Detection of Unreliable Measurements in Multi-sensor Devices

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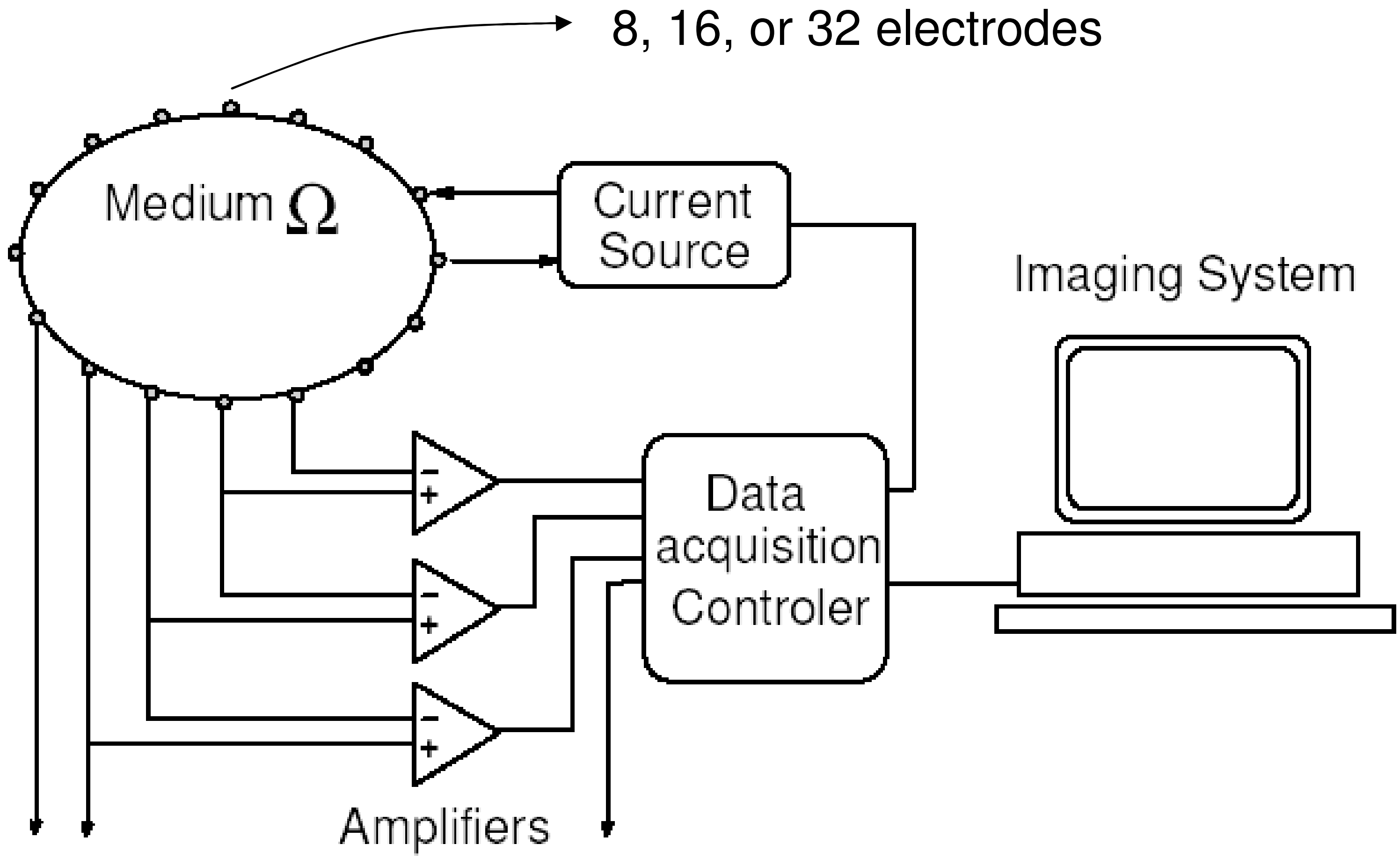
Multi-Sensor Systems

- Multi-sensor systems
  - Class of sensors that measure the same medium
  - Eg. ECG, EIT,EMG
- EIT: measures change in conductivity of a medium
- ECG: measure electrical activity of the heart

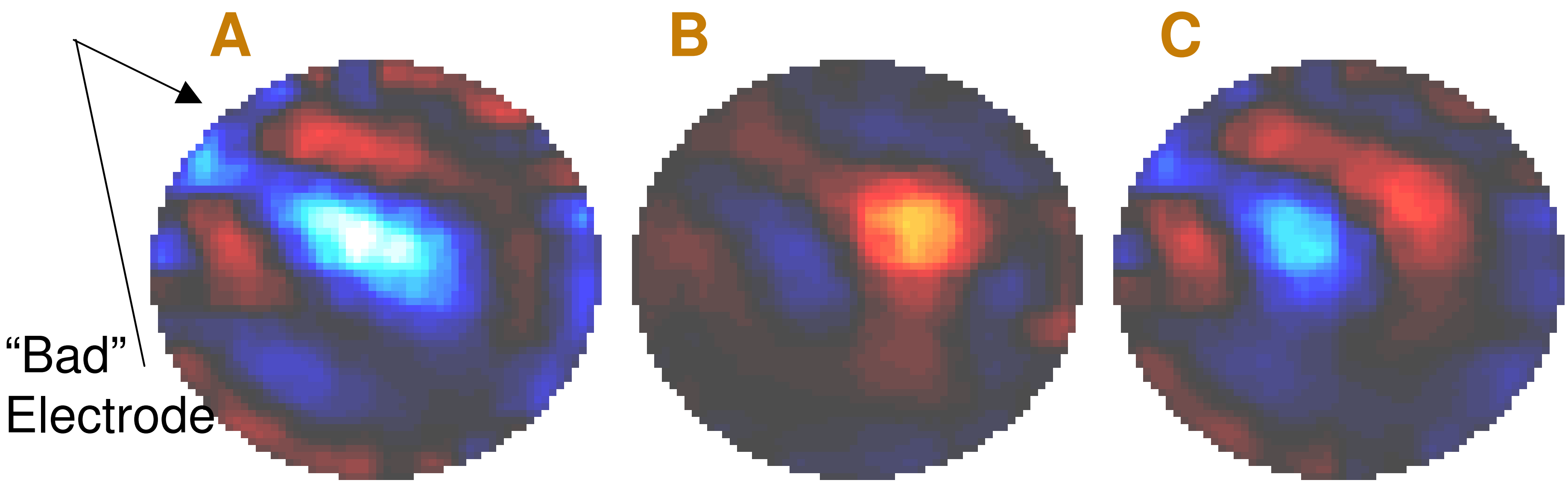
EIT System


8, 16, or 32 electrodes
Medium Ω
Current Source
Imaging System
Data acquisition Controler
Amplifiers

Problem

- Experimental measurements quite often show large errors from sensors
- In EIT and ECG:
  - Electrode Detaching
  - Skin movement
  - Sweat changes contact impedance
  - Electronics Drift

Example of electrode errors



Images measured in anaesthetised, ventilated dog

A. Image of 700 ml ventilation
B. Image of 100 ml saline instillation in right lung
C. Image of 700 ml ventilation and 100 ml saline

Problem

- Logical step forward is:

  How to detect a faulty sensors?

- *Idea*: data from a “bad” sensors are inconsistent with data from “good” sensors

System Model

Linear forward model:

$$\mathbf{z} = \mathbf{H}\mathbf{x} + \mathbf{n} \quad \begin{cases} \mathbf{z} & \textbf{measured signal} \\ \mathbf{H} & \textbf{sensitivity matrix} \\ \mathbf{x} & \textbf{system parameter} \\ \mathbf{n} & \textbf{noise} \end{cases}$$

Linear inverse:

$$\hat{\mathbf{x}} = \mathbf{R}\mathbf{z} \quad \begin{cases} \hat{\mathbf{x}} & \textbf{estimate system parameter} \\ \mathbf{R} & \textbf{reconstruction matrix} \end{cases}$$

System Model-Known

- Underlying principle that defines **H** and **R** is known
- In EIT:
  - **H** is defined by boundary measurement (**z**) and the general background conductivity (**x**):

$$\mathbf{H}_{i,j} = \left.\frac{\partial \mathbf{z}_i}{\partial \mathbf{x}_j}\right|_{\sigma_b=\sigma_0}$$

  - **R** is determined through a regularized scheme

System Model-Unknown

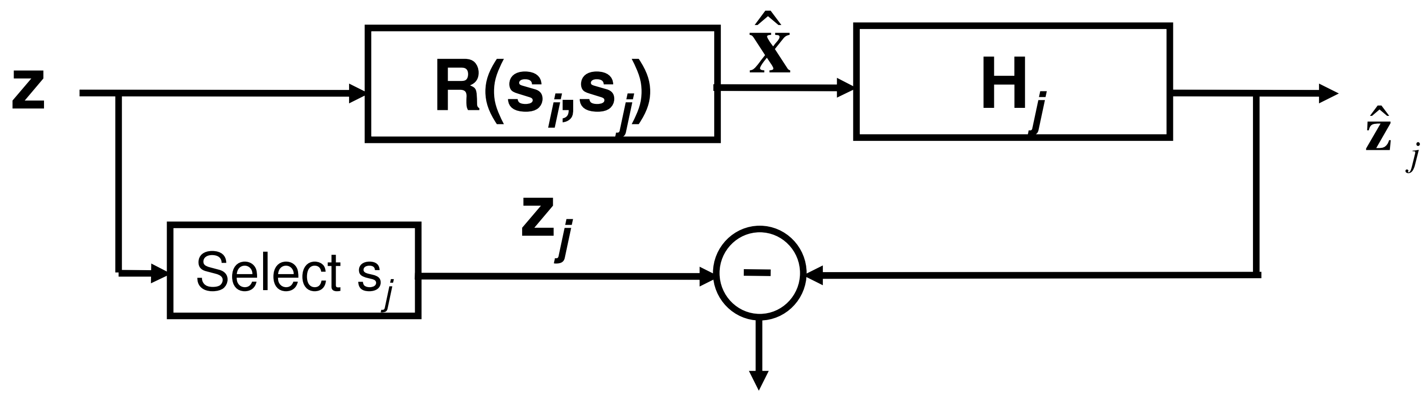
- Use Singular Value Decomposition
  - Measured data from each sensor organized into a matrix (**z**). Enforce non-singularity:

$$\mathbf{D}=\mathbf{z}^{*}\mathbf{z}^{T}$$

  - Applying SVD: $\mathbf{D}=\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{T}$
  - Top *n* dominant eigenvectors used to simulate **H**
  - **R** determined through direct inversion

Estimation Error

- Based on the forward and inverse model we construct an estimation scheme:



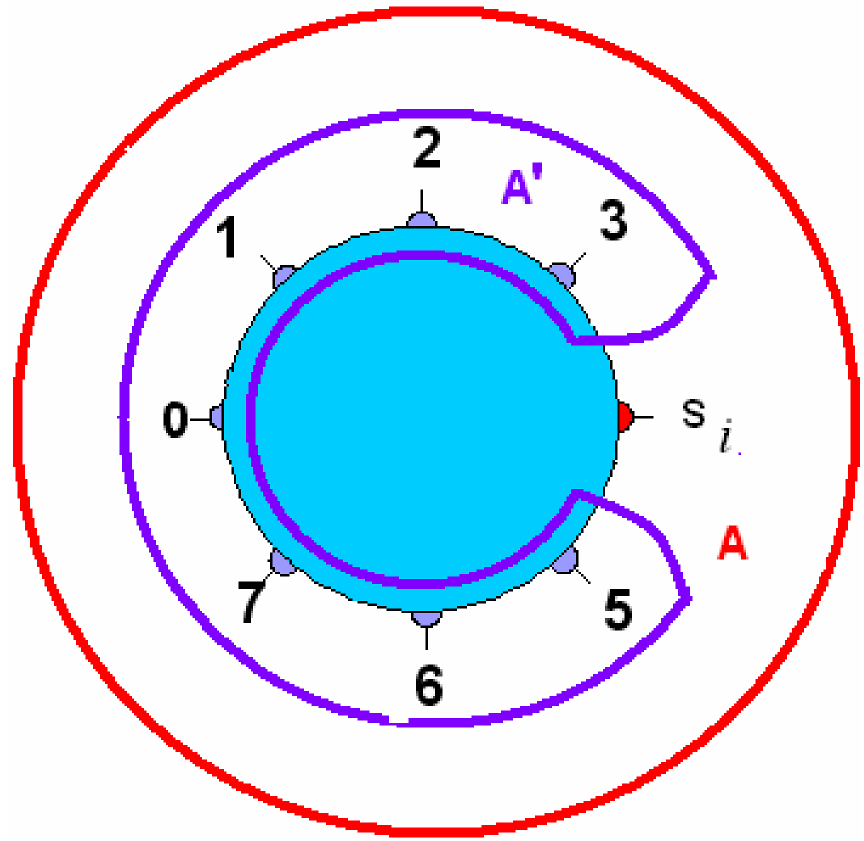
$$E_j = \left\| \mathbf{z}_j - \hat{\mathbf{z}}_j \right\|$$

- $R(s_i,s_j)$: reconstruction matrix where data from s_i , s_j are removed
- E_j is estimation error for sensor j

Method: outer loop

Goal: construct test for each s_i

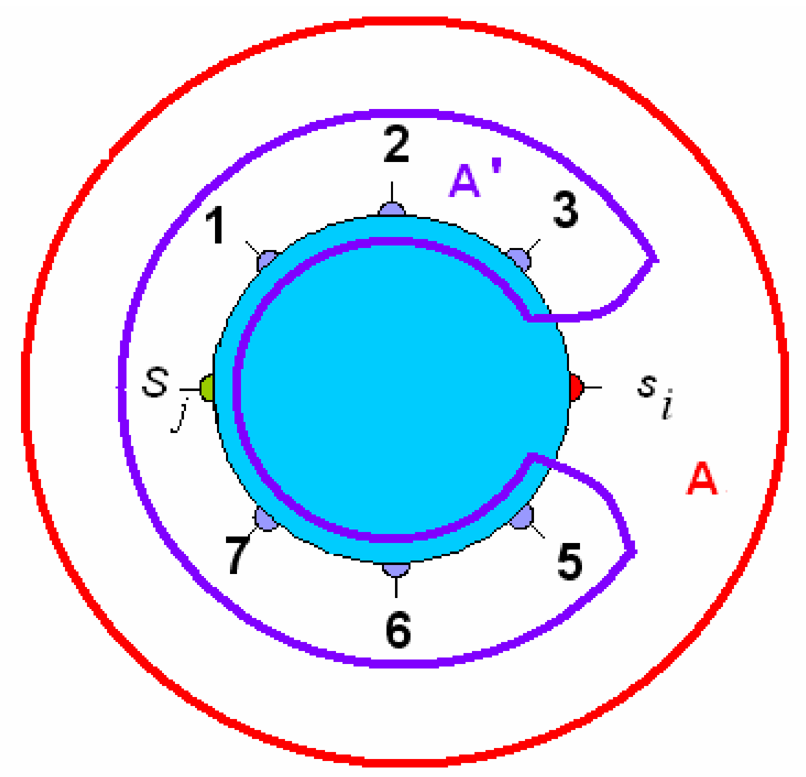
- Remove a candidate sensor s_i from set *A*
- Create a set *A*' that does not include candidate sensor



Method: inner loop (s_j) *Goal: is data in S' consistent?*

- Estimate $\mathbf{z}_j$ and calculate E_j

$$
\begin{aligned}
E_j &= \left\| \mathbf{z}_j - \hat{\mathbf{z}}_j \right\| \\
&= \left\| \mathbf{z}_j - \mathbf{H}_j \mathbf{R}\left(s_i, s_j\right) \mathbf{z} \right\|
\end{aligned}
$$

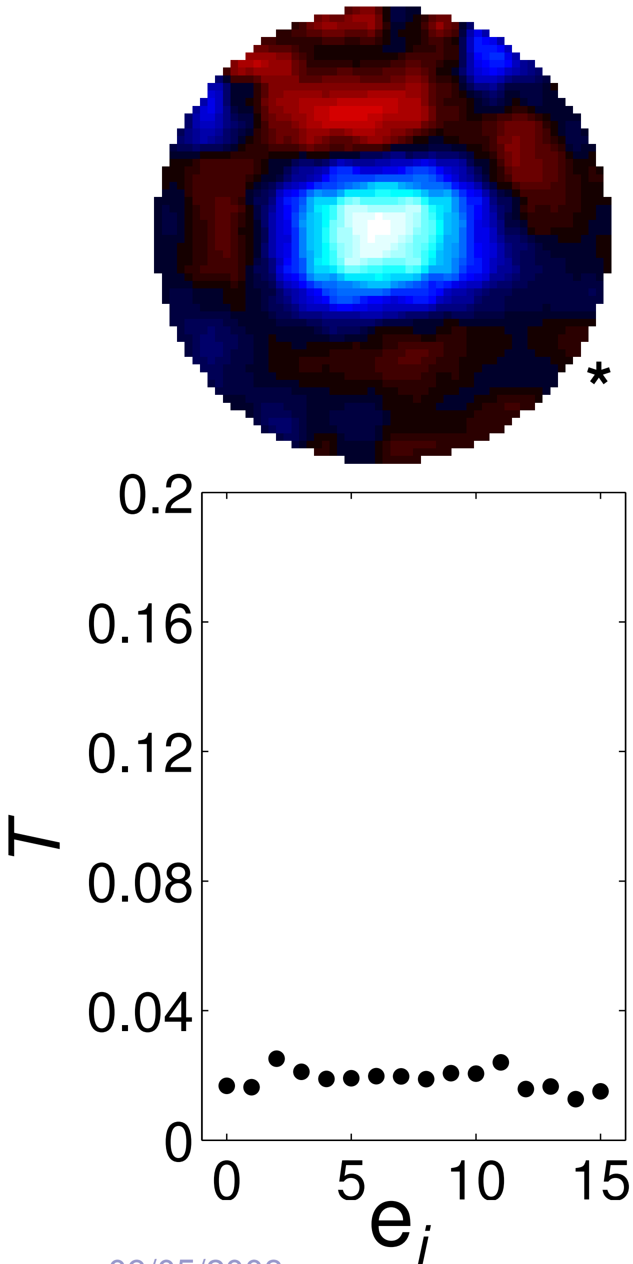


- E_j is low if data in *A'* is consistent

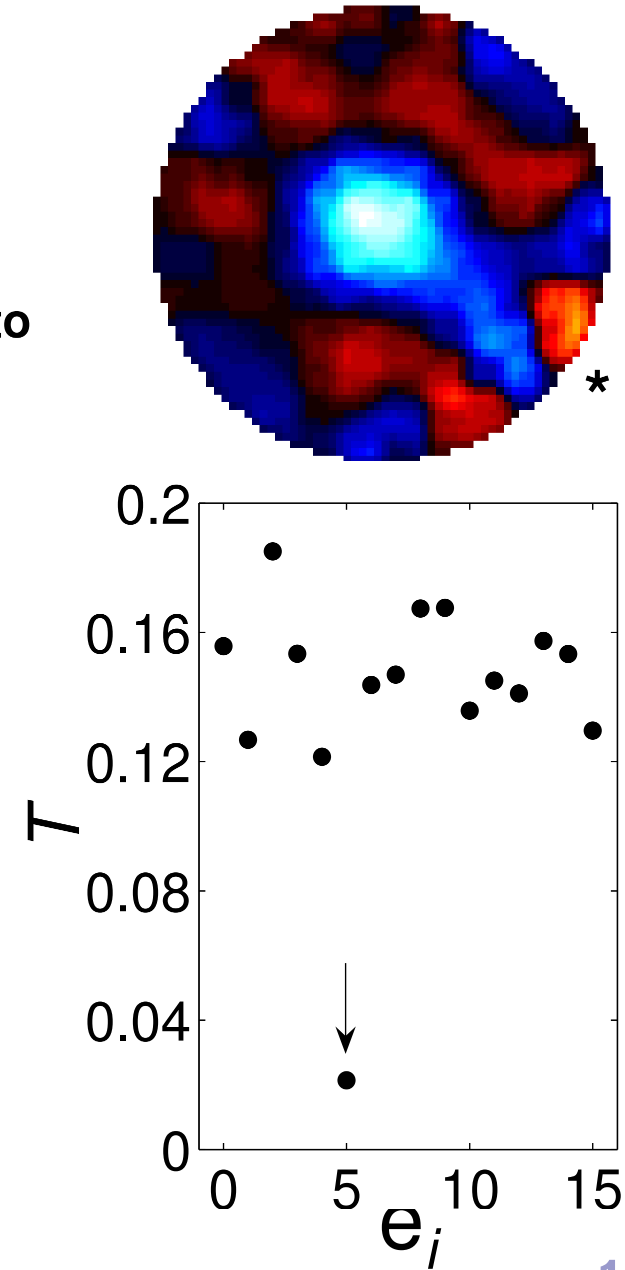
Method: inner loop (s_j)
Goal: is data in S' consistent?

- Known system models: If A' does not contain the erroneous sensor, Estimation error (E_j)*values are* ***low***
- Unknown system models: If A' does not contain the erroneous sensor, Estimation error (E_j)values are ***High***
  - Model is dependent on the data
  - In the presence of dominant noise, the model describes the noise rather than the data

Example: EIT



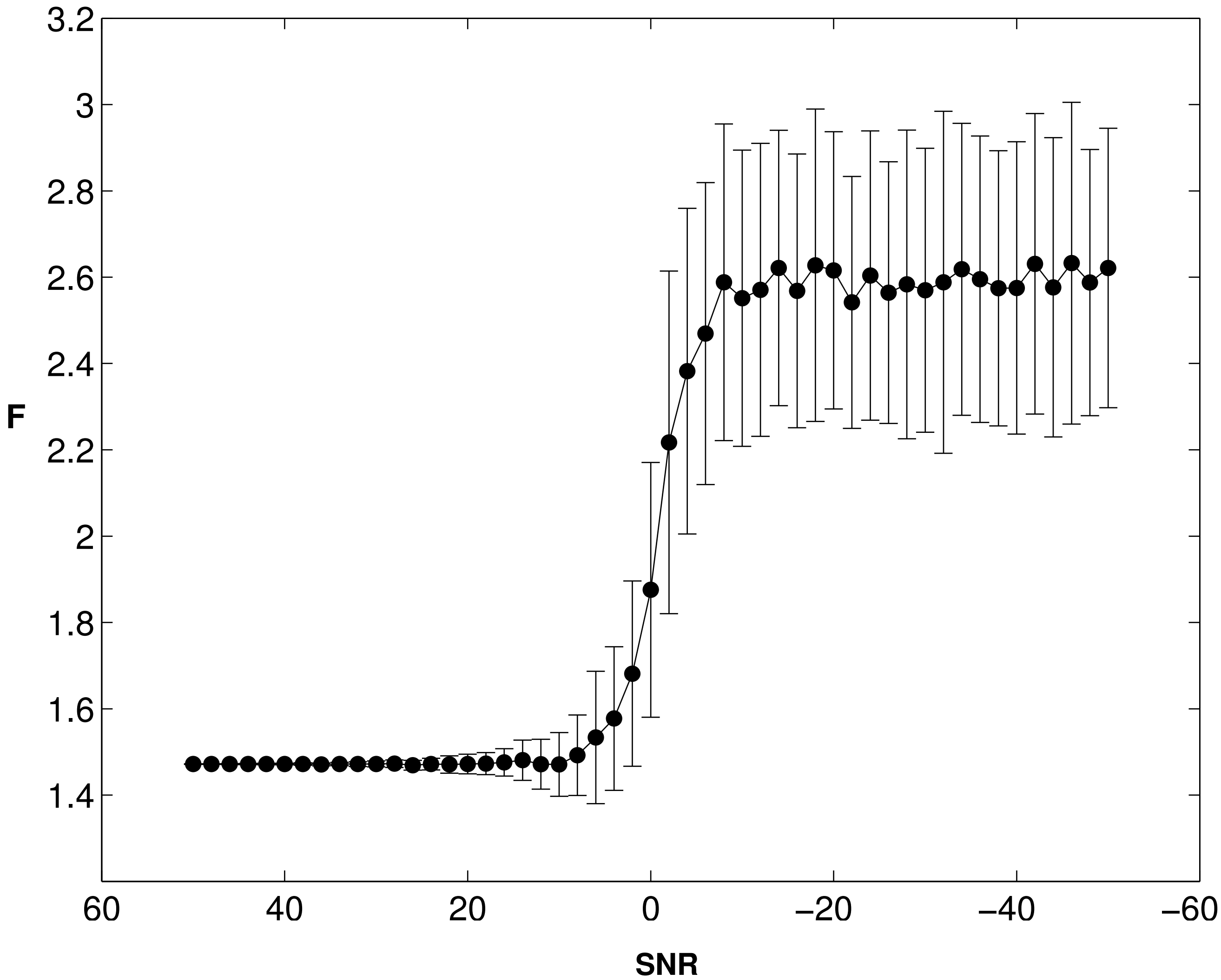
Add white Gaussian noise to electrode 5 (∗) data (SNR=-10dB)



Error Detection sensitivity curve

- Error detection sensitivity curve
  - Selected representative “clean data”
    - Image of 700 ml ventilation
  - Calculate the F value for different noise levels on a single electrode
  - 100 simulations per noise level

F statistic vs. SNR

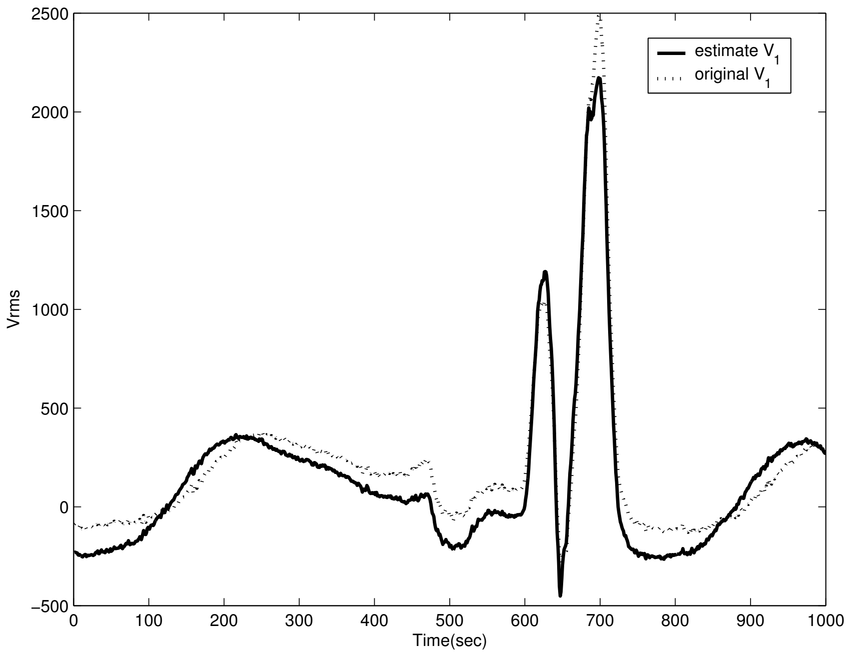


Example: ECG

- 12 Lead System:
  - Sagittal plane (X-Z plane)
  - Frontal plane (Z-Y plane)
  - Transverse plane (X-Y plane)
- Sagittal plane and Frontal plane are constructed from 6 Leads determined by measurements from 3 electrodes
  - High level of dependency
  - Measurement points are on limbs, shoulder and ankle making the signal weaker and susceptible to noise

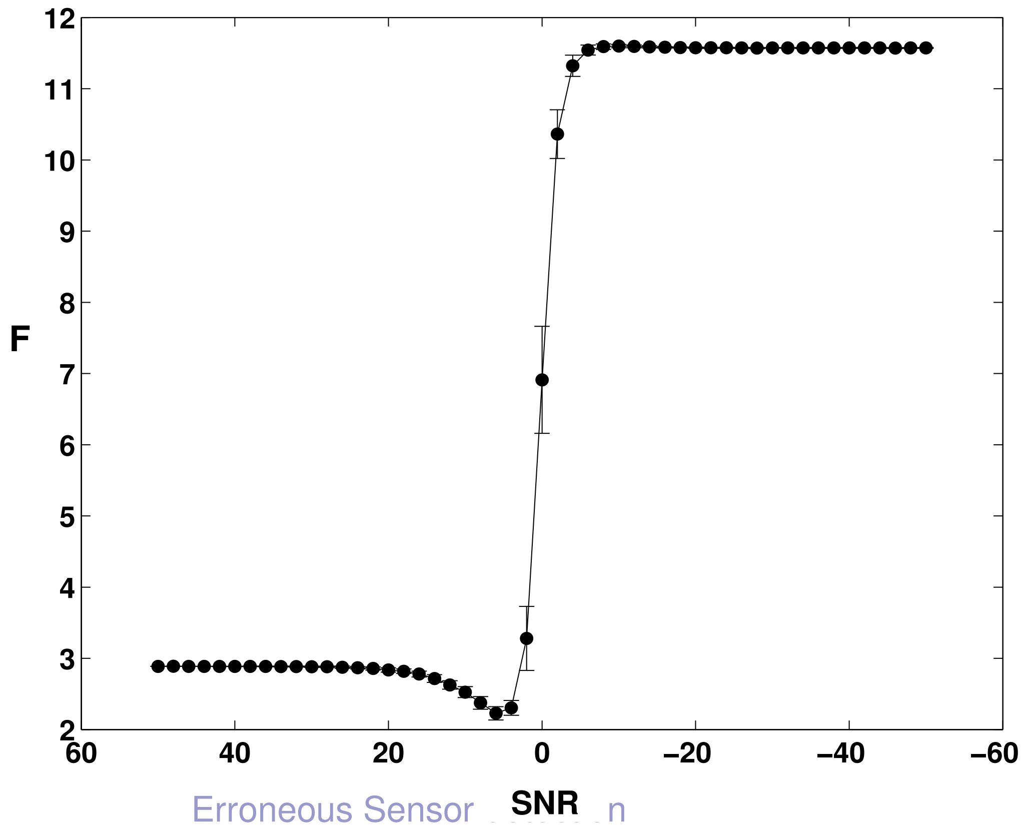
Example: ECG

- Transverse Plane measured from 6 independent electrodes measuring along the X-Y plane
- Data from this plane sufficient to estimate the Original



Example: ECG

- Applying the estimation scheme to the transverse plane, using simulated noise:



Conclusion

- Developed method to detect the presence of erroneous sensors
- Application of the method in EIT and ECG showed promising results
  - Method is sensitive at SNR < 5dB for EIT
  - Method is sensitive at SNR < 0dB for ECG Transversal plane
  - ECG data on Sagittal and Frontal plane was not independent

Q & A

Decision Parameter: ANOVA

- For each candidate sensor s_i of set A:
  - An array of estimation $\mathbf{E}_i$ results for sensors in A'

- Without erroneous sensor the estimation results of array $\mathbf{E}_i$ are ***consistent***

- With erroneous sensor the estimation result for $\mathbf{E}_i$ with erroneous sensor s_i is low, thus ***Inconsistent***

Decision Parameter: ANOVA

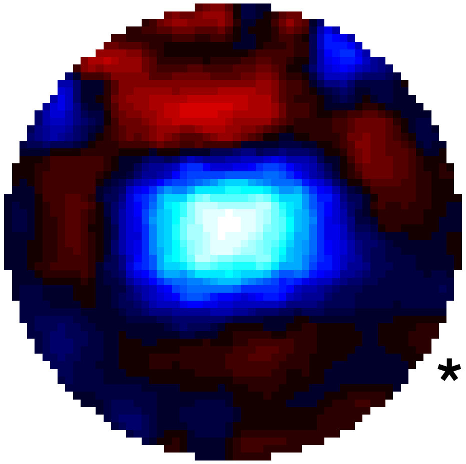
- The Inconsistency of the data groups can be tested using Analysis of Variance (ANOVA)
- ANOVA is used to determine the statistical similarity between Treatments ($\mathbf{E}_i$)

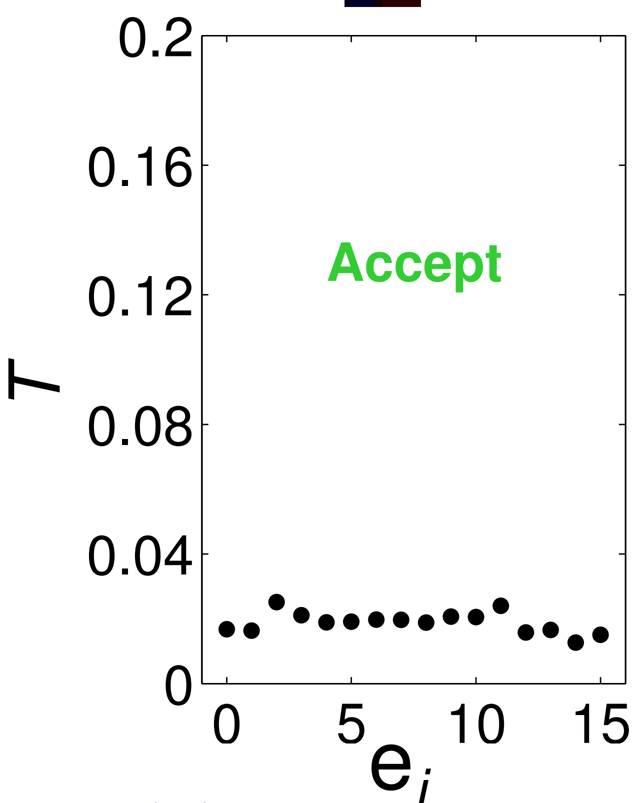
$$\text{F ratio} = \frac{\text{Variation } \textbf{between} \text{ treatments}}{\text{Variation } \textbf{within} \text{ treatments}}$$

Decision Parameter: LSD

- ANOVA determines if a specific data set has an at least one erroneous sensors
- But does not tell us the number and location of these erroneous sensors
- Fisher's Least Significant Difference (LSD) is used to identify the number and location of the erroneous sensors

Example: EIT





H_0 reject at:

$f_0 > f_{0.05,14,239}$

$f_0 > 1.67$

$f_0=1.47$

$f_0=2.71$