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# Structured Decision Forests For Multi-modal Ultrasound Image Registration

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#### MOTIVATION

Interventional procedures in cardiovascular diseases often require ultrasound (US) image guidance. These US images must be combined with pre-operatively acquired tomographic images to provide a roadmap for the intervention. Existing multi-modal US registration techniques often do not achieve reliable registration due to low US image quality. To address this problem, a novel medical image representation based on a trained decision forest named probabilistic edge map (PEM) is proposed. PEMs generate similar anatomical representations from different modalities and can thus guide a multi-modal image registration more robustly and accurately.



Input space:  $\mathcal{X} \in \mathbb{R}^{(M_e)^3}$ Output space:  $\mathcal{Y} \in \mathbb{R}^{(M_a)^3}$ 



clustered into two or more subgroups at each tree node split.

#### PROBABILISTIC EDGE MAPS (PEMS)



Edge Map Properties

- $\Rightarrow$  Modality independent and computationally efficient (20 sec/image)
- $\Rightarrow$  Compared to the self-similarity (SSC) [2] and gradient magnitude (GM) representations, PEMs produce more accurate and smoother anatomical representations.
- $\Rightarrow The classifiers can be trained to be target organ selective (e.g. only my-ocardium)$

#### Structured Regression





#### MULTI-MODAL IMAGE REGISTRATION FRAMEWORK



- ⇒ The images are first mapped into the PEM space, and then they are registered using only the generated PEM representations.
- $\Rightarrow$  Local correlation coefficient is used as the similarity metric.
- $\Rightarrow$  The images are first globally and then locally aligned using robust block matching and B-spline FFD based registration methods.



#### **REGISTRATION RESULTS**

The images are overlaid on top of each other. The US images are shown in green color map and the MR/CT images are in gray in color map.



### $\mathrm{US}/\mathrm{CT}$ and $\mathrm{US}/\mathrm{MR}$ Image Registration Evaluation



#### **Experimental Details**

 $\Rightarrow The distance errors were$ computed using sevenanatomical landmarks:apex (1), apical (2), basal(2), and mid-ventricleparts (2).





US/CT registration errors after rigid (-R) and deformable (-D) alignments



17 pairs of images were used in the evaluation, which are disjoint from the PEM training dataset of cardiac images (50-80 images/modality).
The proposed PEM representation is compared against the self-similarity descriptor (SSC) [2] and local-NMI (LNMI) [3] image similarity based regis-

tration methods.



Spatial Alignment of US/CT & US/MR Images

#### References

[1] Dollár, P., Zitnick, C.L.: Structured forests for fast edge detection. In: ICCV (2013)

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[3] Klein, S., et al.: Automatic segmentation of the prostate in 3D MR images by atlas matching using localized mutual information. Medical Physics 35(4), 1407–17 (2008)