VARIABLE BANDWIDTH MEAN SHIFT FOR SMOOTHING ULTRASONIC IMAGES

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Introduction

Aim Enhance the contrast in ultrasonic images in order to assist the segmentation process

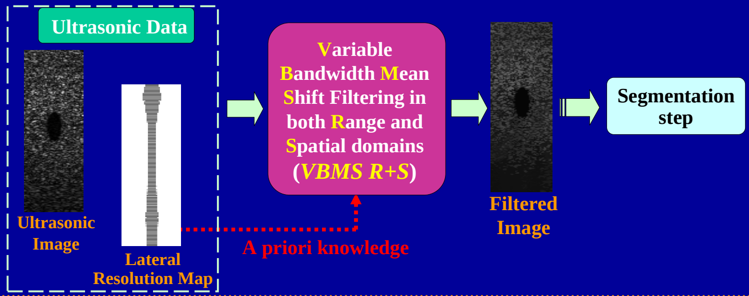
Ultrasonic Images Degradation

- **Speckle noise**
- **Blurring spatial information perpendicular to propagation direction**
- **Variable attenuation of ultrasound**
- **Variable lateral resolution (depending on focalization of ultrasonic beam)**

Definitions

- **Mean Shift : non parametric estimator of density gradient**
- **Lateral resolution : related to the point spread function of the imaging system**

Flowchart

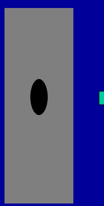


Ultrasonic Data

Simulated Data

Geometric model

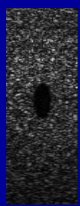
- 40*55 mm tissue mimicking rectangle
- 10 mm diameter cyst mimicking region



Phantom

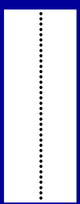
Field software

- 10 000 scatterers in the phantom
- Echogenicity divided by 10 in the cyst
- 3.5 MHz probe, 50 RF-lines sampled at 100 MHz



Simulated Ultrasonic Image

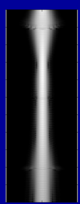
Lateral Resolution Estimation



Scatterers aligned in the propagation axis

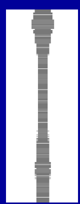
Field software

Same parameters for the probe



Point Spread Function

Width at half maximum



Lateral Resolution Map

VBMS R+S Filtering

Mean Shift Filtering

- **Aim : associate to each input data $\{\mathbf{x}_i\}_{i=1..n}$ the mode of the underlying density estimate $\hat{f}(\mathbf{x}_i)$. Note that $\mathbf{x}_i$ are vectors of the Spatial-Range domain R^{2+1}.**
- **How ? Start from $\mathbf{x}_i = \mathbf{x}_i^{[0]}$ and move $\mathbf{x}_i^{[t]}$ iteratively until convergence, then assign $\mathbf{x}_{i,r}^{[conv]}$ to the filtered data $\{\mathbf{y}_i\}_{i=1..n}$**

(VBMS R+S) Algorithm

1 - Compute the optimal fixed range bandwidth h_0 with the Sheather plug-in rule

2 - For each $\mathbf{x}_i$, compute the values of the local bandwidth matrix $\mathbf{H}_i$

From the Lateral Resolution Map

$$\mathbf{H}_i = \begin{bmatrix} h_{i,s1}^2 & 0 & 0 \\ 0 & h_{i,s2}^2 & 0 \\ 0 & 0 & h_{i,r}^2 \end{bmatrix} \qquad h_{i,r} = h_0 \cdot \left[\frac{\lambda}{\tilde{f}(\mathbf{x}_i)}\right]^{\frac{1}{2}}$$

Pilot density, estimated using $h_{i,s1}$, $h_{i,s2}$ and h_0

λ Geometric mean of $\tilde{f}(\mathbf{x}_i)$

3 - For each $\mathbf{x}_i^{[0]} = \mathbf{x}_i$, run the adaptive mean shift procedure

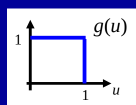
$$\mathbf{x}^{[t+1]} = \left(\sum_{i=1}^{n} \mathbf{Q}_i\left(\mathbf{x}^{[t]}\right)\right)^{-1} \cdot \left(\sum_{i=1}^{n} \mathbf{x}_i . \mathbf{Q}_i\left(\mathbf{x}^{[t]}\right)\right) \quad \text{until} \quad \left\|\mathbf{x}^{[t+1]} - \mathbf{x}^{[t]}\right\| > \varepsilon$$

with

$$\mathbf{Q}_i(\mathbf{x}) = \left(\det[\mathbf{H}_i]\right)^{-\frac{1}{2}} \mathbf{H}_i^{-1} g\left(d[\mathbf{x}, \mathbf{x}_i, \mathbf{H}_i]^2\right)$$

$$d[\mathbf{x}, \mathbf{x}_i, \mathbf{H}_i]^2 = (\mathbf{x} - \mathbf{x}_i)^T \mathbf{H}_i^{-1} (\mathbf{x} - \mathbf{x}_i)$$

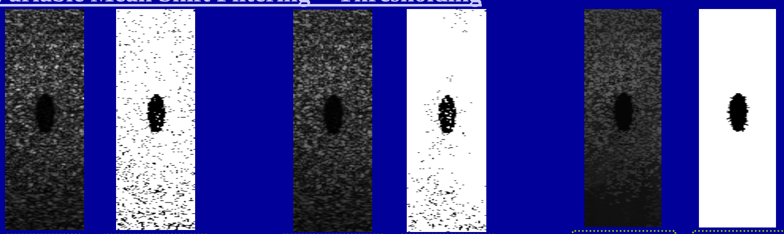
and $g(u)$



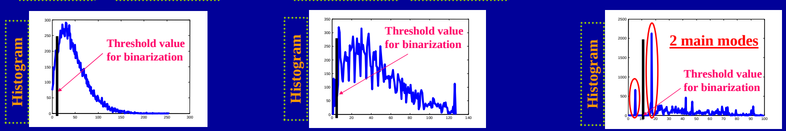
4 - Assign $\mathbf{y}_i = (\mathbf{x}_{i,s}, \mathbf{x}_{i,r}^{[conv]})$

Results and Conclusion

Variable Mean Shift Filtering + Thresholding



Original image | Resulting thresholding | *(VBMS R)* filtered image | Resulting thresholding | *(VBMS R+S)* filtered image | Resulting thresholding



Segmentation

Segmented image obtained by the K-means algorithm | Segmented image obtained by a Bayesian framework algorithm | Segmented image obtained by a multi-resolution Bayesian framework algorithm | Automated thresholding of the *(VBMS R+S)* filtered image

Conclusion

- ***(VBMS R+S)* gives better results than *(VBMS in Range domain only)***
- **No tuning of parameters is needed**
- ***(VBMS R+S)* fits to the variable resolution of the ultrasound probe**

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