TECHNICAL UNIVERSITY OF MUNICH: TUM Data Innovation Lab

Enhancement of clinical optoacoustic and ultrasound images

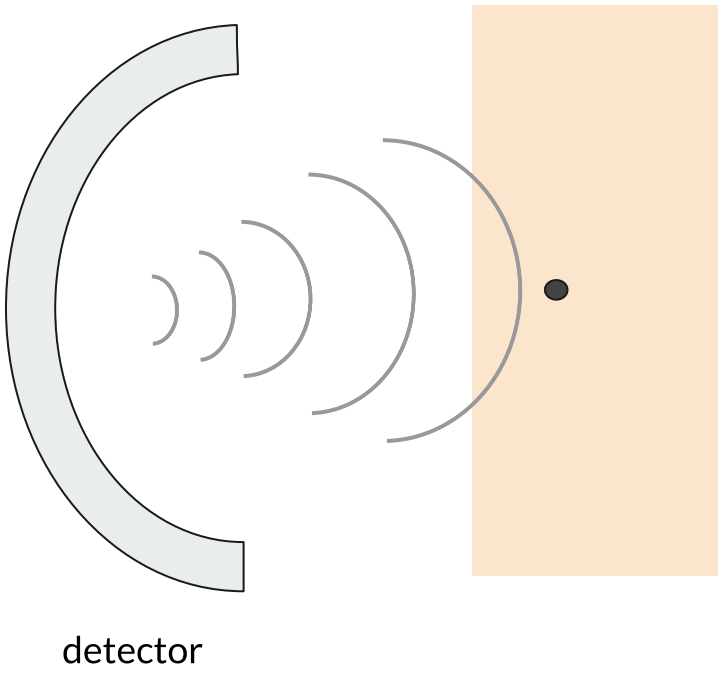
Authors: Sunita Gopal, Eva M. Höck, Fabian Pieroth, Tom H. Wollschläger
Mentors: Dr. Dominik Jüstel, Jan Kukacka MSc, (Institute for Biological and Medical Imaging, Helmholtz Zentrum München)
Co-Mentor: Michael Rauchensteiner MSc
Project Lead: Dr. Ricardo Acevedo Cabra (Department of Mathematics)
Supervisor: Prof. Dr. Massimo Fornasier (Department of Mathematics)

Outline

- **Problem Statement**
- Subproject 1 Ultrasound
- Subproject 1 Optoacoustic
- Subproject 2
- Conclusion

Ultrasound Imaging

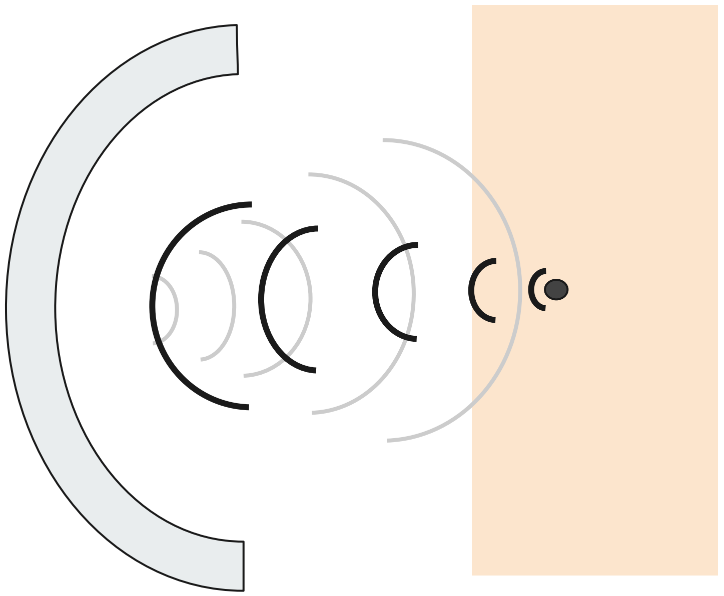
- ultrasonic wave is emitted



Ultrasound Imaging

- ultrasonic wave is emitted
- reflection is detected

- from this detected signal, the image is obtained via solution of an inverse problem



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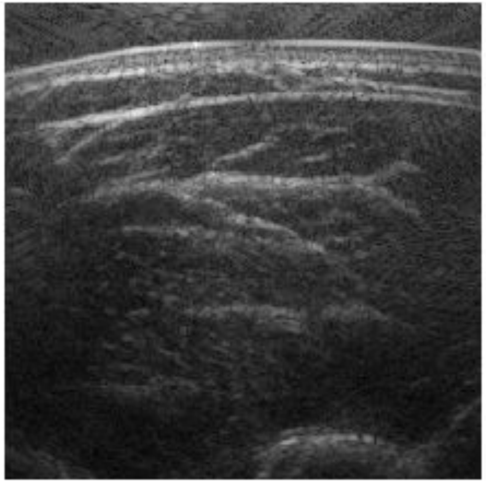
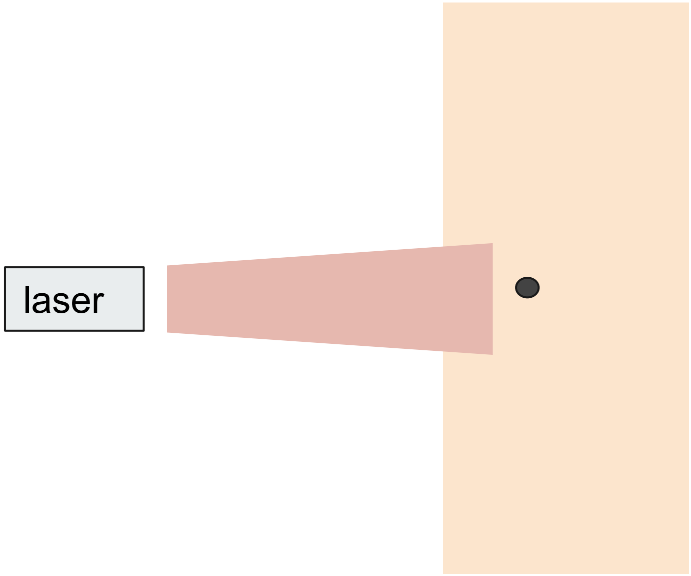


Optoacoustic Imaging

- laser pulse is shot at the tissue
- molecules heat up and generate ultrasonic waves



Optoacoustic Imaging

- laser pulse is shot at the tissue
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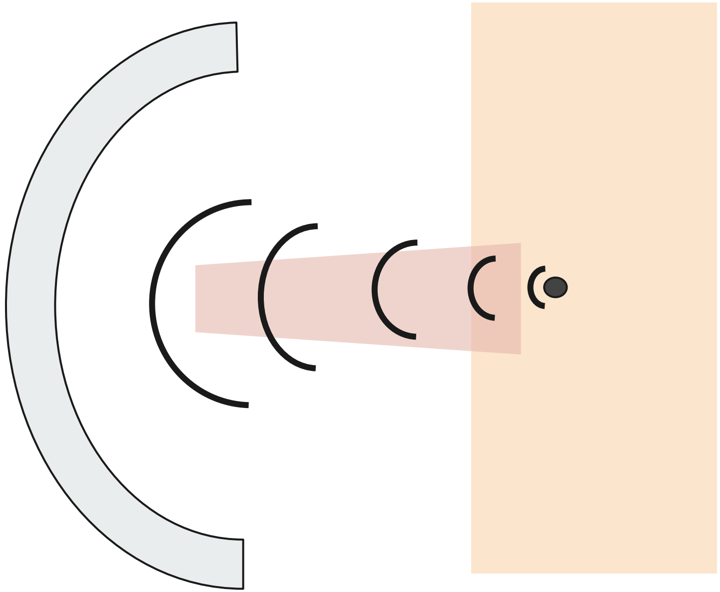
- from this detected signal, the image is obtained via solution of an inverse problem
- in our case:
  28 laser wavelengths → 28 image channels



detector

Optoacoustic Imaging

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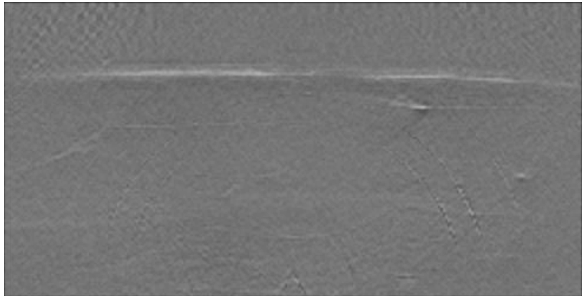

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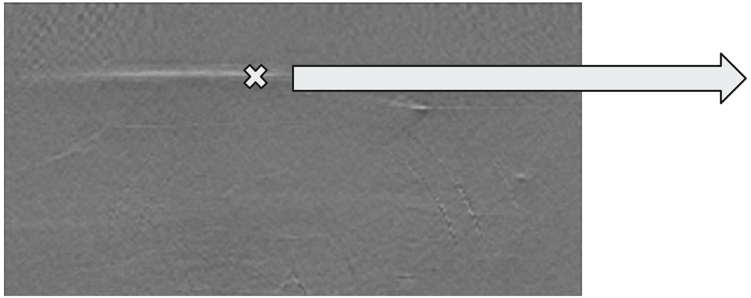
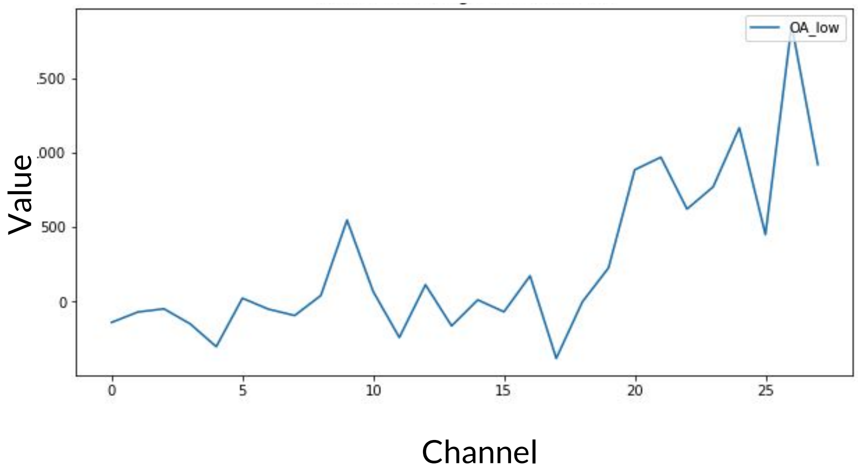
Optoacoustic imaging: Spectral information



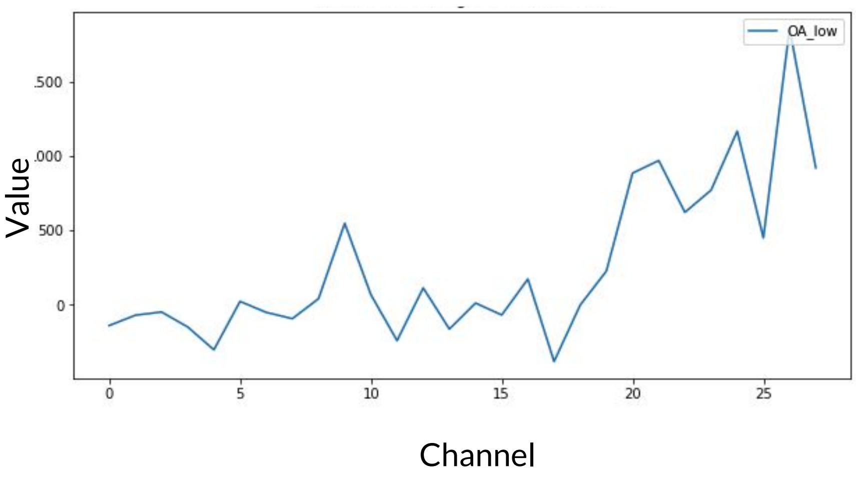
Spectrum of one pixel



Optoacoustic imaging: Spectral information

- The molecules heat up dependent on their chromophore type and the laser wavelength

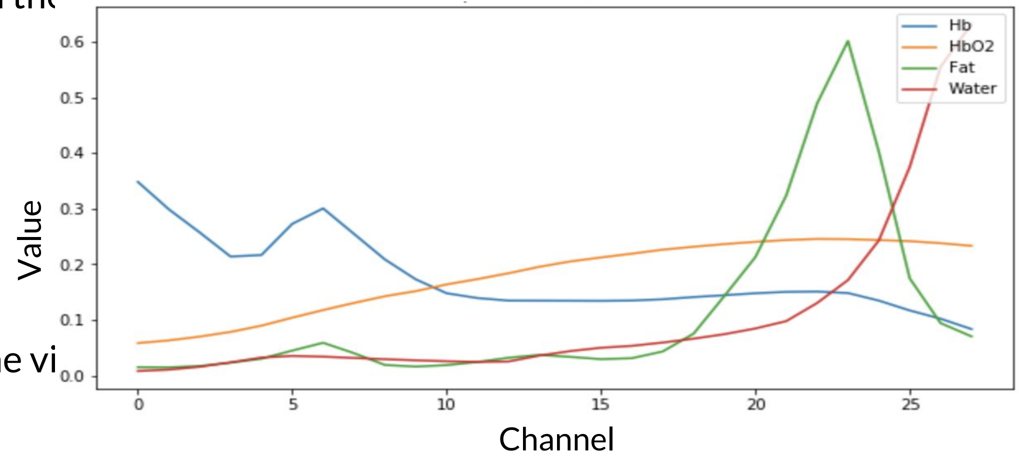
Spectrum of one pixel



Optoacoustic imaging: Spectral information

- The molecules heat up dependent on the chromophore type and the laser wavelength
- **base spectra:**
  - **blood (Hb, HbO2)**
  - **fat**
  - **water**
- decomposition in base spectra is done vi *linear unmixing*, i.e. regression

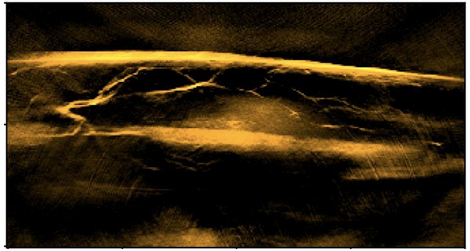
Absorption spectra of main tissue types



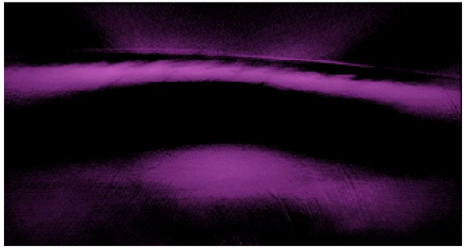
Optoacoustic imaging: Spectral information

- We display the optoacoustic images in 3 components separately

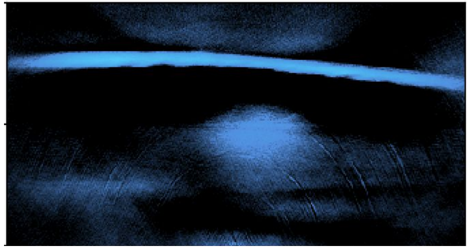
Total blood volume



Fat



Water

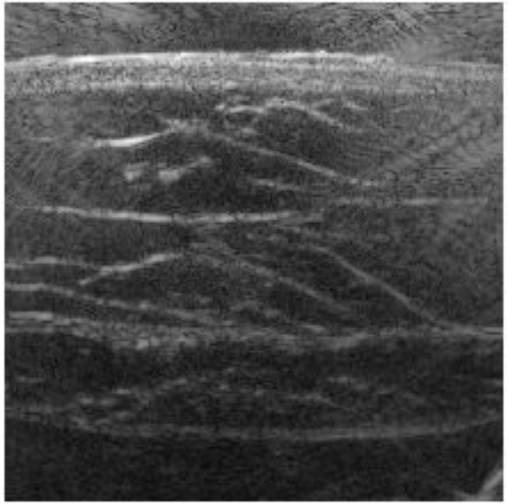


From signal to image

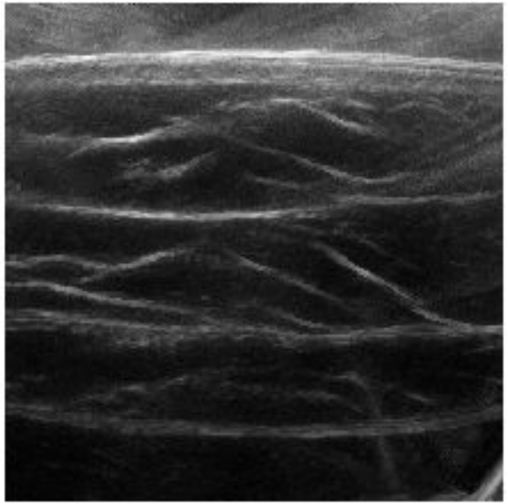
- To reconstruct the images from the signals, one needs model assumptions
- In our project we distinguish
  - ***low quality*** images (simplified assumptions, fast algorithms)
  - ***high quality*** images (more complex assumptions, more expensive)

Low and high quality ultrasound images

low quality

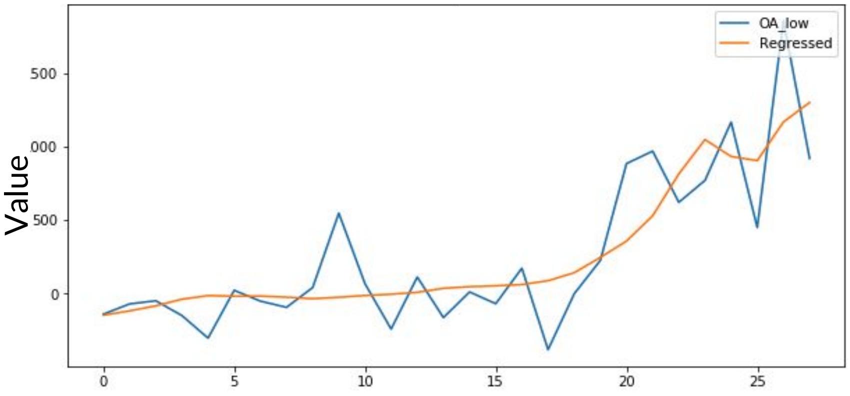


high quality



Low and high quality optoacoustic images

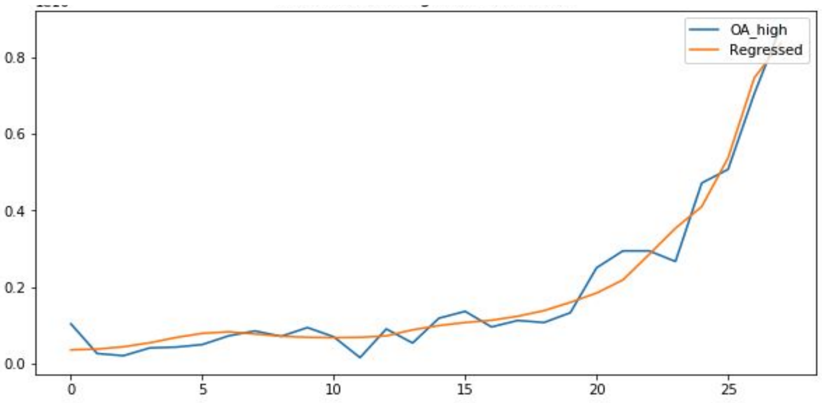
regressed low quality spectrum



Value

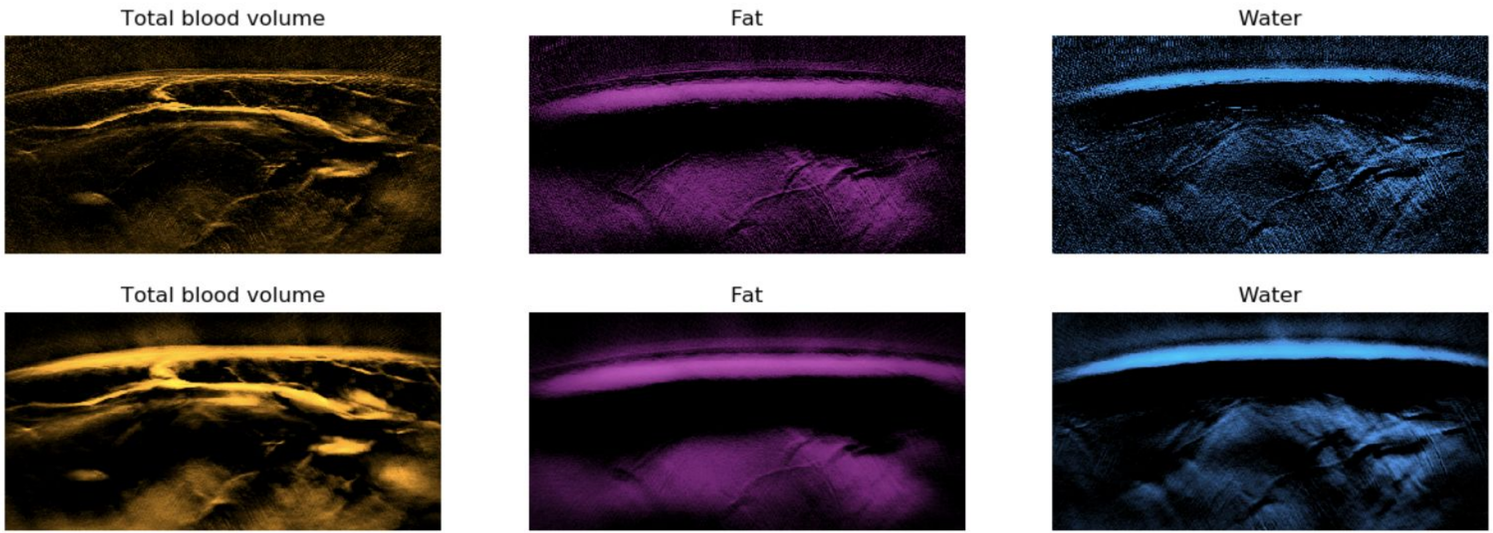
Channel

regressed high quality spectrum



Channel

Low and high quality optoacoustic images

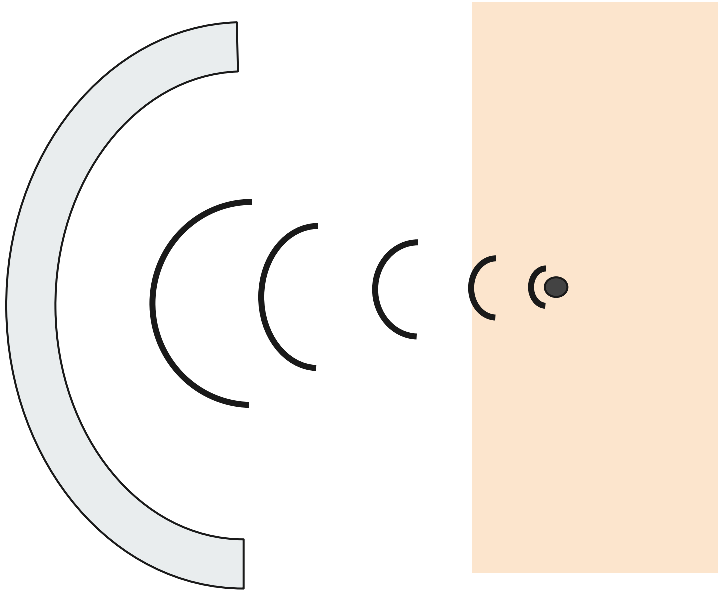


low quality

high quality

Speed of sound models

- For the reconstruction of the location and shape inside the tissue, one needs a model for the speed of sound (sos).
- 2 simple models:
  - single/homogeneous sos model
  - dual sos model



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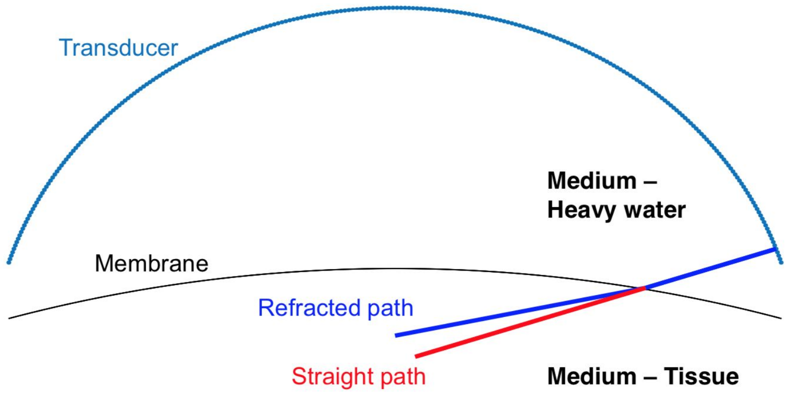
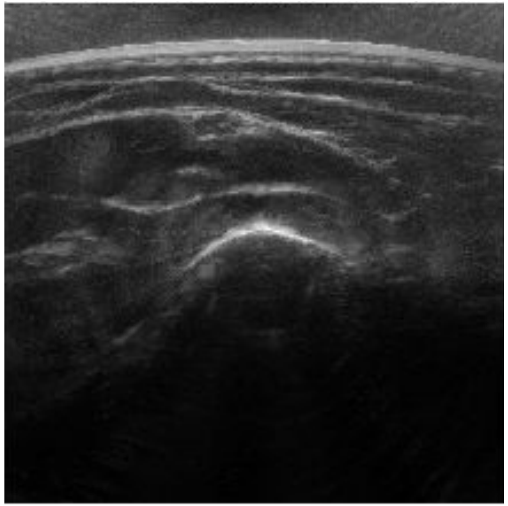


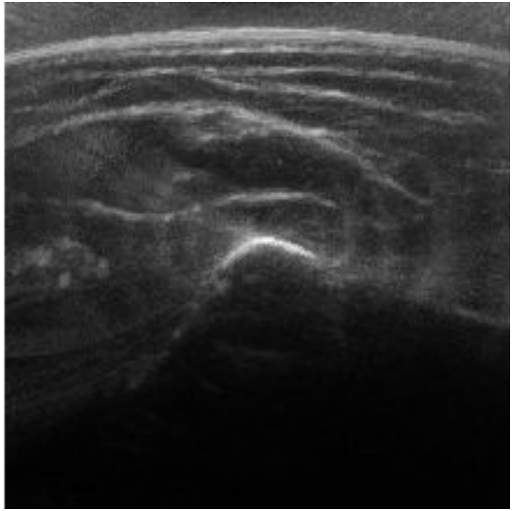
Figure taken from: D. Jüstel. TUM data innovation lab project: Enhancement of clinical optoacoustic and ultrasound images (internal presentation). IBMI/CBI, TUM, Helmholtz Zentrum München, 2018.

Different speed of sound models

single sos



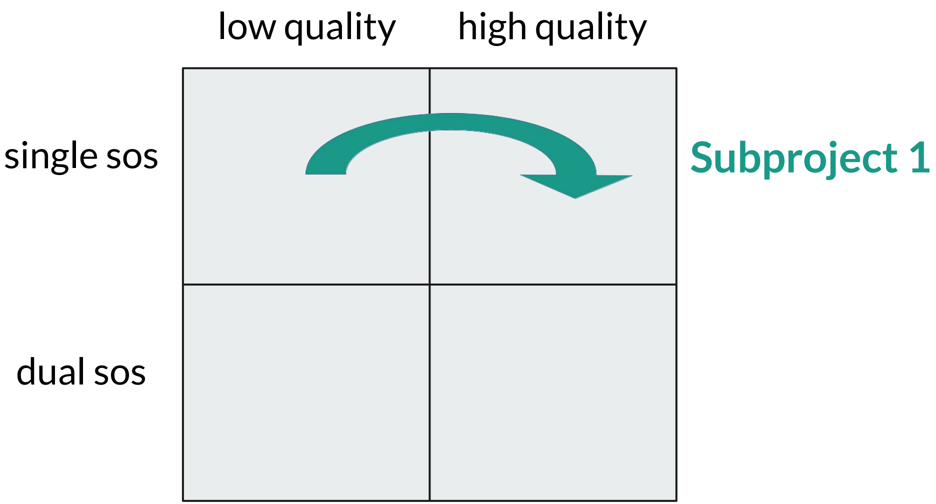
dual sos



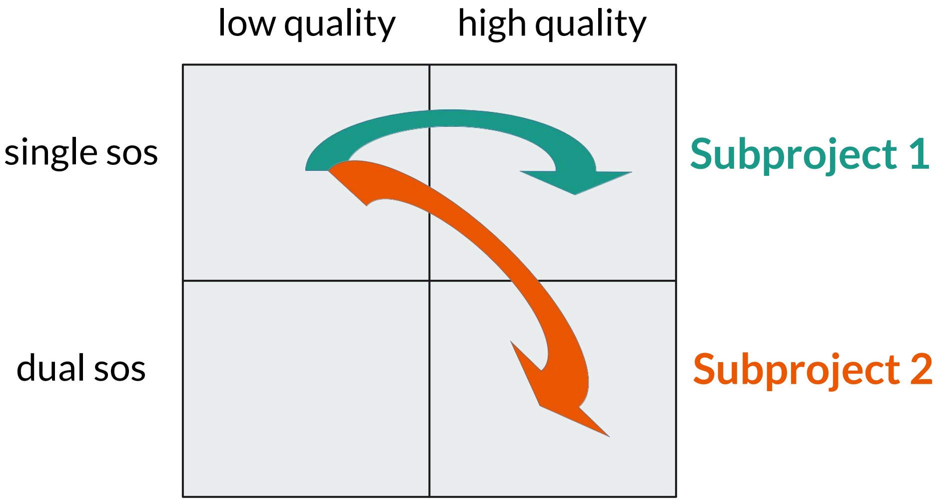
Problem statements of this project

	low quality	high quality
single sos		
dual sos		

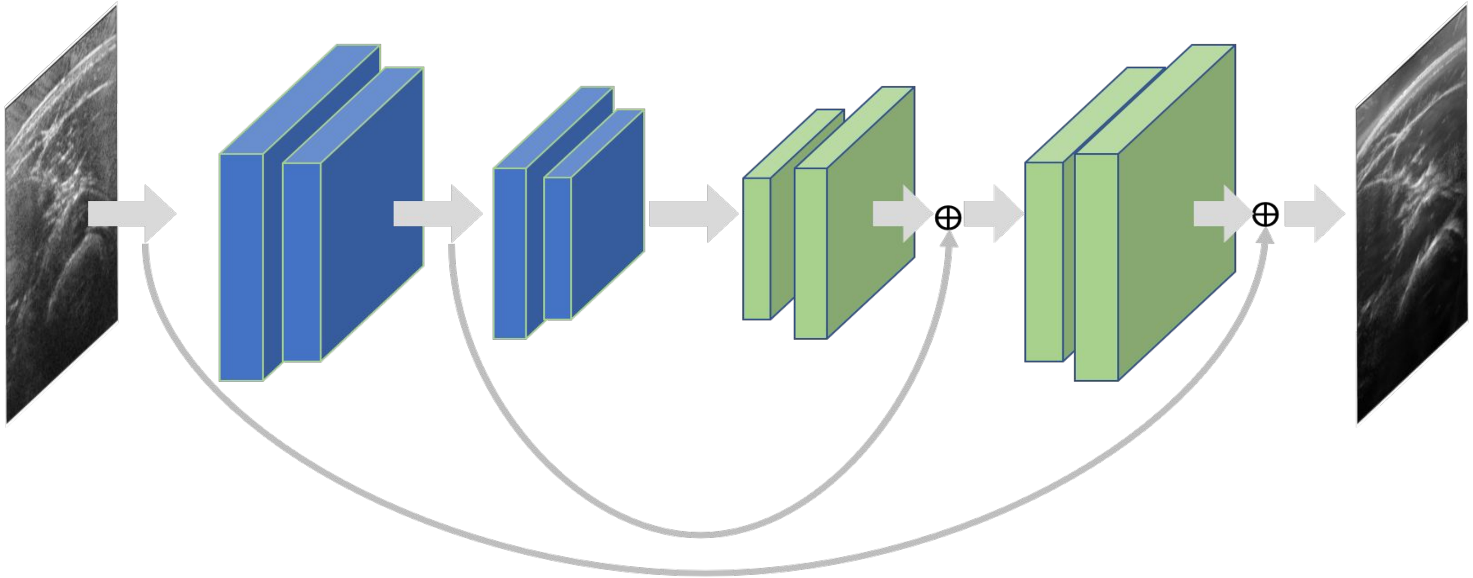
Problem statements of this project



Problem statements of this project



Base Model: Fully-Convolutional Encoder-Decoder with skip connections



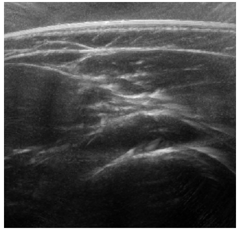
Thoughts behind framework

- Convolution: extract important features
- Transpose convolution: up-sample extracted features into the image
- Skip connection:
  - modeling the error term
  - help propagating the gradients
  - keep detailed information of the image

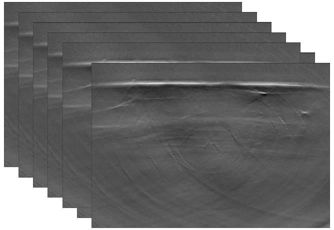
Data - Challenges

- Limited number of images
    - 100 (approx.) images
- Large data size
    - Total memory required
    - Subproject 1 (US - 3.6GB, OA - 50.4GB)
    - Subproject 2 (US - 90GB)
- High Dimensional Data
    - OA - 28 channels

Ultrasound



Optoacoustic

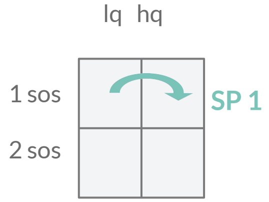


Data - Consequences

- Limited images - Used augmentations (flip, deform, crop, blur, speckle noise)
- Continuous integration of data throughout project
  - Train-Validation : 90:10
  - “Test” : 2 Images
- High dimensional data
  - Cannot compute using local machine
  - Used LRZ GPU resources

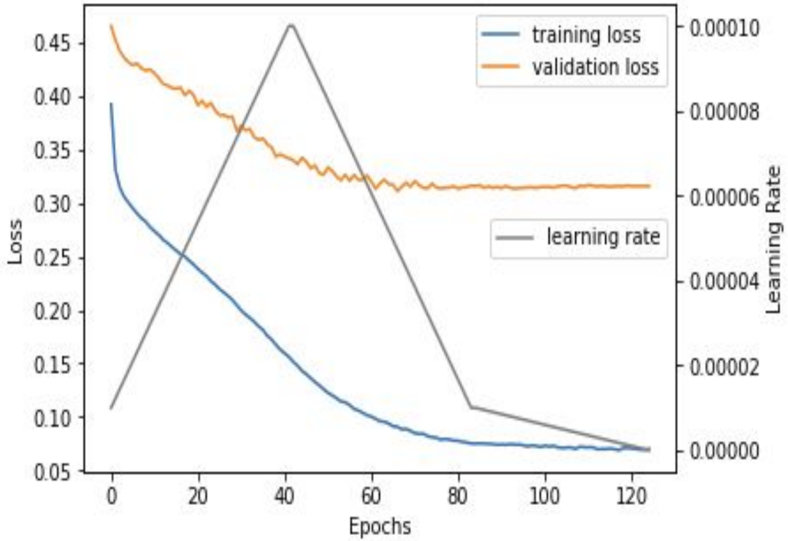
Outline

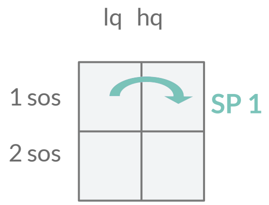
- ➢ Problem Statement
- ➢ **Subproject 1 Ultrasound**
- ➢ Subproject 1 Optoacoustic
- ➢ Subproject 2
- ➢ Conclusion



Approach

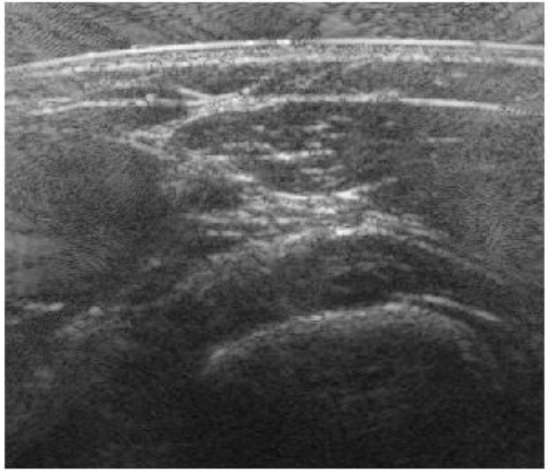
- Data: low quality input, high quality target
- Augmentations: flip, deform, crop, blur, speckle noise
- Architecture: Base Model
- 7 Conv, 7 Transpose conv layers stride 2
- Adding skip connections



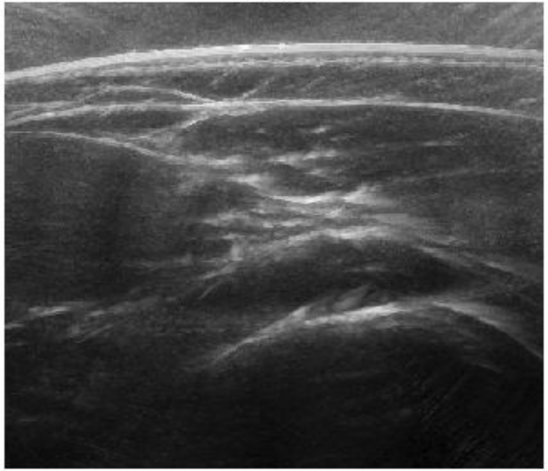


Test Results

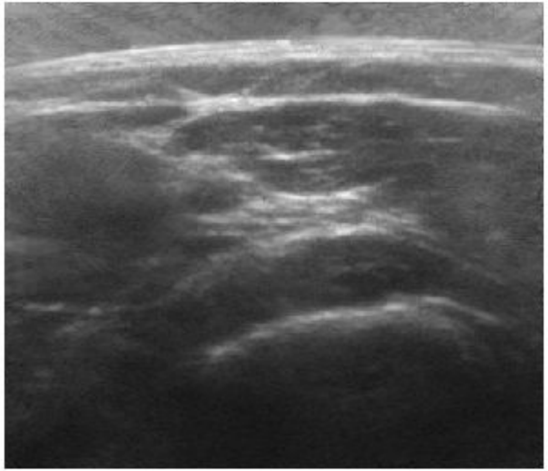
Input



Target



Predict



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- ➢ Subproject 1 Ultrasound
- ➢ **Subproject 1 Optoacoustic**
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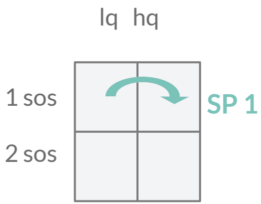
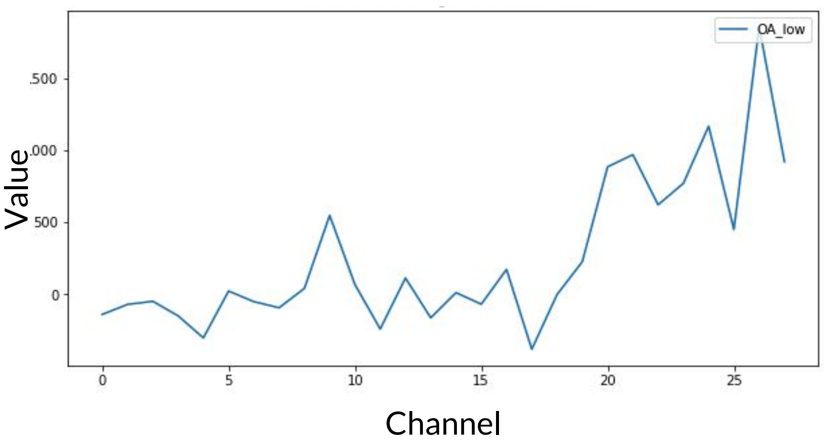
- ➢ Conclusion

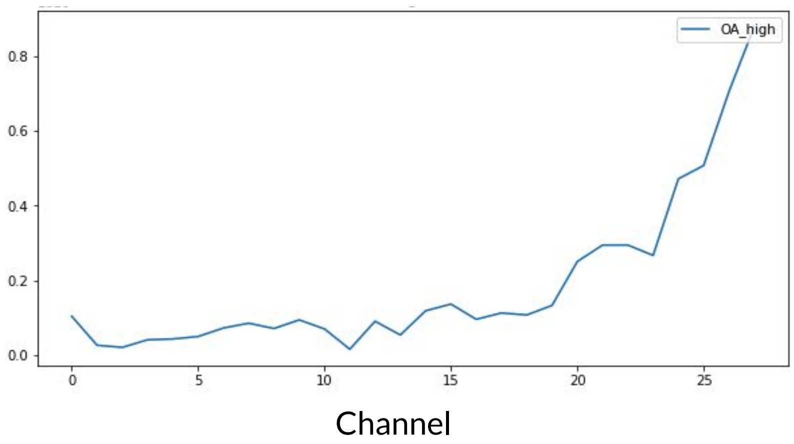


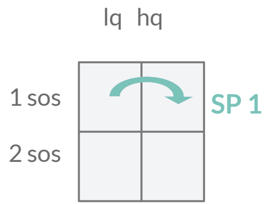
Comparison low and high quality spectra

Low quality spectrum

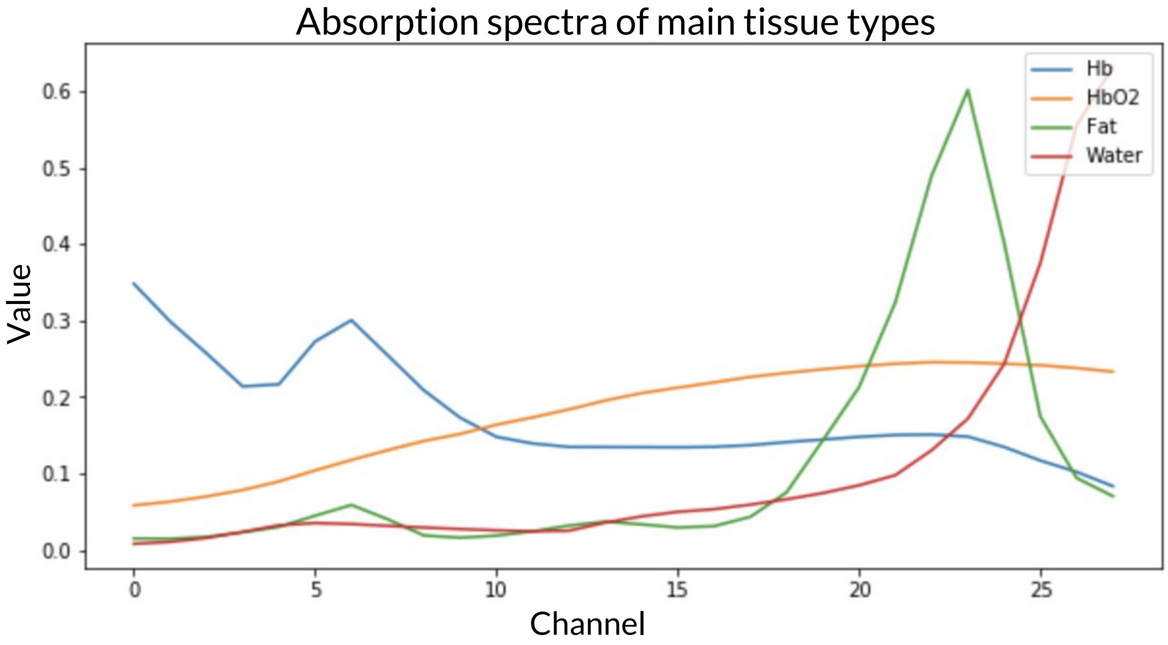


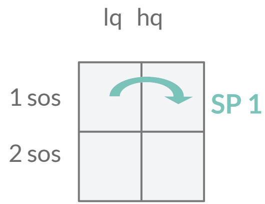
High quality spectrum





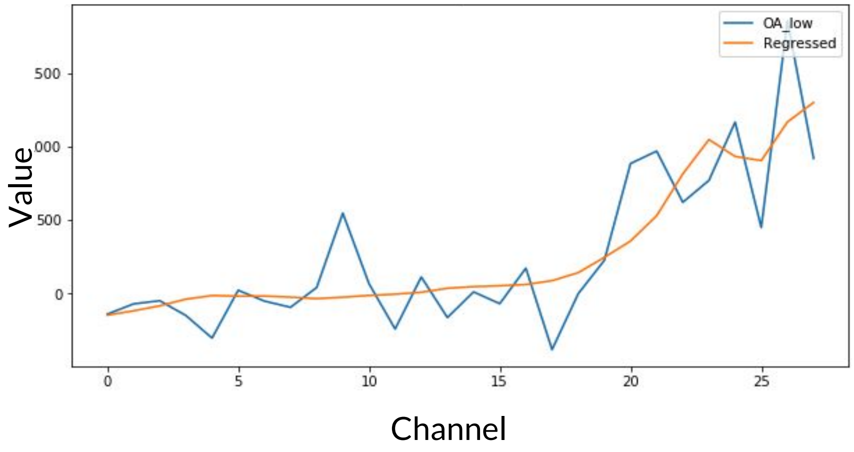
Base Spectra and Regression



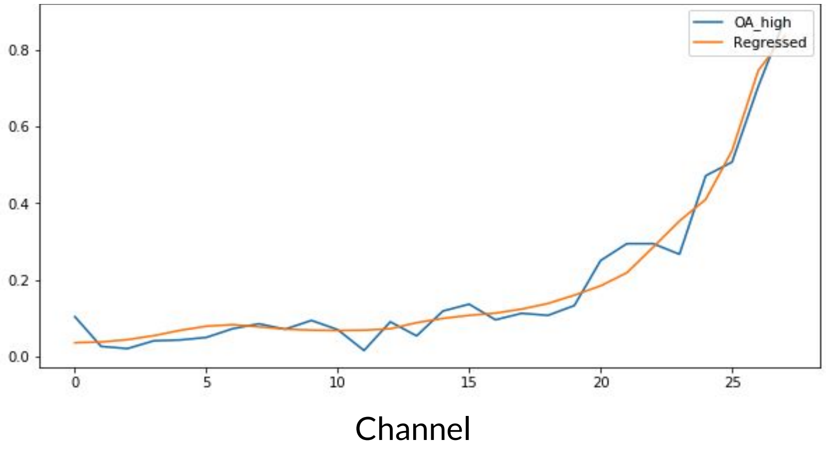


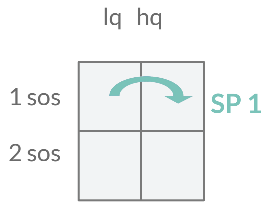
Comparison low and high quality spectra

regressed low quality spectrum



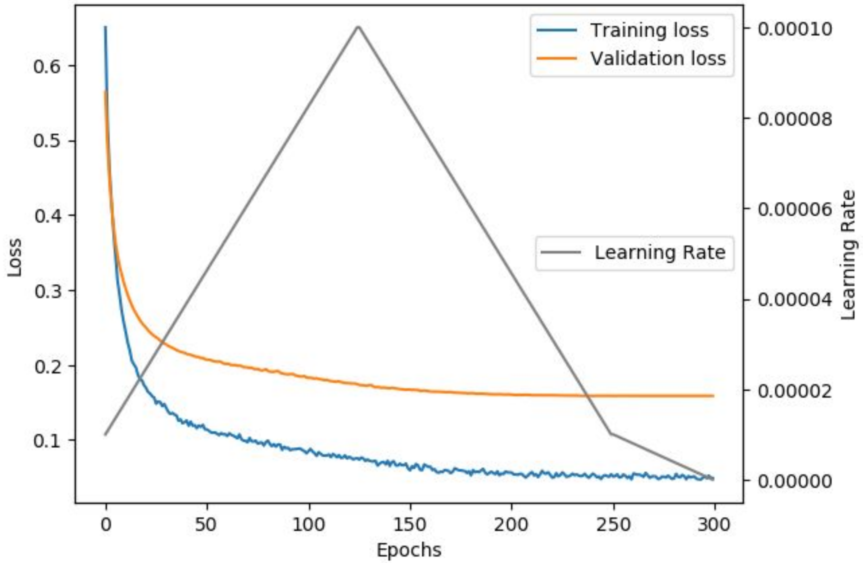
regressed high quality spectrum

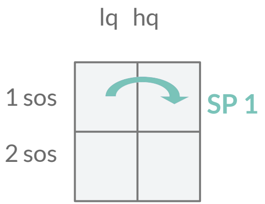




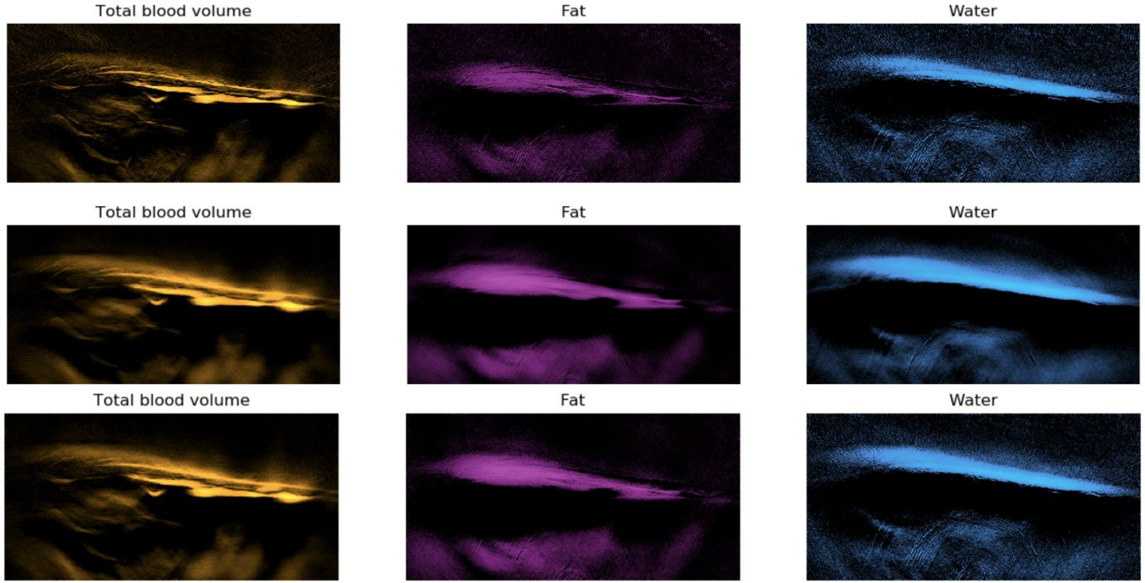
Approach

- Data:
    - low quality input (201, 401, 4)
    - high quality target (201, 401, 4)
- Augmentations: flip, deform
- Architecture: Base Model
- 5 Conv, 5 Transpose conv layers stride 2





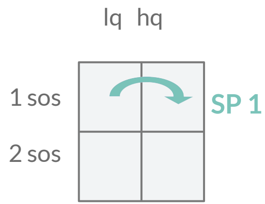
Results - validation images



Input

Target

Predict



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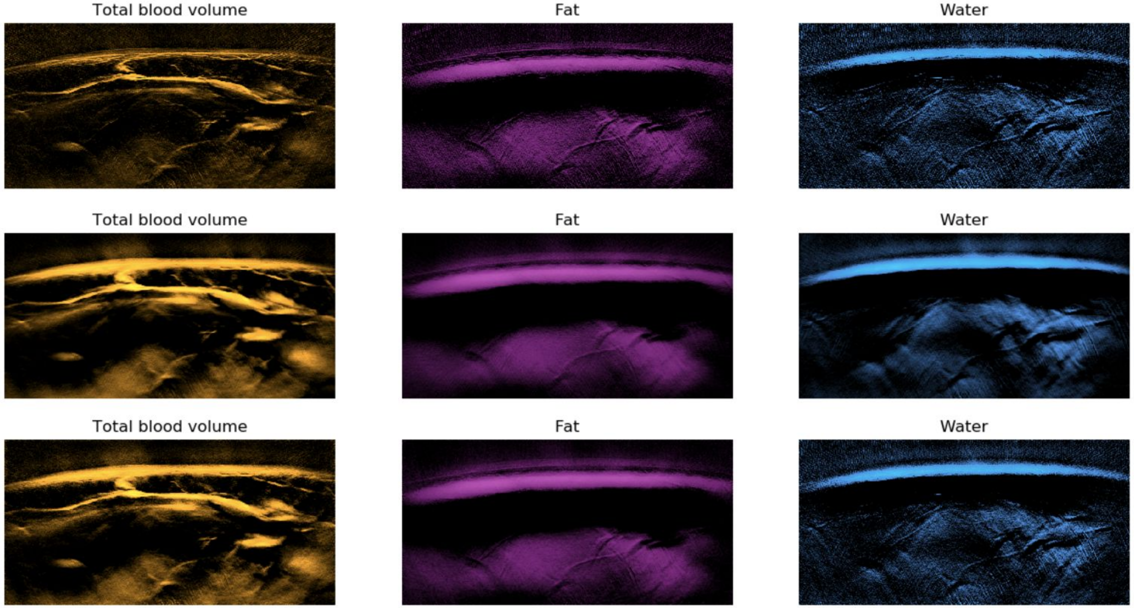

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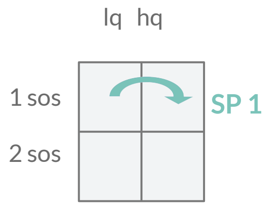
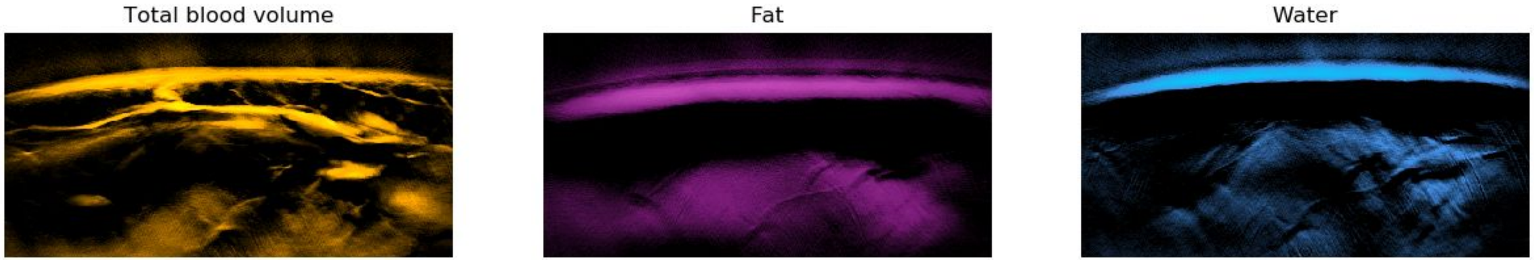
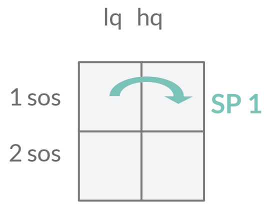


Results - Comparison

Target





Results - Comparison

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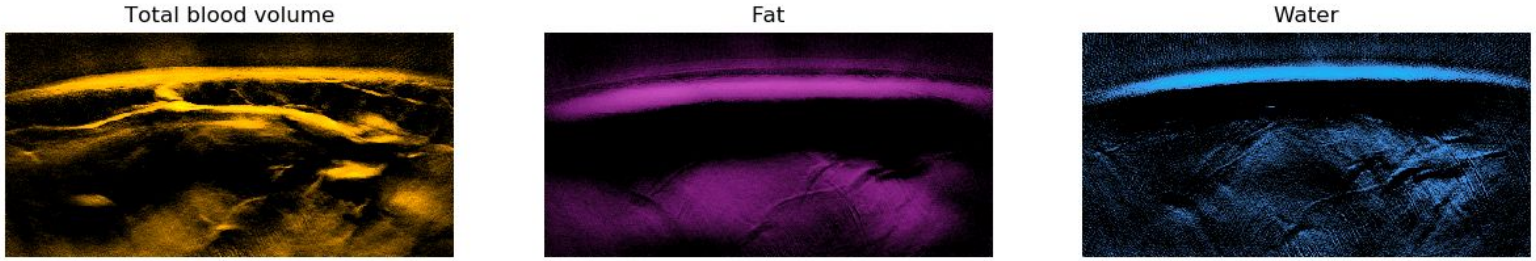

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- **Subproject 2**
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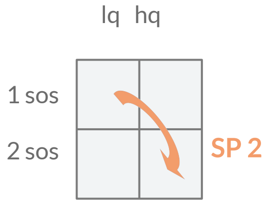
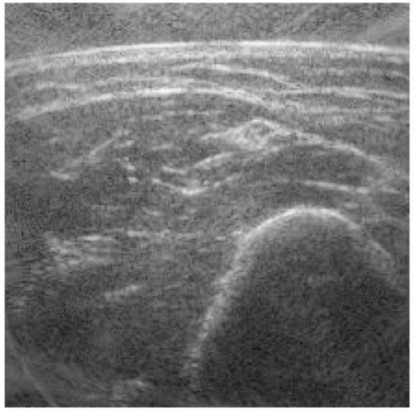


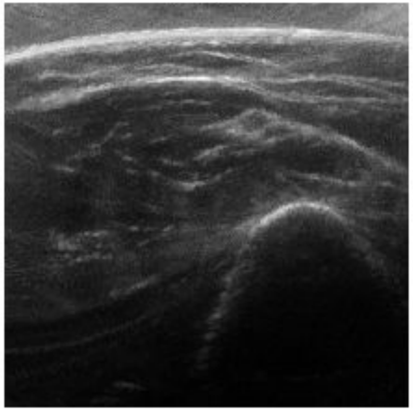
Data Exploration

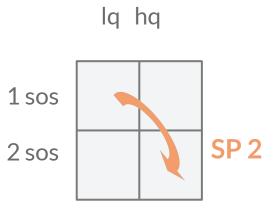
- Big variety in Input

Input



Target





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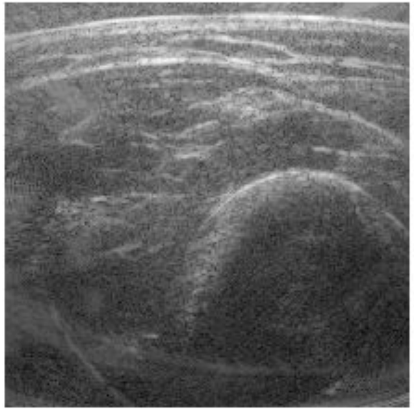

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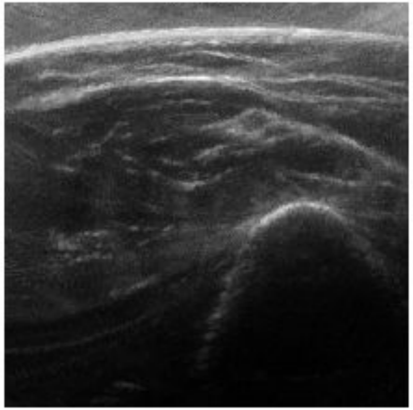

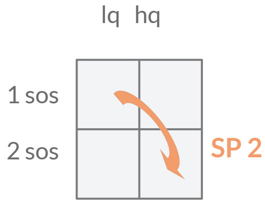

Data Exploration

- Big variety in Target

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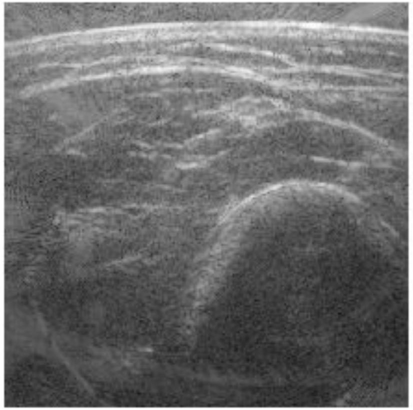

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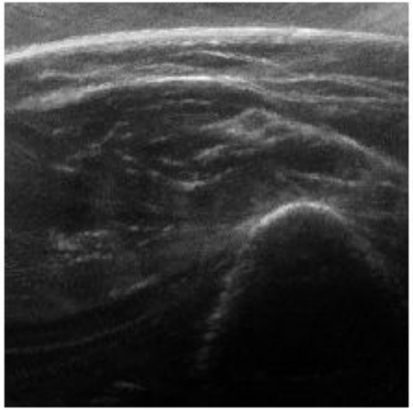

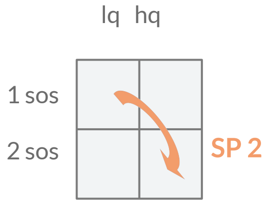

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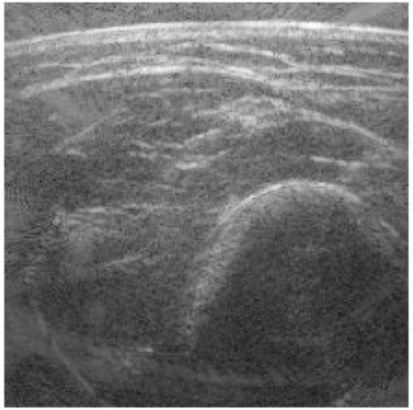
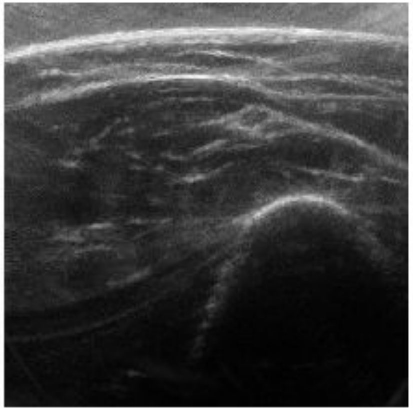
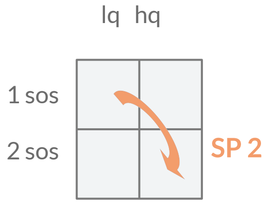


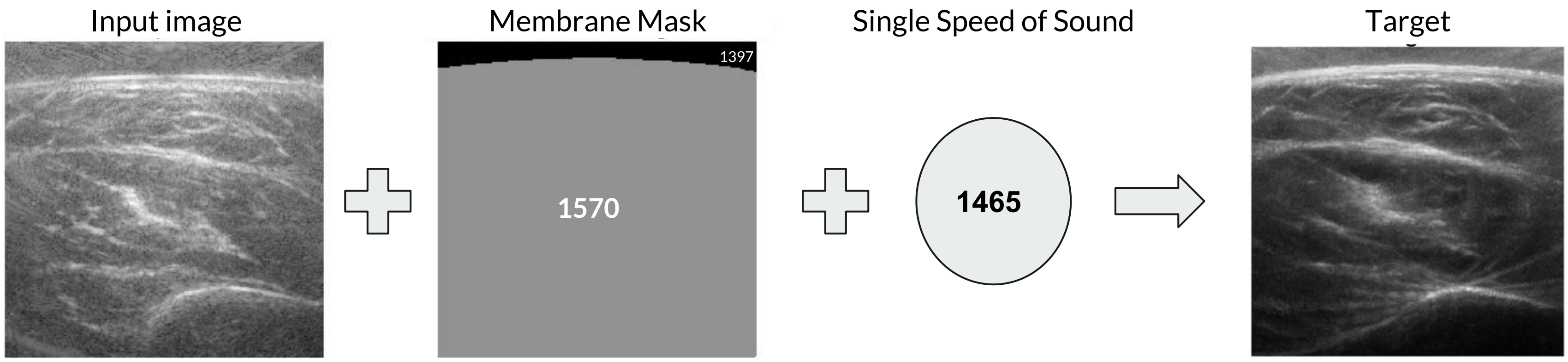
Target

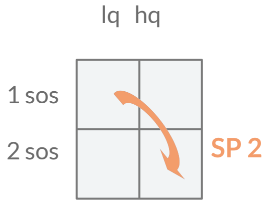




Data Exploration

- Complete mapping information

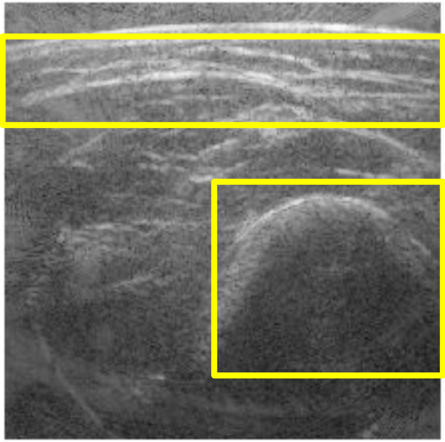




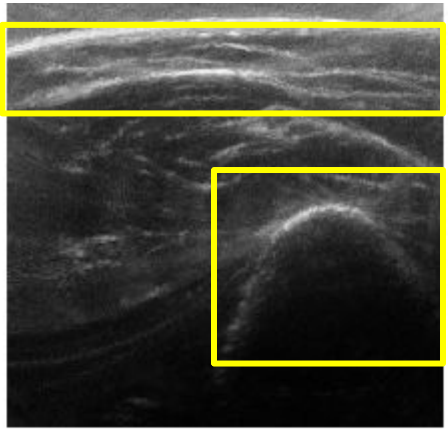
Data Exploration

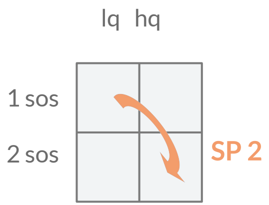
- Subtle change in the upper image, stronger deformation in the lower part

Input

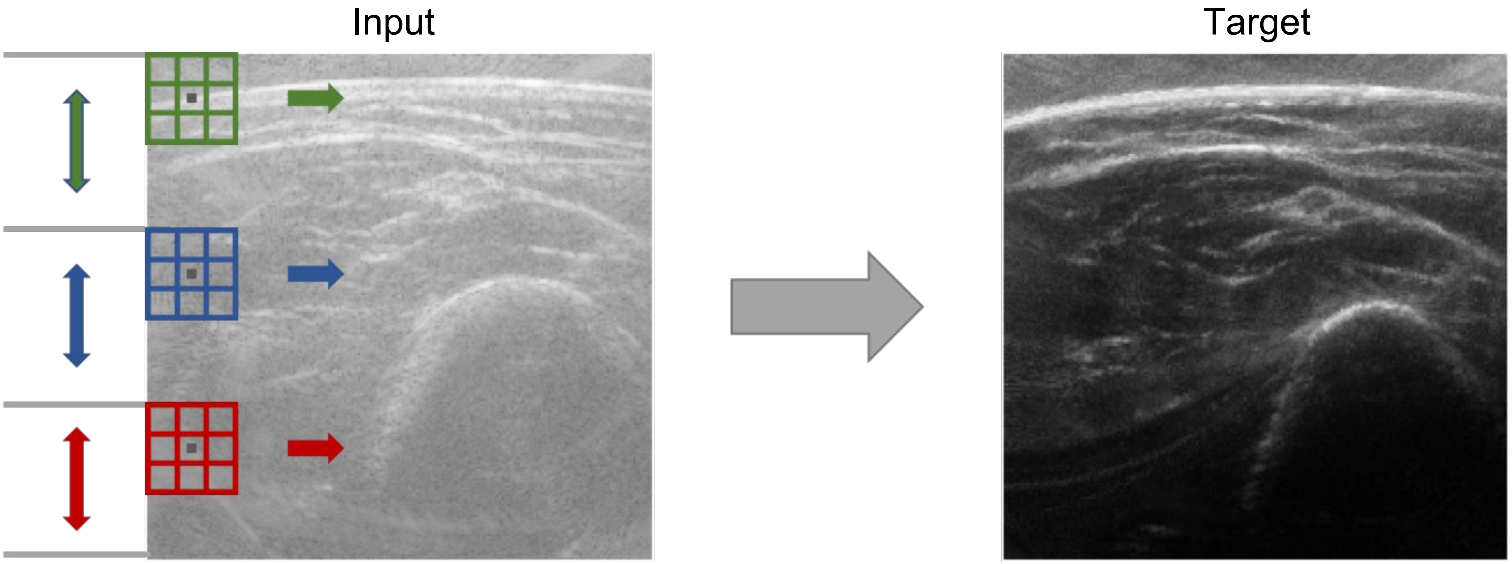


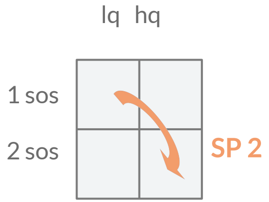
Target



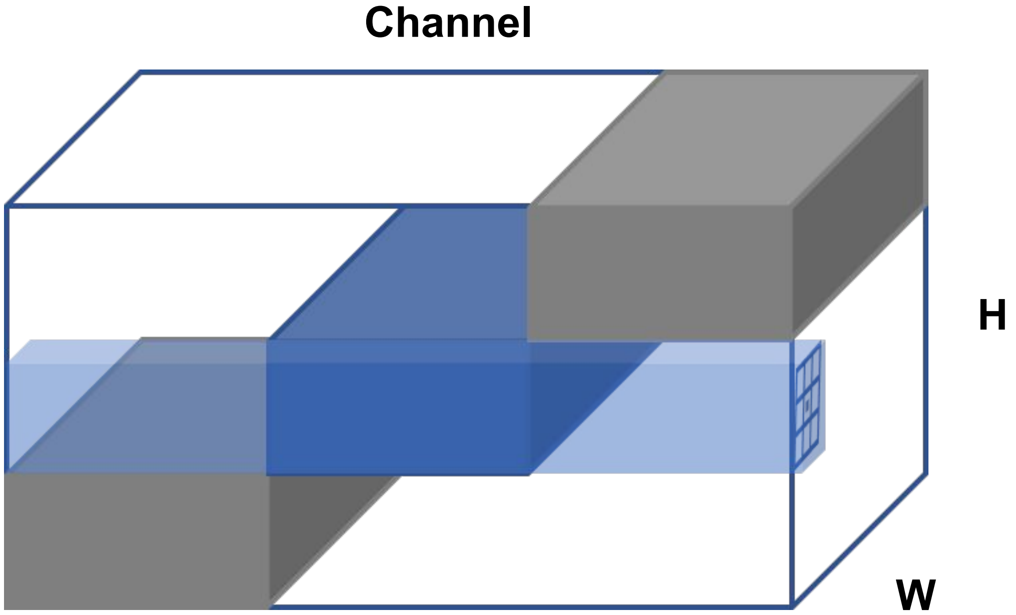


Idea

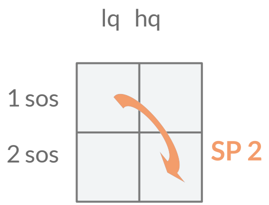


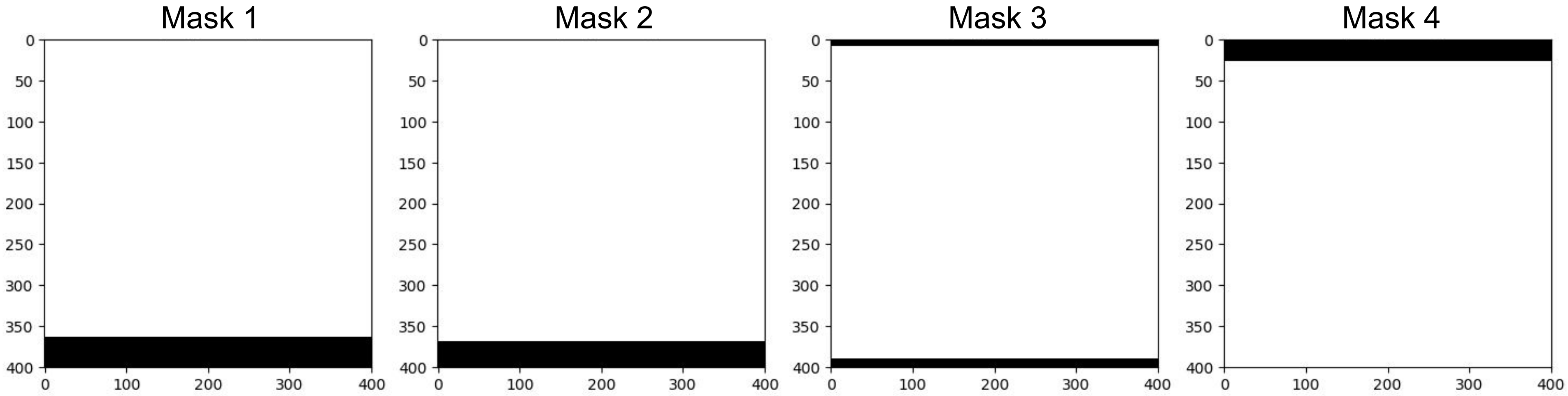


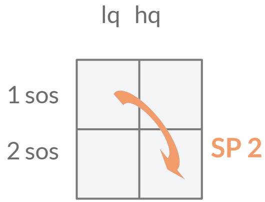
Solution: Masking the image



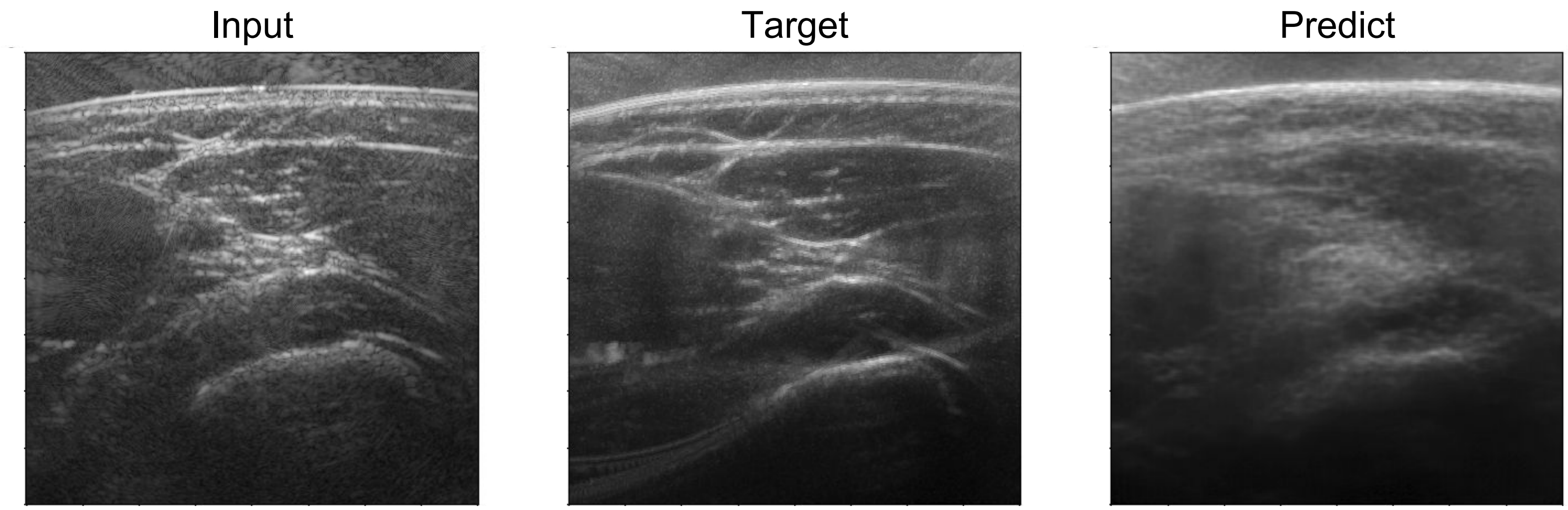
Used attention masks



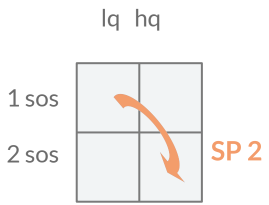


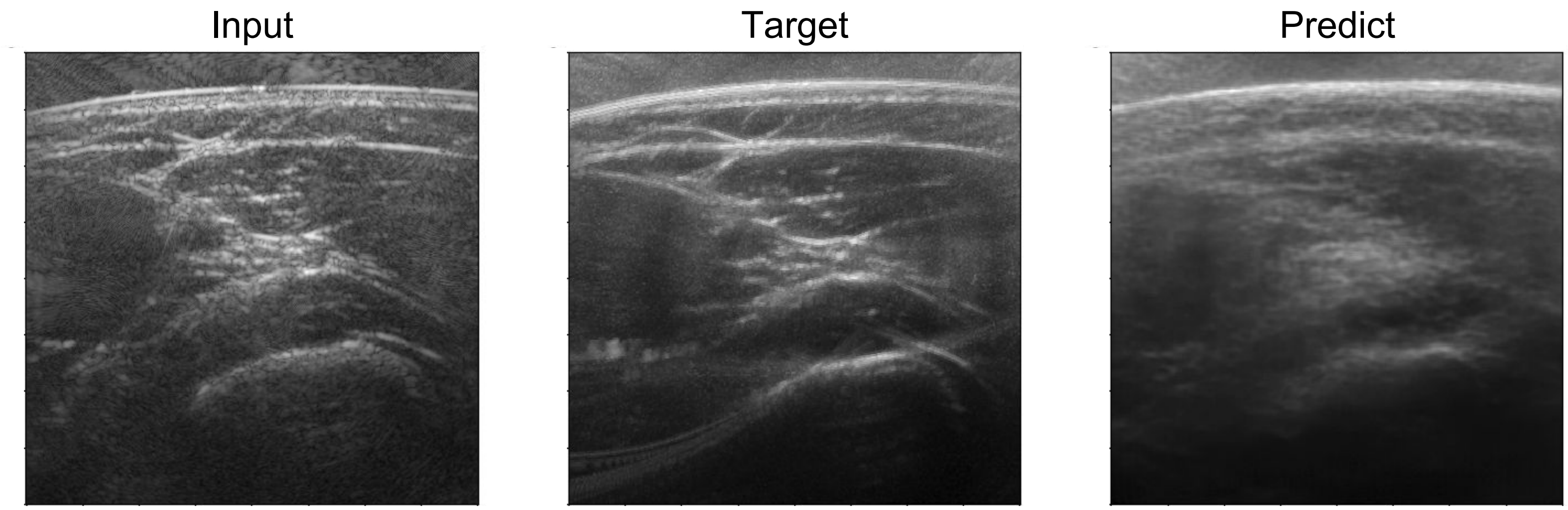


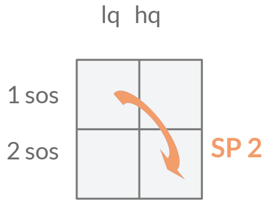
Results



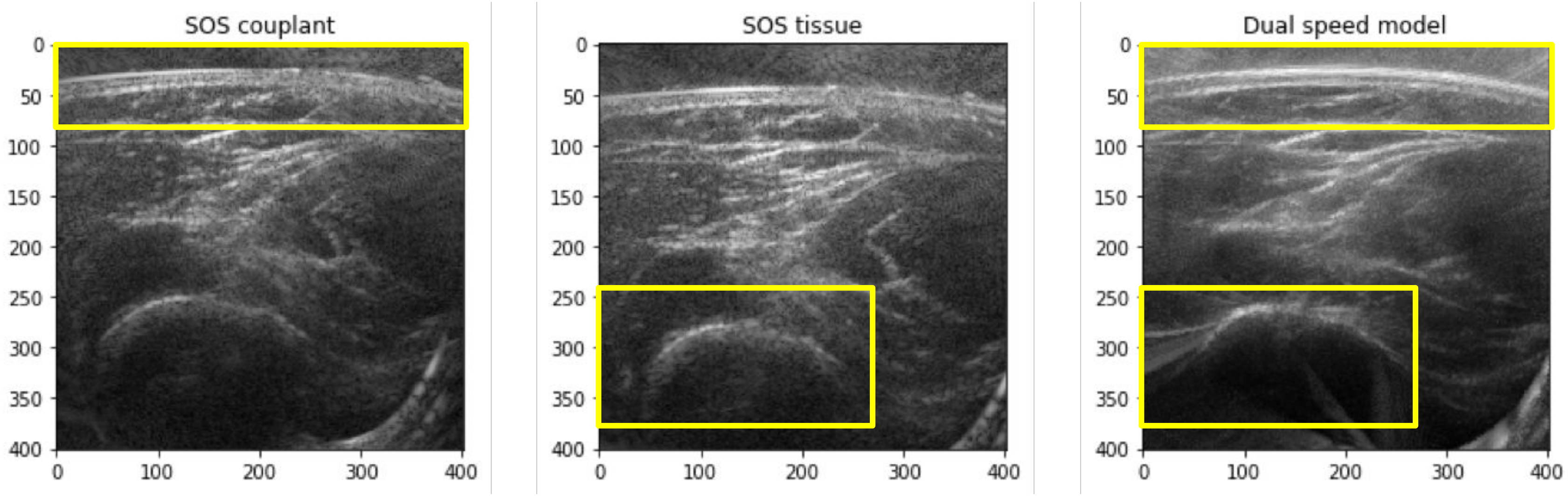
Results

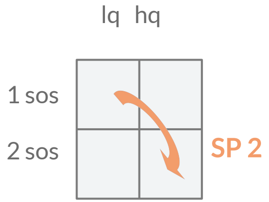






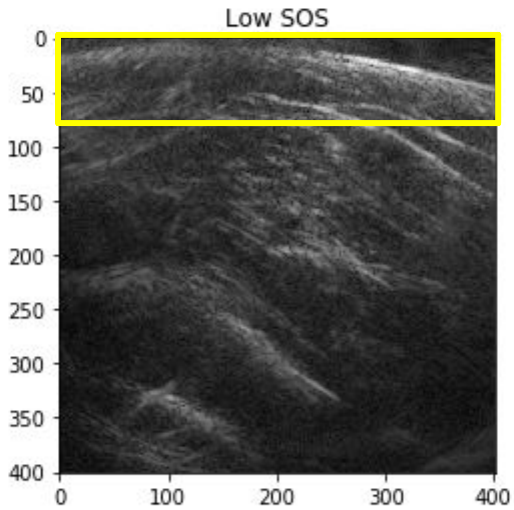
Relaxing the problem

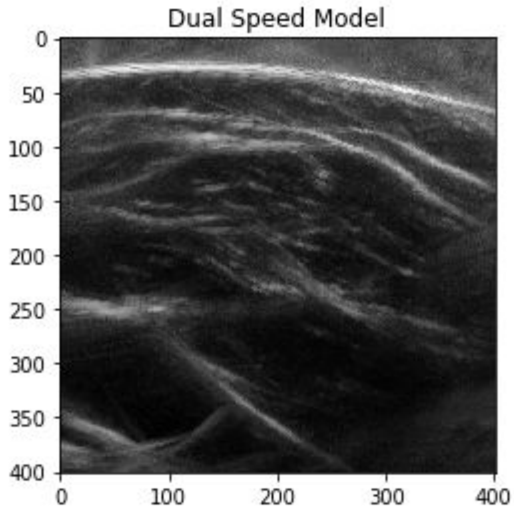


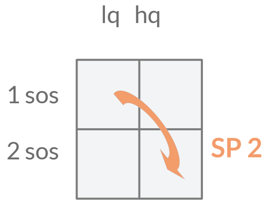


Another look on the data

- Receptive field is limited for skip connections







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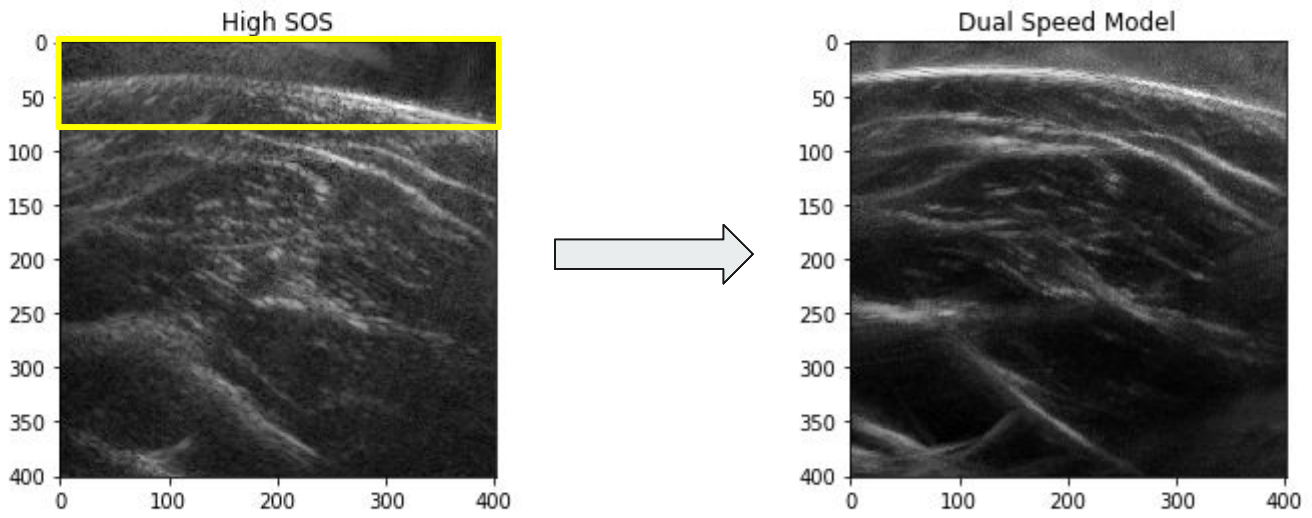
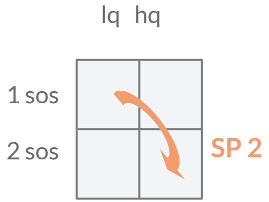


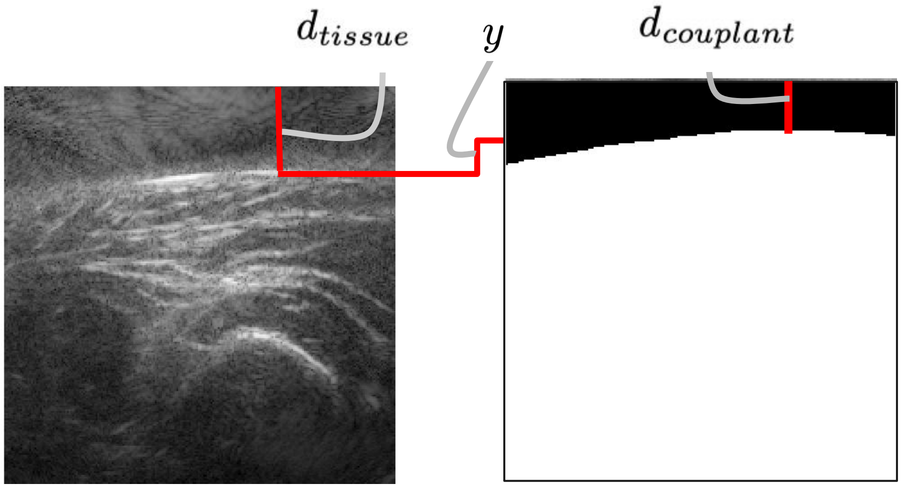


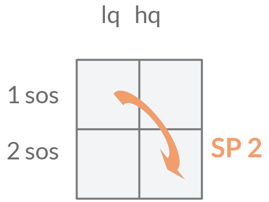
Translating one input

- Calculate the difference y based on the membrane difference

$$y = d_{tissue} - d_{couplant} \approx t \cdot (c_{tissue} - c_{couplant})$$

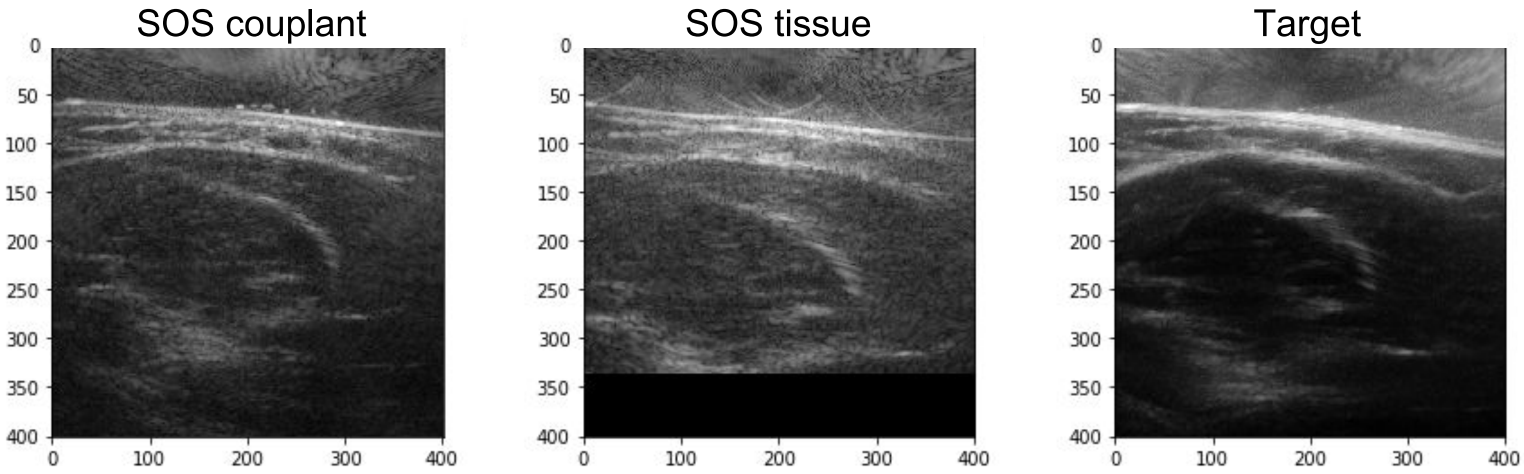
$$t \approx \frac{d_{real}}{c_{couplant}} = \frac{0.04 + d_{couplant}}{c_{couplant}}$$

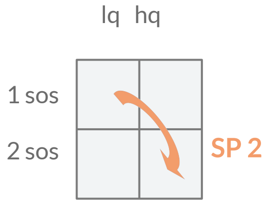




Relaxed Problem - Translation

- Translated SOS tissue image



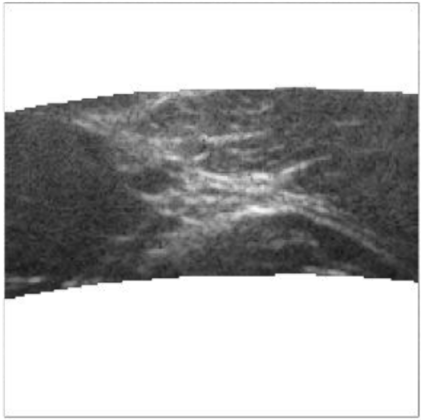


Attention mask used

SOS Couplant

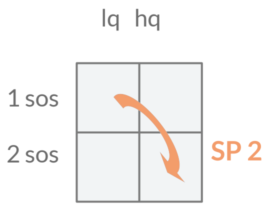
SOS Couplant

SOS Tissue

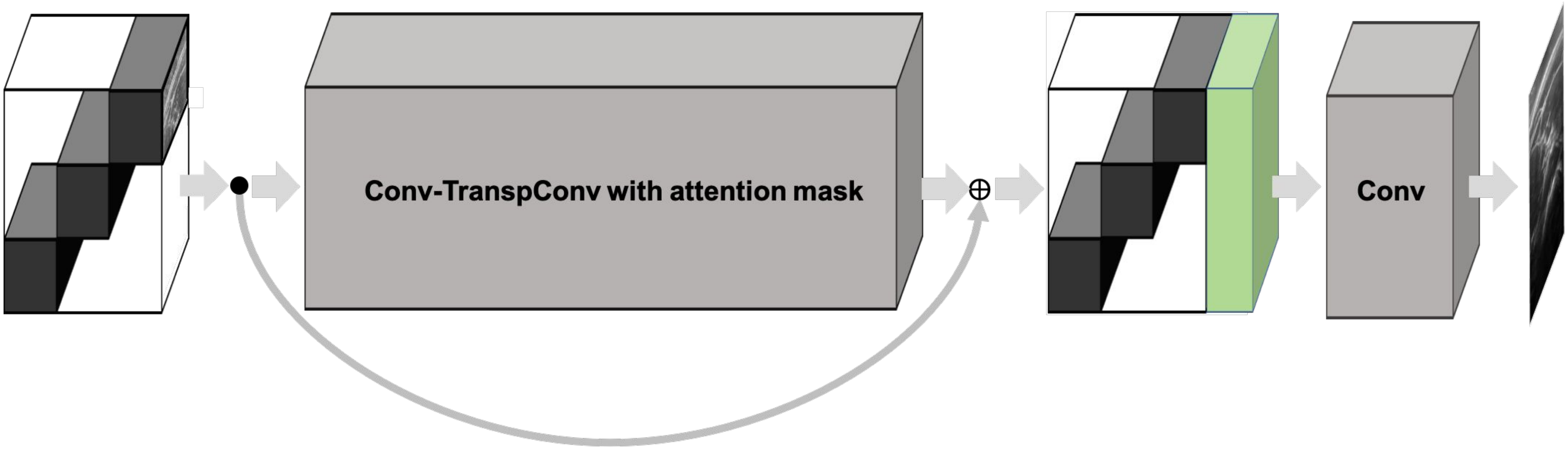


SOS Tissue

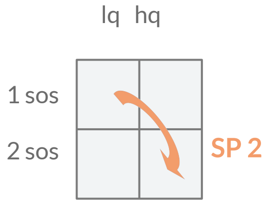
Model



lq
hq
1 sos
2 sos
SP 2

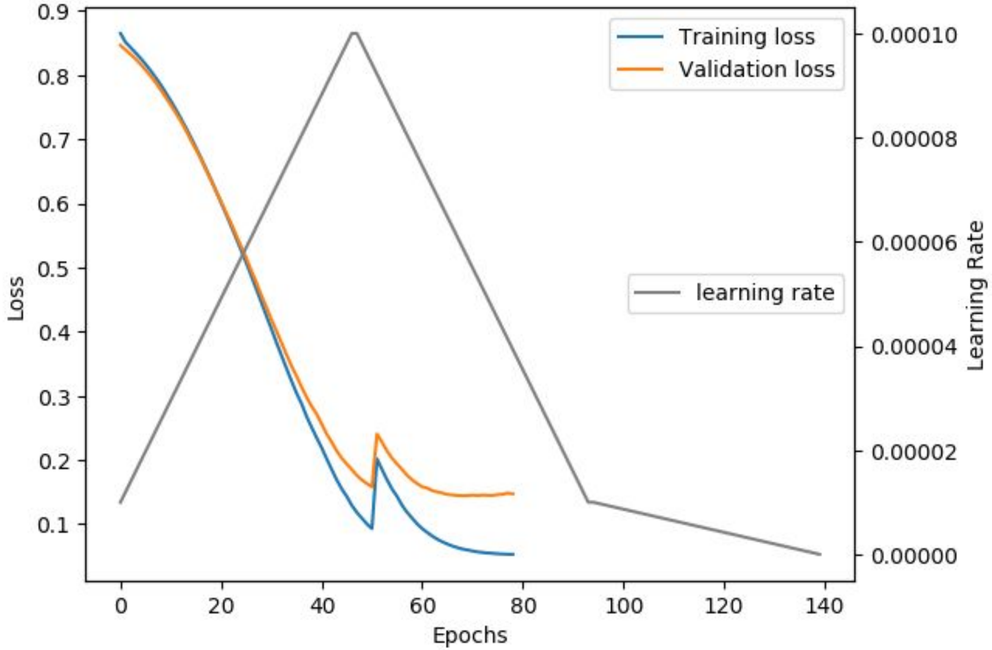


Conv-TranspConv with attention mask
⊕
Conv

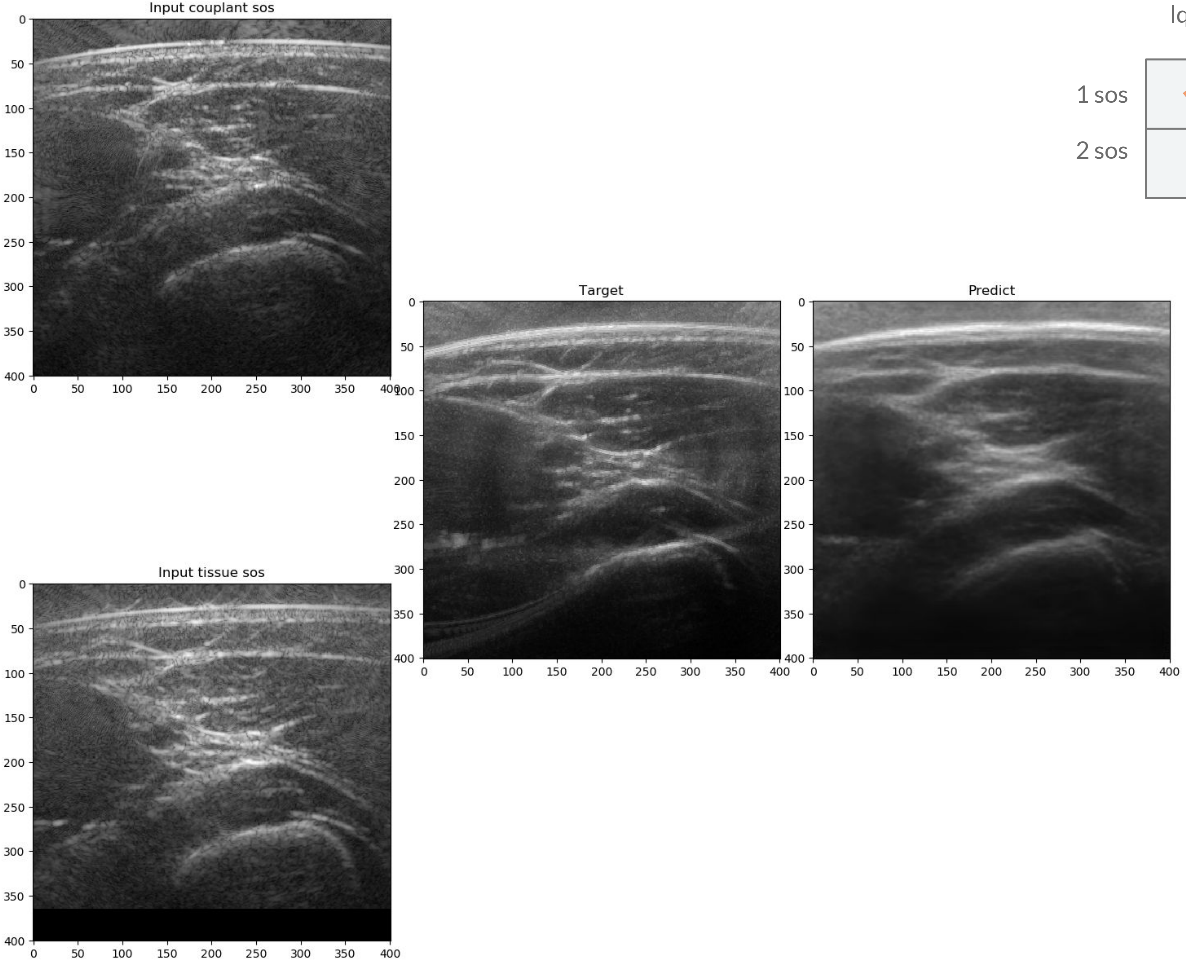


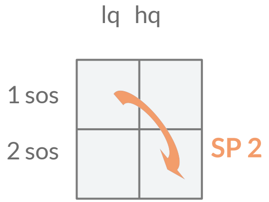
Approach

- Data: sos couplant, sos tissue, masks
- Augmentations: flip, speckle noise, blur
- Architecture: Base Model + Conv Net
- 5 Conv, 5 Transpose conv layers + 2 Conv

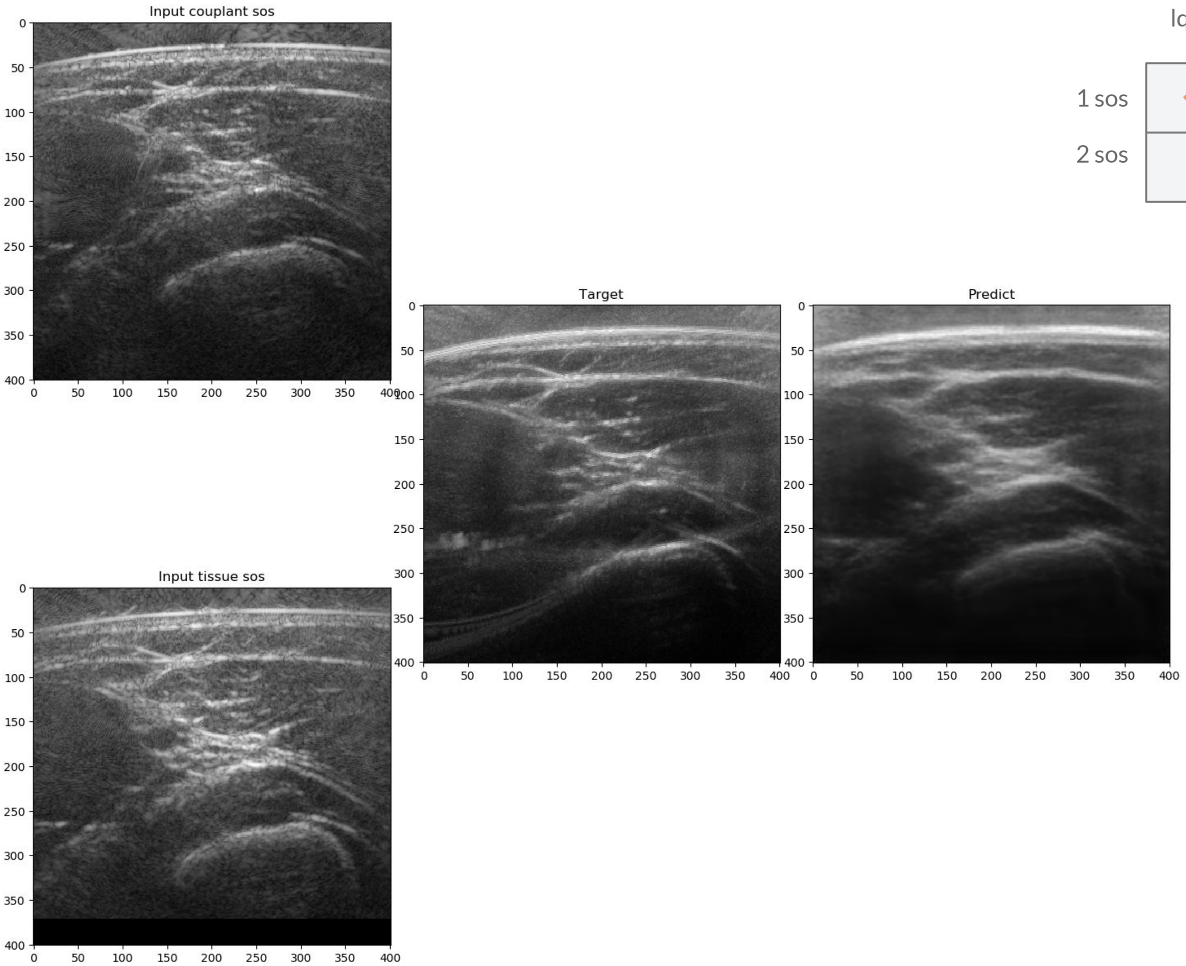


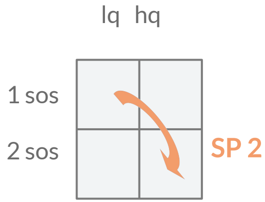
Results


Input couplant sos
Target
Predict
Input tissue sos

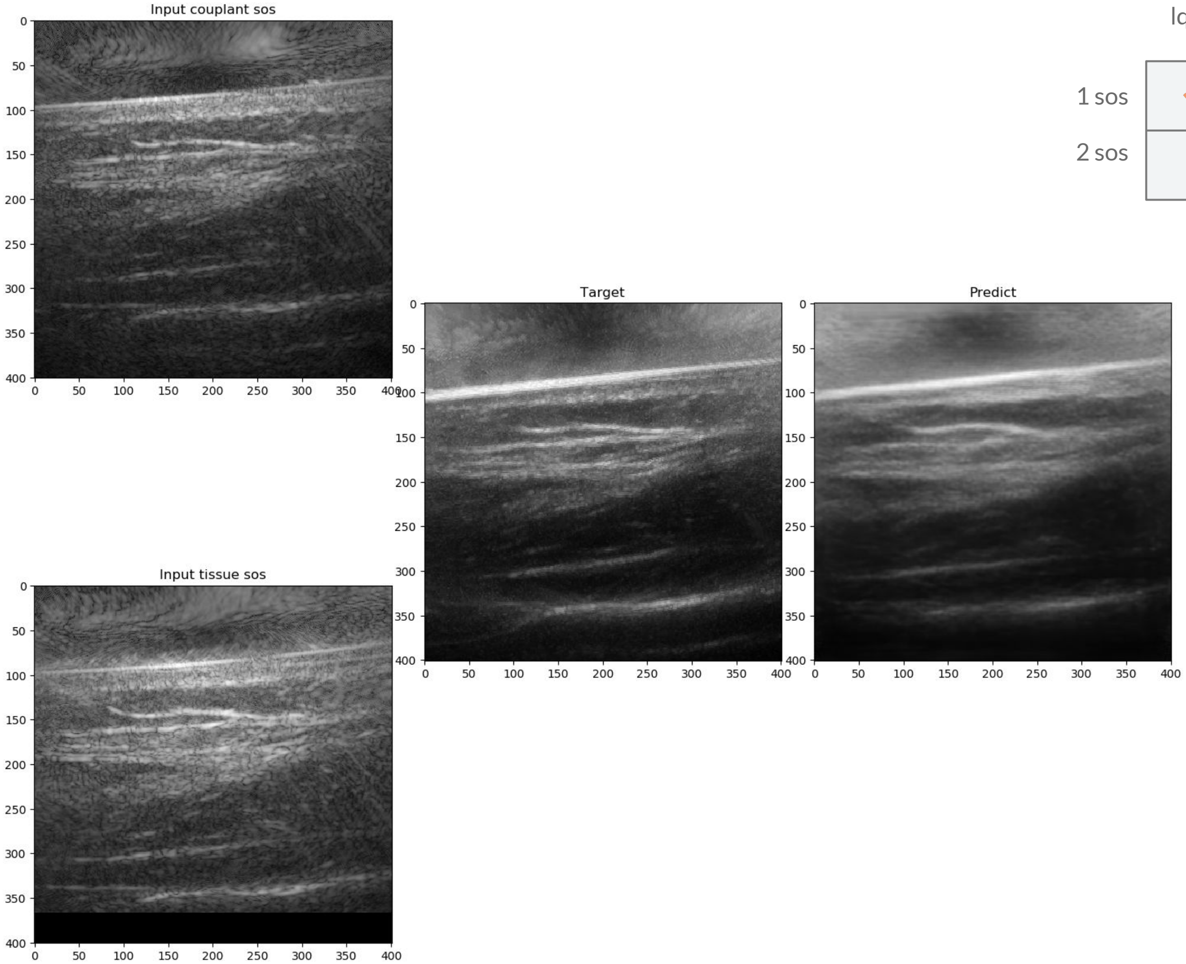

lq
hq
1 sos
2 sos
SP 2

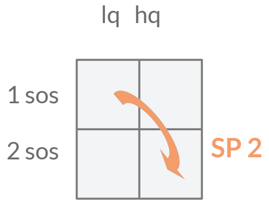
Results


Input couplant sos
Input tissue sos
Target
Predict

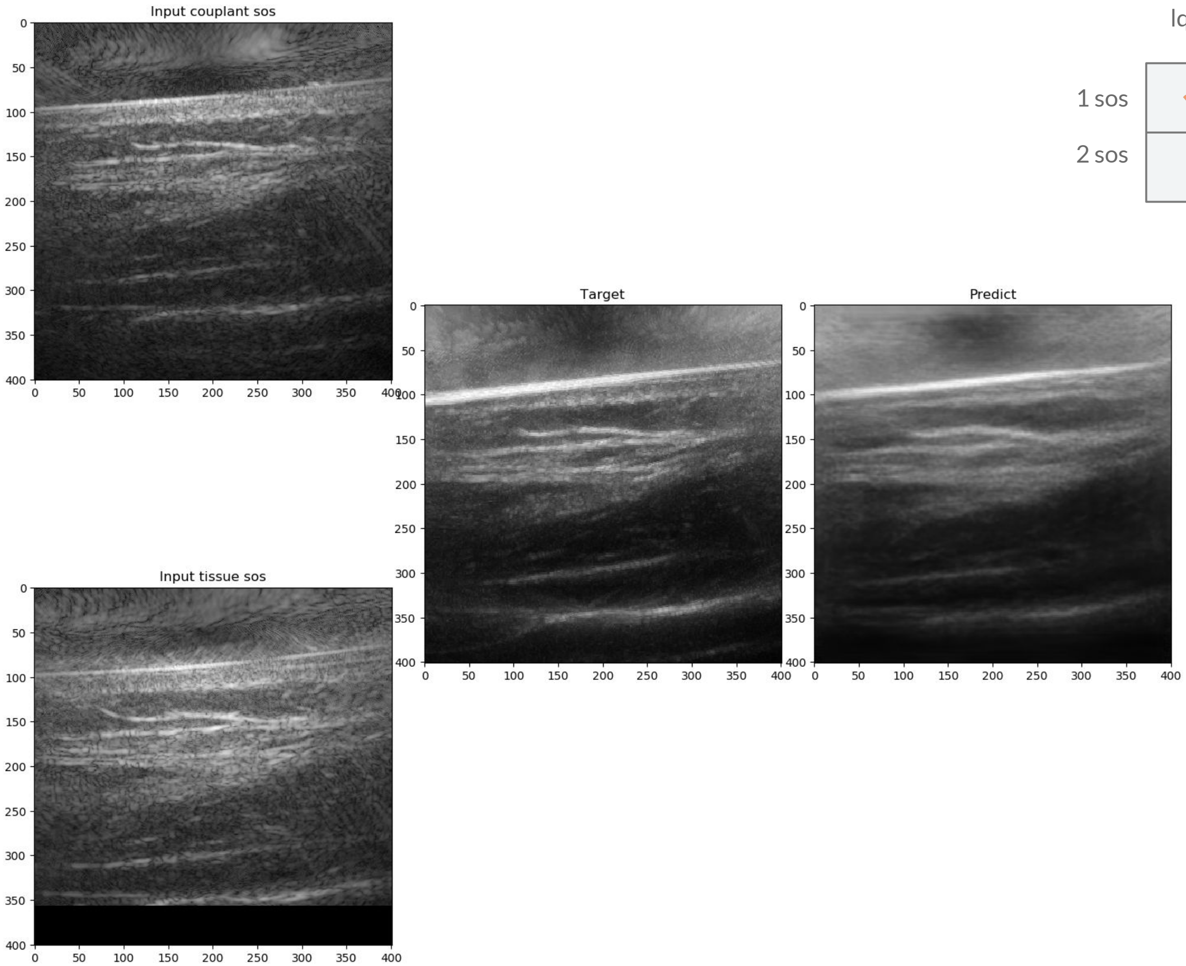

lq hq
1 sos
2 sos
SP 2

Results

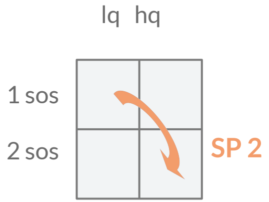

Input couplant sos
Input tissue sos
Target
Predict


lq hq
1 sos
2 sos
SP 2

Results



Input couplant sos
Input tissue sos
Target
Predict



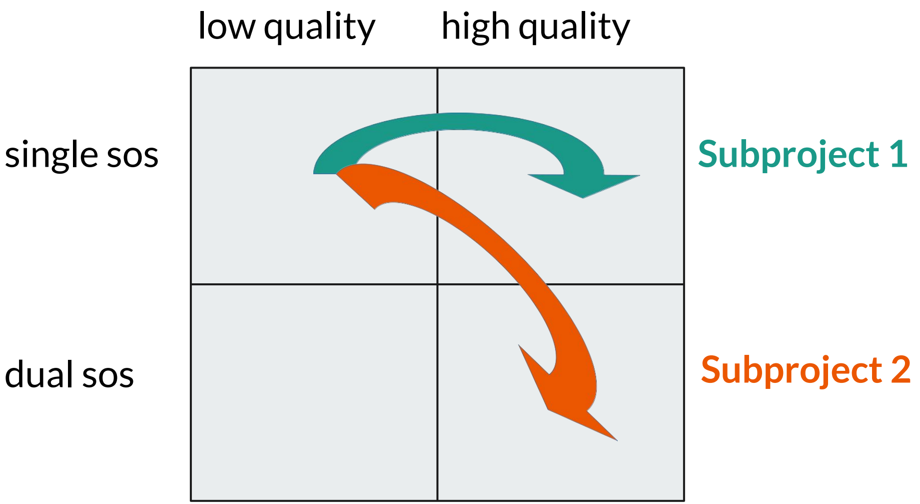
lq hq
1 sos
2 sos
SP 2

Key facts

- Better results on relaxed problem
- Relaxed problem could still be used on the machine
- We used a computationally more complex network

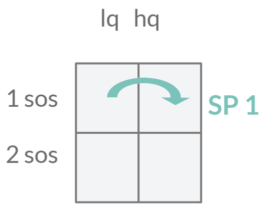
Outline

- ➢ Problem Statement
- ➢ Subproject 1 Ultrasound
- ➢ Subproject 1 Optoacoustic
- ➢ Subproject 2
- ➢ **Conclusion**



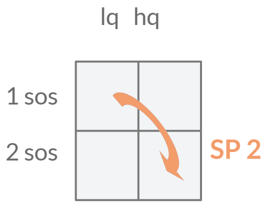
Conclusion

Subproject 1



Ultrasound	Optoacoustic
Good results as warm-up project	Very good results based on our evaluation methods

Subproject 2



Original	Relaxed
Learned deformations at the cost of image quality	Learned deformations with better visual quality

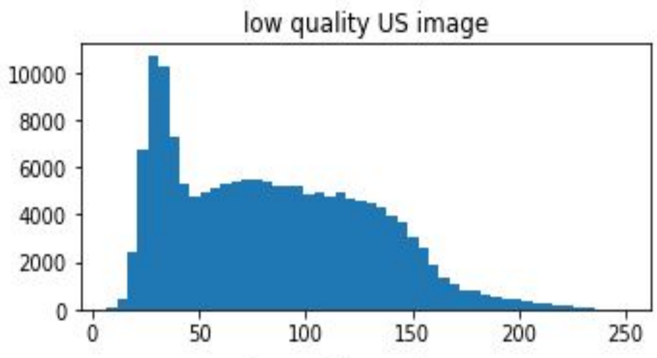
Thank you for your attention!

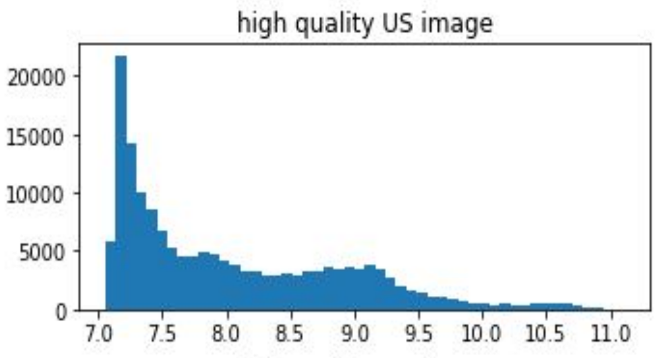
Backup slides

- **Preprocessing, Augmentation**
- Convolutional Networks
- Optimization
- Evaluation by experts
- Optoacoustic approaches
- More on SP2

Data Preprocessing: Scaling

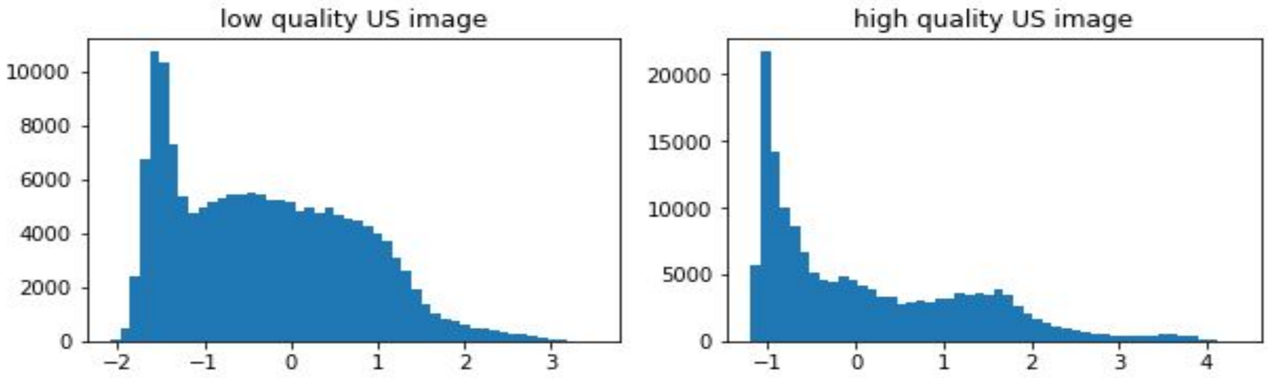
histograms of unscaled low and high quality ultrasound images





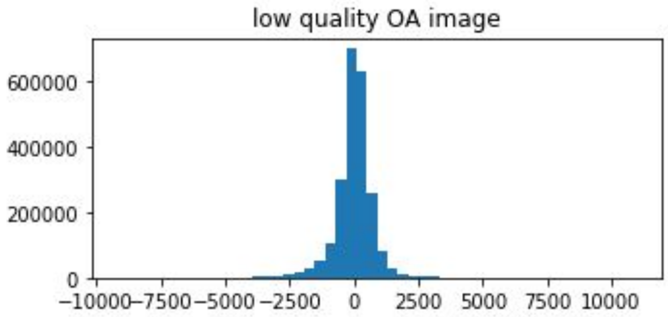
Data Preprocessing: Scaling

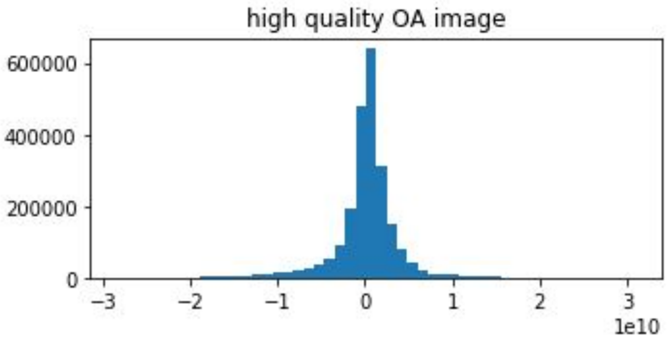
histograms of **scaled** low and high quality ultrasound images



Data Preprocessing: Scaling

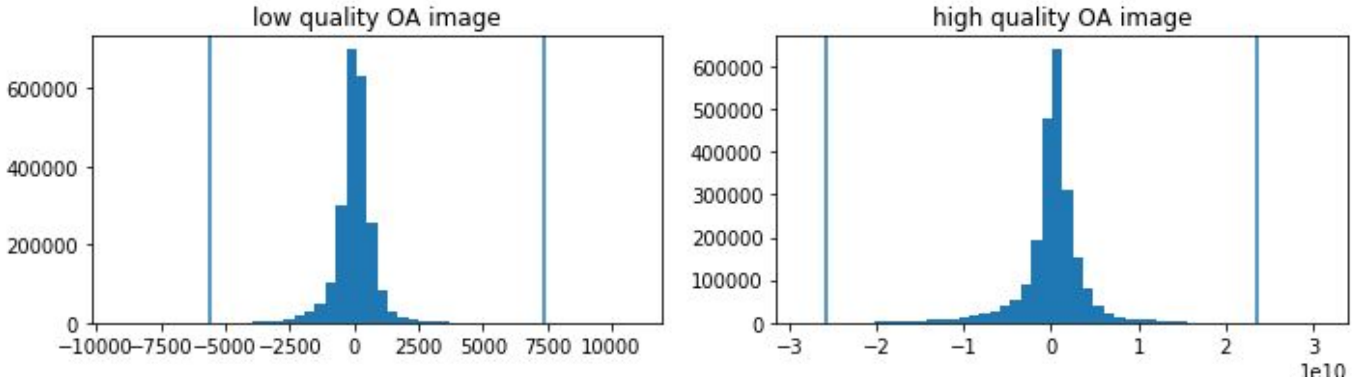
histograms of unscaled low and high quality optoacoustic images





Data Preprocessing: Truncating OA images

histograms of unscaled low and high quality optoacoustic images with 0.01 and 99.99% quantiles



Data augmentation

- Generating more data from the data you have
- method to increase number of training samples, makes model more robust

Our augmentation methods:

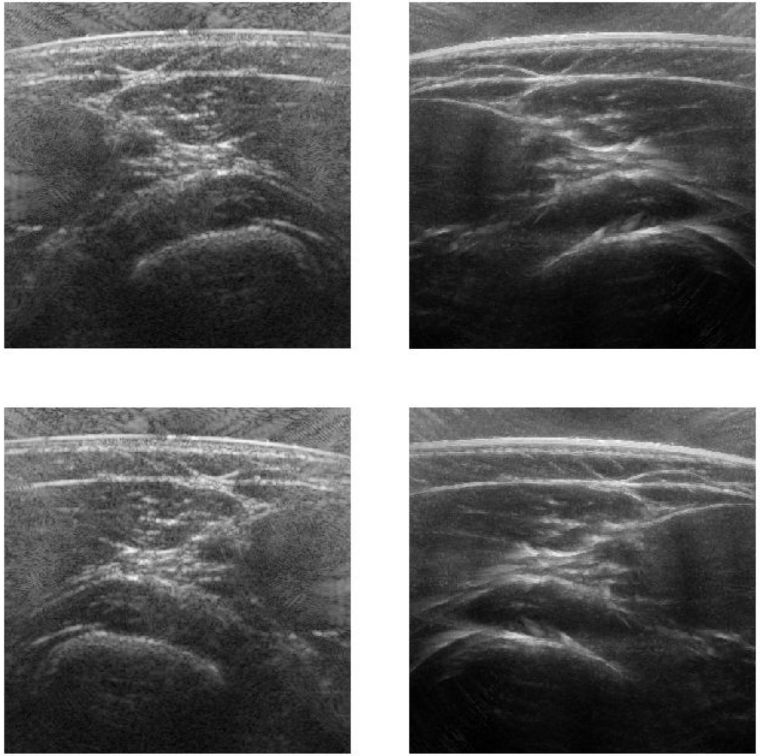
- flip
- crop
- deform
- additional frames
- blur
- speckle noise

Augmentation: Flip

- Flips the image horizontally

original

augmented



low quality

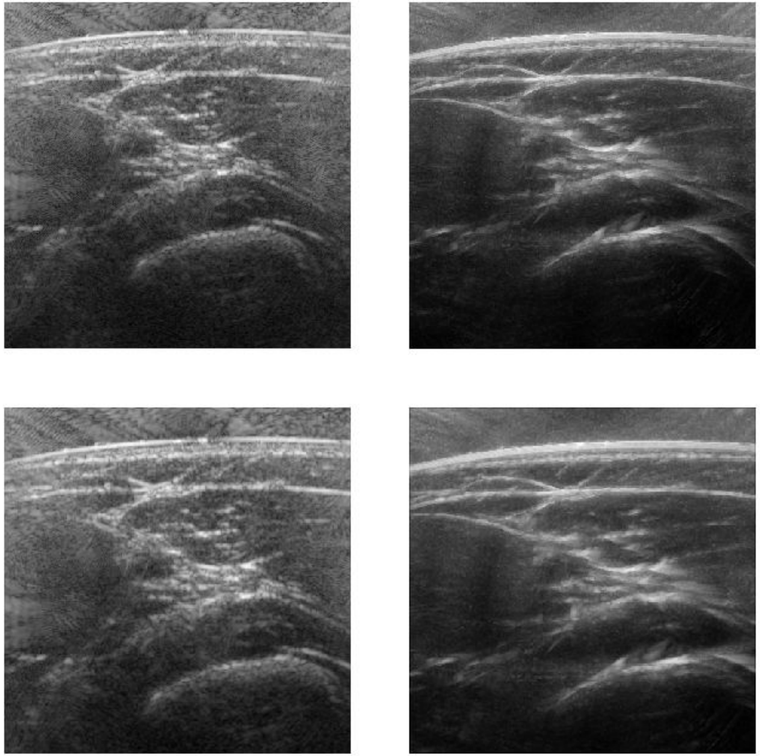
high quality

Augmentation: Crop

- Crops the lower and either the left or the right side
- random component in side chosen and size of crop

original

augmented

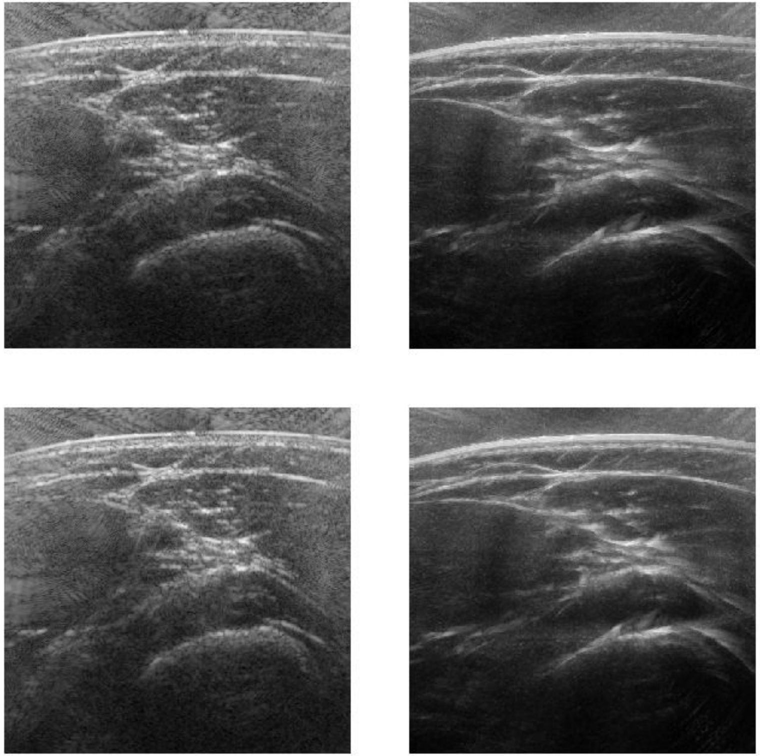


low quality

high quality

Augmentation: Deform

- Applies an elastic deformation to the images
- inspired by U-Net, not exactly the same method
- 3 different deformations per image



original

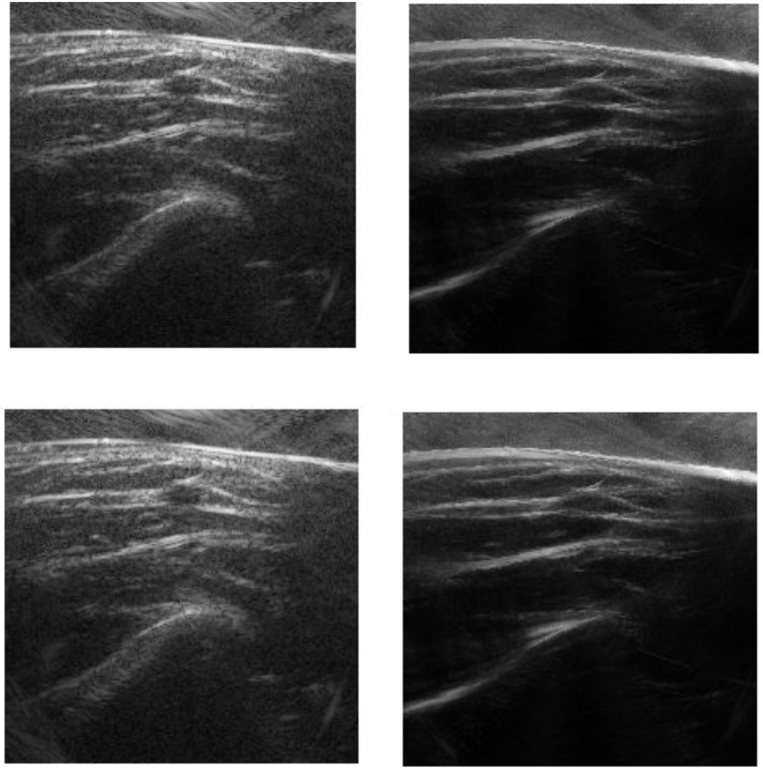
augmented

low quality

high quality

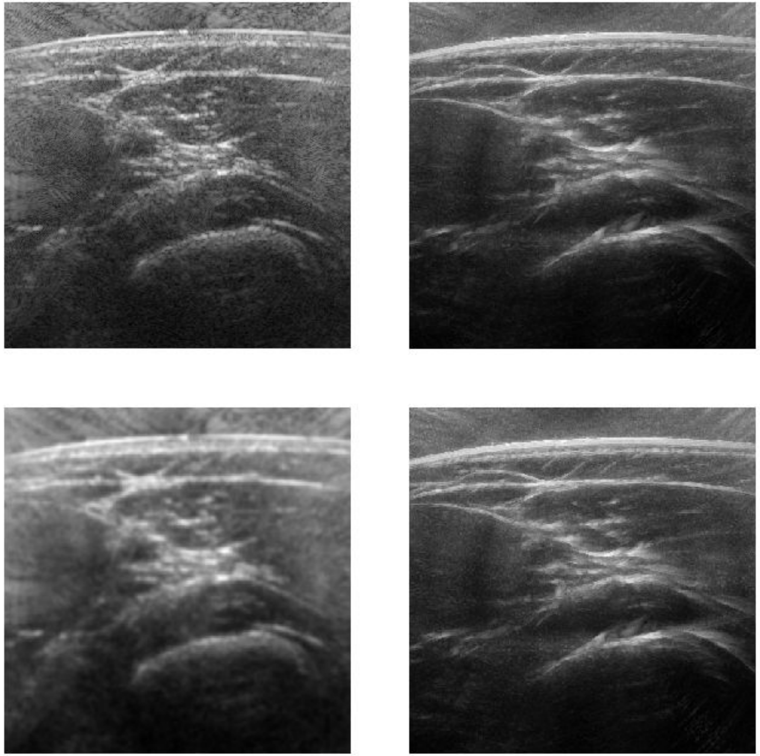
Augmentation: Additional frames

- Additional frames captured shortly after each other
- cannot be considered independent



Augmentation: Blur

- Blurs the low quality image with a gaussian filter
- only for US data



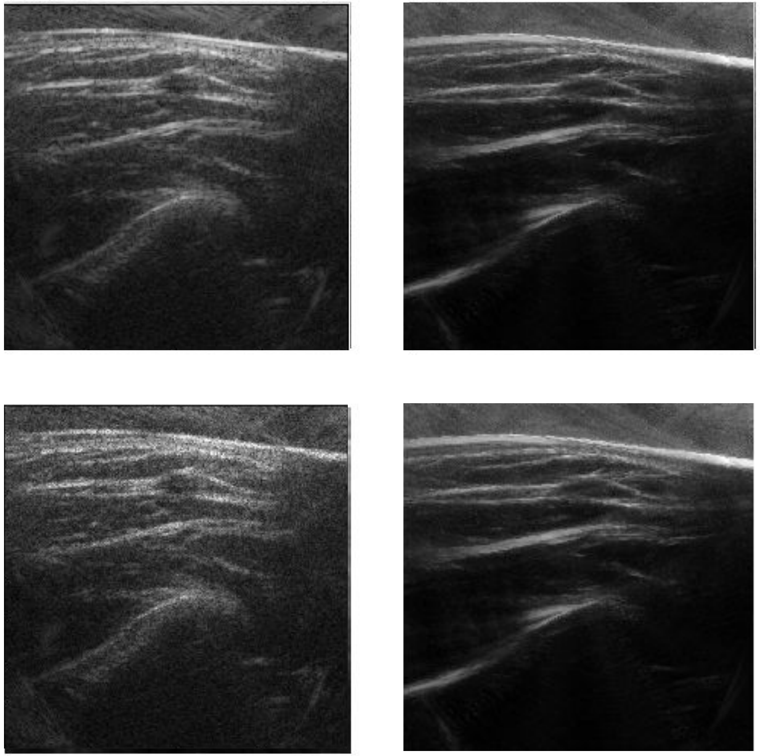
Augmentation: Speckle noise

- multiplicative Gaussian noise
- simulates speckle noise, often found in US images

- only for US data

original

augmented



low quality

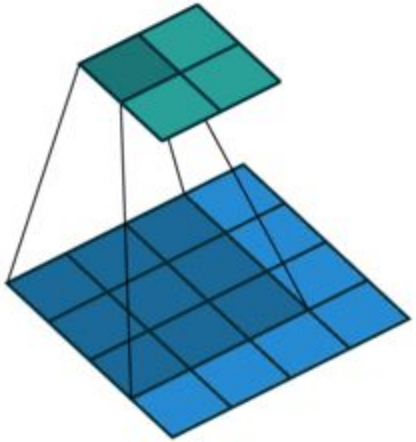
high quality

Backup slides

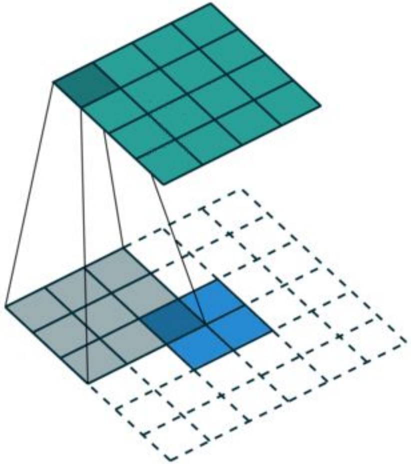
- ➢ Preprocessing, Augmentation
- ➢ **Convolutional Networks**
- ➢ Optimization
- ➢ Evaluation by experts
- ➢ Optoacoustic approaches
- ➢ More on SP2

Convolution and Transpose Convolution

Convolution



Transpose-Convolution



[1] Vincent Dumoulin, Francesco Visin - [A guide to convolution arithmetic for deep learning]

Backup slides

- ➢ Preprocessing, Augmentation
- ➢ Convolutional Networks
- ➢ **Optimization**
- ➢ Evaluation by experts
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- ➢ More on SP2

Weight regularization

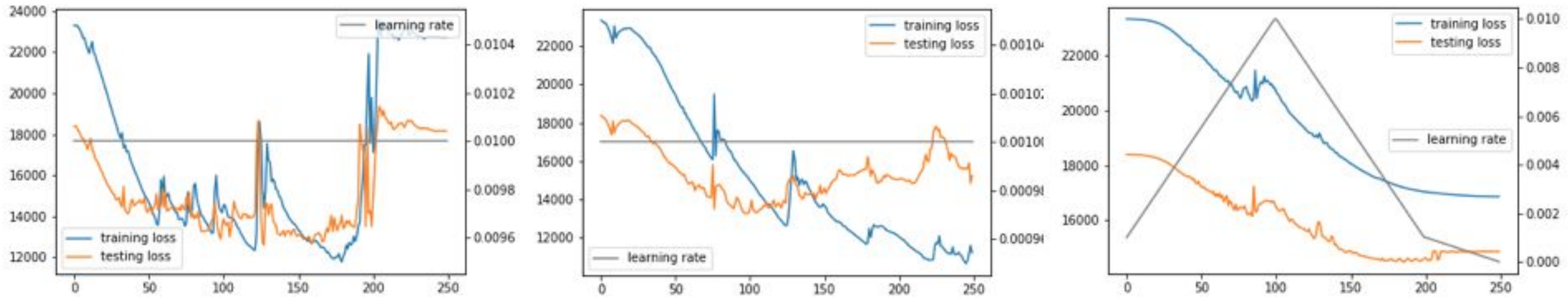
2 popular forms:

- **l2 regularization:** $\mathcal{L}$(predict, target) = L(predict, target) + reg_param/2*||weights||^2
- **weight decay:** directly change the step the optimizer takes:

  new_weights = weights - normal_update - reg_param*learn_rate*weights
- for standard SGD, these are equivalent, not so for Adam

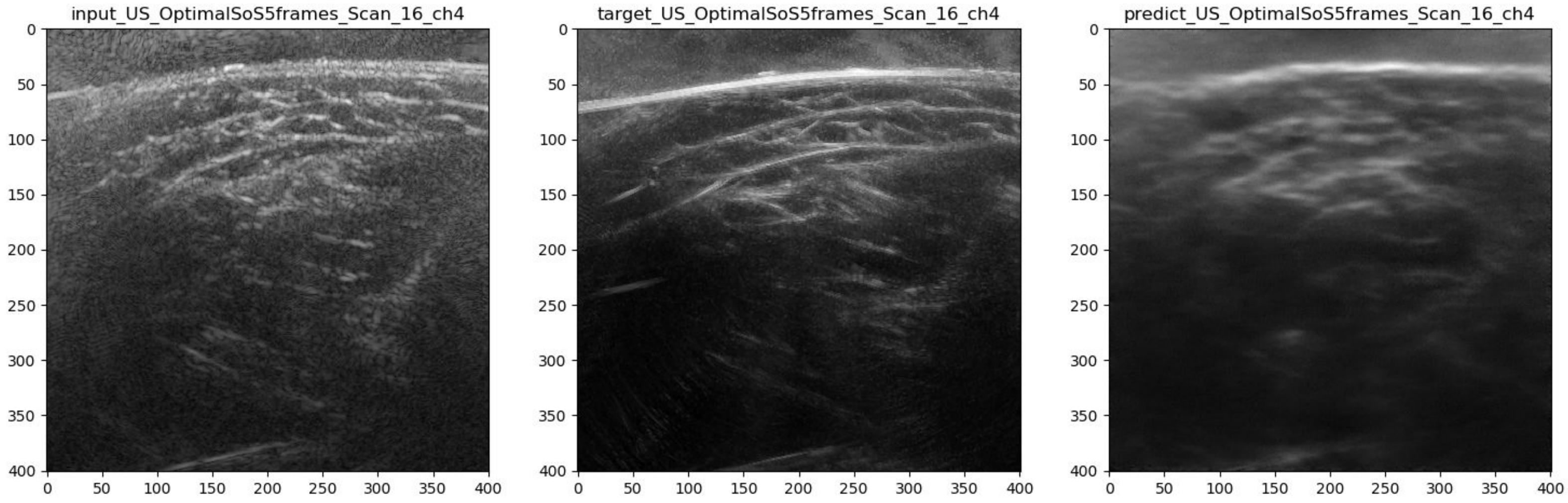
AdamW: implementation of weight decay for Adam (Loshchilov, Hutter 2017)

Learning rate schedule - One Cycle



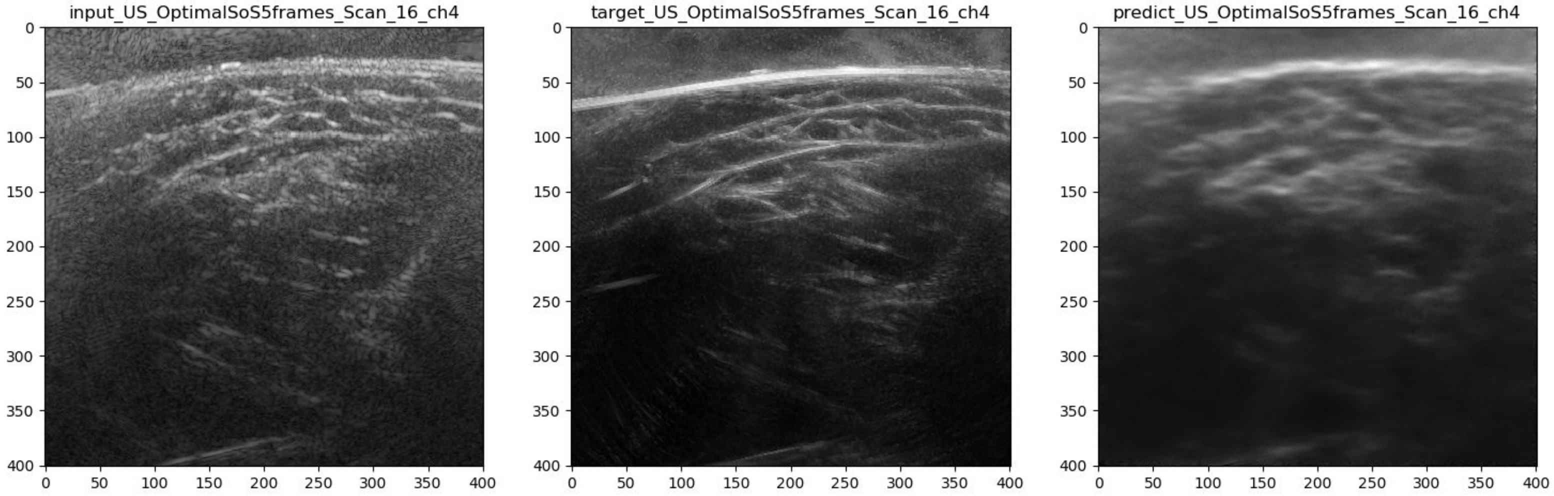
Loss function evaluation

Smooth L1 Loss:



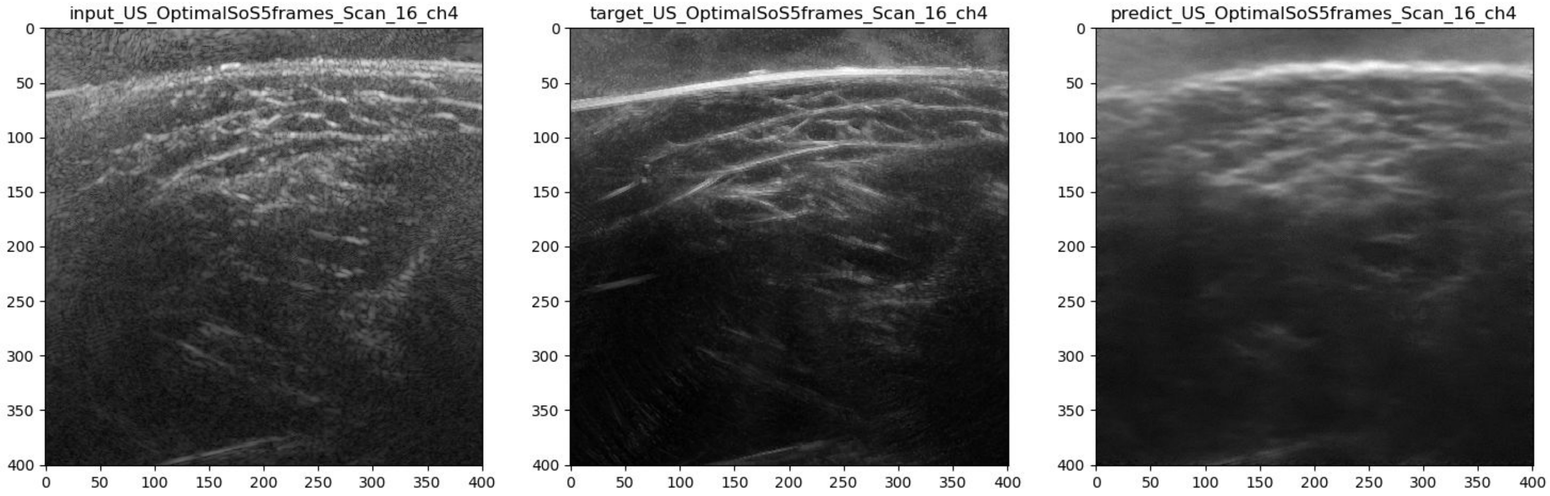
Loss function evaluation

L1 Loss:



Loss function evaluation

MSE Loss:



Backup slides

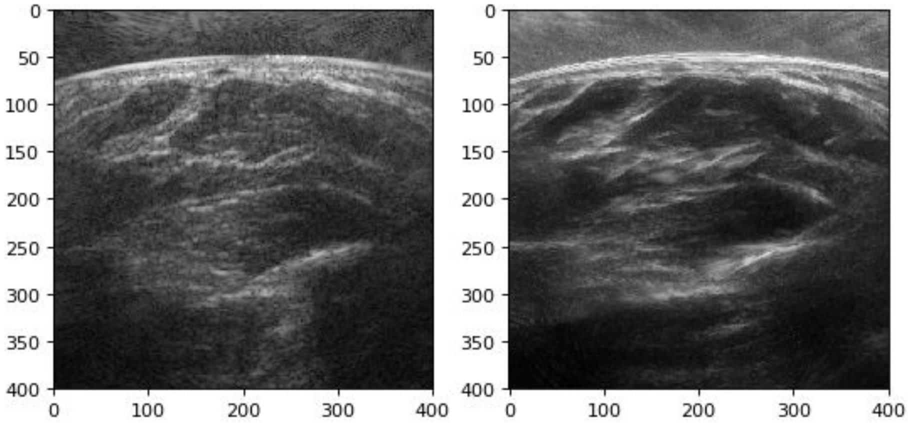
- ➢ Preprocessing, Augmentation
- ➢ Convolutional Networks
- ➢ Optimization
- ➢ **Evaluation by experts**
- ➢ Optoacoustic approaches
- ➢ More on SP2

Proposal for the evaluation by professionals

Doctors are presented with a series of image pairs

and are asked questions about:

- image quality
- image content

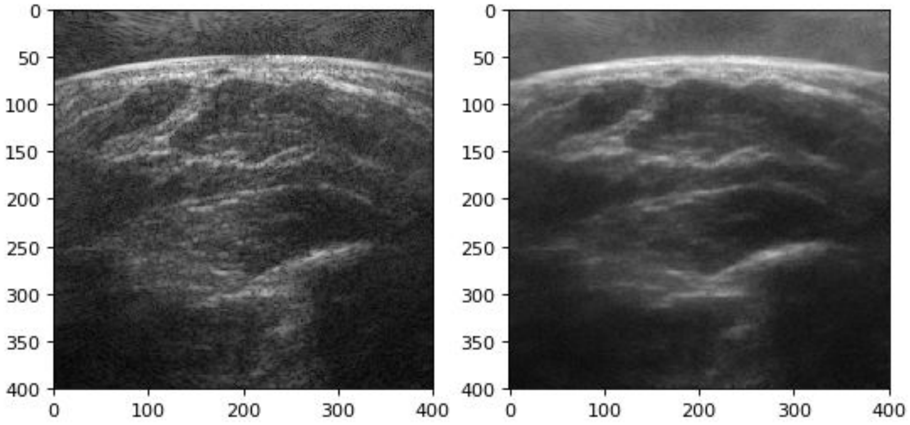


Proposal for the evaluation by professionals

Doctors are presented with a series of image pairs

and are asked questions about:

- image quality
- image content

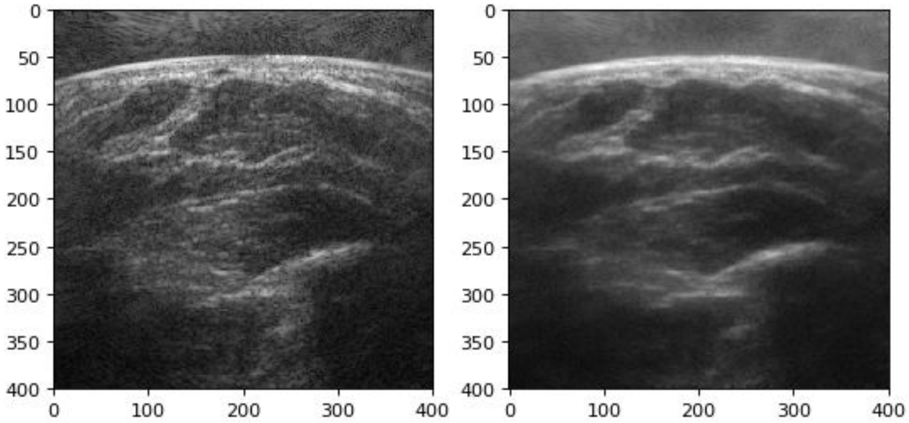


Proposal for the evaluation by professionals

image quality

“Taking the left image as a baseline (quality score 0), how would you rate the quality of the right image on a scale from -10 to 10?”

-10 0 10



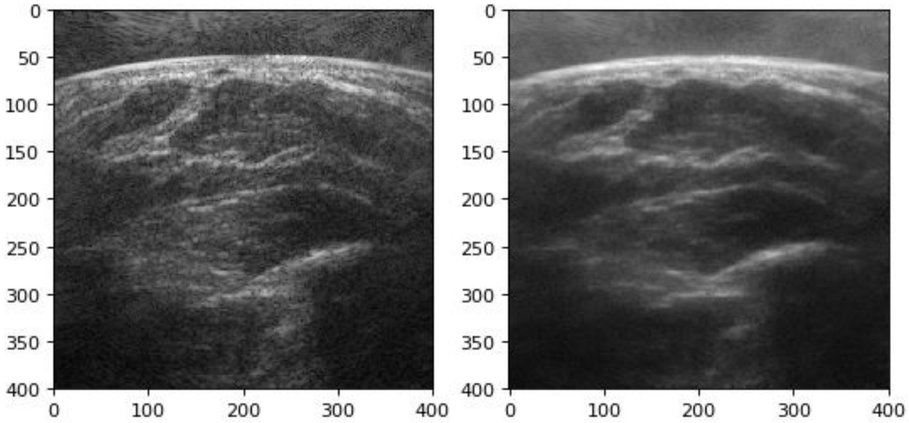
Proposal for the evaluation by professionals

image content

“Are there differences in the content of the images? (apart from noise)

For example:

- something present in the right that isn’t there in the left
- something missing in the right that is present in the left image



If so, please describe the difference and its location in the images.”

Proposal for the evaluation by professionals

How to interpret results:

- **image content:** read comments, look at images

Proposal for the evaluation by professionals

How to interpret results:

- image content: read comments, look at images
- **image quality:**
  - produces data like this
  - we want to test that our images are not worse than the target images
  - can be tested with a **noninferiority test**

	target	pred.
Scan 1	4	3
Scan 2	6	6
Scan 3	2	3
...	...	...

Proposal for the evaluation by professionals

How to interpret results:

- image content: read comments, look at images
- **image quality:**
    - produces data like this
    - we want to test that our images are not worse than the target images
    - can be tested with a **noninferiority test**

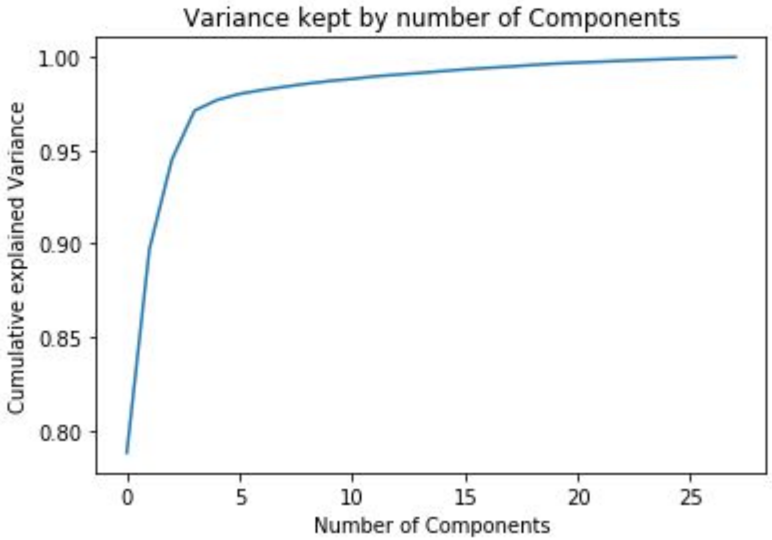
	target	pred.	pred.-target
Scan 1	4	3	-1
Scan 2	6	6	0
Scan 3	2	3	1
...	...	...	

Backup slides

- ➢ Preprocessing, Augmentation
- ➢ Convolutional Networks
- ➢ Optimization
- ➢ Evaluation by experts
- ➢ **Optoacoustic approaches**
- ➢ More on SP2

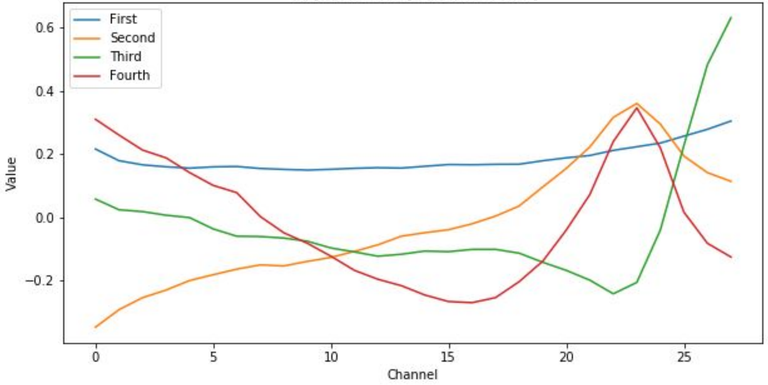
Optoacoustic - PCA Approach

- PCA fitted on high quality training data
- almost all of the variance kept with 4 components

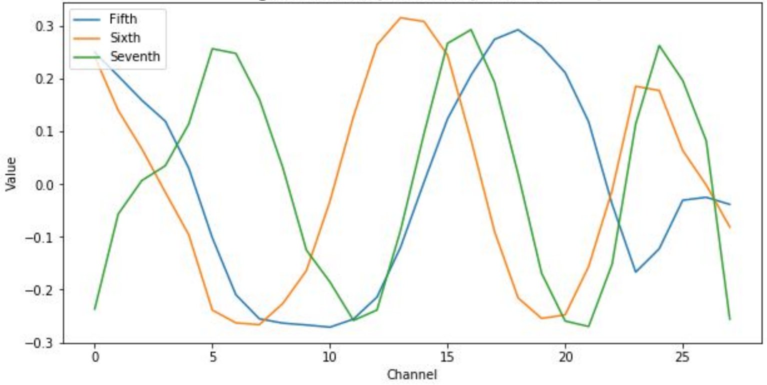


Optoacoustic - PCA Approach

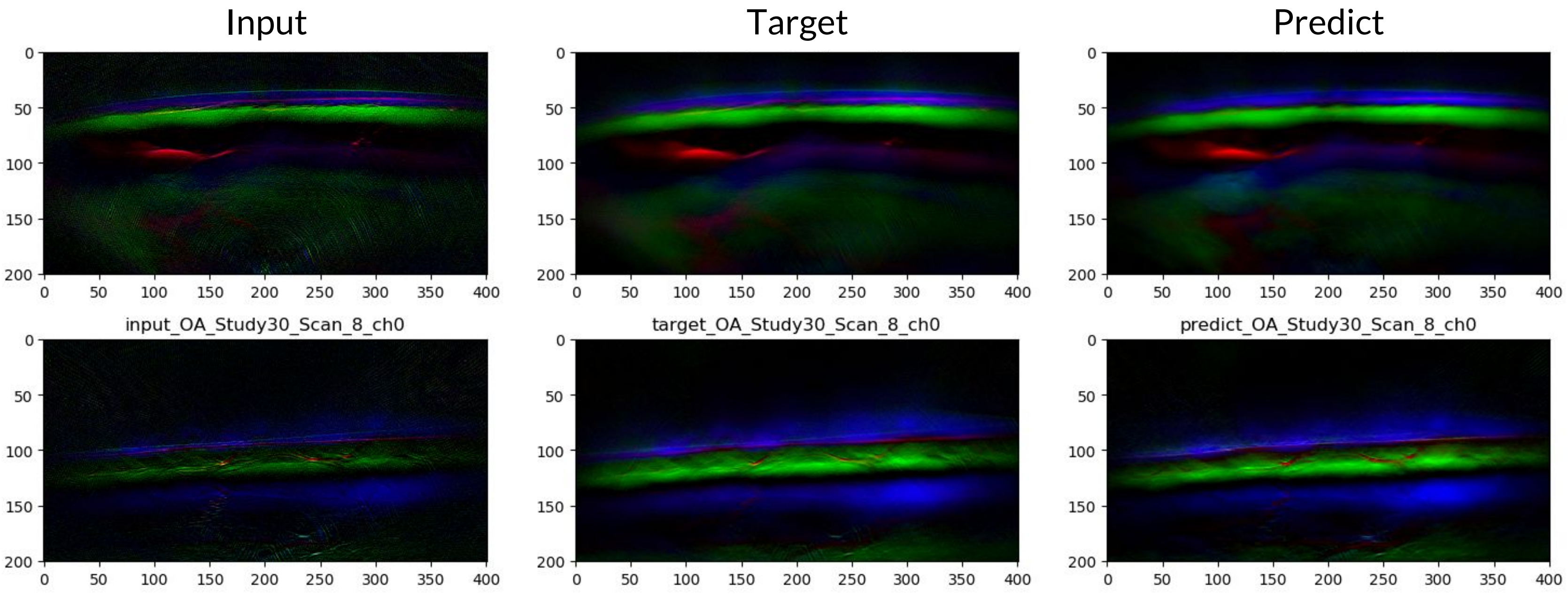
Frist four principle components



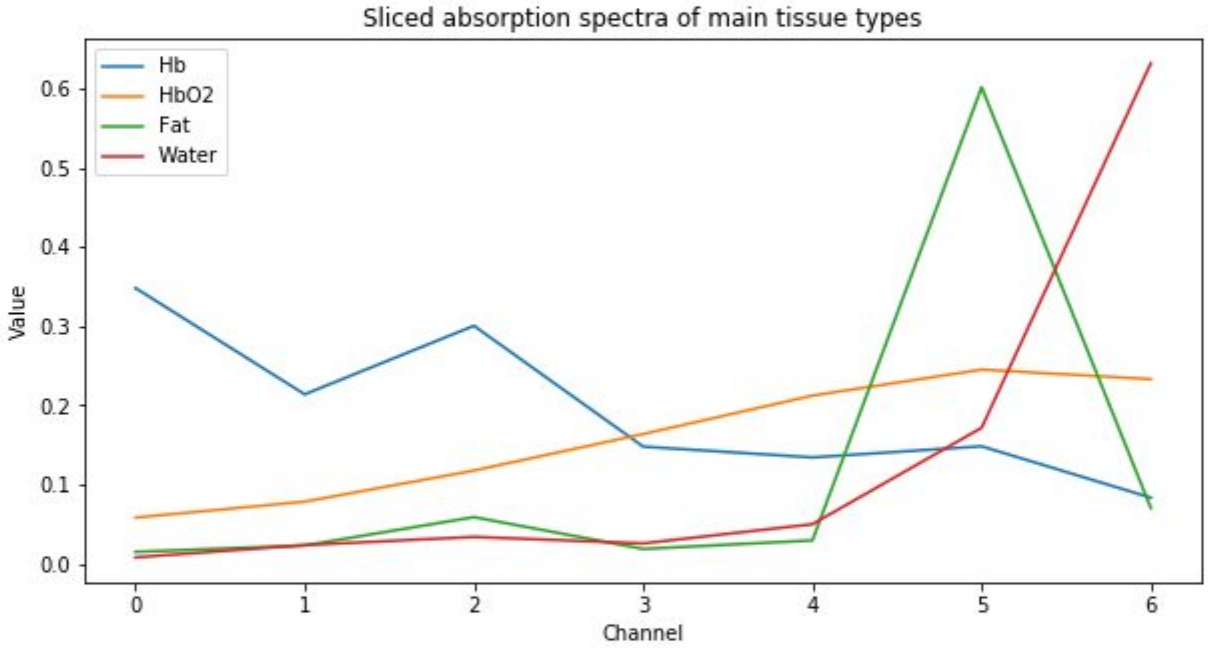
Following three principle components



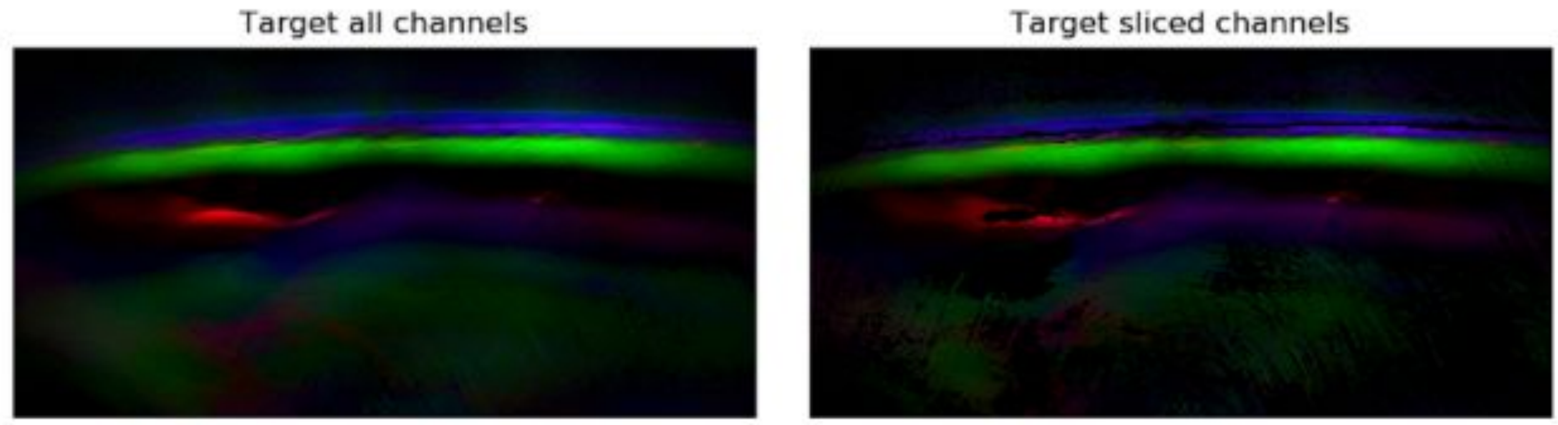
Optoacoustic - PCA Approach



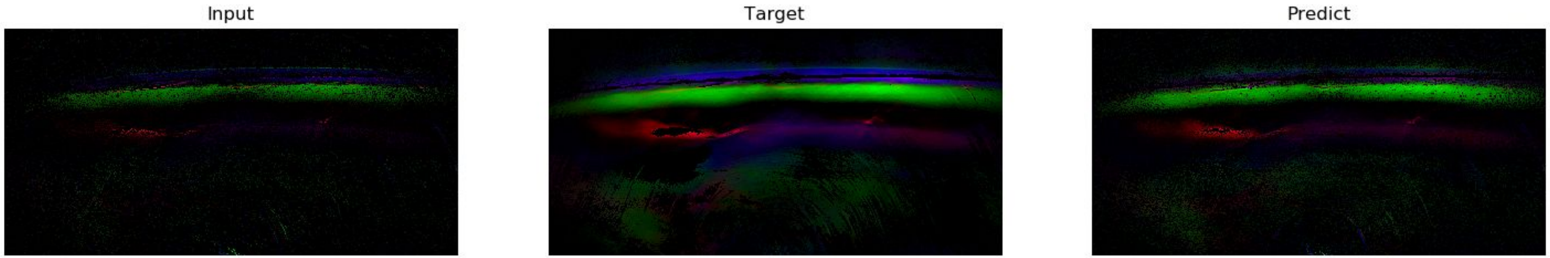
Optoacoustic - Sliced Approach



Optoacoustic - Sliced Approach



Optoacoustic - Sliced Approach



Backup slides

- ➢ Preprocessing, Augmentation
- ➢ Convolutional Networks
- ➢ Optimization
- ➢ Evaluation by experts
- ➢ Optoacoustic approaches
- ➢ **More on SP2**

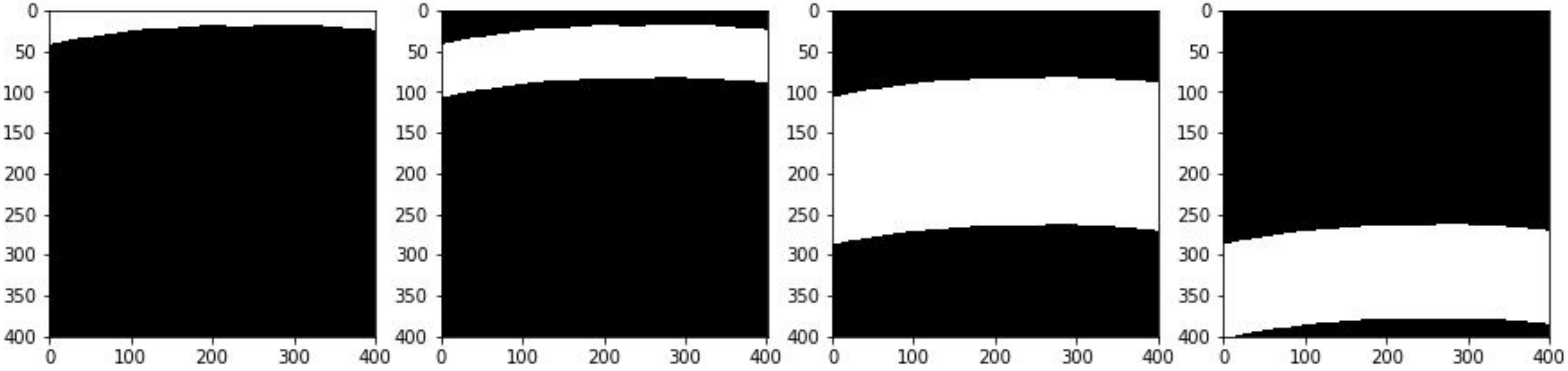
Subproject 2 - Extended Relaxed Approach

Main Differences:

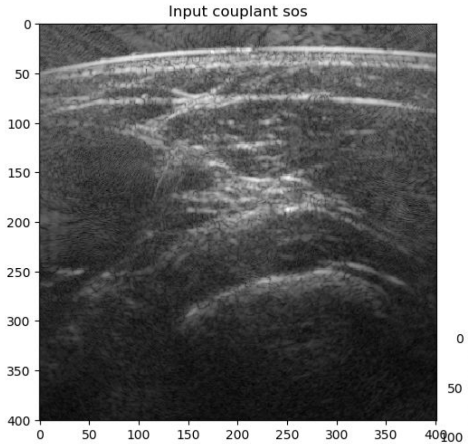
- Individual Calculation of the needed translation of the input tissue speed of sound
- Passing over the whole input to the large convolutions in the end
- Using no block attention masks, but the membrane mask of each sample
- Long training process → Used weights from previously trained model

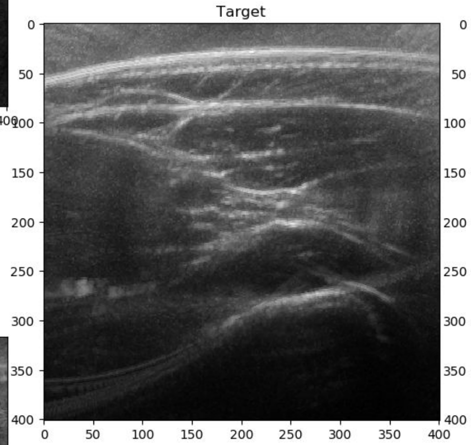
Subproject 2 - Extended Relaxed Approach

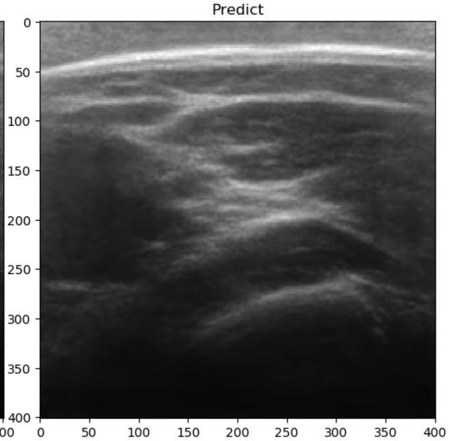
New Attention Masks

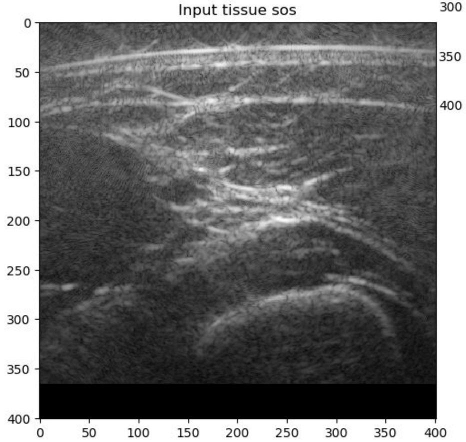


Subproject 2 - New Results

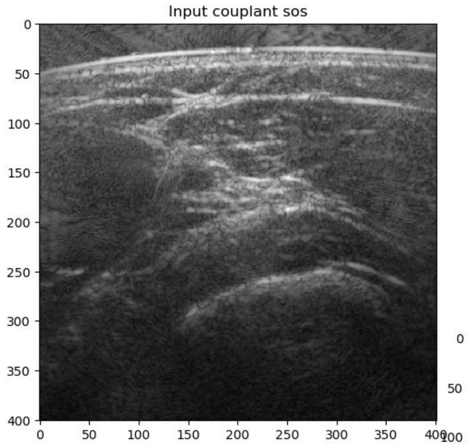


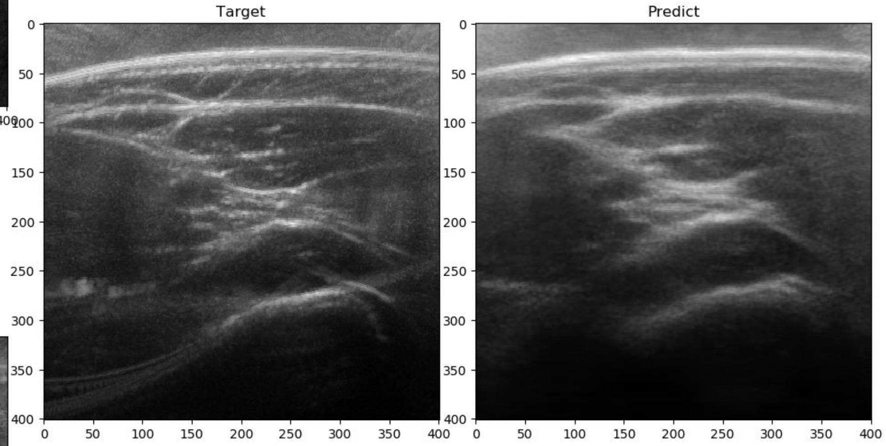


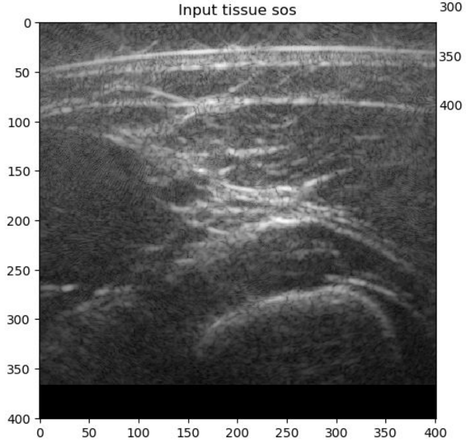




Subproject 2 - Old Results

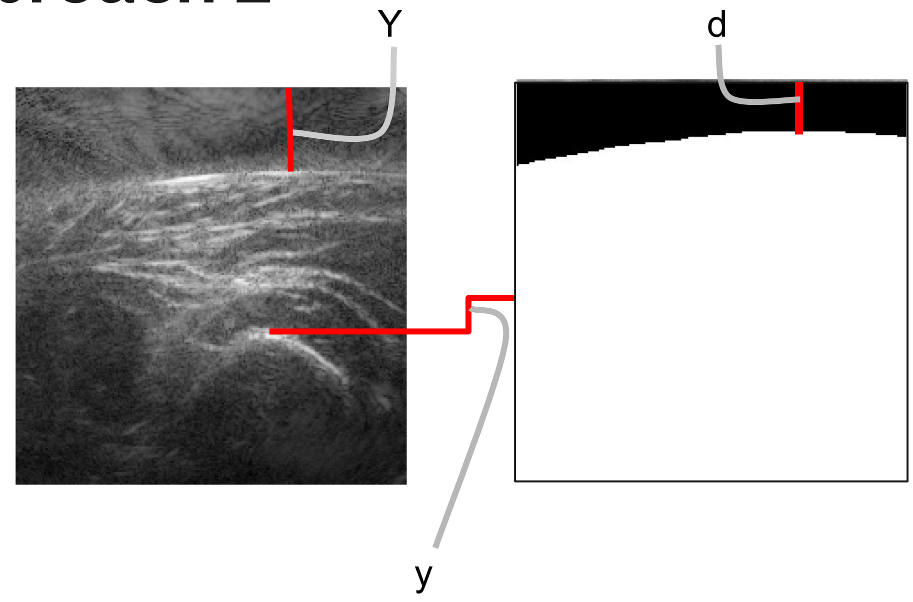




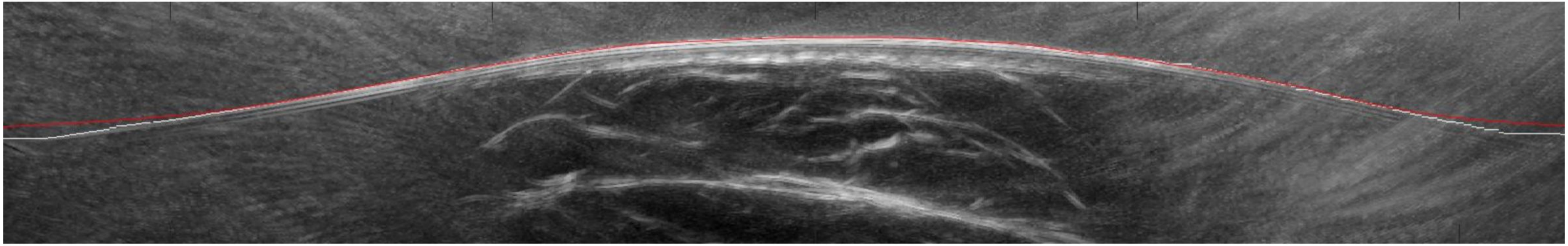


Relaxed Problem - Approach 2

- Assume deformation of membrane is linear in the difference of speed
- $\rightarrow \quad y = (sos_{tissue} - sos_{couplant}) * \alpha$
- $Y - d = (sos_{tissue} - sos_{couplant}) * \alpha$

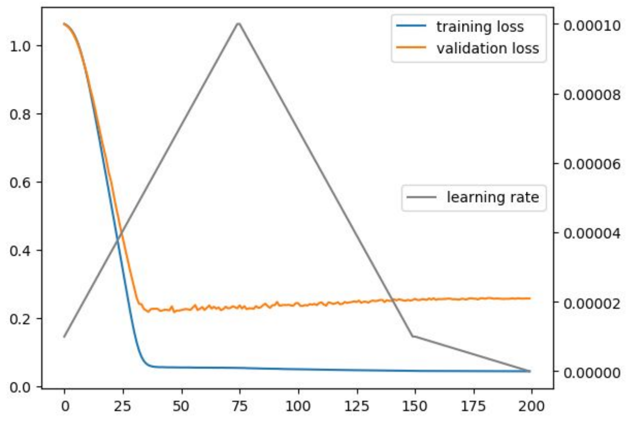


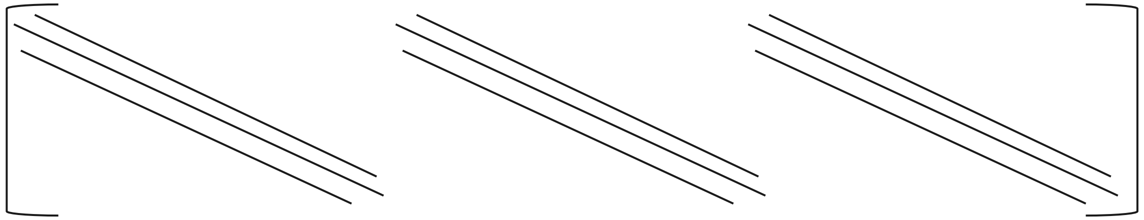
Relaxed Problem - Approach 2



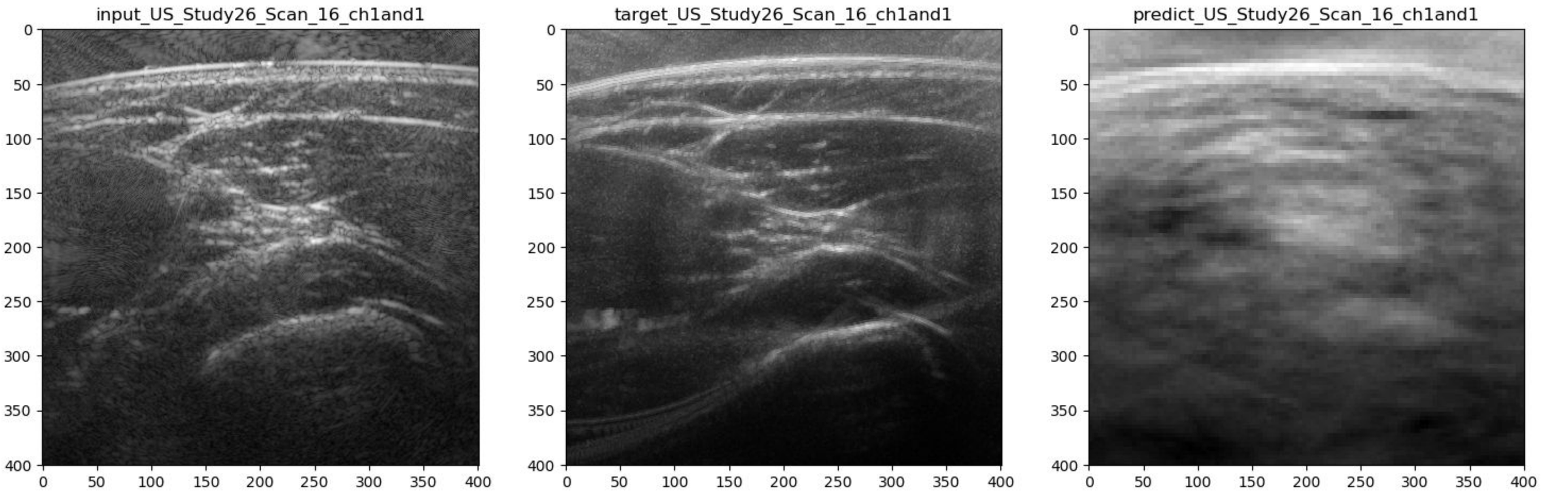
SP2: Linear Deformer

- linear layer between input and output
- manually set the weights outside the diagonal and one above and below to zero
- to get it into memory we still need to make the image smaller:
- → conv - linear - deconv
- conv with kernel(4,4) and stride 4

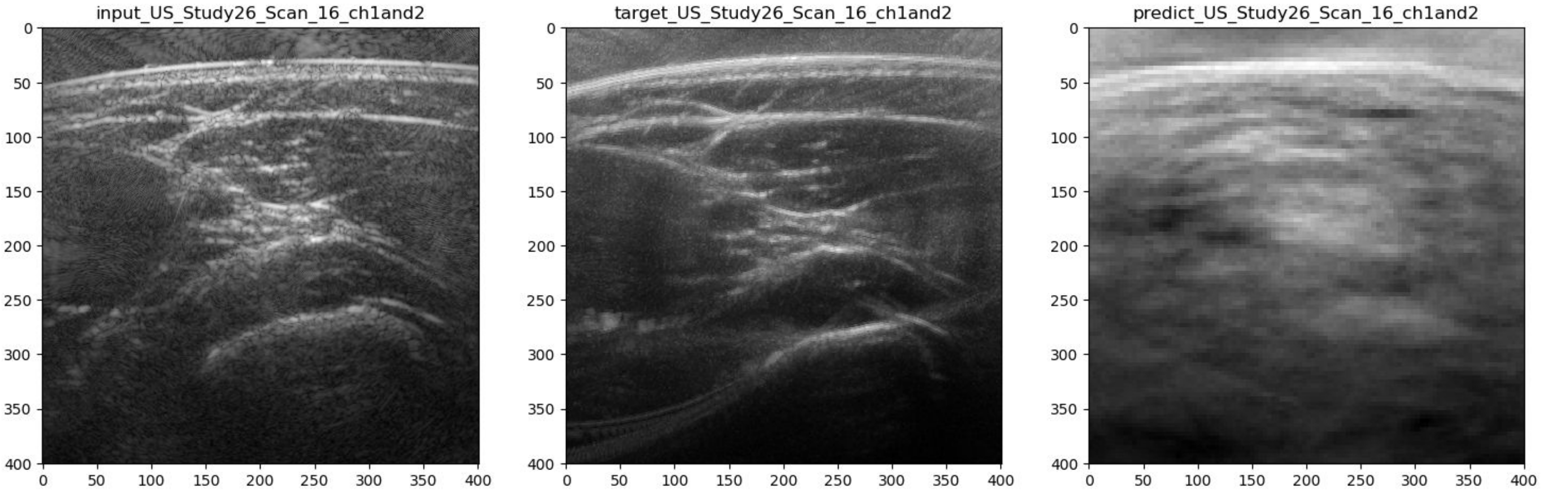




SP2: Linear Deformer - Test Results

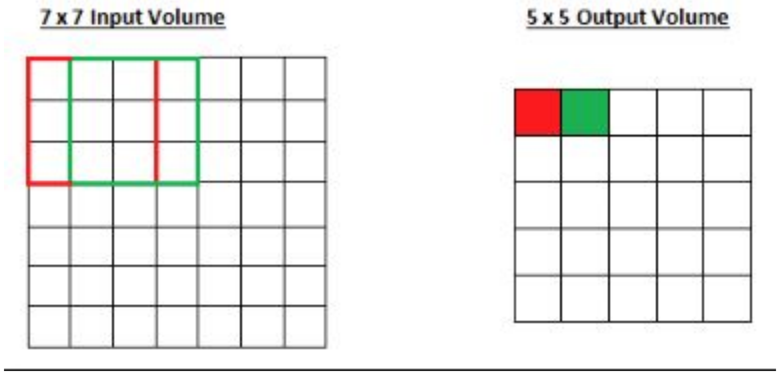


SP2: Linear Deformer - Test Results



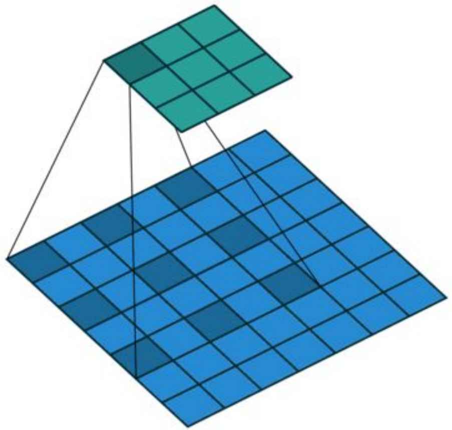
Locally Connected

Own filter for each pixel

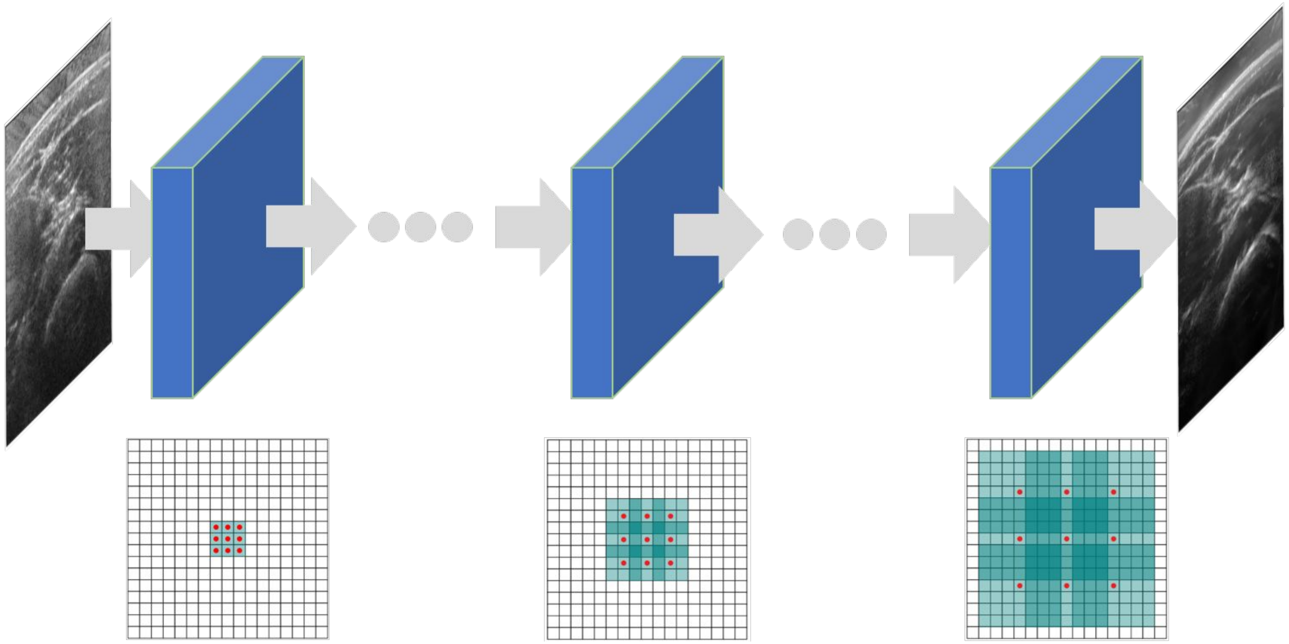


Model

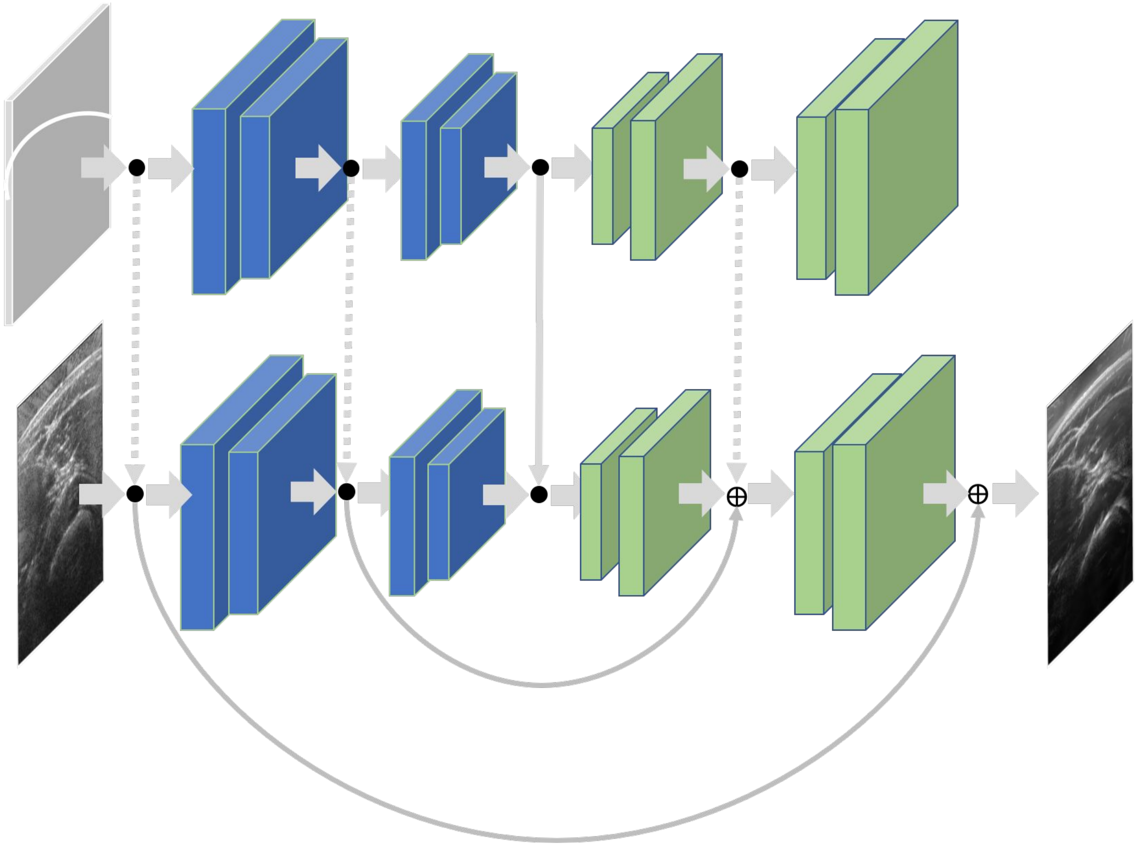
- New model class: test models in a fast and easy way
- Second approach: dilated convolution



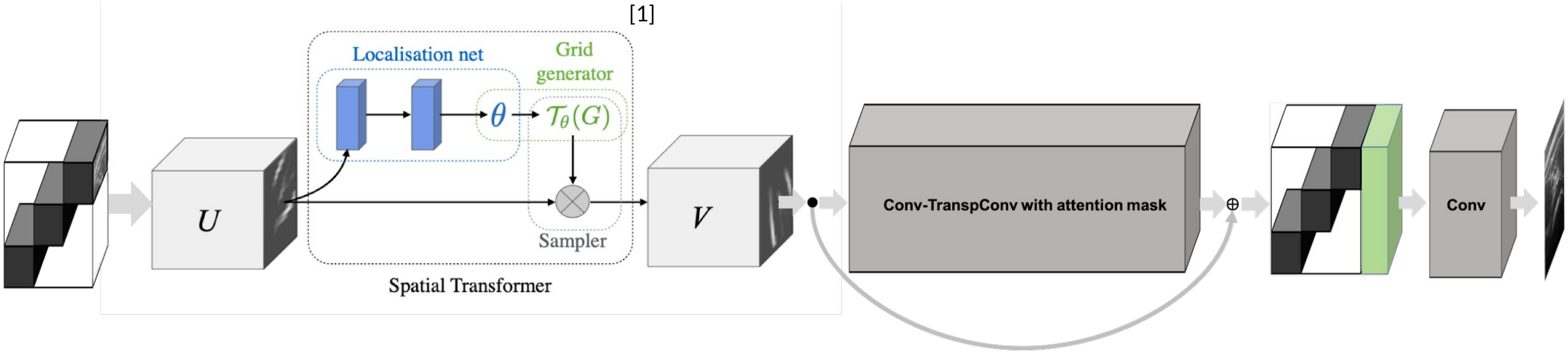
Dilated Convolutional Model



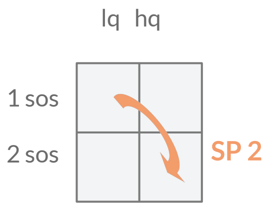
Approach 1



Convolutional Spatial Transformer



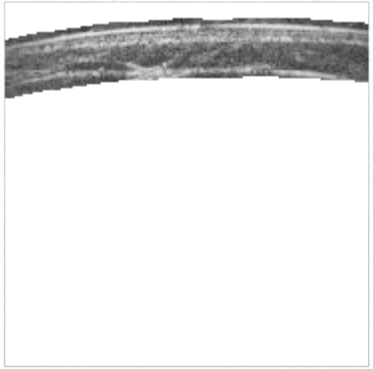
[1] M. Jaderberg, K. Simonyan, A. Zisserman, et al. Spatial transformer networks. In Advances in Neural Information Processing Systems (NIPS), 2015.



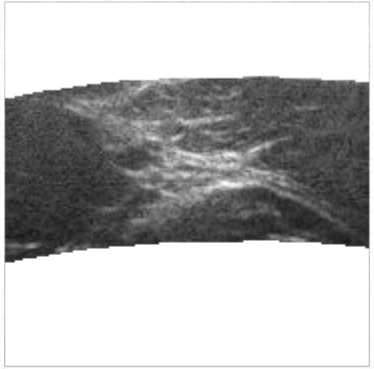
Attention mask used - fewer animations

SOS Couplant

SOS Couplant



SOS Tissue



SOS Tissue