

# Attenuation Imaging Using Ultrasound Transmission Tomography

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# 1. Introduction

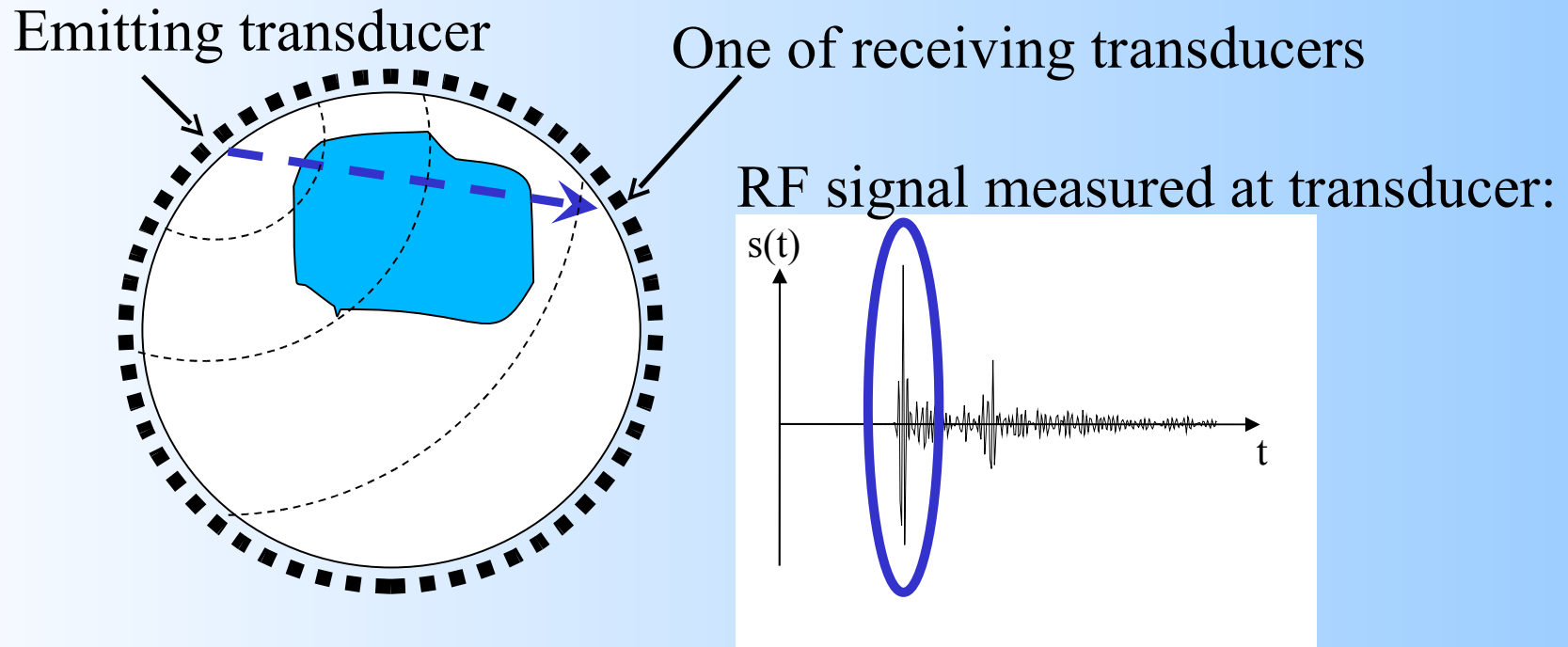
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## **Ultrasound attenuation imaging:**

- correction for ultrasound reflection tomography imaging
- stand-alone imaging modality – ultrasound attenuation coefficient closely related to the pathological tissue state

## 2. Transmission tomography imaging

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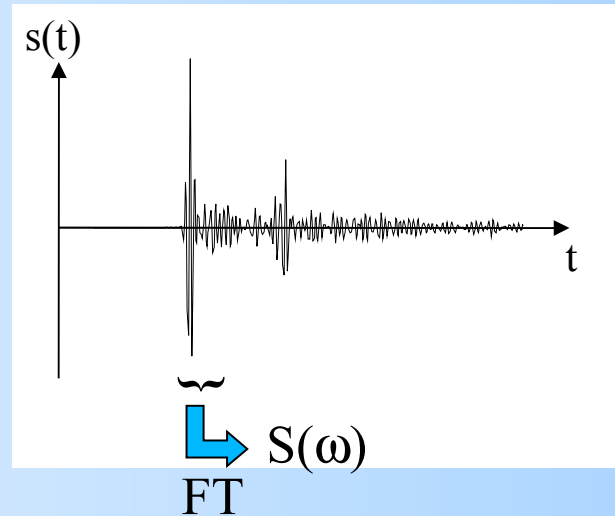
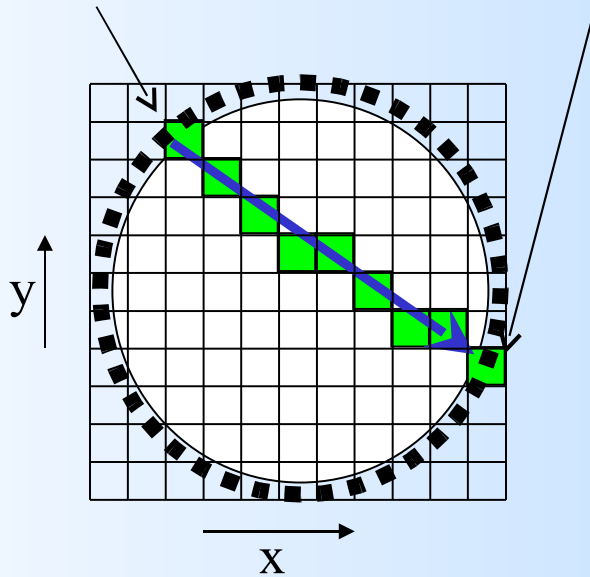


- each time one transducer in the emitter mode, all other transducers record the received RF signals
- all combinations of sending and receiving elements
- undirected wave

# 3. Attenuation imaging

sending transducer

receiving transducer



measured      empty measurement      attenuation

$$|S(\omega)| = |S_0(\omega)| e^{-\bar{\beta} d \left| \frac{\omega}{2\pi} \right|}$$

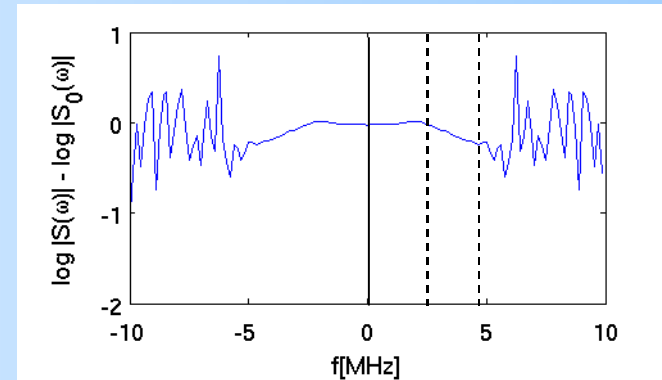
$\bar{\beta}$  — mean attenuation coef. along the path

$d$  — length of the path

### 3. Attenuation imaging

#### Estimation of the mean attenuation coefficient:

$$|S(\omega)| = |S_0(\omega)| e^{-\bar{\beta} d \left| \frac{\omega}{2\pi} \right|}$$
$$\bar{\beta} = \frac{\log|S(\omega)| - \log|S_0(\omega)|}{-d \left| \frac{\omega}{2\pi} \right|}$$



#### Estimation of the local attenuation coefficients (ART):

$$\bar{\beta} d = \sum_{i \in l} \beta_i d_i$$

$l$  — pixels along the path

$\beta_i$  — local att. coef. within  $i$ -th pixel along the path

$d_i$  — length of the pixel along the path

Path 1:  $\sum_{i \in l_1} \beta_i d_i = \bar{\beta}_1 d_1$

Path 2:  $\sum_{i \in l_2} \beta_i d_i = \bar{\beta}_2 d_2$

...

Path  $m$ :  $\sum_{i \in l_m} \beta_i d_i = \bar{\beta}_m d_m$

**Rf = p**

### 3. Attenuation imaging

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<b>Problems (errors in estimates of mean att. coef.)</b>	<b>Possible solutions</b>
diffraction	synthetic aperture focusing, subset of correct equations, <i>regularization of the ART</i>
pulse detection (uncertainty in the pulse position)	constrained maximum search, speed-of-sound and geometry correction, <i>regularization of the ART</i>
overlap of the transmission pulse and the scattered/ reflected wave signal	synthetic aperture focusing, <i>regularization of the ART</i>
noise in RF data	<i>regularization of the ART</i>

# Regularization Technique for USCT

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Technical University Brno, Brno, Czech Republic

3rd International Workshop on Data – Algorithms – Decision  
Making 2007

# Non-Regularized Solution

- the system  $Rf = p$ , where  $R$  and  $p$  are input data,  $f$  is the image being reconstructed
- $M$  equations with  $N$  variables  $\rightarrow$  overdetermined  $M \times N$  system  $\rightarrow$  no exact solution
- the solution computed as minimization:

$$\hat{f} = \operatorname{argmin}_f(J_1(f))$$

where  $J(f)$  is a functional being minimized:

$$J_1(f) = \|p - Rf\|^2$$

- naïve approach: solution of *normal equations*— $N \times N$  square system  $R^T Rf = R^T p$



# Edge-Preserving Regularization

- inspired by the techniques from image deconvolution:
  - homogeneous regions
  - edges (step changes of the att. coefficient)
- minimization of augmented functional [Char99]:

$$f = \operatorname{argmin}_f (J_1(f) + \lambda^2 J_2(f))$$

- $J_2$  is regularizing term

$$J_2(f) = \sum_k \varphi[(D_x f)_k] + \sum_k \varphi[(D_y f)_k]$$

where

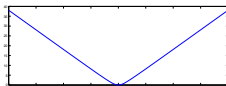
$$(D_x f)_{ij} = (f_{i,j+1} - f_{i,j})/\delta \quad (D_y f)_{ij} = (f_{i+1,j} - f_{i,j})/\delta$$

- parameters: two scalars  $(\lambda, \delta)$  and the *potential function*  $\varphi$

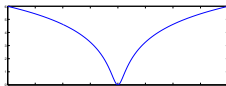
# Potential Functions and Parameters

- the potential function assigns cost to every value of the image gradient
- threshold for the edge penalization (smoothing)

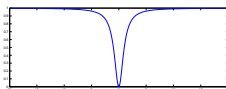
- $\varphi_{HS}(t) = 2\sqrt{1+t^2} - 2$



- $\varphi_{HL}(t) = \log(1+t^2)$



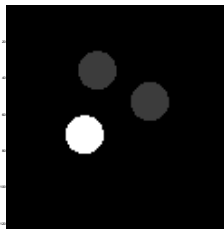
- $\varphi_{GM}(t) = \frac{t^2}{1+t^2}$



- parameter  $\delta$  sets a threshold for edges, compromise edges preservation vs. noise suppression
- parameter  $\lambda$  is weight of the regularization

# Experimental Data

- simulated RF data (based on Huygens principle)
- reconstruction of image  $50 \times 50$  pixels, (1576 variables)
- overdetermined system of 7228 equations
- right-hand side vector affected by additive Gaussian noise
- the parameters chosen experimentally together with  $\varphi_{GM}$  potential function

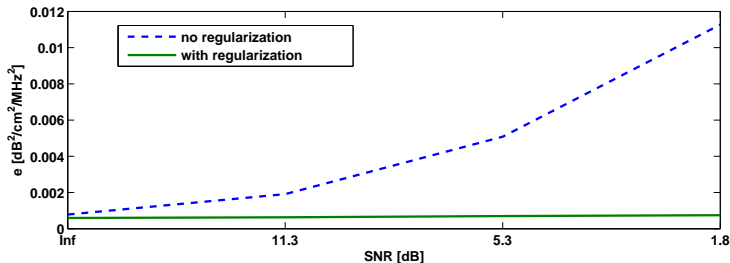


# Experimental Results I.

- error measured by square image difference

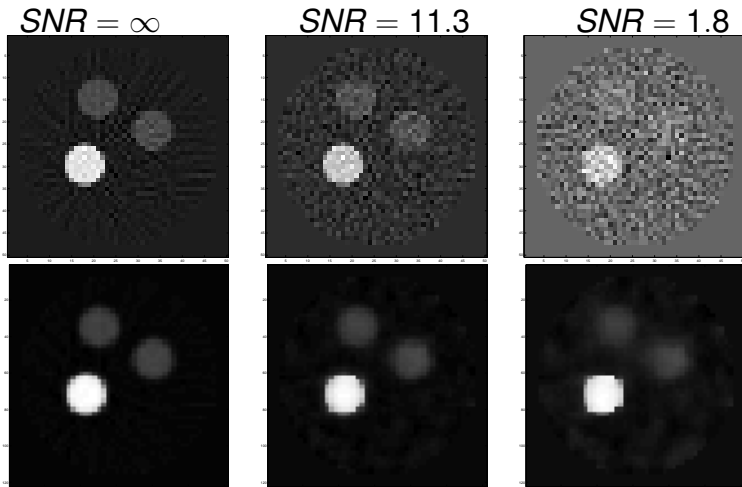
$$e = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N \left[ f_{ref}(m, n) - \hat{f}(m, n) \right]^2$$

- effect of the regularization for various SNR



# Experimental Results II.

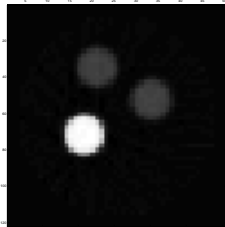
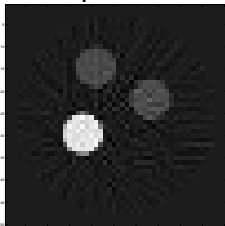
- effect of the regularization for various SNR (cont'd)



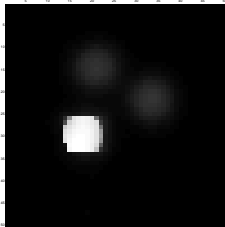
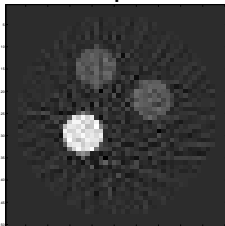
# Experimental Results III.

- some equations left out (e.g. due to out-of-range right-hand value)

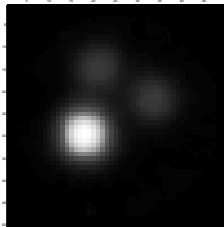
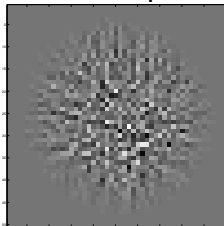
7228 equations



2409 equations



1807 equations



# Conclusion and Future Work

- one specific topic of the project aimed at attenuation image reconstruction in ultrasound transmission tomography
- importance of the regularization to cope with
  - inaccurate estimates of the mean attenuation coefficients
  - low degree of overdetermination
- future work and goals
  - non-negativity constraints
  - testing on real 2D and 3D data
  - larger local neighborhood