Enhancement of US-CT registration accuracy for spinal surgery

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Background presentation – Advanced Computer-Integrated Surgery (601.656)

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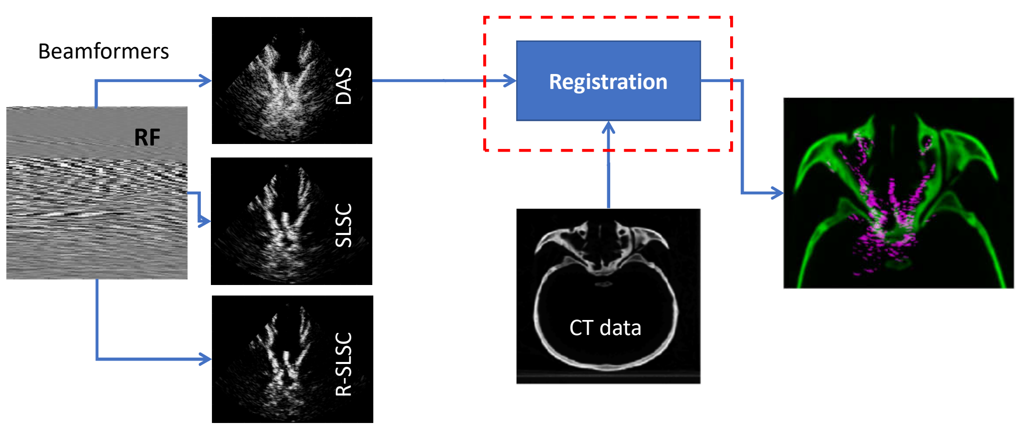
Summary of the project

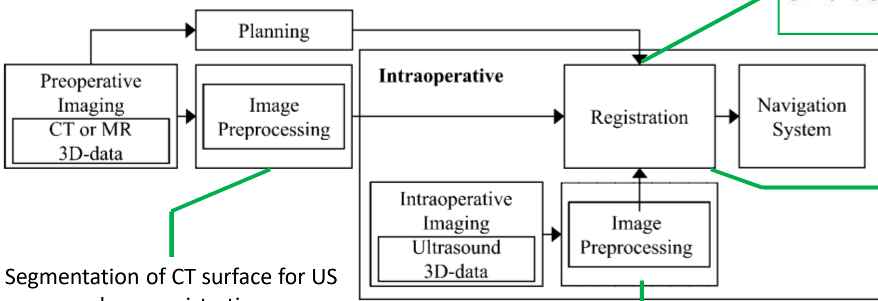
Goal: Explore methods to improve accuracy of US-CT image registration through improved US image resolution

Still needs to be tunned

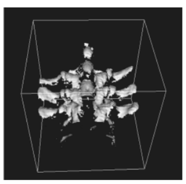


Registration: maximizing intensity

$$\bar{g}(\alpha,\beta,\gamma,\bar{g}) = \frac{1}{N}\sum_{i=1}^{N} UV(\mathbf{A}(\alpha,\beta,\gamma)\cdot\vec{p}_i+\vec{q})$$



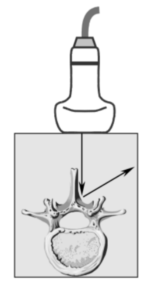
Segmentation of CT surface for US volume registration



Not any noticeable pre processing (just resampling)

Tested with several segmented CT surfaces

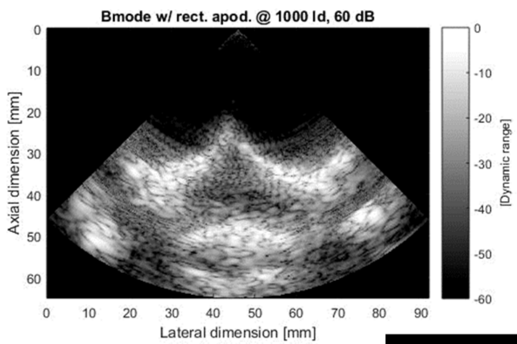
- Varying threshold
- Varying the angle of incidence

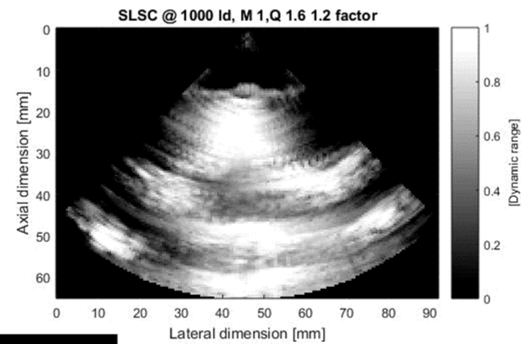


Registration: maximizing intensity

- Successfully implemented in MATLAB
- Since it is a mapping function to an unknown image, $UV(\mathbf{A}(\alpha,\beta,\gamma)\cdot\vec{p}_i+\vec{q})$ cannot be decomposed analytically in gradient operations for conventional optimizers
- Solution: brute force but is computationally expensive
- We will keep using the mattes mutual information optimizer and LMS for registration

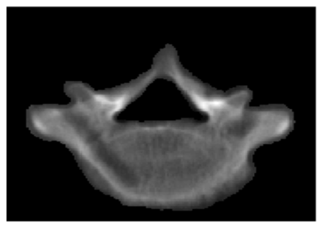
Input images: varying reconstruction parameters





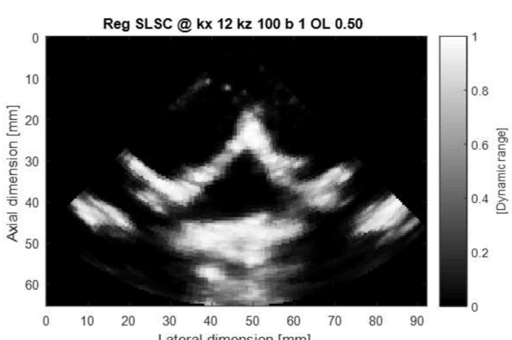
Delay And Sum (DAS)

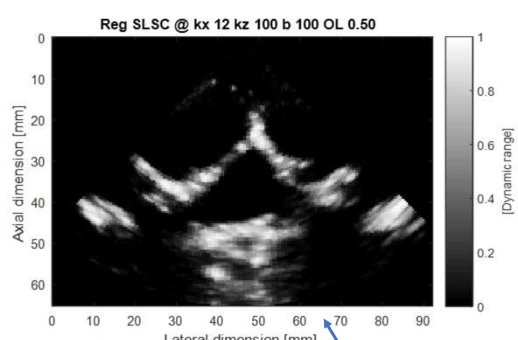
CT



Short Lag Spatial Coherence (SLSC)

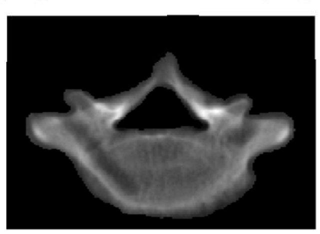
Input images: varying reconstruction parameters





Regularized SLSC (Reg-SLSC)

CT



High regularization parameter

Metric: Partial Intensity Uniformity

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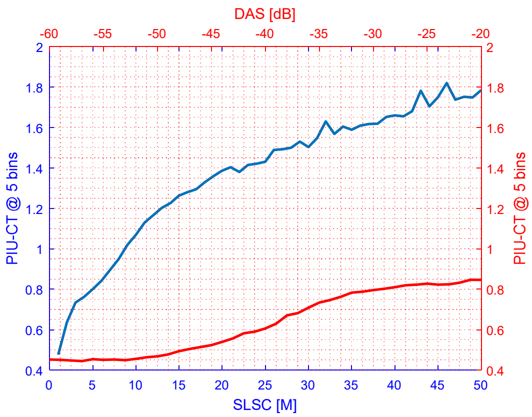
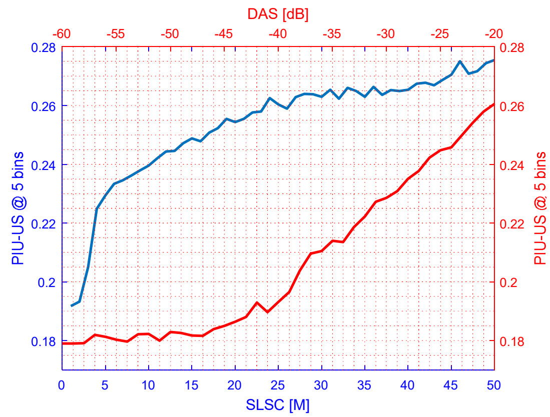
$$\mathrm{PIU}_B = \sum_a \frac{n_a}{N}\frac{\sigma_B(a)}{\mu_B(a)} \quad \Downarrow \quad \mathrm{PIU}_A = \sum_b \frac{n_b}{N}\frac{\sigma_A(b)}{\mu_A(b)}$$





Metric: Partial Intensity Uniformity

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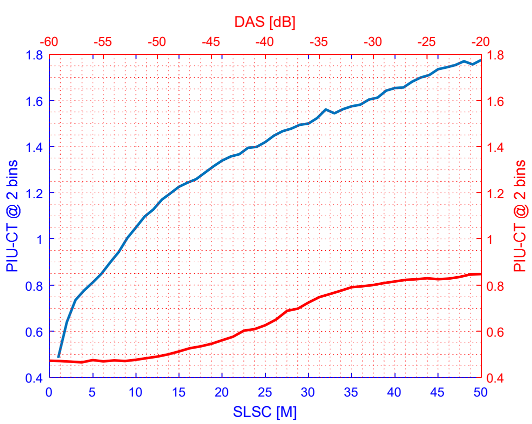

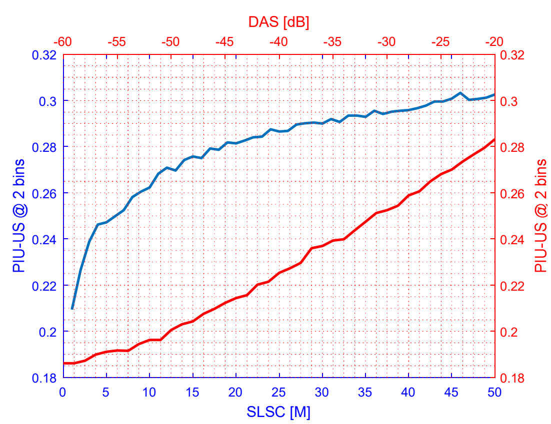

Metric: Mutual Information

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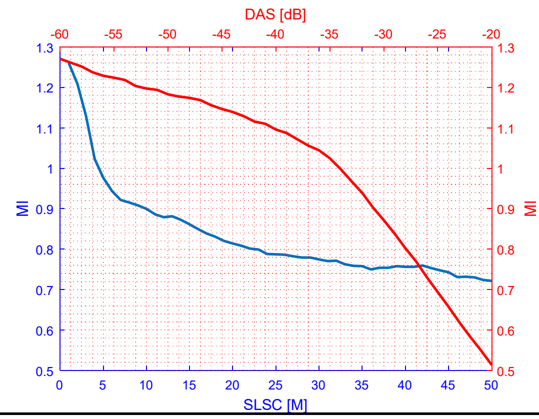
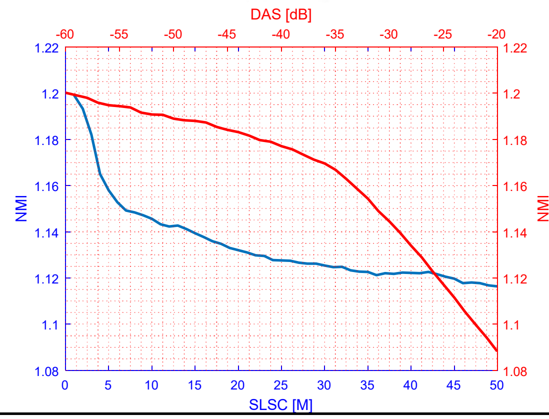
$$H(A) = -\sum_a p_A^{\mathrm{T}}(a)\log p_A^{\mathrm{T}}(a) \quad H(B) = -\sum_b p_B^T(b)\log p_B^T(b) \quad H(A,B) = -\sum_a\sum_b p_{AB}^T(a,b)\log p_{AB}^T(a,b)$$

$$H(A) + H(B) - H(A,B)$$

$$\frac{H(A)+H(B)}{H(A,B)}$$





Metric: Normalized Cross / Gradient correlation

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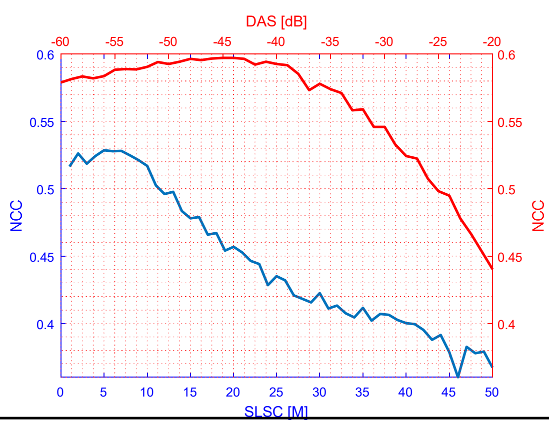
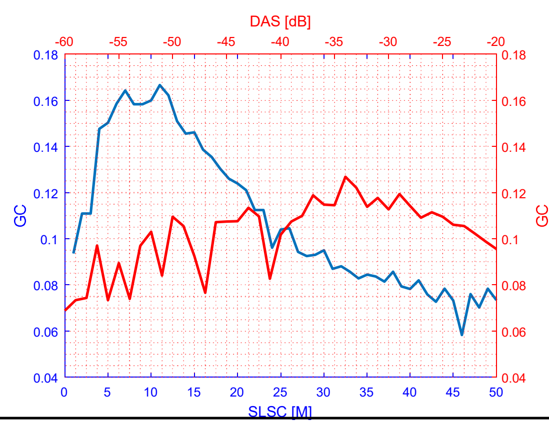
$$\mathrm{NCC} = \frac{\sum_{(i,j)\in\Omega^T}[A(i,j)-\bar{A}][B^T(i,j)-\bar{B}]}{\sqrt{\sum_{(i,j)\in\Omega^T}[A(i,j)-\bar{A}]^2\sum_{(i,j)\in\Omega^T}[B^T(i,j)-\bar{B}]^2}}.$$

$$0.5[\mathrm{NCC}(\frac{\partial A(i,j)}{\partial i}, \frac{\partial B(i,j)}{\partial i}) + \mathrm{NCC}(\frac{\partial A(i,j)}{\partial j}, \frac{\partial B(i,j)}{\partial j})]$$





Metric: Gradient difference

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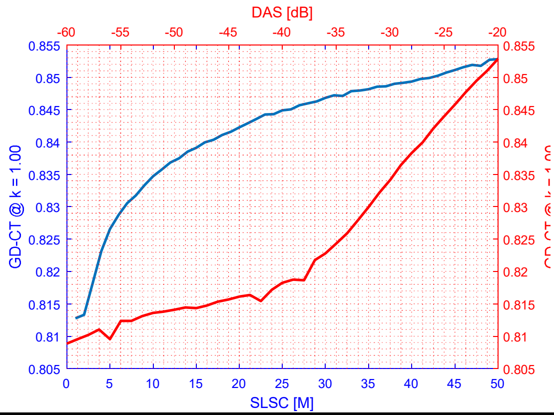
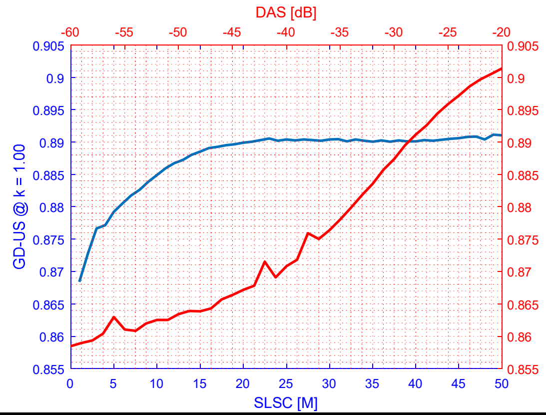
$$\mathrm{GD}(k) = \frac{1}{2N}\left(\sum_{i,j}\frac{A_v}{A_v + (I_{difV}(i,j)^2)} + \sum_{i,j}\frac{A_h}{A_h + (I_{difH}(i,j)^2)}\right)$$

$$I_{\mathrm{dif}\ V}(i,j) = \frac{\partial A(i,j)}{\partial i} - k\frac{\partial B(i,j)}{\partial i}, \qquad I_{\mathrm{dif}\ H}(i,j) = \frac{\partial A(i,j)}{\partial j} - k\frac{\partial B(i,j)}{\partial j}$$





Metric: Gradient difference

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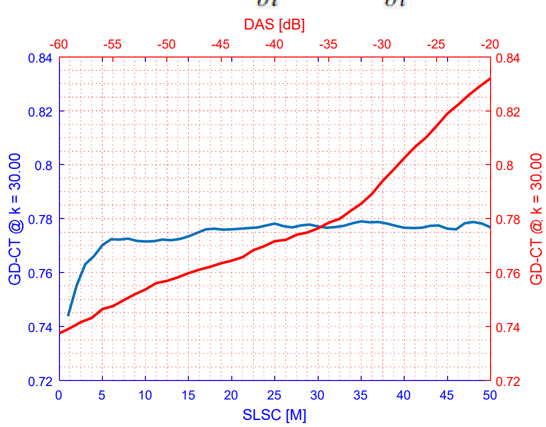

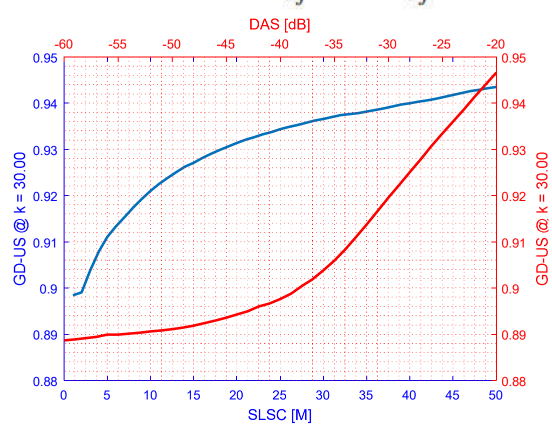

$$\mathrm{GD}(k) = \frac{1}{2N}\left(\sum_{i,j}\frac{A_v}{A_v + (I_{difV}(i,j)^2)} + \sum_{i,j}\frac{A_h}{A_h + (I_{difH}(i,j)^2)}\right)$$

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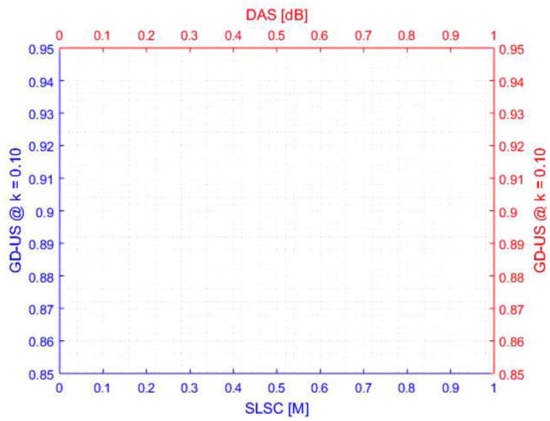

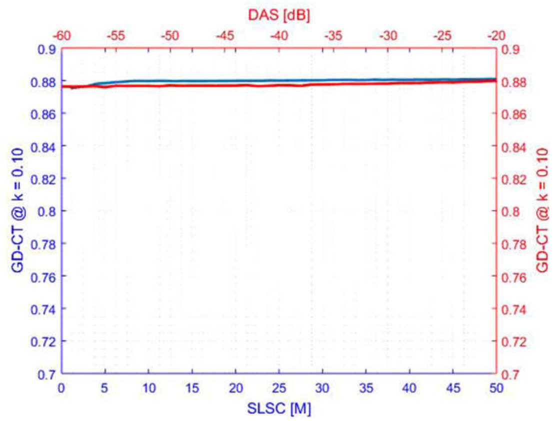

LW-SLSC results of selected metric

Kx	alpha	OL	GC	GD_CT (1)	GC_US (1)	GC_CT (30)	GC_CT (30)
10	5	0.6	0.2355	0.8416	0.8941	0.7729	0.9288
10	5	0.7	0.2377	0.8417	0.8945	0.7737	0.9291
12	2	0.5	0.2348	0.8392	0.8893	0.7659	0.9237
12	5	0.5	0.2331	0.8401	0.8906	0.7702	0.9257
12	100	0.5	0.1979	0.8458	0.8938	0.7842	0.9341
12	200	0.5	0.1762	0.8471	0.8942	0.7856	0.9359
12	50	0.5	0.2049	0.8452	0.8939	0.7825	0.9327

Pre-segmenting the CT vertebra

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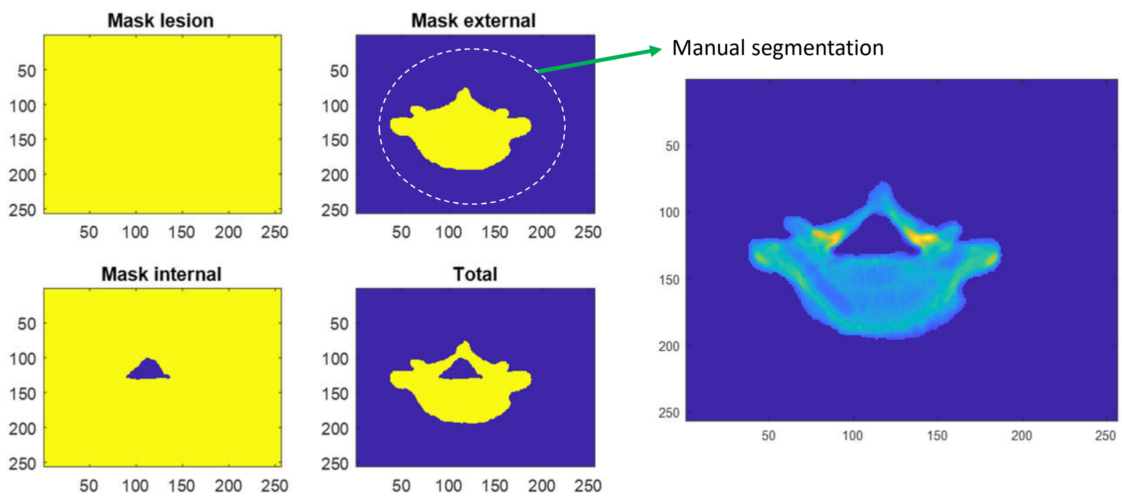

Improved results in the GC

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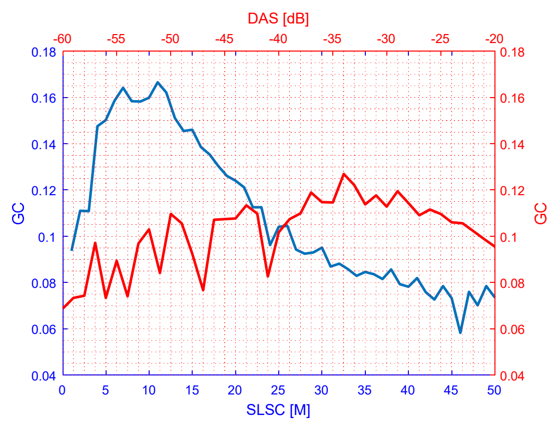
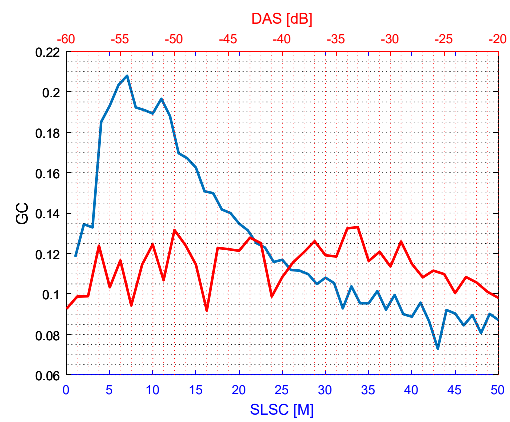


No segmentation



Pre-segmentation

Without segmenting the vertebra at 0 degrees misalignment

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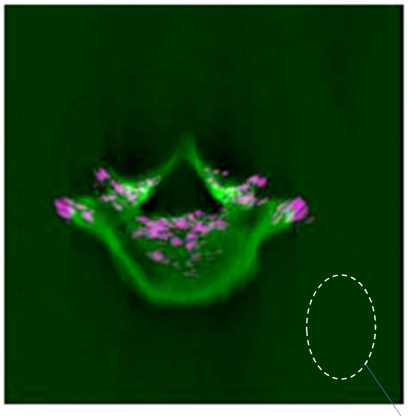
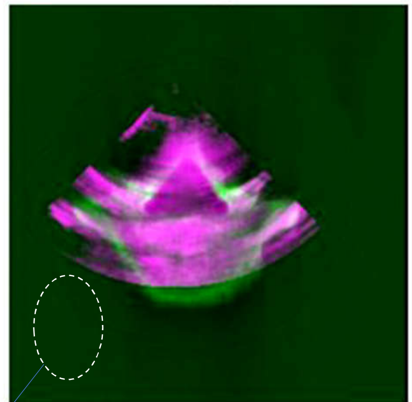
B-mode @ 20 dB



SLSC @ 1 M



Noisy CT background

Pre-segmenting the vertebra at 0 degrees misalignment

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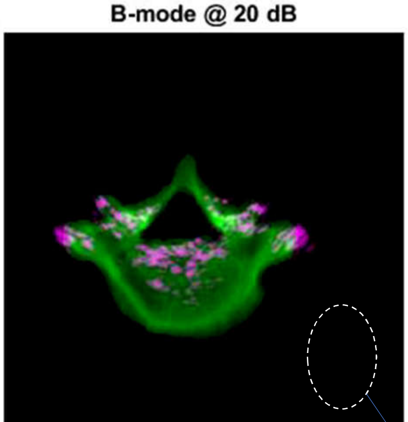
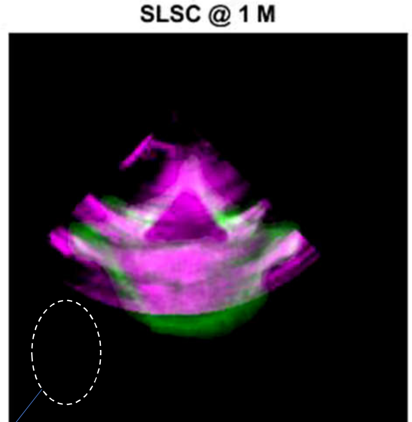
B-mode @ 20 dB

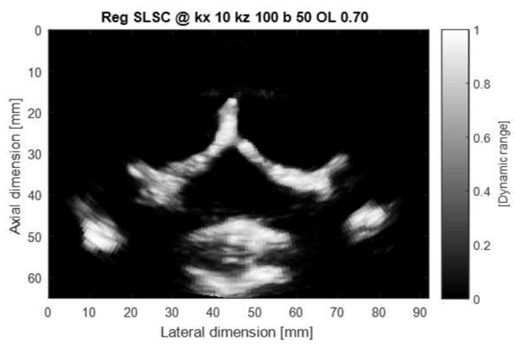


SLSC @ 1 M

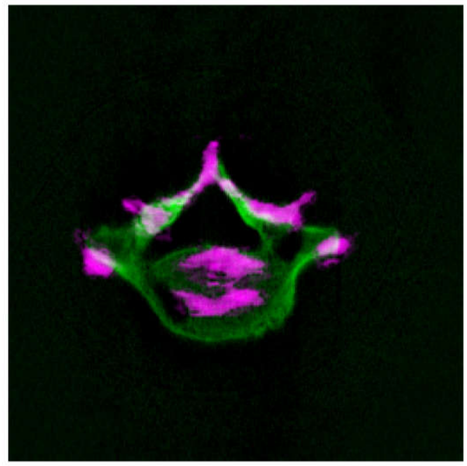


No CT background

Pre-segmenting the vertebra at 0 degrees misalignment



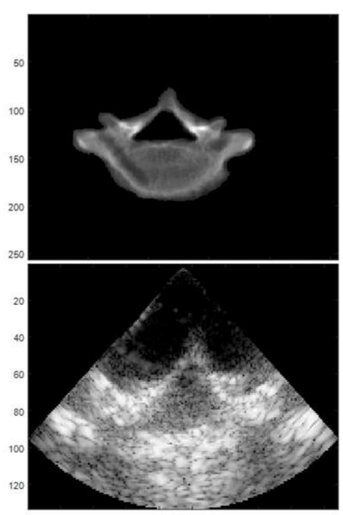
(Reg-SLSC)



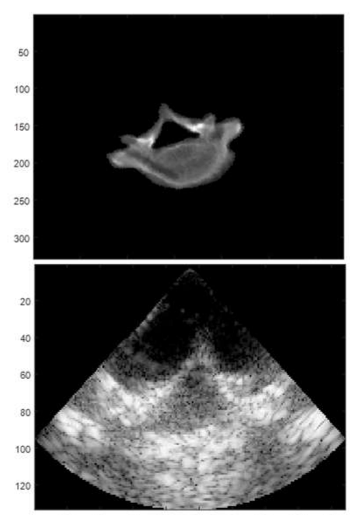
Evaluate what happens if the initial images are not correctly aligned

CT

DAS



20 grad shift



CT

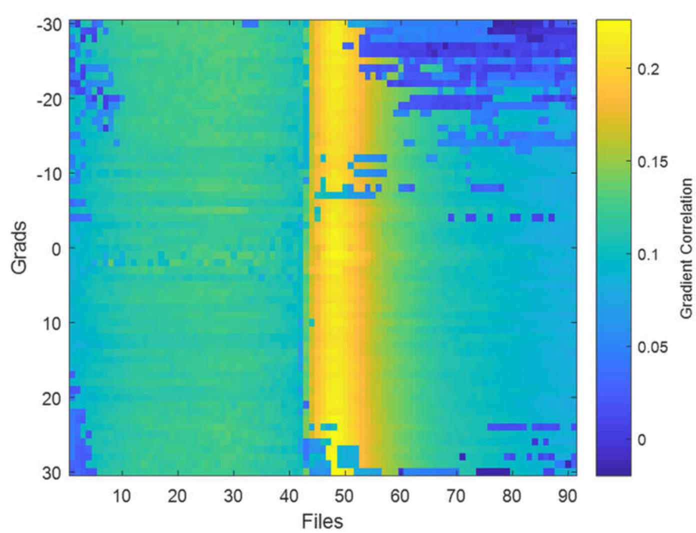
DAS

Current optimizer and metric setup for registration

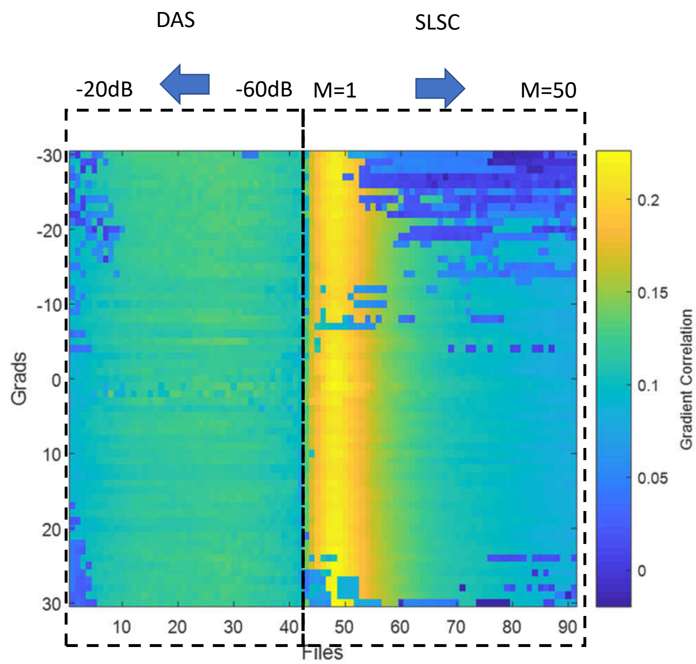
Optimizer: One plus One Evolutionary		Metric: Mattes Mutual Information	
Maximum Iterations	1 000 000 (not reached)	Number of Bins	8
Grow Factor	1.05	Number spatial samples	500 (not evaluated)
Initial Radius	0.0009	Use All Pixels	true
Epsilon	1.5e-6		

Fixed registration !

Misalignment results

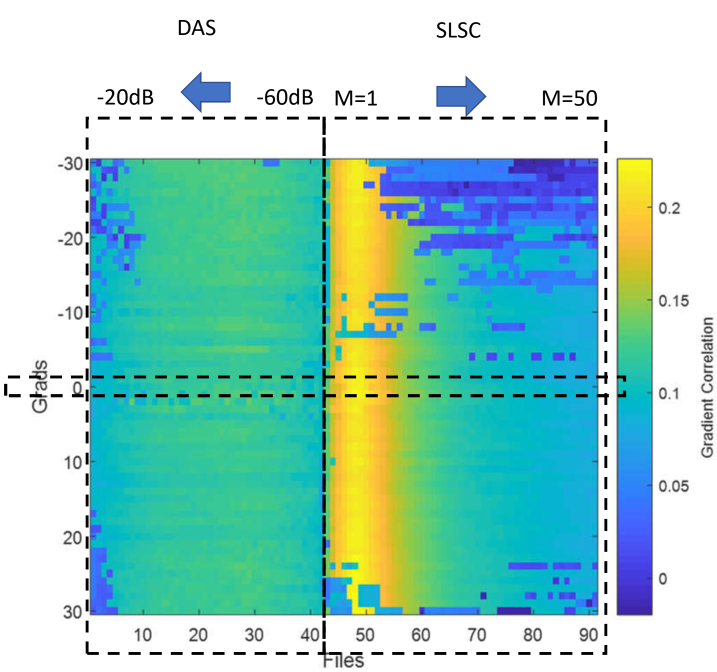


Results



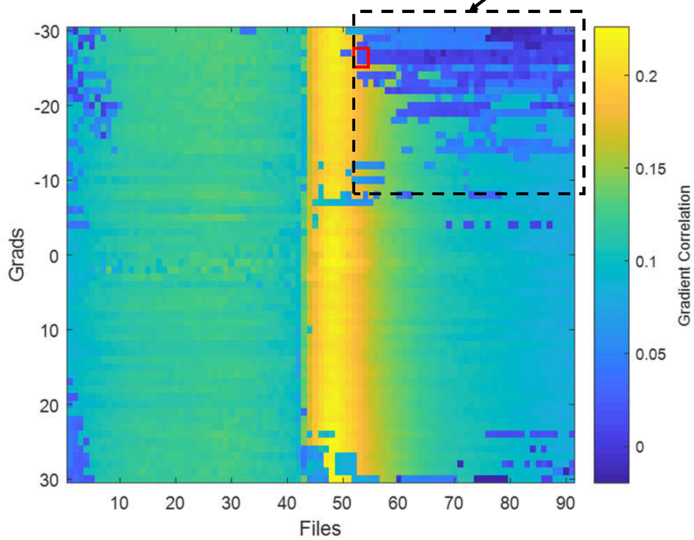
Results

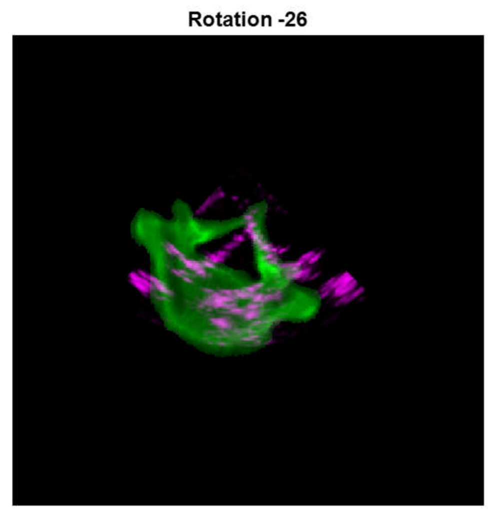
No misalignmet (0 grad difference between initial images)



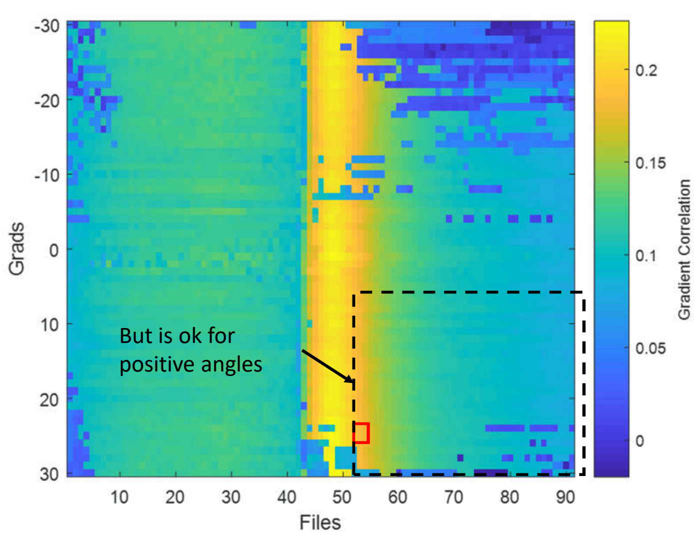
Results

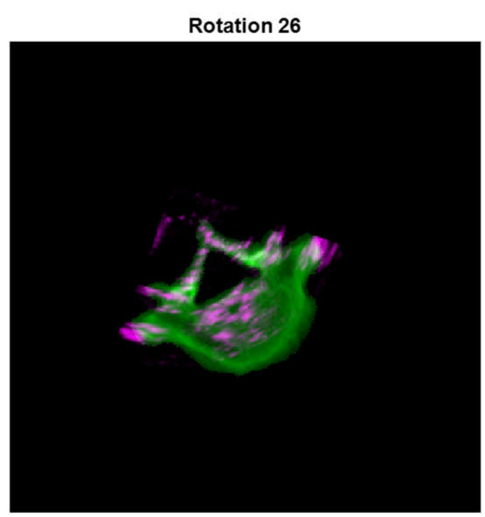
Around M>12 starts to fail for angle <-10



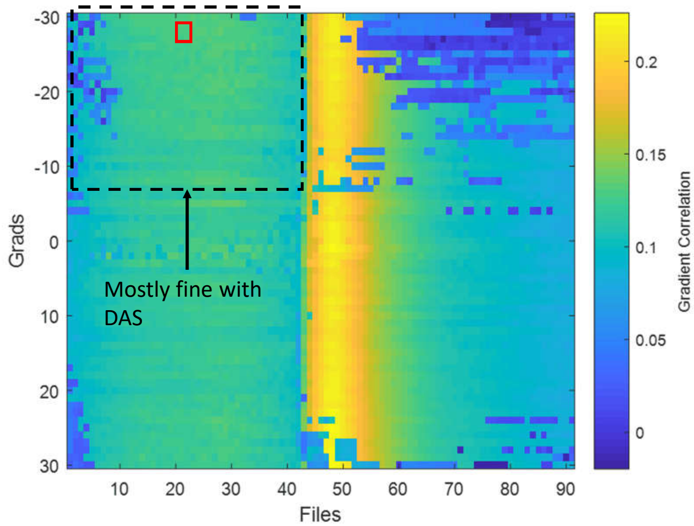


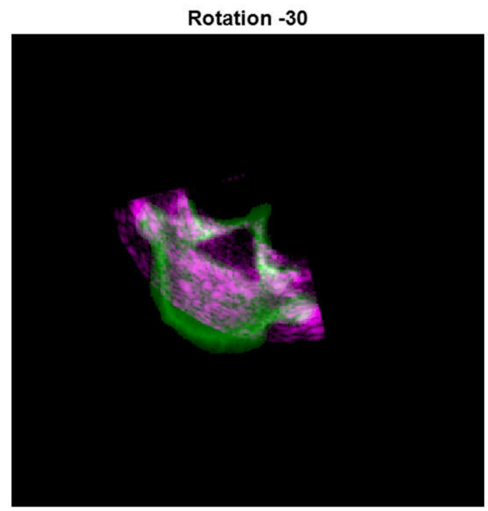
Misalignment results



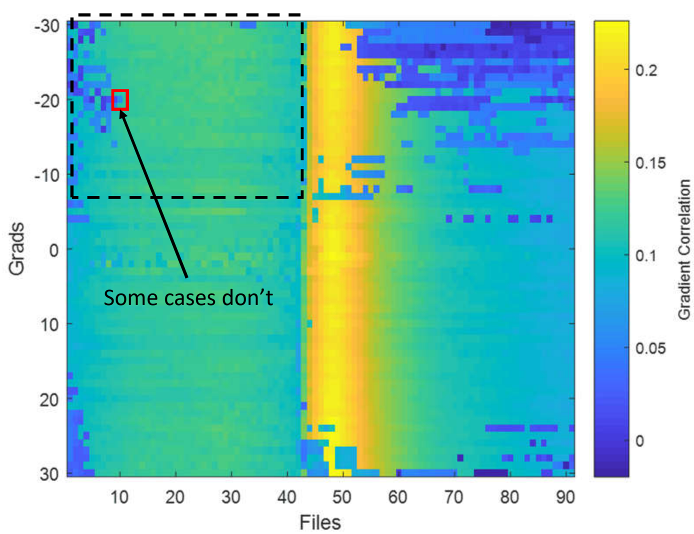


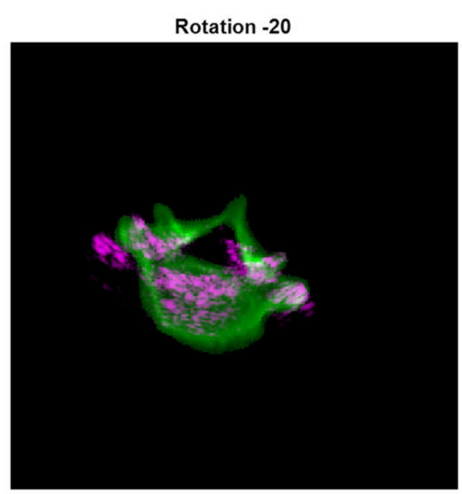
Misalignment results





Misalignment results





Deliverables

Minimum (March 8th)	Expected (April 5th)	Maximum (April 19th)
Images: Automatic registration of SLSC/DAS US images to CT images of spine specimen (hard tissue)	**Images:** add robust SLSC to registration framework	**Images**: add PA to registration framework
Equation: Propose algorithm for a robust SLSC technique		
Graph: Show registration performance when varying quality parameters for SLSC and DAS	**Graph:** add quality parameters for robust SLSC (e.g., kernel size and regularization parameters)	**Graph**: compare CT-PA and CT-US registration performance using PA images

Discussion

- Changing the parameters of the optimizer/metric could potentially improve the registration robustness
- Applying morphological closing could improve the bone structure for SLSC/DAS
- The structure is well defined for Reg-SLSC, therefore should be more robust at high angle deviation

Conclusion

- More experiments with different metrics and optimizer parameters are needed to verify the robustness of the algorithm with SLSC, Reg-SLSC and DAS images.
- Segmentation of the vertebra is well performed for initial lags of SLSC and all Reg-SLSC, but is poor for DAS images
- Addition of CT markers could be another feature to further test the registration performance

Weekly work plan

Week	Days	
1	April 2nd-April 6th	Generate L-curve testing for optimal regularization parameter
2	April 9th-April 13th	Implement registration of background article 1 / Compare
3	April 16th-April 20th	Compare registration results with misaligment start
4	April 23rd-April 27th	Test registration performance with CT - markers
5	May 1st-May 5th	Add photoacustic imaging to the registration framework
6	May 8th-May 12th	Additional processing if needed