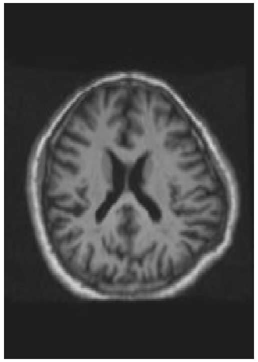
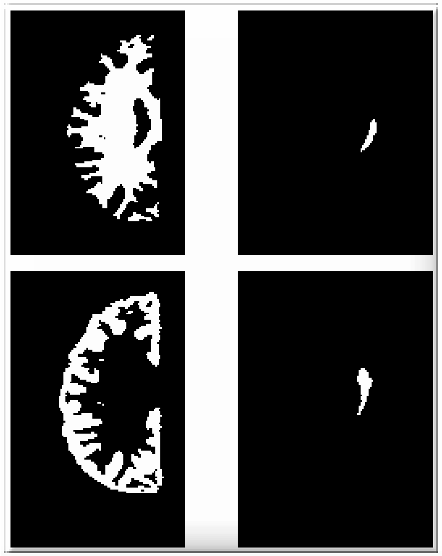
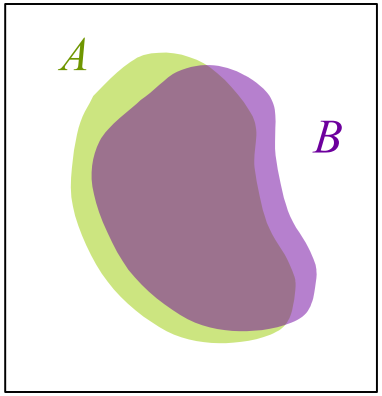


Image labels



Warp



Label overlap tests

MANCHESTER
1824

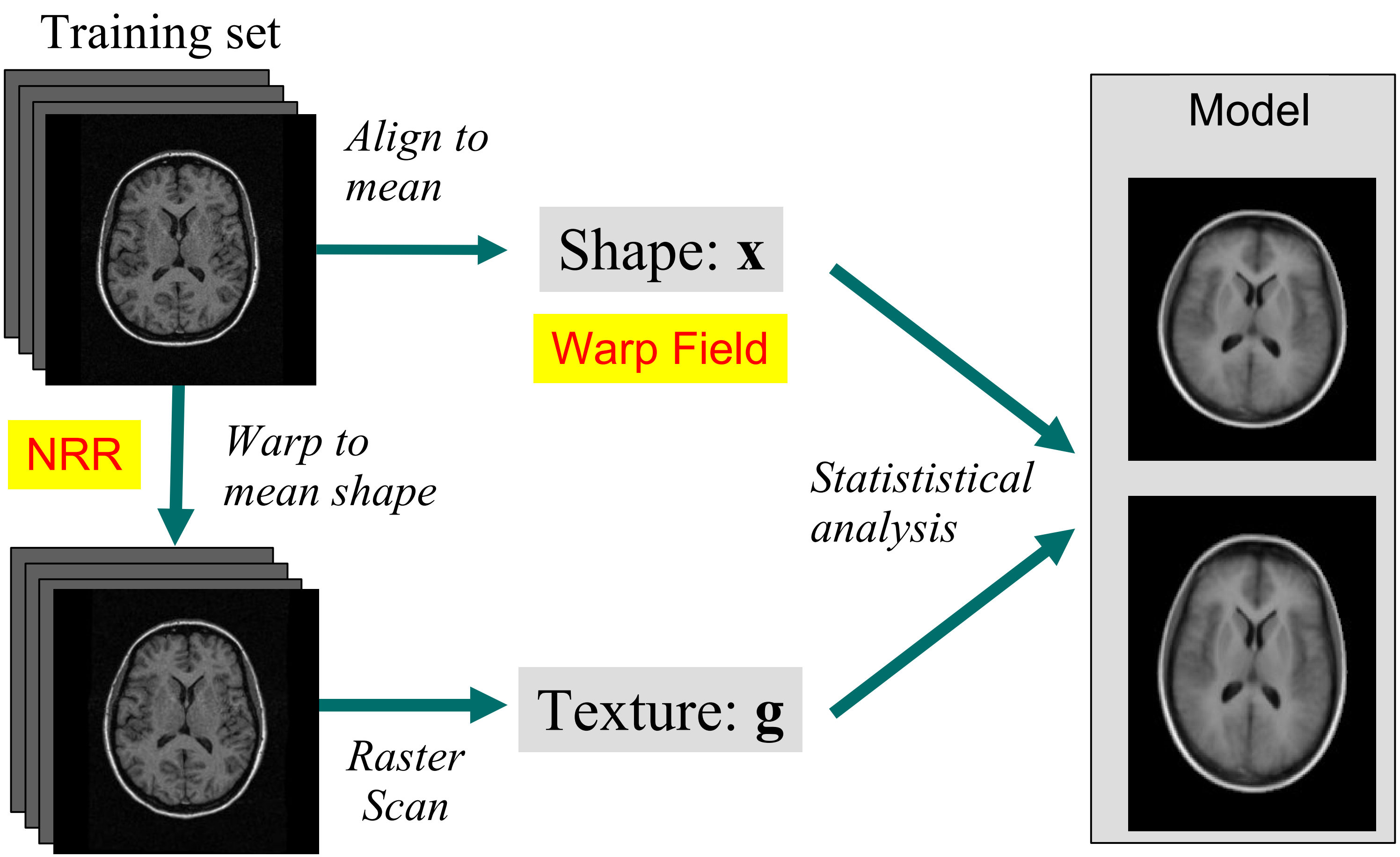
The University
of Manchester

Model-Based Assessment

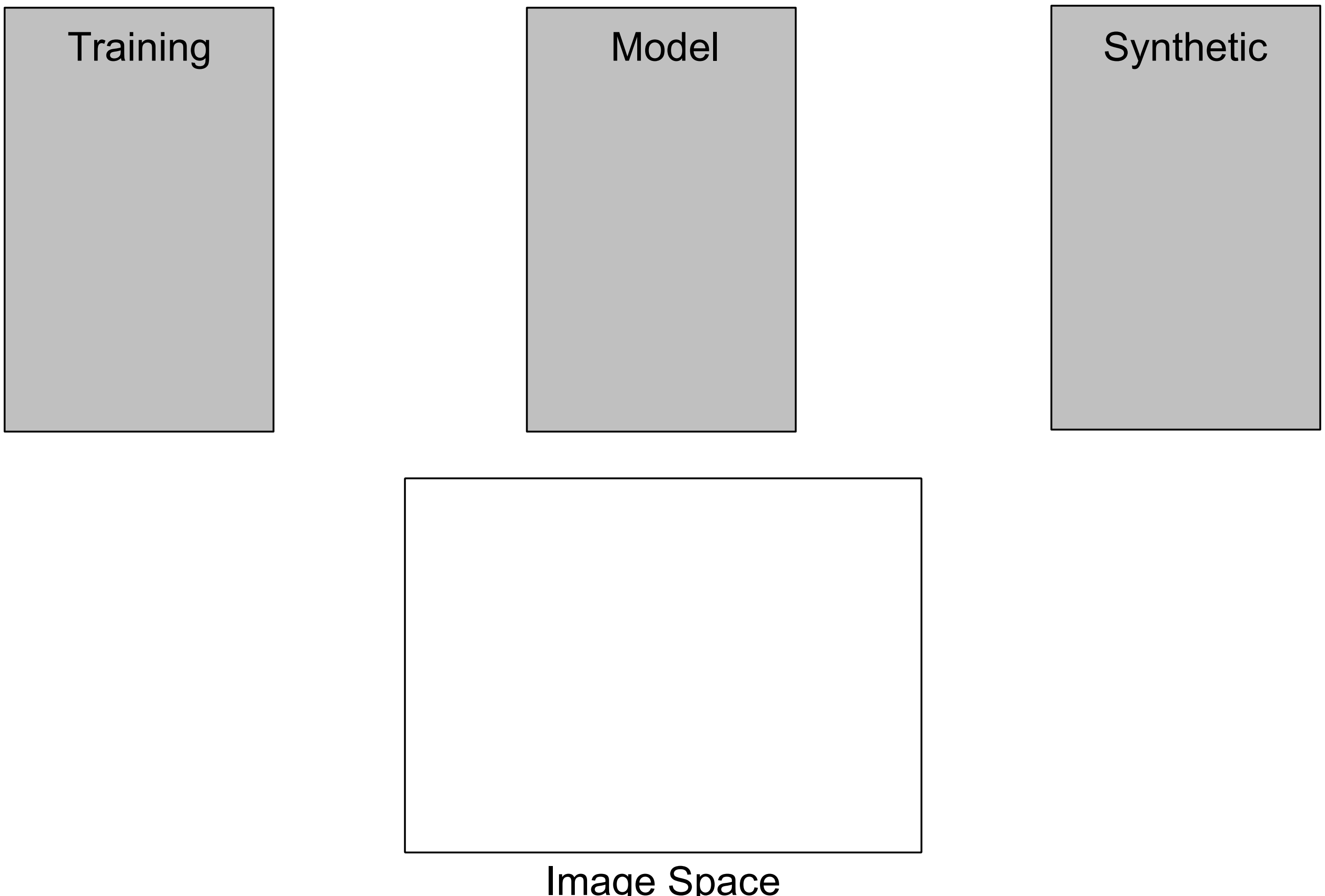
Model-based Framework

- Registered image set $\Rightarrow$ statistical appearance model
- Good registration $\Rightarrow$ good model
  - generalises well to new examples
  - specific to class of images
- Registration quality $\Leftrightarrow$ Model quality
  - problem transformed to defining model quality
  - ground-truth-free assessment of NRR

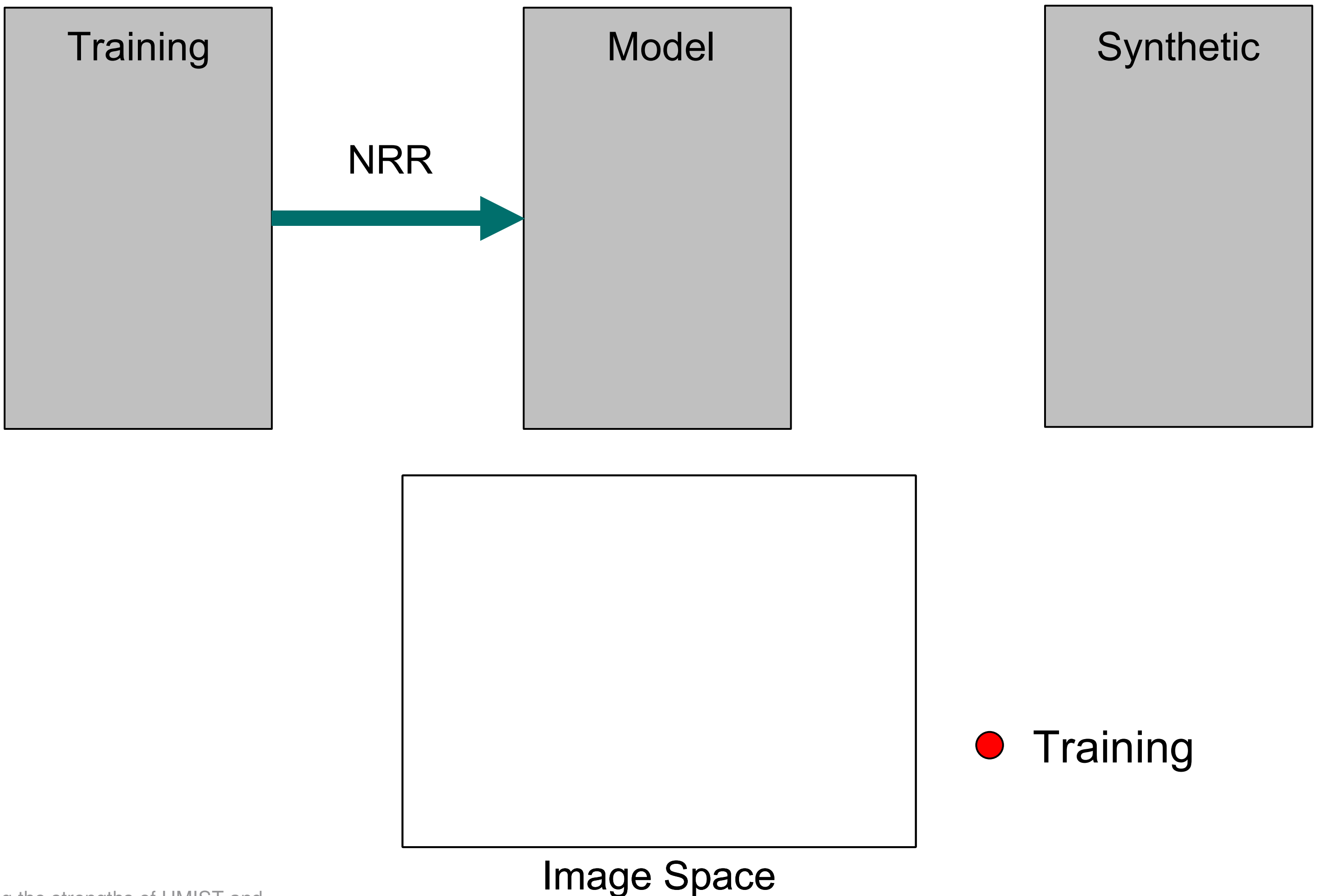
Building an Appearance Model



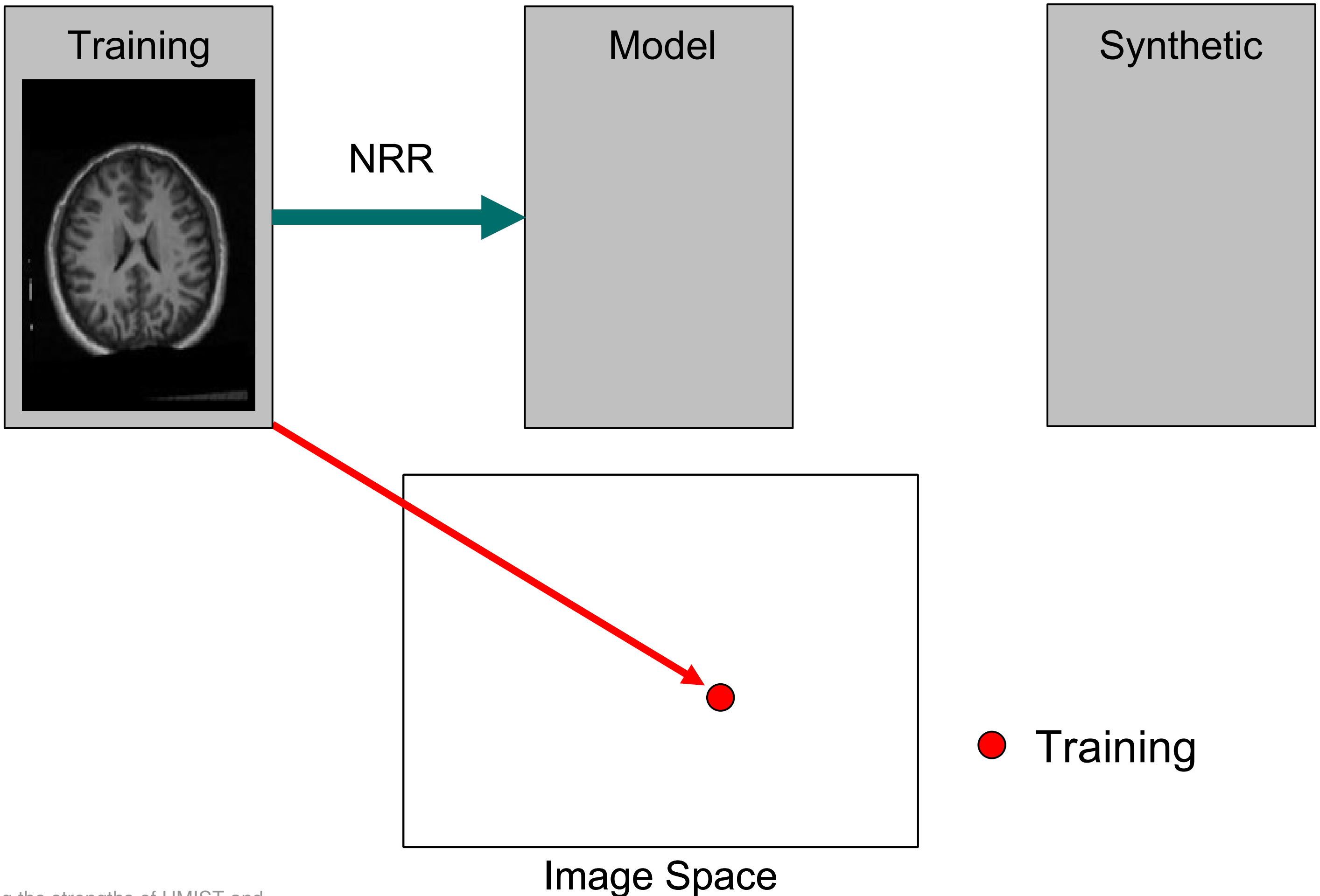
Training and Synthetic Images



Training and Synthetic Images



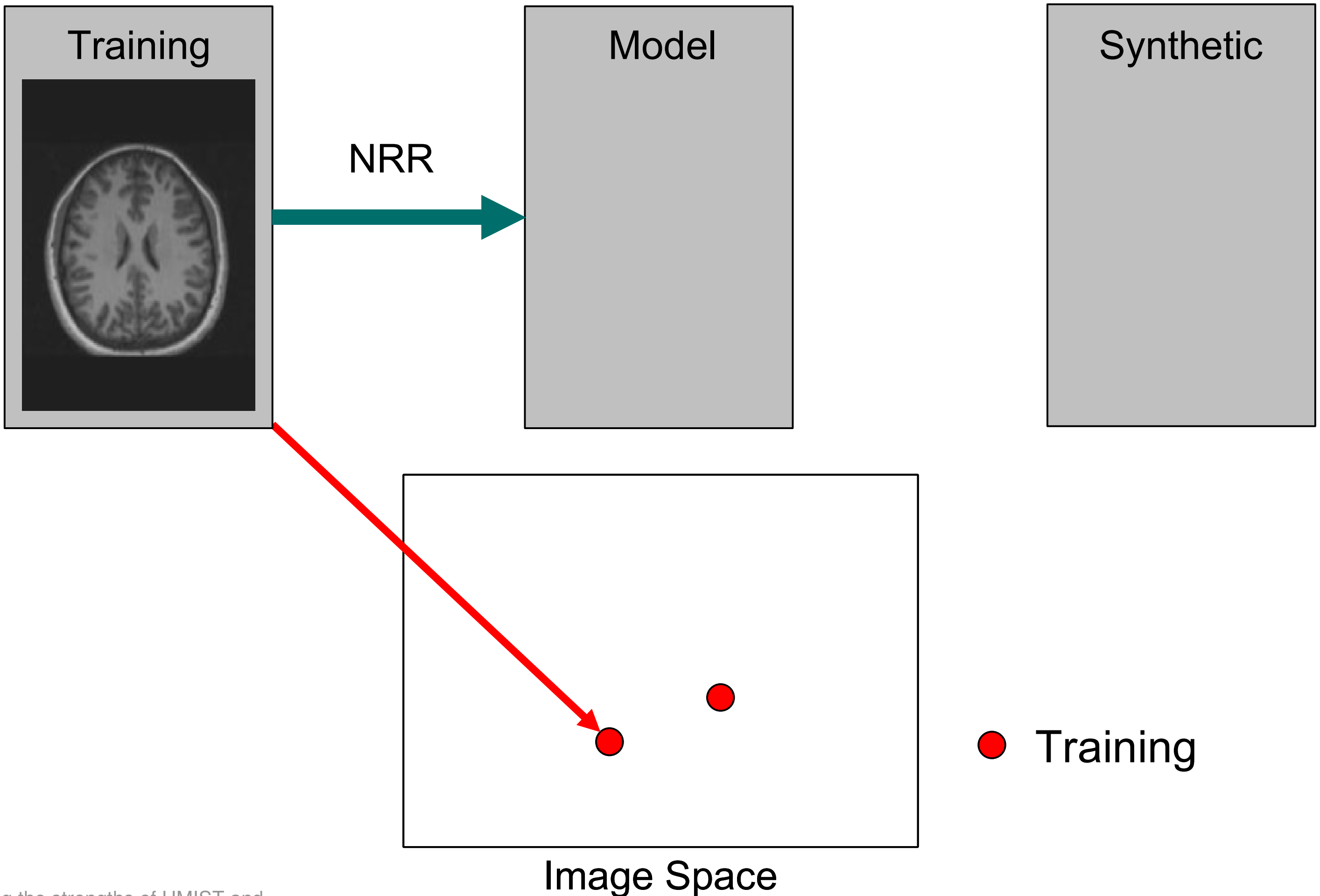
Training and Synthetic Images



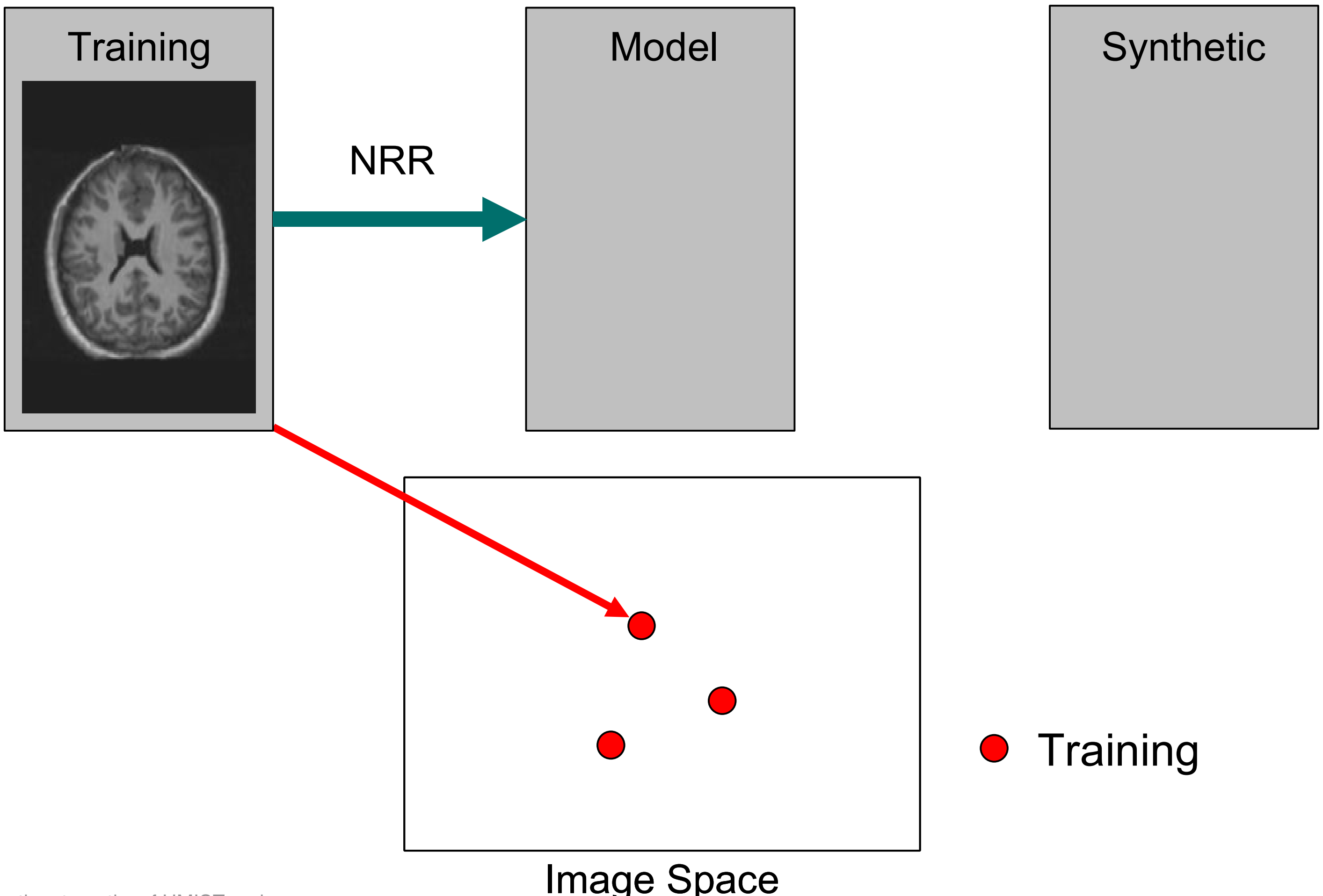
MANCHESTER 1824

The University of Manchester

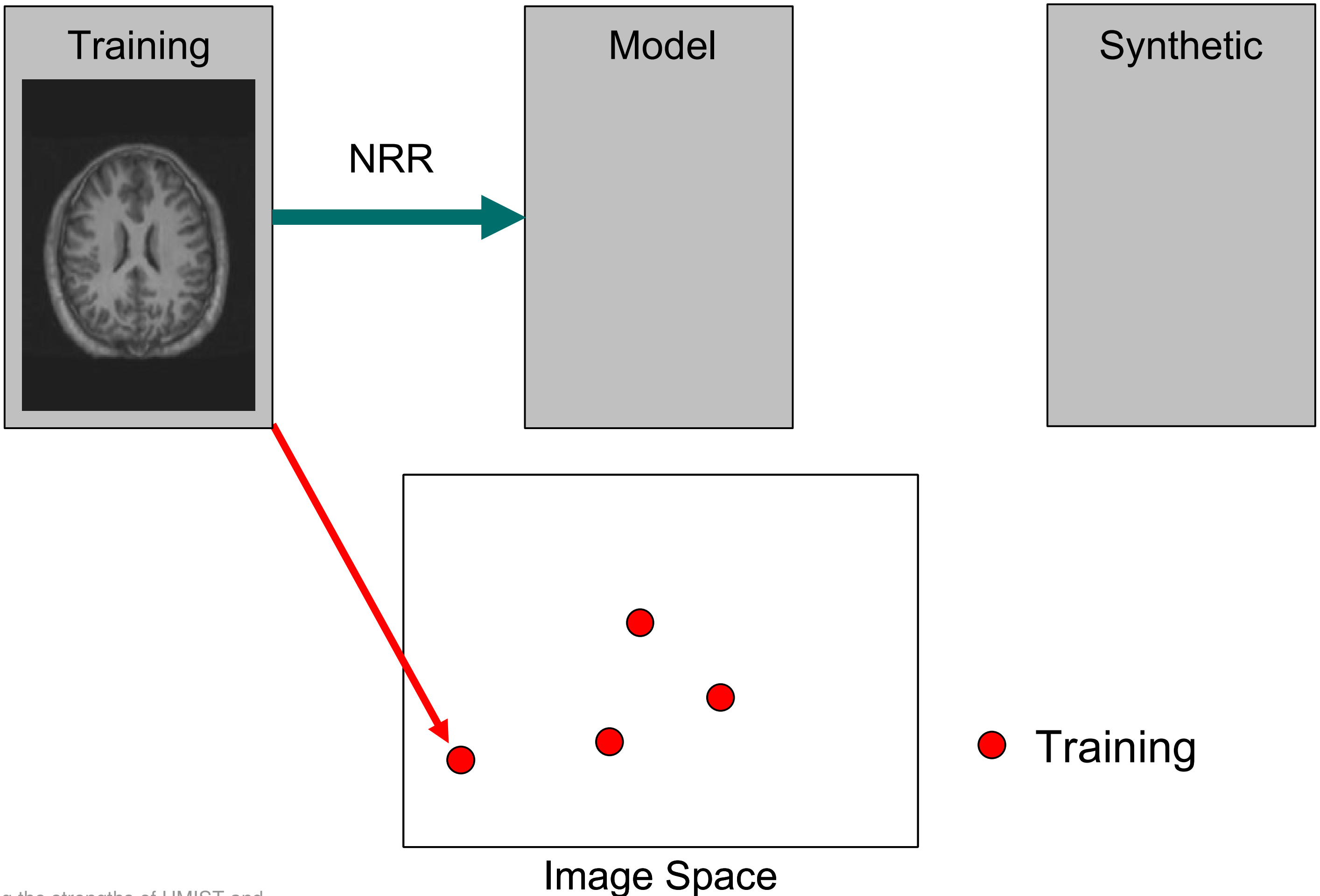
Training and Synthetic Images



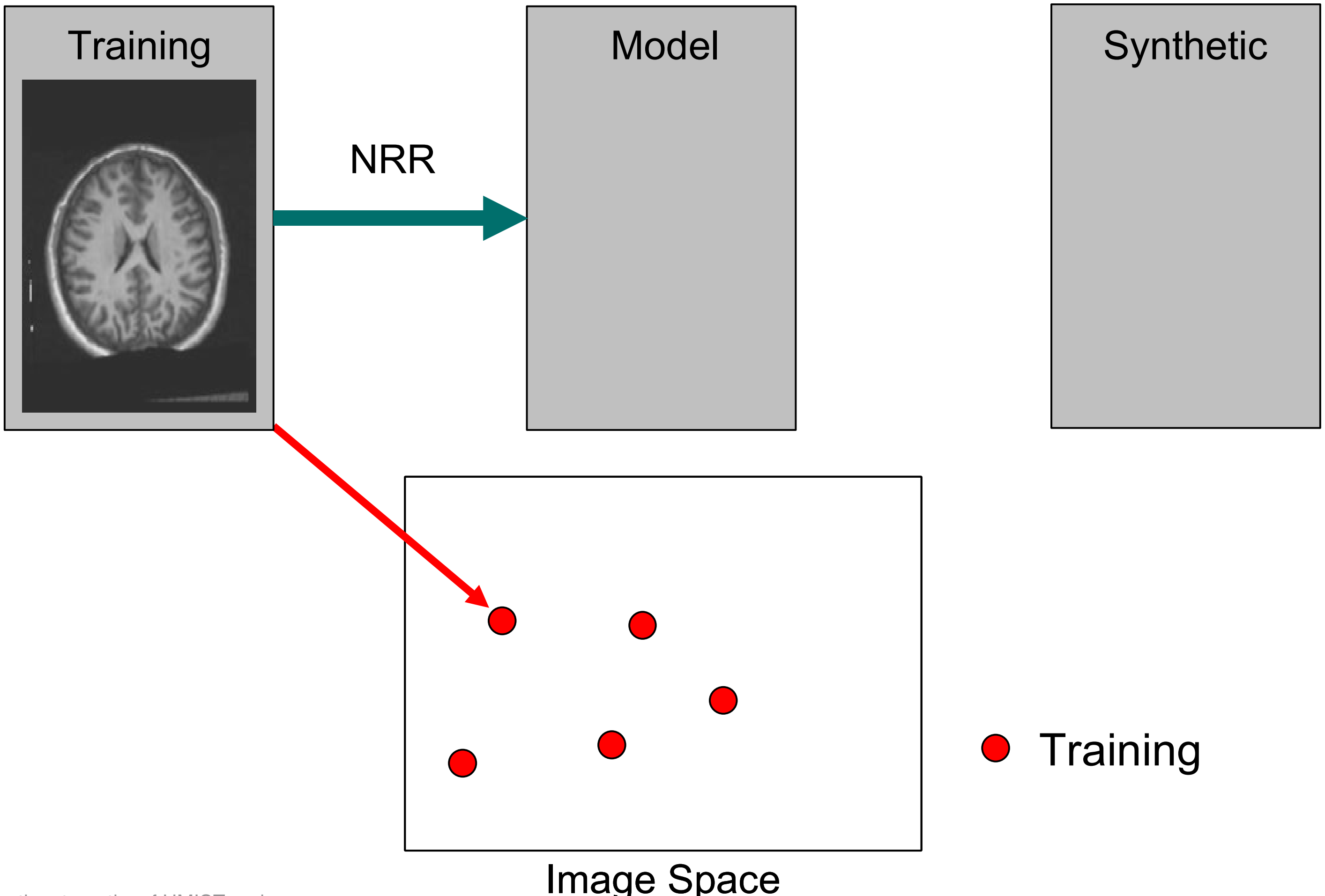
Training and Synthetic Images



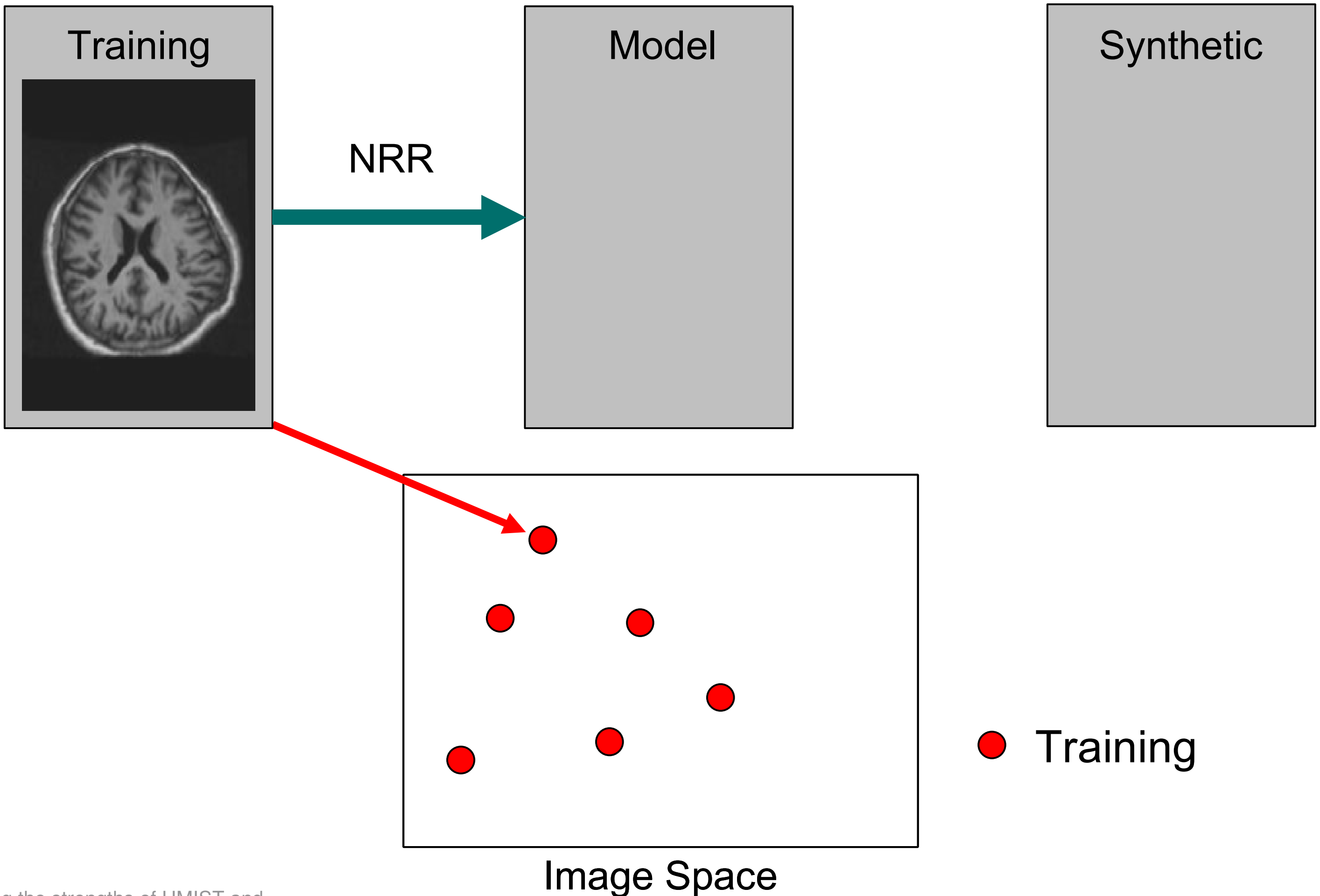
Training and Synthetic Images



Training and Synthetic Images



Training and Synthetic Images

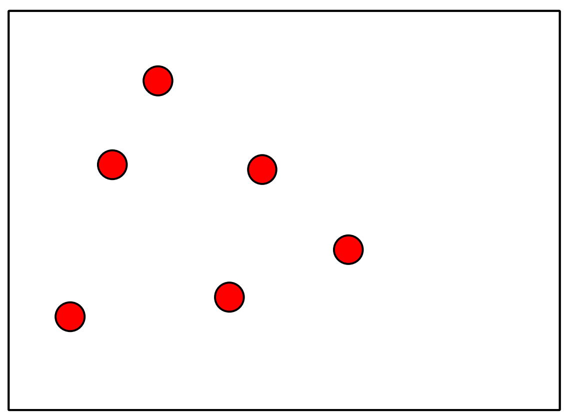


Training and Synthetic Images

Training

Model

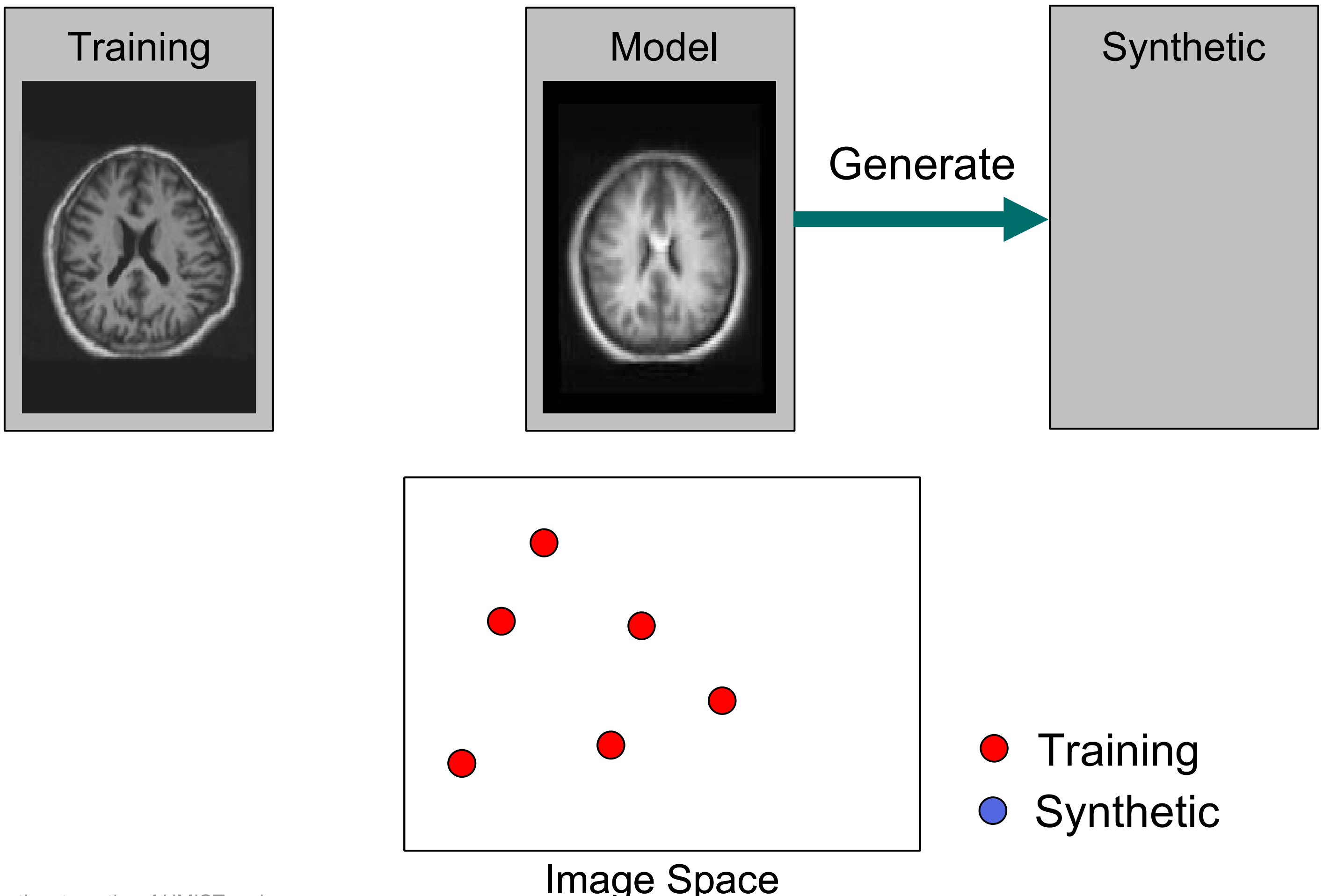
Synthetic



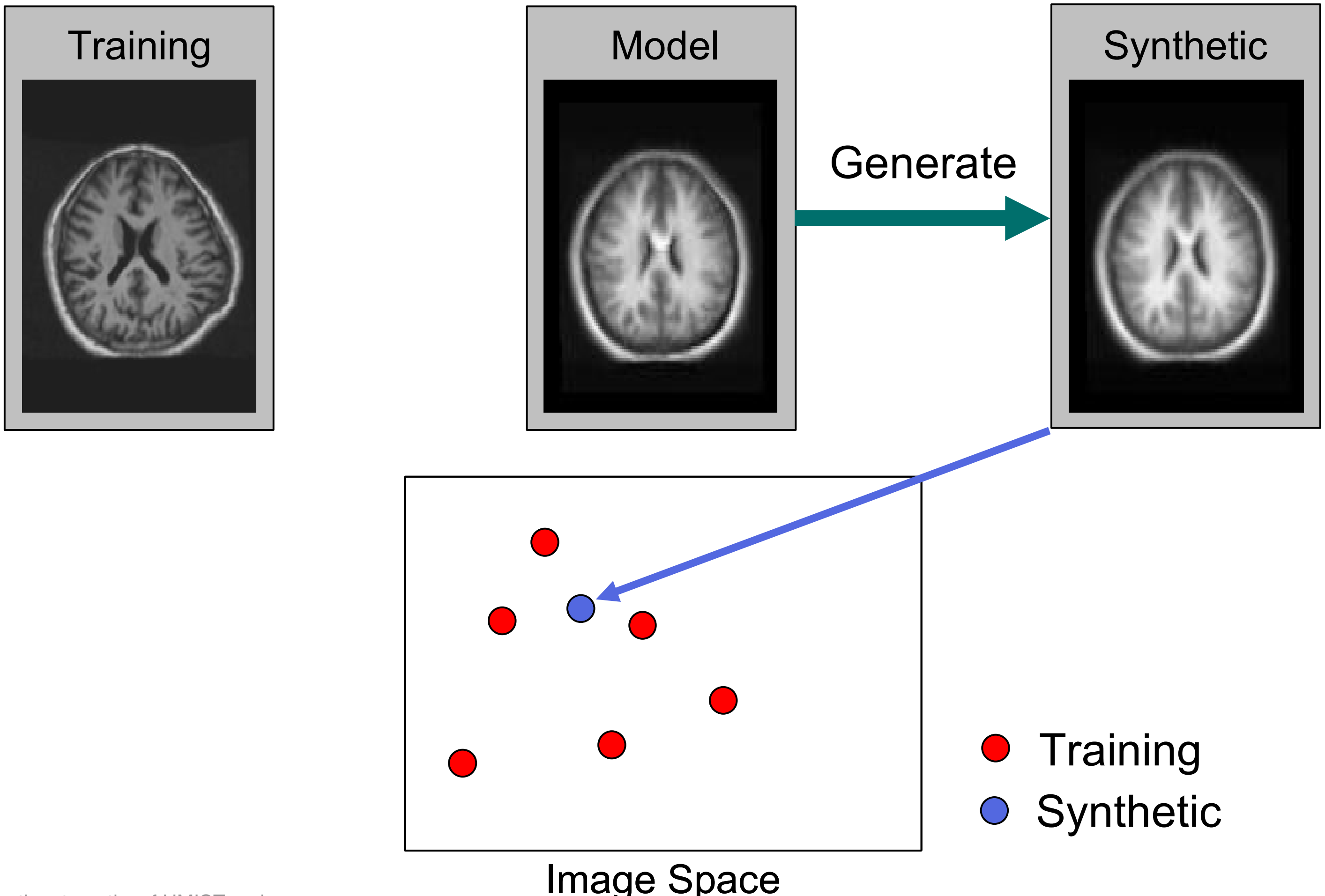
● Training

Image Space

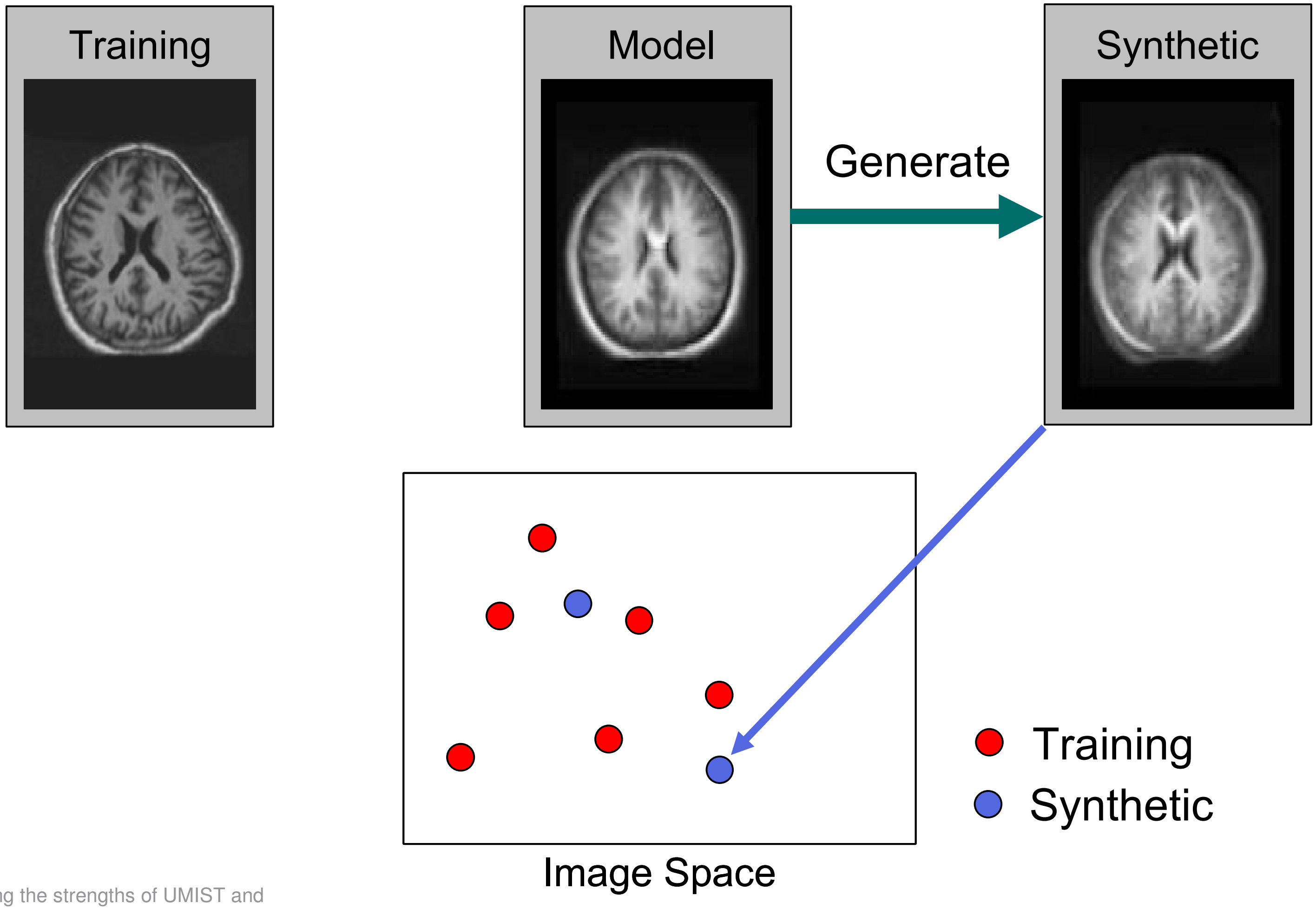
Training and Synthetic Images



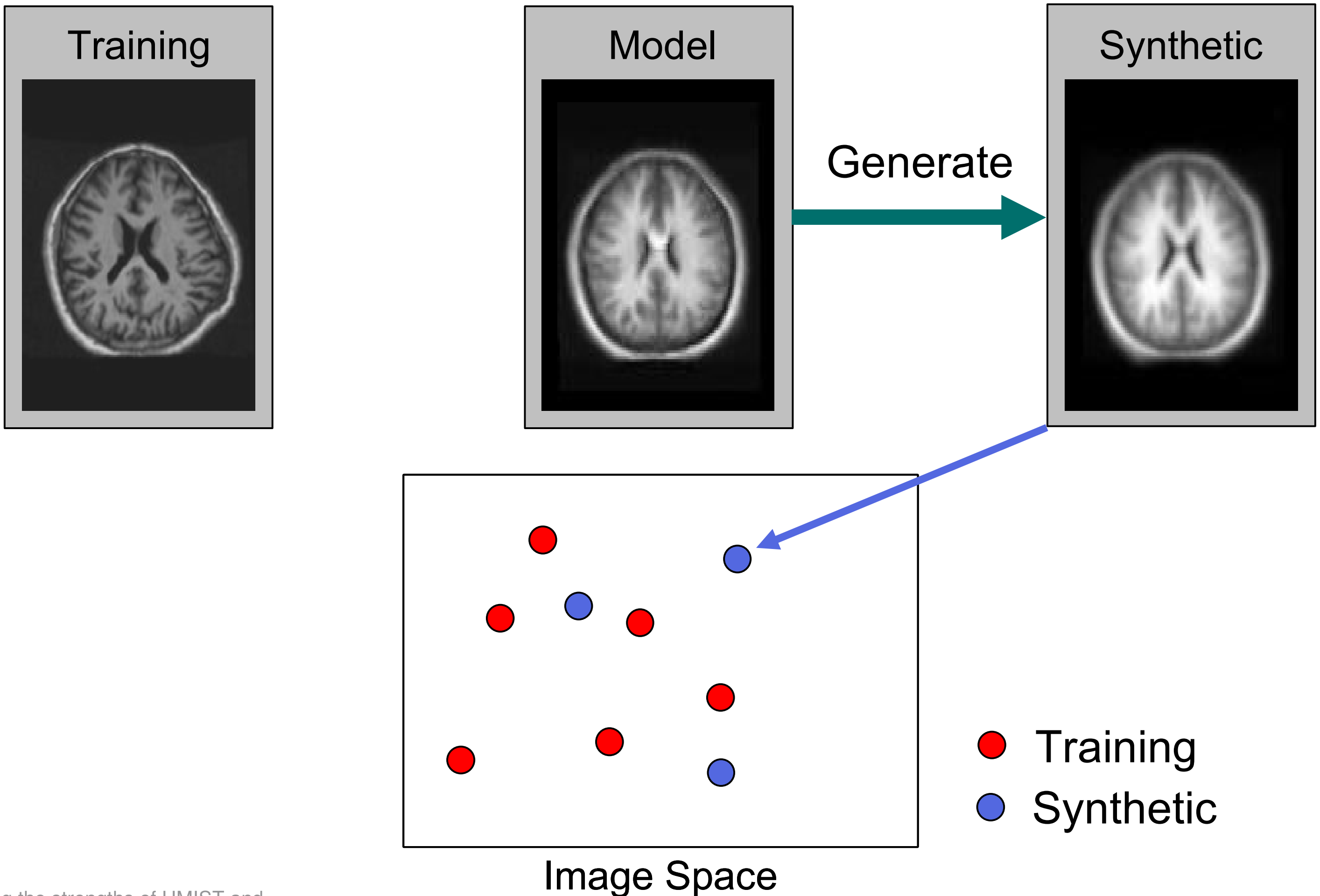
Training and Synthetic Images



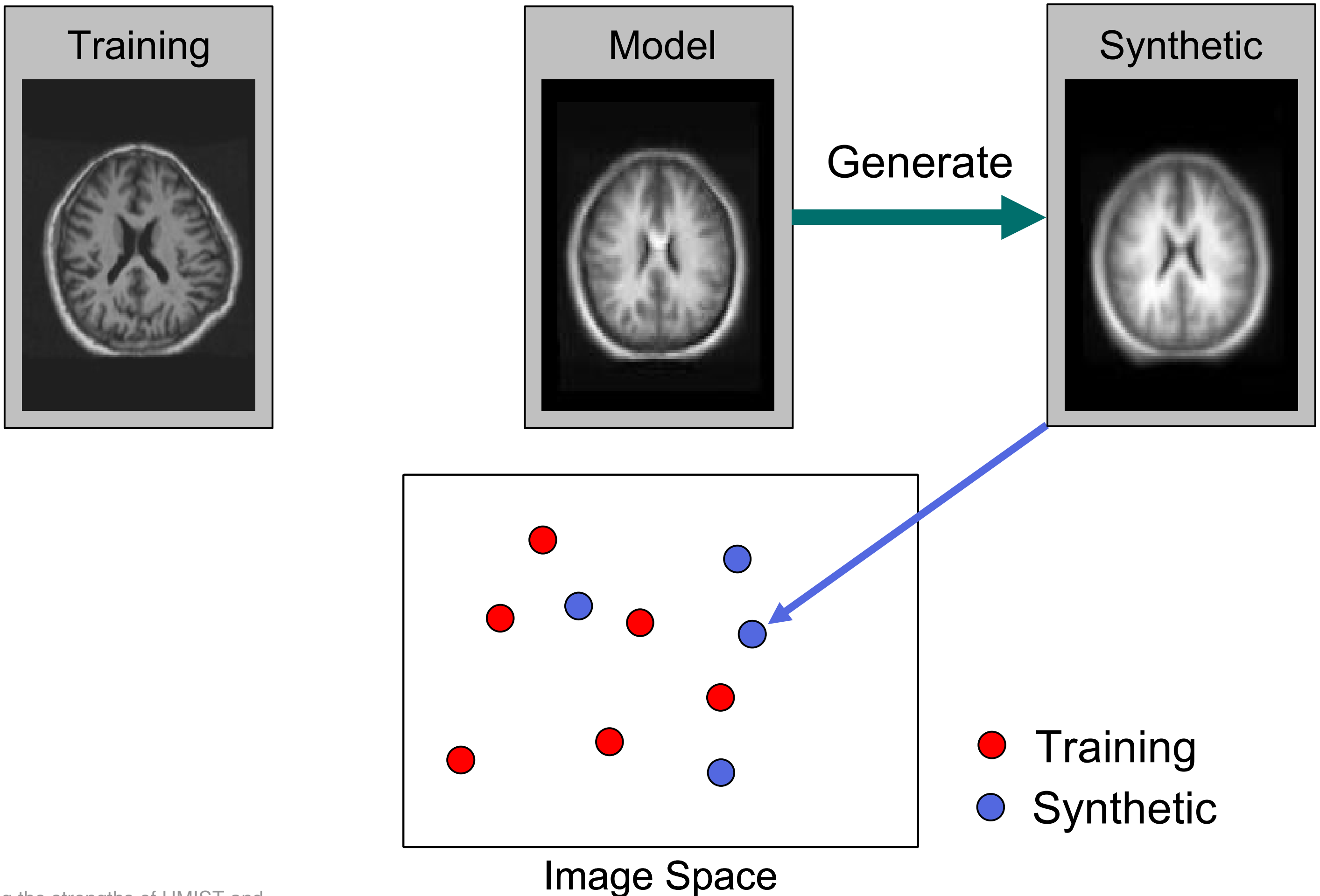
Training and Synthetic Images



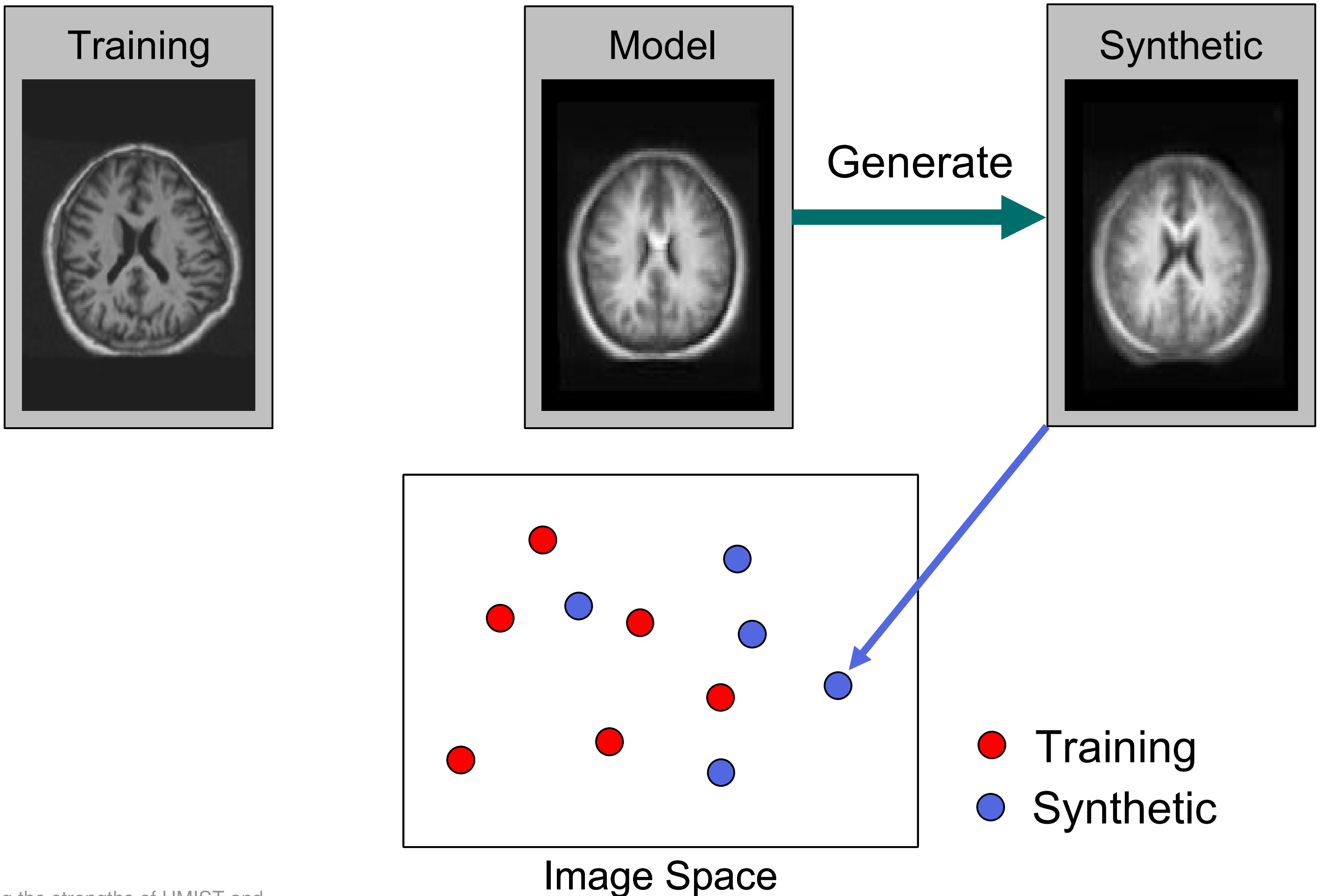
Training and Synthetic Images



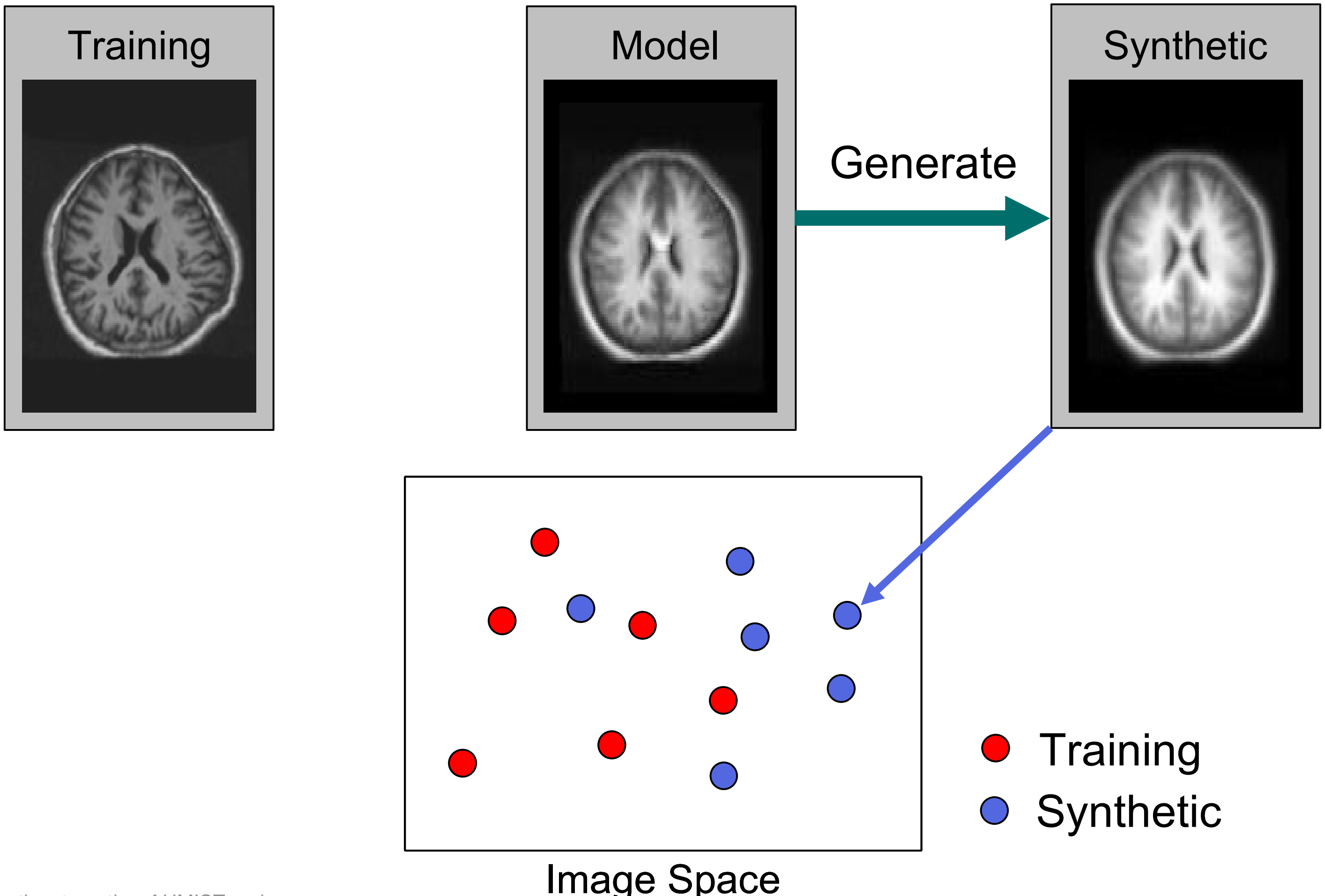
Training and Synthetic Images



Training and Synthetic Images



Training and Synthetic Images



Training and Synthetic Images

Training

Model

Synthetic

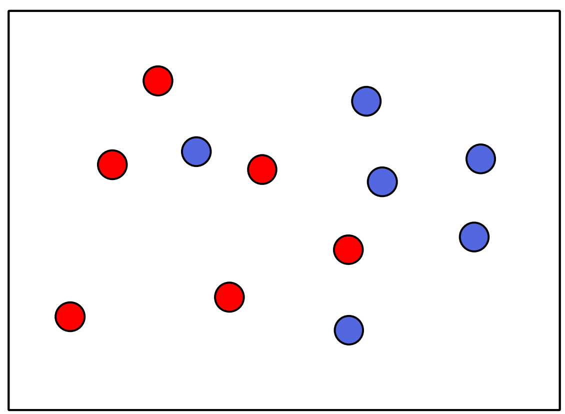


Image Space

Training

Synthetic

Training and Synthetic Images

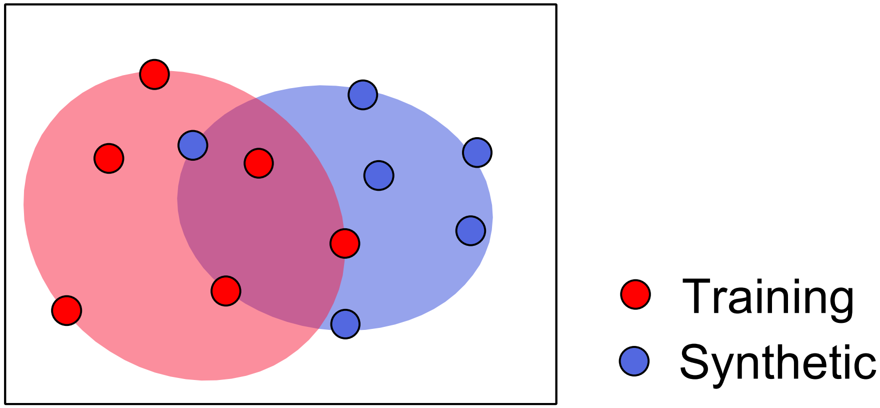
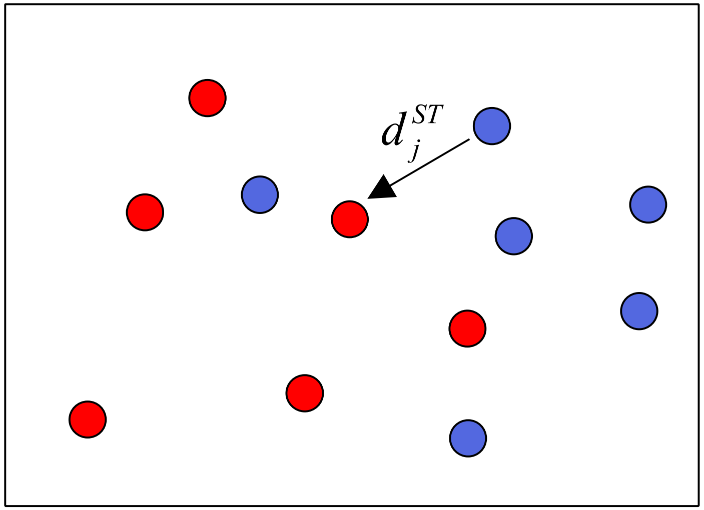


Image Space

Model Quality



Training

Synthetic

Given measure d of image distance

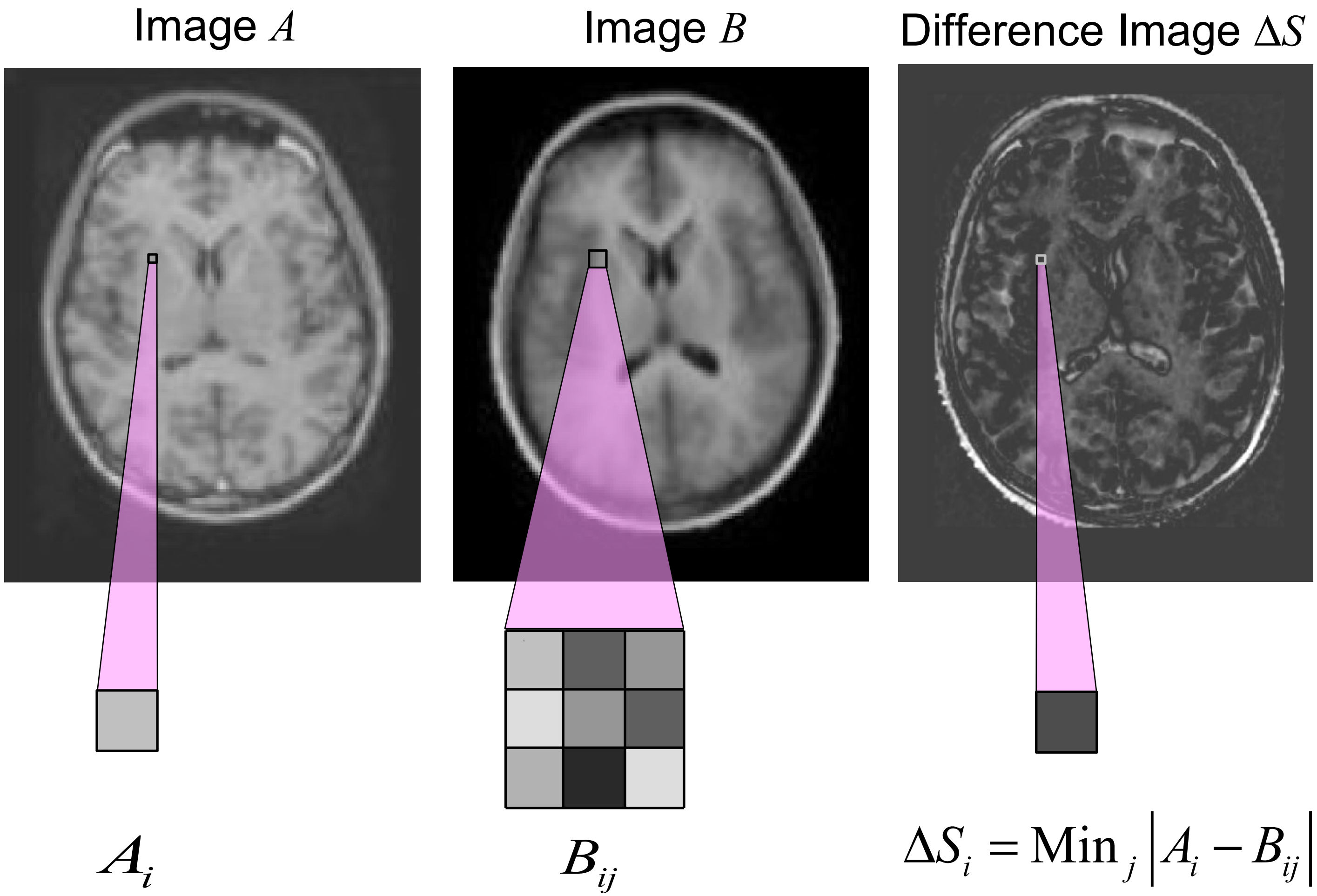
$$Specificity = \sum_{j=1}^{m} \left| d_j^{ST} \right| \Big/ m$$ Mean distance to nearest training image

d can be Euclidean or shuffle distance between images

Measuring Inter-Image Distance

- Euclidean
  - simple and cheap
  - sensitive to small misalignments
- Shuffle distance
  - neighbourhood-based pixel differences
  - less sensitive to misalignment

Shuffle Distance



$$\Delta S_i = \mathrm{Min}_j \left| A_i - B_{ij} \right|$$

Varying Shuffle Radius

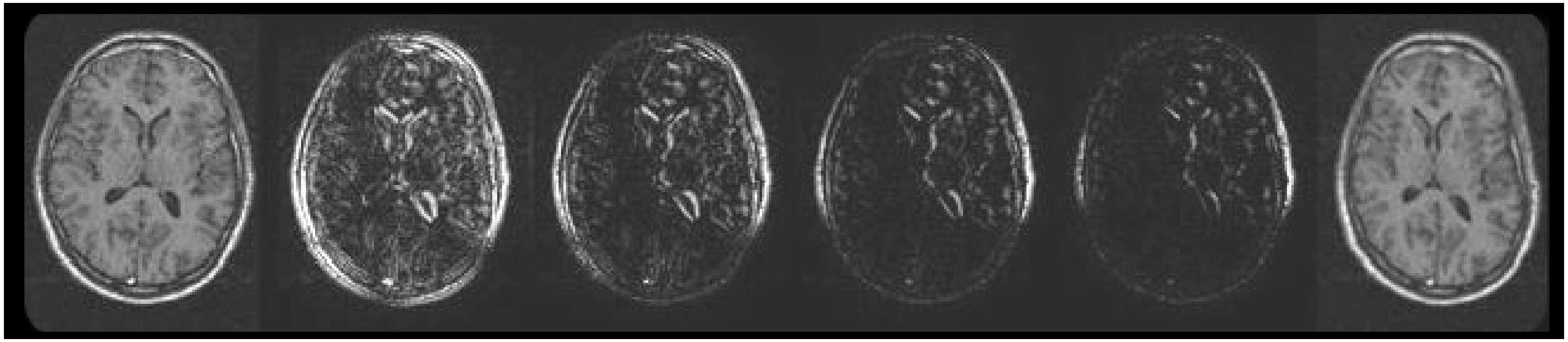


Image A r = 1 r = 1.5 r = 2.1 r = 3.7 Image B

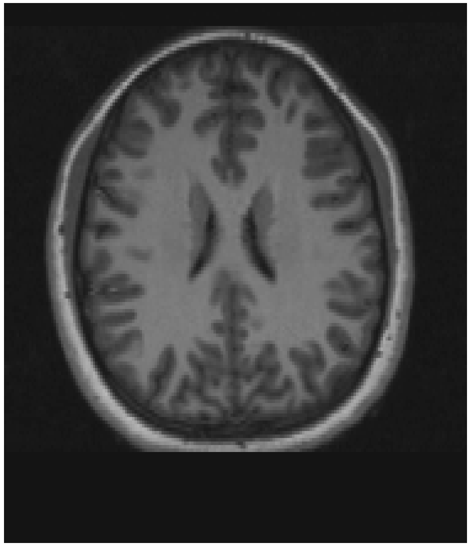
Validation Experiments

Experimental Design

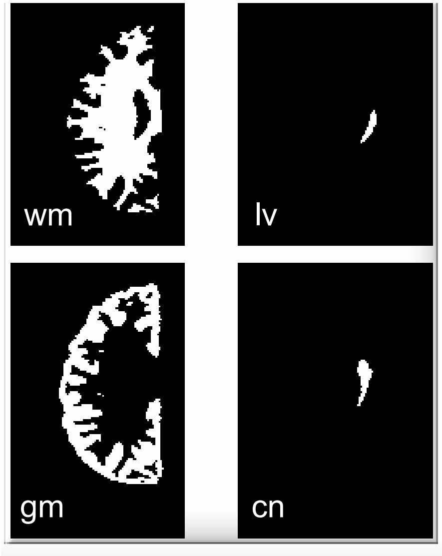
- MGH dataset (37 brains)
- Selected 2D slice
- Initial ‘correct’ NRR
- Progressive perturbation of registration
  - 10 random instantiations for each perturbation magnitude
- Comparison of the two different measures
  - overlap
  - model-based

Brain Data

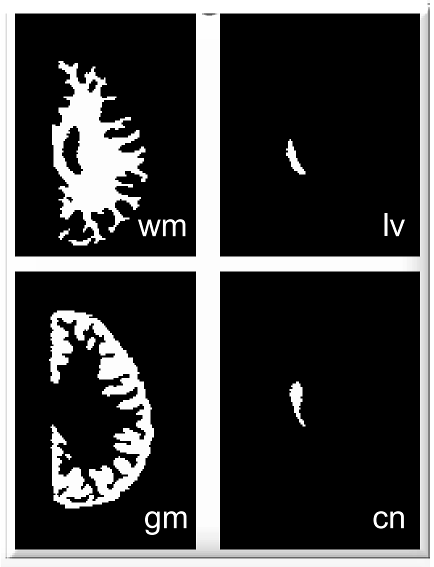
- Eight labels per image
  - L/R white/grey matter
  - L/R lateral ventricle
  - L/R caudate nucleus



Image



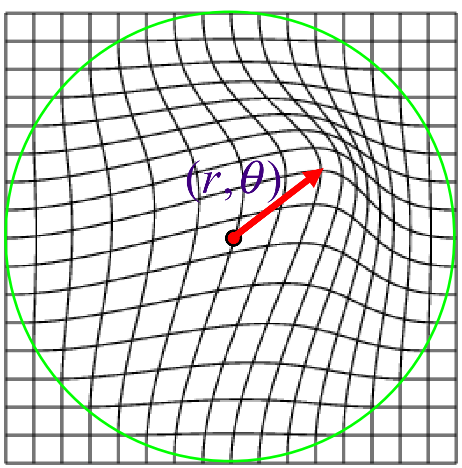
LH Labels



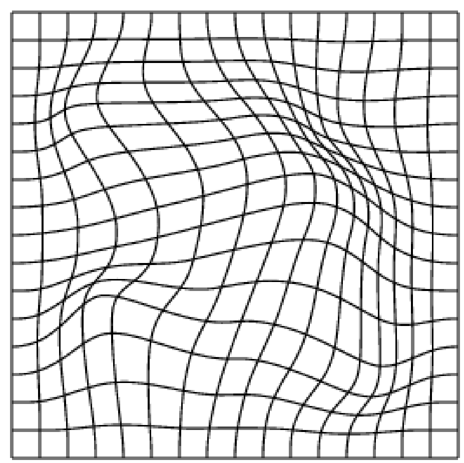
RH Labels

Perturbation Framework

- Alignment degraded by applying warps to data
- Clamped-plate splines (CPS) with 25 knot-points
- Random displacement (r,θ) drawn from distribution

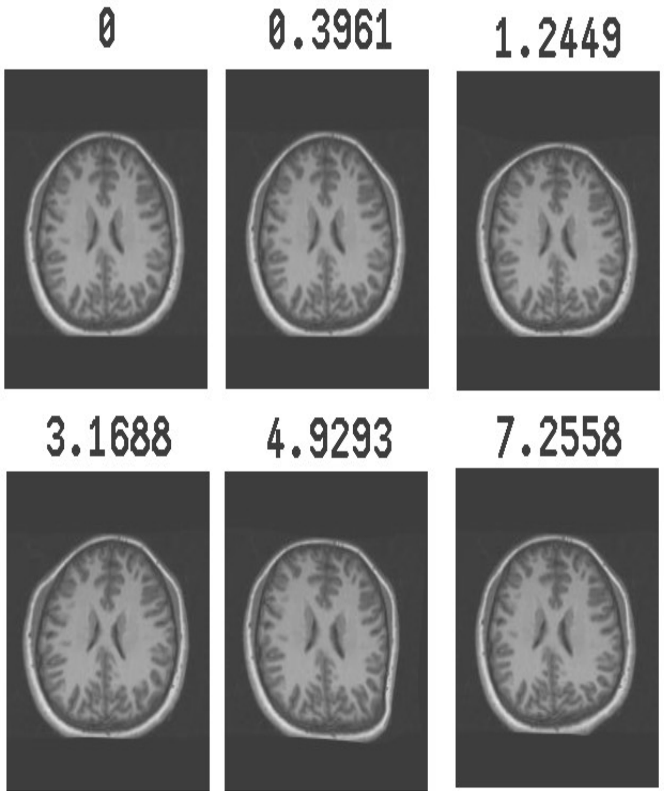


CPS with 1 knot point

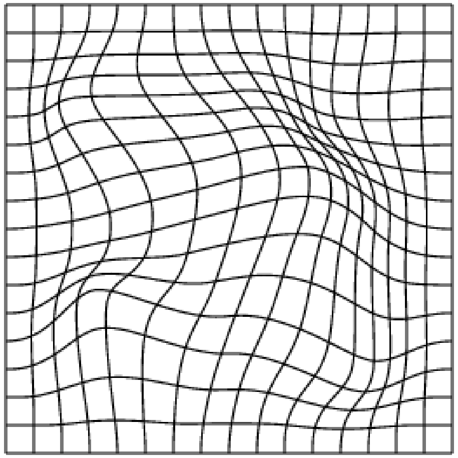


Multiple knot points

Examples of Perturbed Images



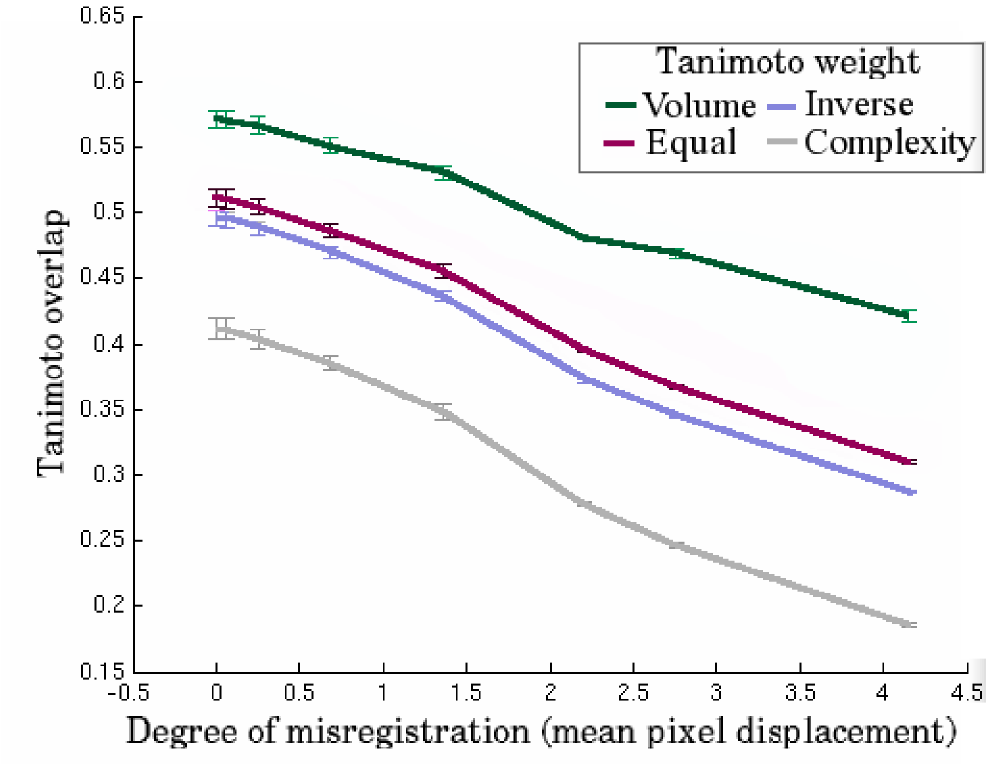
Increasing mean pixel displacement



Example warp

Results – Generalised Overlap

- Overlap decreases monotonically with misregistration

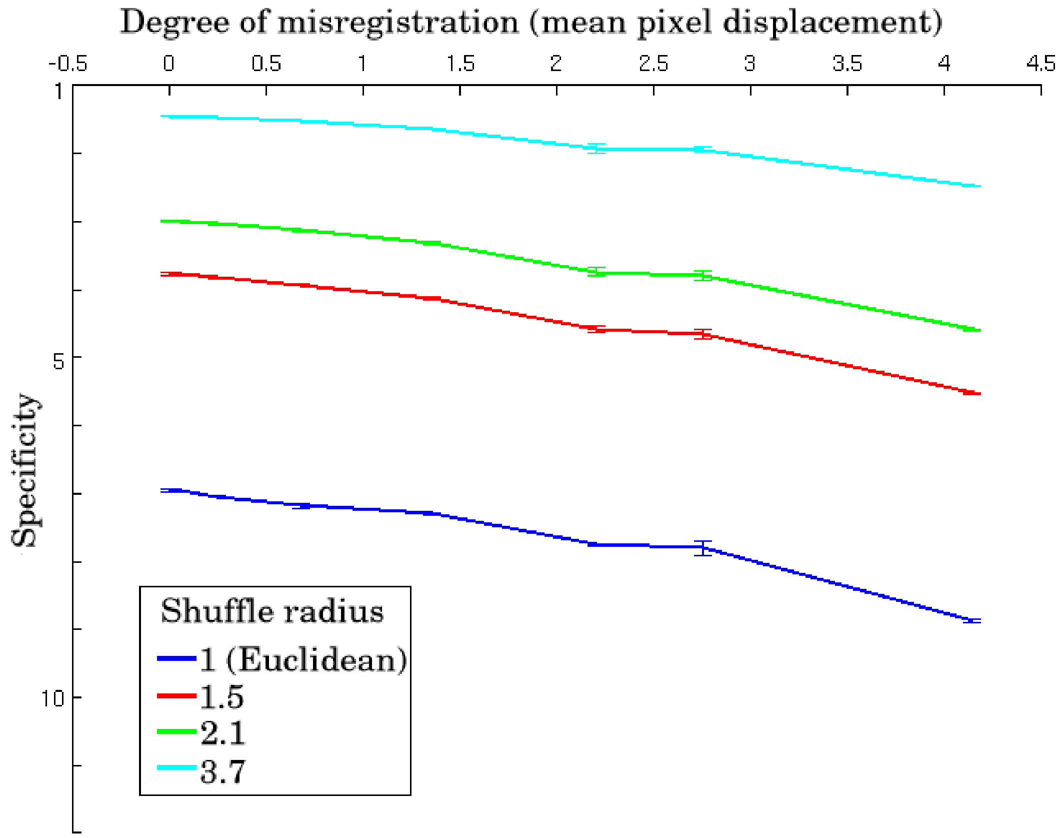


MANCHESTER 1824

The University of Manchester

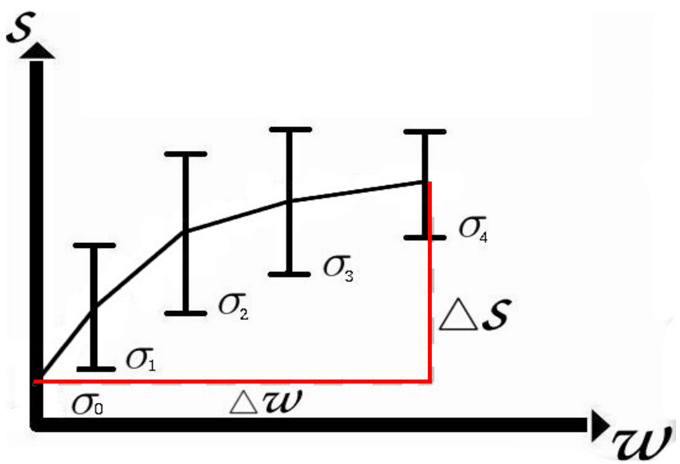
Results – Model-Based

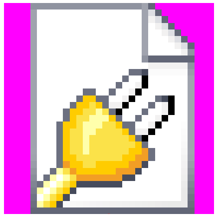
- Measures increase monotonically with misregistration



Results – Comparison

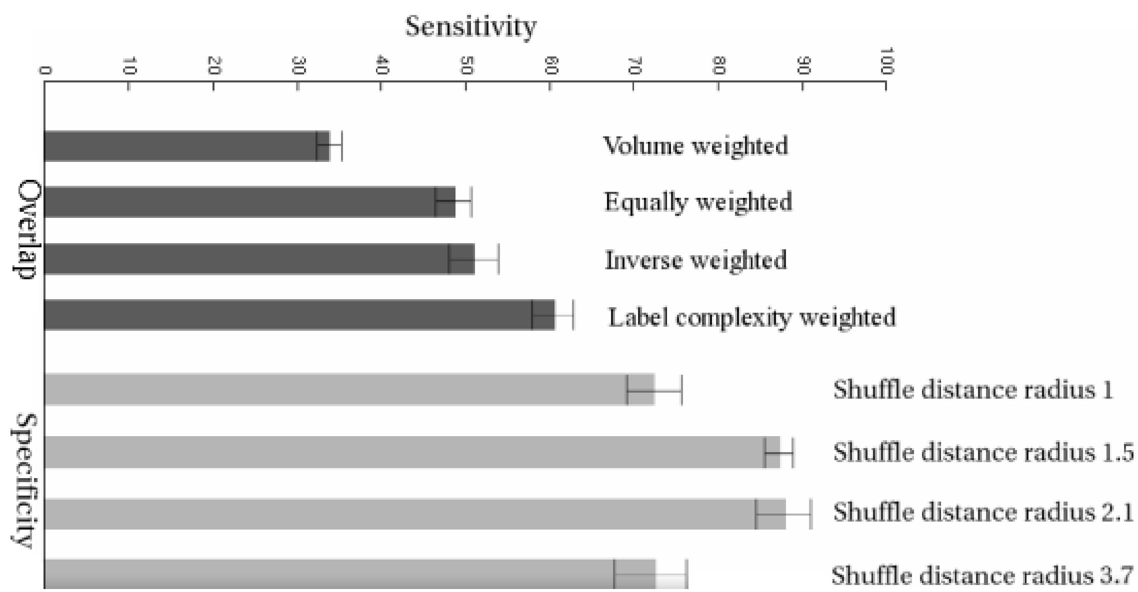
- All three measures give similar results
  - overlap-based assessment requires ground truth (labels)
  - model-based approach does not need ground truth
- Compare sensitivity of methods
  - ability to detect small changes in registration





Results – Sensitivities

- Specificity most sensitive method



Further Tests – Noise

- A measure of robustness to noise is sought
- Validation experiments repeated with noise applied
  - each image has up to 10% white noise added
  - two instantiations of set perturbation are used
- Results indicate that the model-based method is robust
  - changes in Generalisation and Specificity remain detectable
  - curves remain monotonic
  - noise can potentially exceed 10%

Practical Application – NRR Benchmark

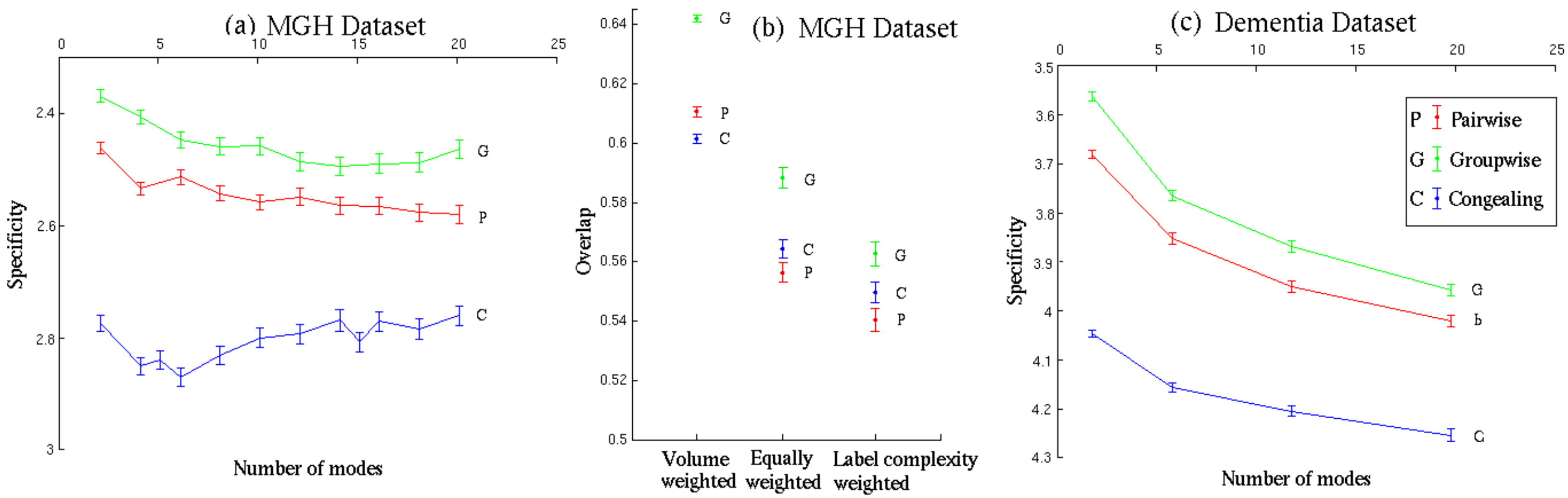
Practical Application

- 3 registration algorithm compared
  - Pair-wise registration
  - Group-wise registration
  - Congealing
- 2 brain datasets used
  - MGH dataset
  - Dementia dataset
- 2 assessment methods
  - Model-based (Specificity)
  - Overlap-based

The University of Manchester

Practical Application - Results

- Results are consistent
- Group-wise NRR outperforms pair-wise, which outperforms congealing



Extension to 3-D

- The method was implemented and tested in 3-D
- Shuffle neighbourhood to be considered can be a
  - box;
  - cube;
  - plane-based comparison (slice-by-slice);
  - or sphere
- Validation experiments too laborious to replicate
- Instead, 4-5 NRR algorithms are compared
- Ongoing work using annotated IBIM data
- Results can be validated by measuring label overlap

Conclusions

- Overlap and model-based approaches ‘equivalent’
- Overlap provides ‘gold standard’
- Specificity is a good surrogate
  - monotonically related
  - robust to noise
  - no need for ground truth
  - only applies to groups (but any NRR method)