### **IEEE Ultrasonic symposium 2002**



#### Short Course 6: Flow Measurements

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Internet-site for short course: http://www.ifbt.ntnu.no/~hanst/flowmeas02/index.html

Lecture 4: Advanced methods





## **Go to lecture 1**?

#### **Doppler signal from one range** Pulse no





# Blood detection and velocity estimation from 2D signal

- Increased number of range samples M give better performance but lower spatial resolution
- Best spatial resolution with M=1
- In this work optimum estimators for the case M=1 is treated
- Extension to the case M > 1 is straight forward



## **1D Signal Model**

• Signal vector for each sample volume:

 $\mathbf{x} = [x(1), \dots, x(N)]^{T}$ 

- Zero mean complex Gaussian process
- Three independent signal components:

Signal = Clutter + White noise + Blood  $\mathbf{x} = \mathbf{c} + \mathbf{n} + \mathbf{b}$ 

• Signal correlation function:



$$R_x(m) = \langle x(k)^* x(k+m) \rangle = R_c(m) + \delta(m) + R_b(m)$$



## Probability density function for the complex signal vector **x**

$$p(x|v) = \frac{1}{\pi^{N}|C(v)|} e^{-x'C^{-1}(v)x}$$

$$C(v) = \left\{ R_x(k-n) \right\}_{k,n}$$
$$C(v) = C_c + I + C_b(v)$$

v = radial velocity component of blood flow



Log likelihood function and Cramer - Rao lower bound

$$l(v|x) \equiv \log p(x|v) = -x^T C^{-1}(v) x - |C(v)|$$

$$\operatorname{var}_{\min} = \left\langle \frac{\partial^2}{\partial^2 v} l(v|x) \right\rangle^{-1}$$



## **Maximum Likelihood estimator**





## Cramer - Rao lower bound Approximation

$$\left\langle \frac{\partial^2}{\partial^2 v} l(v|x) \right\rangle = -\left\langle x^T C^{-1}(v)''(v)x \right\rangle - \left| C(v) \right|''$$
$$\left| C(v) \right|'' \approx 0 \; ; \; R_b(m) = \left| R_b(m) \right| e^{i2mkTv}$$
$$\frac{\partial}{\partial v} \left| R_b(m) \right| \approx 0$$



## Cramer - Rao lower bound Approximation

$$\left\langle \frac{\partial^2}{\partial^2 v} l(v|x) \right\rangle \approx -\sum_{m,n} c(m,n) b(m,n)$$
$$C = \left\{ c(m,n) \right\}_{m,n} = C_C + I + C_b$$
$$B = \left\{ b(m,n) \right\}_{m,n} = C^{-1} \left( 2C_b' C^{-1} C_b' - C_b'' \right) C^{-1}$$



## Signal simulation model



Frequency **2.5 MHz** Beam width 3 mm **Pulse length** 2 mm PRF 5 kHz packet size 10 samples Signal level 20 dB Clutter level 80 dB Blood velocity 0.2 -0.8 m/s Angle blood flow 20 deg.



## Numerical simulations maximum likelihood estimator



## Maximum likelihood estimator bias





## Maximum likelihood estimator properties



Hans Torp

ML estimator is unbiased, but not efficient (minimum variance)

## Max. likelihood method for blood velocity estimation





## Autocorrelation method for blood velocity estimation



- Clutter Rejection filter formulated as a matrix multiplication
- Includes FIR filter, initialized IIR filter, and regression filter

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## **FIR filter**

$$A = \begin{bmatrix} b_1 & b_2 & b_3 & b_4 & b_5 & b_6 & 0 & . & . & 0 \\ 0 & b_1 & b_2 & b_3 & b_4 & b_5 & b_6 & & . \\ . & b_1 & b_2 & b_3 & b_4 & b_5 & b_6 & & . \\ . & b_1 & b_2 & b_3 & b_4 & b_5 & b_6 & 0 \\ 0 & . & . & 0 & b_1 & b_2 & b_3 & b_4 & b_5 & b_6 \end{bmatrix}$$

 $\mathbf{X}$ 

FIR filter orderM=5Packet sizeN=10Output samples:N-M= 5

+ Improved clutter rejection

**Increasing filter order** 

- Increased estimator variance



## Clutter suppression by high pass filtering



Packet size N=10

**Order M=6: 4 samples left after initialization** 

**Order M=8: 2 samples left after initialization** 

Hans Torp FIR filter

## **Polynomial regression filter**



## Clutter suppression by high pass filtering



**FIR filter** 

lans Torp TNU, Norway Polynom regression filter

## **Blood velocity estimator bias**



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## Blood velocity estimator variance



**Hans Torp** NTNU, Norway

## Conclusion Optimum velocity estimation

- ML estimator is unbiased, but probably not minimum variance
- Polynomial regression filter showed estimator variance comparable to the ML estimator when above filter cut off frequency
- Polynomial regression filter gave substantial bias for low velocities
- FIR filter give no bias, but significant increase in variance



## **Optimum clutter filtering**

**1.** Adaptive filters

**2.** Optimum detection of blood vessel in clutter noise

#### **Frequency Responses**



Other quality measures for clutter filters than the frequency response?

#### Signal Model

• Signal vector for each sample volume:

 $\mathbf{x} = [x(1), \dots, x(N)]^{\mathsf{T}}$ 

- Zero mean complex Gaussian process
- Three independent signal components:

Signal = Clutter + White noise + Blood = c + n + b

• Signal correlation matrix:

$$R_{x} = R_{c} + \sigma_{n}^{2}I + R_{b}$$

## **Optimal Basis of Clutter Space**

• Eigenvalue decomposition of the clutter correlation matrix:

$$\mathbf{R}_{c}\mathbf{e}_{i} = \lambda_{i}\mathbf{e}_{i}$$
$$\mathbf{R}_{c} = \sum_{i=1}^{N} \lambda_{i}\mathbf{e}_{i}\mathbf{e}_{i}^{h}$$

- Use the eigenvectors e<sub>i</sub> as a basis for the clutter space (Karhunen-Loeve transform)
- This basis provides maximum energy concentration

## **Adaptive Regression Filter**



#### **Detection of Blood**

A rule for deciding between the two hypotheses:  $H_0$ : No blood is present  $H_1$ : Blood is present

The detector is characterized by

- Probability of false alarm
   P<sub>F</sub> = P(choose H<sub>1</sub> | H<sub>0</sub> is true)
- Probability of detection
   P<sub>D</sub> = P(choose H<sub>1</sub> | H<sub>0</sub> is true)

#### Coronary artery

#### **The Optimal Detector I**

The Neyman-Pearson lemma:

 $P_D$  is maximized under the constraint  $P_F \le \alpha$  by a likelihood ratio test (LRT)

$$L(\mathbf{x}) = \frac{p_{\mathbf{x}|H_1}(\mathbf{x}|H_1)}{p_{\mathbf{x}|H_0}(\mathbf{x}|H_0)} \stackrel{H_1}{\underset{H_0}{\gtrless}} \gamma$$

#### **The Optimal Detector II**

For a Gaussian signal, the LRT can be simplified to:

$$I(\mathbf{x}) = \|\mathbf{A}\mathbf{x}\|^2 \underset{\mathsf{H}_0}{\overset{\mathsf{H}_1}{\gtrsim}} \eta$$

where  $A=(I-(I+L)^{-1})^{1/2} E^{*T}$ , and E and L are the solution of the generalized eigenvalue problem

$$\mathbf{R}_{b}\mathbf{E}=\mathbf{R}_{x|H_{0}}\mathbf{E}\mathbf{L}$$

#### The Optimal Detector III



The same structure as conventional color flow systems, but signal dependent filter matrix **A** 

#### **Detector Performance I**

• The detection performance is summarized in a receiver operating characteristic (ROC)



## **Detector Performance II**

- *l*(x) is a sum of exponentially distributed variables
- $P_D$  and  $P_F$  is equal to:



## **Data Acquisition**

- Digital RF data recorded with GE Vingmed Ultrasound System Five ultrasound scanner
- Complex baseband signals transferred to external computer for processing

#### Acquisition parameters

Center freq.	5.7 MHz
PRF	5 kHz
Rad. samp. freq	. 2 MHz
Temp. samples	9



Thyroid gland

## **Signal Characteristics**

• The correlation matrix is estimated by spatial averaging in a region with uniform motion:

$$\hat{\mathbf{R}}_{c} = \frac{1}{M} \sum_{i=1}^{M} \mathbf{x}_{i} \mathbf{x}_{i}^{H}$$

- Estimated signal parameters:
  - Mean probe movement: 1.0 cm/s
  - Clutter to white noise ratio: 52 dB
- Blood signal:
  - Modeled as a single frequency signal
  - Blood signal to white noise ratio set to 6 dB

#### **ROCs for the Different Filters**



Optimal detector — IIR proj. init. — FIR min. phase
 Adaptive reg. filter IIR step init. — FIR linear phas
 Pol. reg. filter

## **Image Improvement**

Polynomial regression filter

Example of image improvement with adaptive regression filter



#### Adaptive regression filter



## **Conclusions Clutter filter**

- Polynomial regression filters and projection initialized IIR filters have similar performance and are best among the non-adaptive filters
- The computational complexity of the projection initialized IIR filter is equal to the regression filter
- The adaptive regression filter has close to optimum performance

## Spatial and temporal averaging

Signal samples from M points in time/space with identical statistical properties

$$x_{k} = x_{k}(1), ..., x_{k}(N); k = 1, ..., M$$

$$p(x_{k}) = \frac{1}{\pi^{N}|C|} e^{-x_{k}'C^{-1}x_{k}}$$

$$x_{k}'C^{-1}x_{k} = \sum_{n,m=1}^{N} a_{n,m}x_{k}(n) * \cdot x_{k}(m)$$

How to combine these for optimum detection and velocity estimation?

## Spatial and temporal averaging

Joint probability function (uncorrelated signals)

$$p(x_1,..x_M) = \prod_{k=1}^M \frac{1}{\pi^N |C|} e^{-x_k' C^{-1} x_k}$$

Log probability function

$$l(x_1, ..., x_M) = -\sum_{k=1}^M x_k' C^{-1} x_k - \pi^{NM} |C|^M$$
$$= -\sum_{n,m} a_{n,m} \sum_{k=1}^M x_k(n) * \cdot x_k(m) - \pi^{NM} |C|^M$$

#### **Spatial and temporal averaging**

$$l(x_1,..x_M) = -\sum_{n,m} a_{n,m} \hat{R}_x(n,m) - \pi^{NM} |C|^M$$

The covariance estimates

$$\hat{R}_x(n,m) = \sum_{k=1}^M x_k(n) \cdot x_k(m)$$

are sufficient statistics for the detection / estimation problem

This means that the optimum detector, as well as min. variance estimators for signal power, mean frequency, and bandwidth, are a function of the covariance estimates

## Temporal averaging for mean frequency estimator

 $\hat{R}_k(1) = \sum_{n=1}^N x_k(n) \cdot x_k(n+1)$  k=1:4, uncorrelated signal packets

**Example:** 

Effect of averaging R1 :

Variance of angle(R1) reduced by factor 24!

**Effect of averaging angle(R1):** 

Variance reduction factor=4



## Spatial/temporal averaging summary

- Efficient variance reduction of signal power, mean frequency and bandwidth can be achieved by averaging data from uncorrelated signal segments.
- Optimum variance reduction is achieved by averaging the complex correlation estimates before calculating the spectral parameters

## Further reading/work

Textbooks Jørgen Arendt Jensen: <u>Estimation of Blood Velocities Using Ultrasound, A Signal Processing</u> <u>Approach</u>, Cambridge University Press, 1996. http://www.it.dtu.dk/~jaj/book.html

B.A.J. Angelsen: <u>Ultrasound Imaging, Waves, Signals, and Signal Processing</u> http://www.ultrasoundbook.com/

**Internet-site for this course**:

http://www.ifbt.ntnu.no/~hanst/flowmeas02/index.html