

Applying Constraints to the Electrocardiographic Inverse Problem

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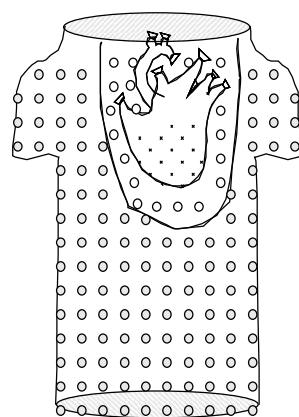
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Electrocardiography



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Electrocardiographic Mapping

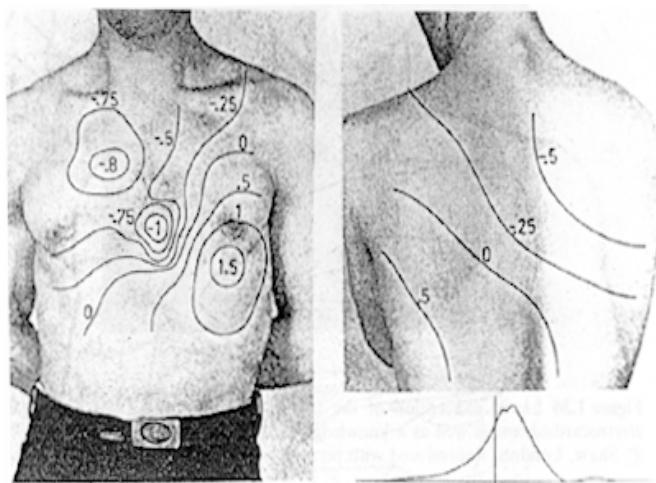


- Bioelectric Potentials
- Goals
 - Higher spatial density
 - Imaging modality
- Measurements
 - Body surface
 - Heart surfaces
 - Heart volume



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Body Surface Potential Mapping

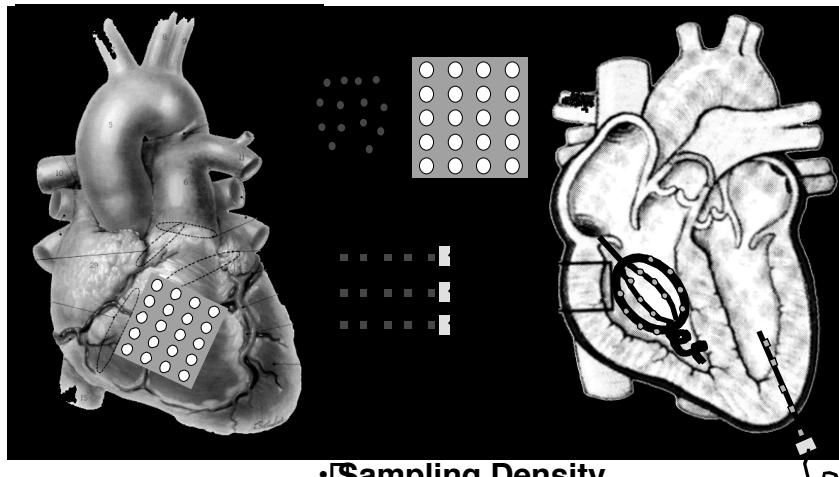


Taccardi
et al,
Circ.,
1963



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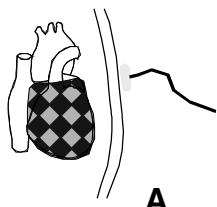
Cardiac Mapping



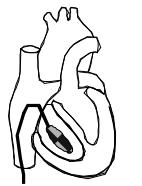
- Sampling Density
- Surface or volume

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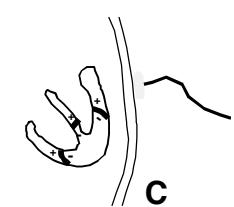
Inverse Problems in Electrocardiography



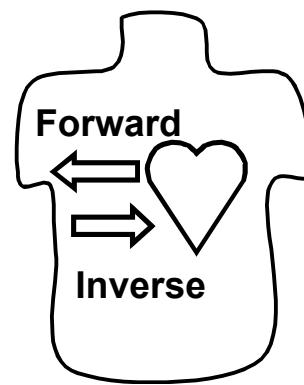
A



B



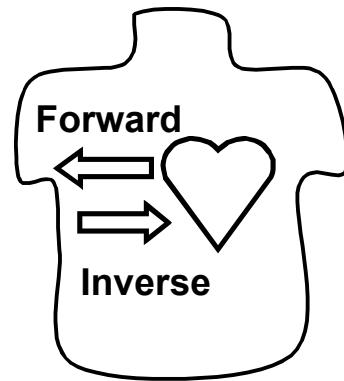
C



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Epicardial Inverse Problem

- **Definition**
 - Estimate sources from remote measurements
- **Motivation**
 - Noninvasive detection of abnormalities
 - Spatial smoothing and attenuation

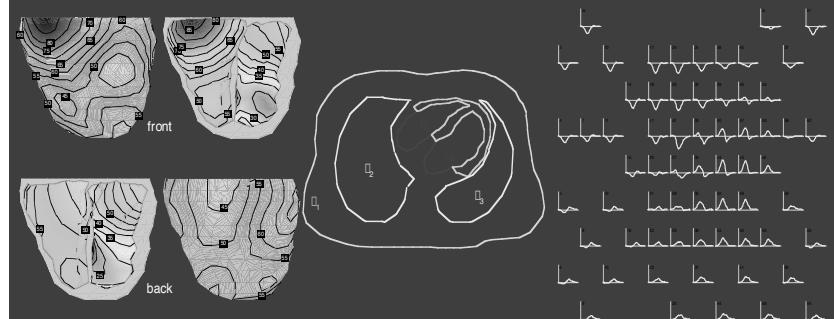


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Forward/Inverse Problem

Forward problem

Epicardial/Endocardial Activation Time Geometric Model Body Surface Potentials



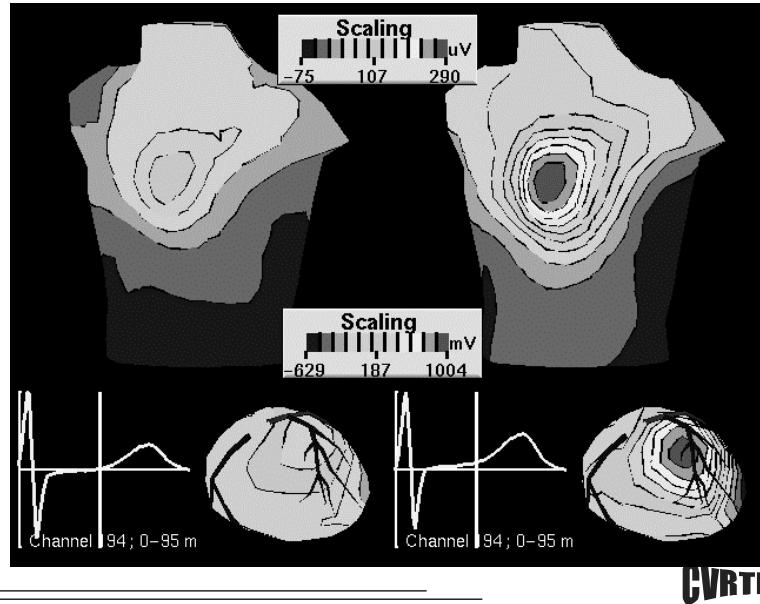
Inverse problem

Thom Oostendorp,
Univ. of Nijmegen

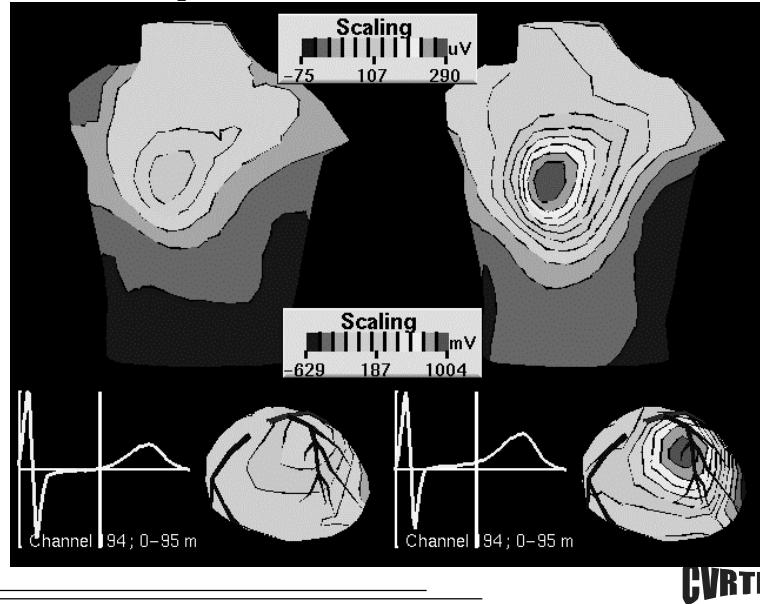
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Sample Problem: PTCA



Sample Problem: PTCA



Elements of the Inverse Problem

- Components
 - Source description
 - Geometry/conductivity
 - Forward solution
 - “Inversion” method (regularization)
- Challenges
 - Inverse is ill-posed
 - Solution ill-conditioned



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Inverse Problem Research

- Role of geometry/conductivity
- Numerical methods
- Improving accuracy to clinical levels
- Regularization
 - *A priori* constraints versus fidelity to measurements



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Regularization

- **Current questions**
 - Choice of constraints/weights
 - Effects of errors
 - Reliability
- **Contemporary approaches**
 - Multiple Constraints
 - Time Varying Constraints
 - Tuned constraints
 - Multisource constraints



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Tikhonov Approach

Problem formulation

$$\mathbf{y}(k) = \mathbf{A} \cdot \mathbf{h}(k) + \mathbf{e}(k) \quad k = 1, 2, \dots, L$$

Constraint

$$\hat{\mathbf{h}}_\lambda = \arg \min_{\mathbf{x}} \left(\|\mathbf{y} - \mathbf{Ax}\|^2 + \lambda^2 \|\mathbf{Rx}\|^2 \right),$$

Solution

$$\hat{\mathbf{h}}_\lambda = (\mathbf{A}^T \mathbf{A} + \lambda^2 \mathbf{R}^T \mathbf{R})^{-1} \mathbf{A}^T \mathbf{y}$$



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Multiple Constraints

For k constraints

$$\hat{\mathbf{h}}_{\lambda} = \arg \min_{\mathbf{x}} \left(\|\mathbf{y} - \mathbf{Ax}\|^2 + \sum_{i=1}^k \lambda_i^2 \|\mathbf{R}_i \mathbf{x}\|^2 \right)$$

with solution

$$\hat{\mathbf{h}}_{\lambda} = [\mathbf{A}^T \mathbf{A} + \sum_{i=1}^k \lambda_i^2 \mathbf{R}_i^T \mathbf{R}_i]^{-1} \mathbf{A}^T \mathbf{y}.$$



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Dual Spatial Constraints

For two spatial constraints:

$$\hat{\mathbf{h}}_{\lambda} = (\mathbf{A}^T \mathbf{A} + \lambda_1^2 \mathbf{R}_1^T \mathbf{R}_1 + \lambda_2^2 \mathbf{R}_2^T \mathbf{R}_2)^{-1} \mathbf{A}^T \mathbf{y}.$$

Note: two regularization factors required



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Joint Time-Space Constraints

Redefine y , h , A :

$$\bar{y} = \bar{A}\bar{h} + \bar{e}$$

$$\bar{A} = \begin{pmatrix} A & 0 & 0 & \cdots & 0 \\ 0 & A & 0 & \cdots & 0 \\ 0 & 0 & A & \cdots & 0 \\ & & & \ddots & \\ 0 & 0 & 0 & \cdots & A \end{pmatrix}.$$

And write a new minimization equation:

$$\hat{h} = \arg \min_{\bar{x}} \left(\|\bar{A}\bar{x} - \bar{y}\|^2 + \sum_{i=1}^{k_s} \lambda_i^2 \|\bar{R}_i \bar{x}\|^2 + \sum_{i=1}^{k_t} \eta_i^2 \|\bar{T}_i \bar{x}\|^2 \right).$$



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Joint Time-Space Constraints

General solution:

$$\hat{h} = (\bar{A}^T \bar{A} + \sum_{i=1}^{k_s} \lambda_i^2 \bar{R}_i^T \bar{R}_i + \sum_{i=1}^{k_t} \eta_i^2 \bar{T}_i^T \bar{T}_i)^{-1} \bar{A}^T \bar{y}$$

For a single space and time constraint:

$$\begin{aligned} \hat{h} &= (\bar{A}^T \bar{A} + \lambda^2 \bar{R}^T \bar{R} + \eta^2 \bar{T}^T \bar{T})^{-1} \bar{A}^T \bar{y} \\ &= [\mathbf{I}_L \otimes (\mathbf{A}^T \mathbf{A}) + \lambda^2 \mathbf{I}_L \otimes \mathbf{R}^T \mathbf{R} + \eta^2 (\mathbf{T}^T \mathbf{T}) \otimes \mathbf{I}_N]^{-1} \cdot \\ &\quad \cdot (\mathbf{I}_L \otimes \mathbf{A}^T) \bar{y}. \end{aligned}$$

Note: two regularization factors and implicit temporal factor



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Determining Weights

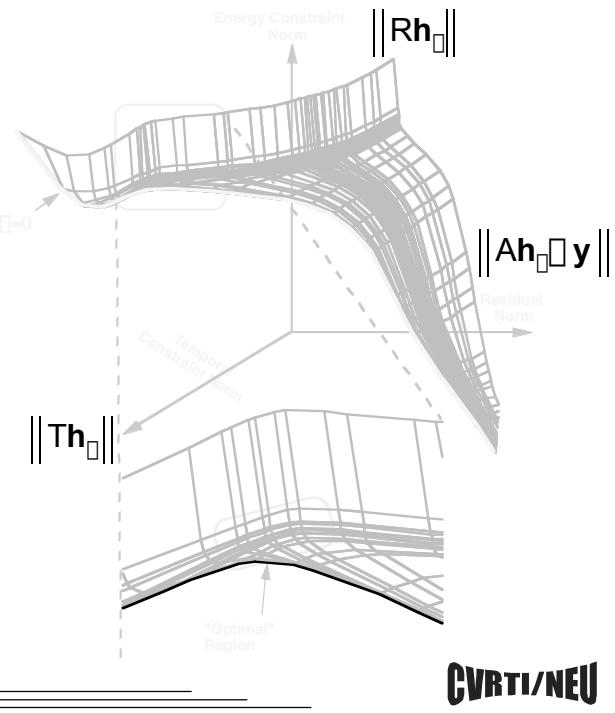
- Based on *a posteriori* information
- Ad hoc schemes
 - CRESO: composite residual and smooth operator
 - BNC: bounded norm constraint
 - AIC: Akaike information criterion
 - L-curve: residual norm vs. solution seminorm



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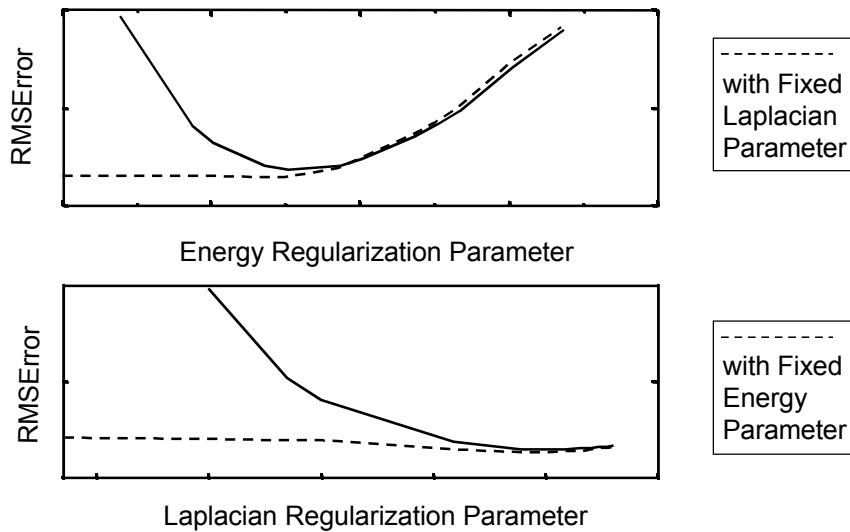
L-Surface

- Natural extension of single constraint approach
- “Knee” point becomes a region



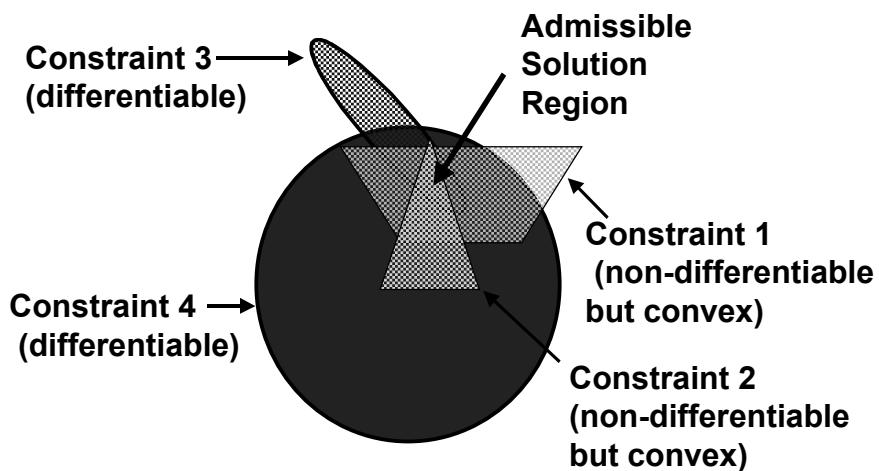
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Joint Regularization Results



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Admissible Solution Approach



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Single Constraint

Define $\square(\mathbf{x})$ s.t.

$$\phi(\mathbf{x}) : \mathcal{R}^N \rightarrow \mathcal{R}$$

with the constraint such that

$$\phi(\mathbf{x}) - \epsilon < 0.$$

that satisfies the convex condition

$$\phi(\alpha\mathbf{x} + (1 - \alpha)\mathbf{y}) \leq \alpha\phi(\mathbf{x}) + (1 - \alpha)\phi(\mathbf{y}) \quad \forall \alpha \in [0, 1].$$



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Multiple Constraints

Define multiple constraints $\square_i(\mathbf{x})$

$$(\phi_i(\mathbf{x}) - \epsilon_i) \in \mathcal{H}, \text{ for } i = 1, 2, \dots, m.$$

so that the set of these

$$\{\mathbf{x} : \phi(\mathbf{x}) < 0\}$$

represents the intersection of all constraints. When they satisfy the joint condition

$$\phi(\mathbf{x}) \leq 0$$

Then the resulting \mathbf{x} is the *admissible solution*



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Examples of Constraints

- **Residual constraint**

$$\phi(\mathbf{x}) = \|\mathbf{Ax} - \mathbf{y}\|_2^2$$

- **Regularization constraints**

$$\phi(\mathbf{x}) = \|\mathbf{Rx}\|_2^2$$

- **Tikhonov constraints**

$$\phi_\lambda(\mathbf{x}) = \left\| \begin{pmatrix} \mathbf{A} \\ \sqrt{\lambda}\mathbf{R} \end{pmatrix} \mathbf{x} - \begin{pmatrix} \mathbf{b} \\ \mathbf{0} \end{pmatrix} \right\|_2^2$$

- **Spatiotemporal constraints**

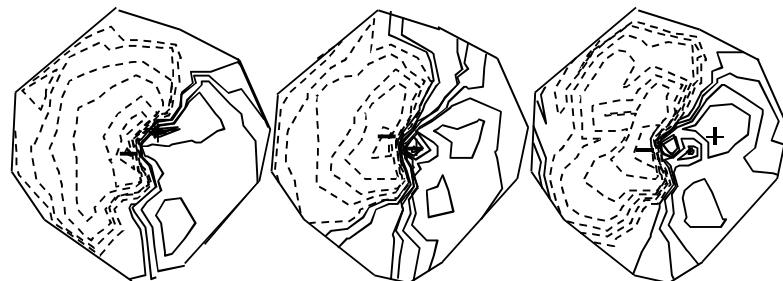
- **Weighted constraints**

- **Novel constraints**



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Admissible Solution Results



Original

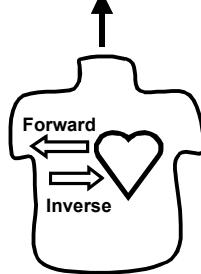
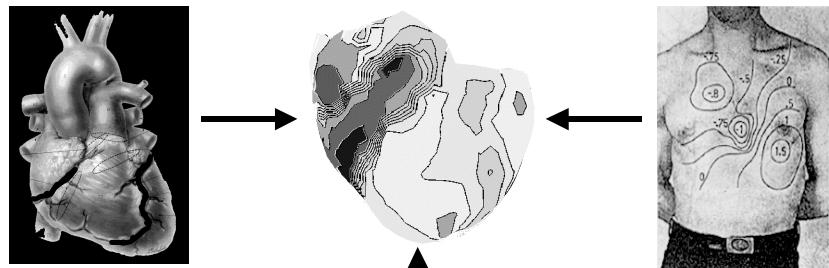
Regularized

Admissible
Solution



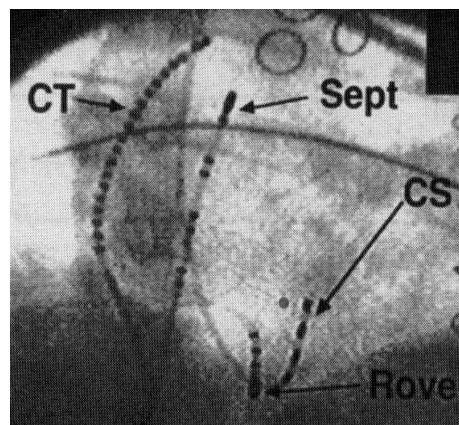
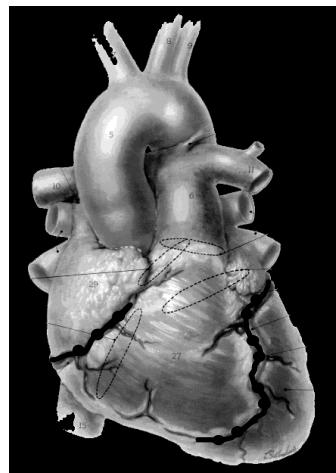
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Combining Information Sources



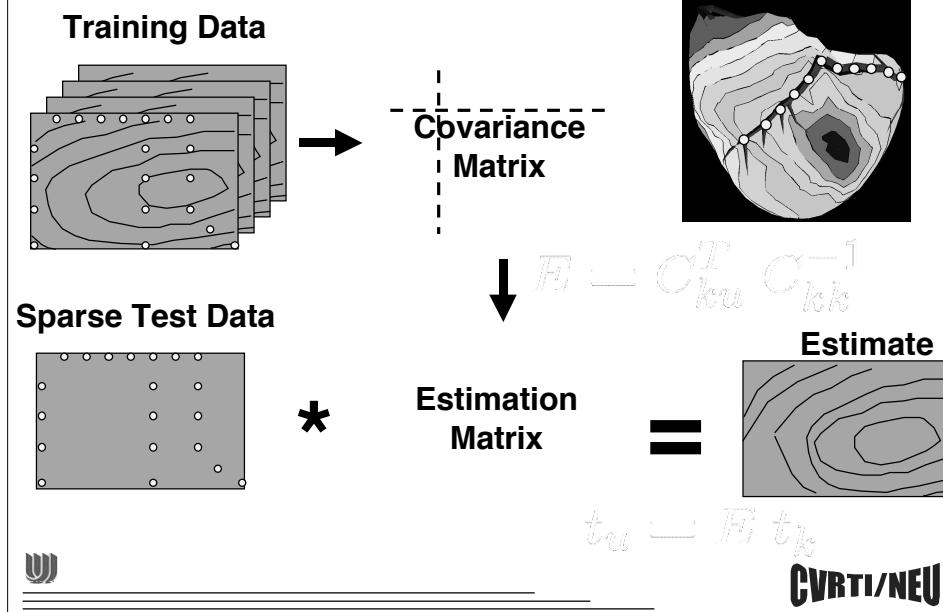
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Venous Catheter Based Mapping

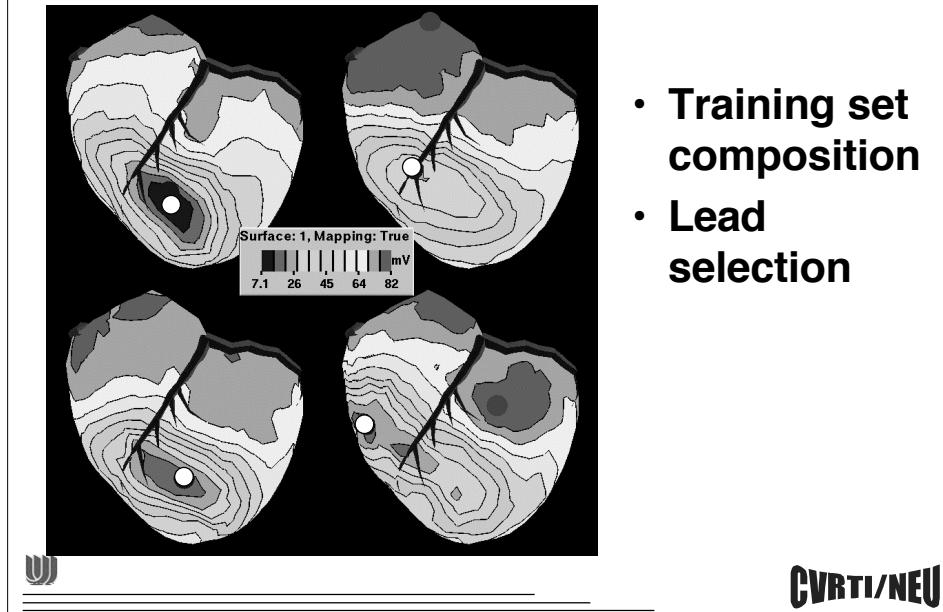


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Statistical Estimation



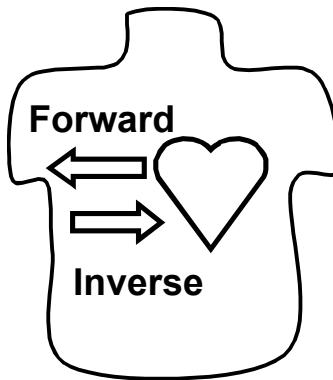
Estimated Activation Maps



Augmented Inverse Problem

Torso geometry
+
Body-Surface Potentials
+
Sparse Epicardial Potentials
+
Inverse Solution

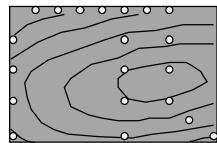
Epicardial Map



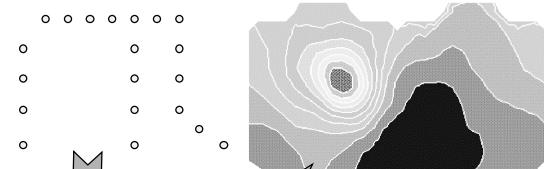
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Subtraction Approach

Unknown

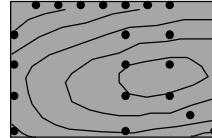


Known



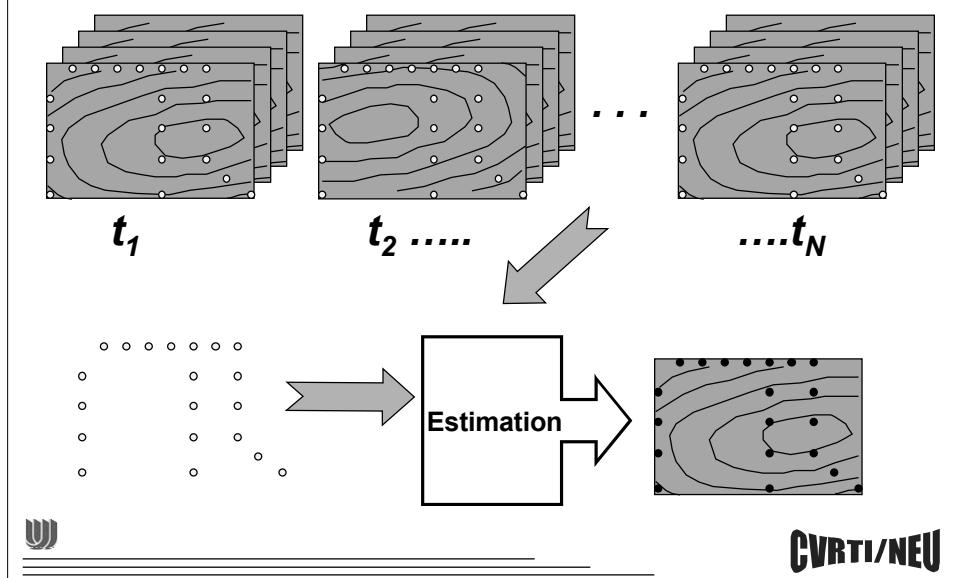
- 1) Subtract known epicardial potentials
- 2) Solve reduced inverse problem

Inverse
(Tikhonov)

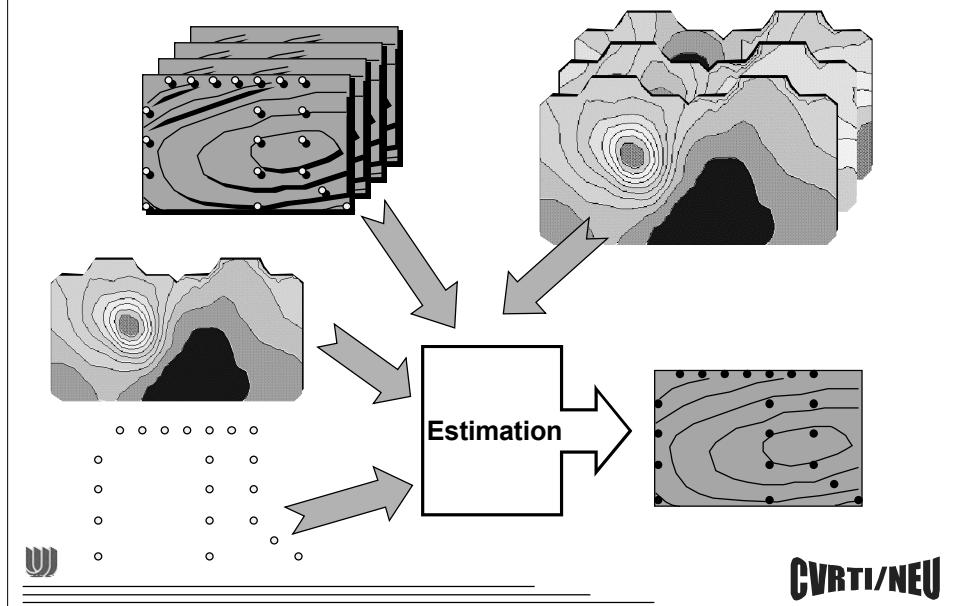


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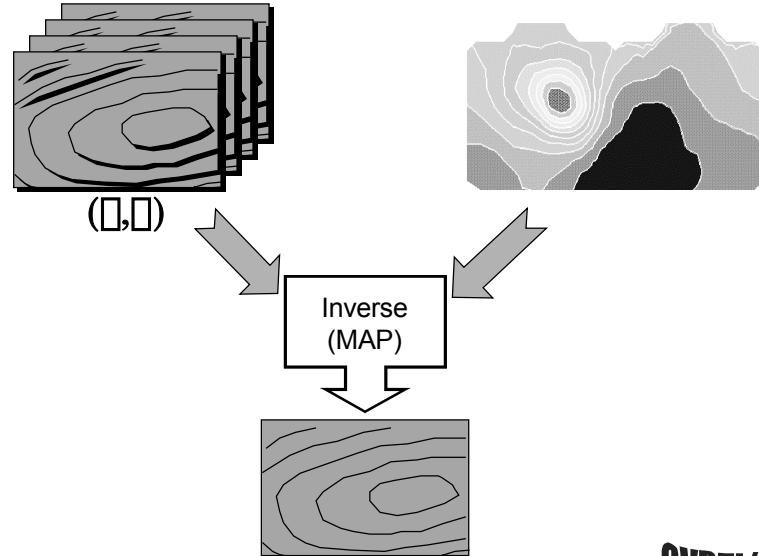
Epicardial Estimation



Combined Estimation

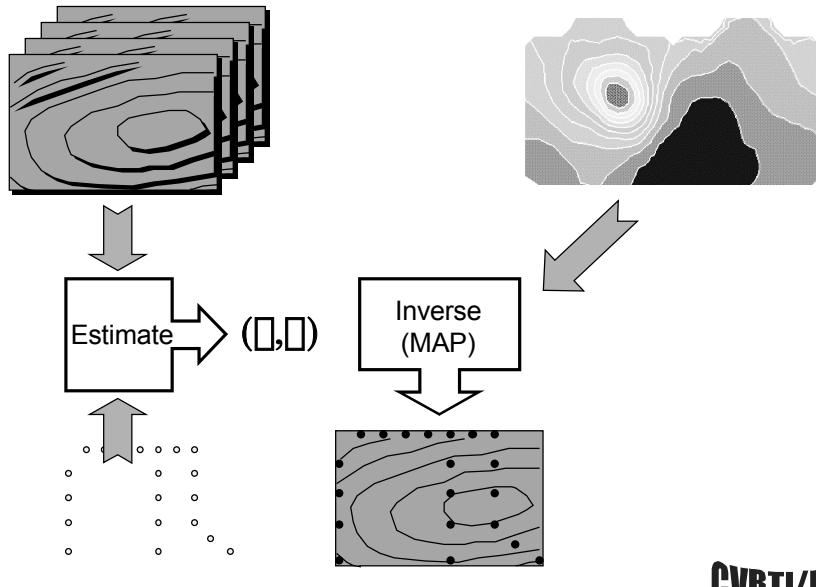


Bayesian Approach



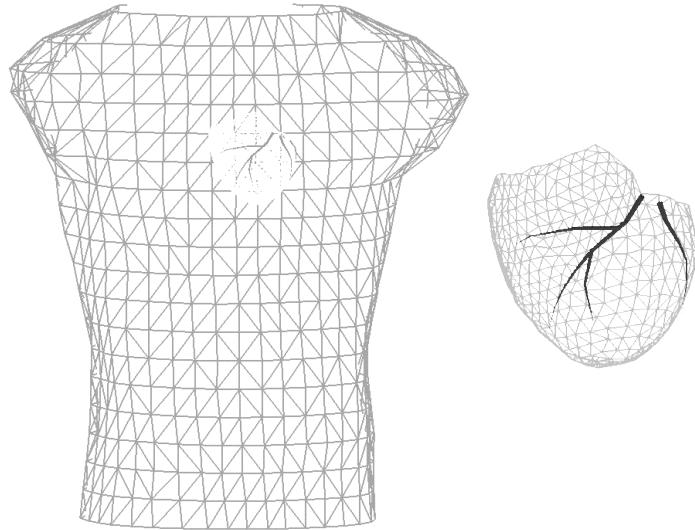
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Hybrid Approach



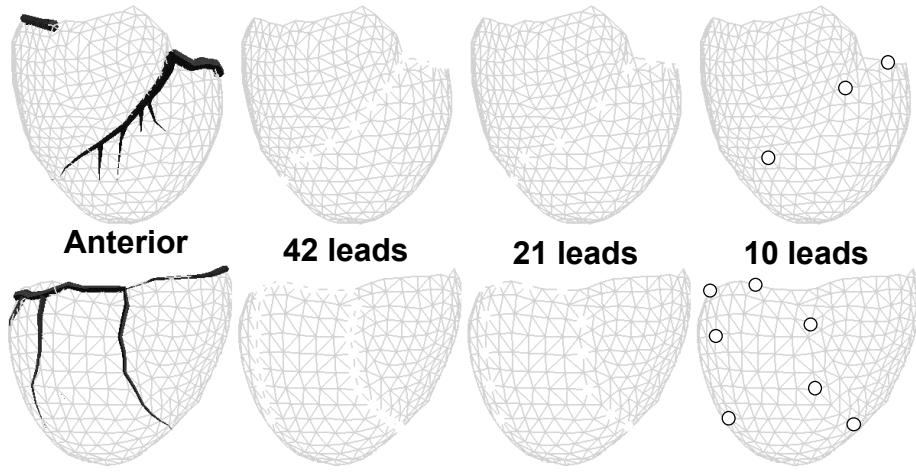
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Tank/Heart Geometry



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Test Lead Sets



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Simulation Study

- 490 lead measured sock data
- Surrogate catheter potentials
 - 42 sites
 - + Gaussian noise
- Torso potentials
 - Calculated noise-free using forward model
 - + Gaussian noise



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Leave-One-Experiment Out Protocol

Training Data

LV Paced
Beats



Test Data

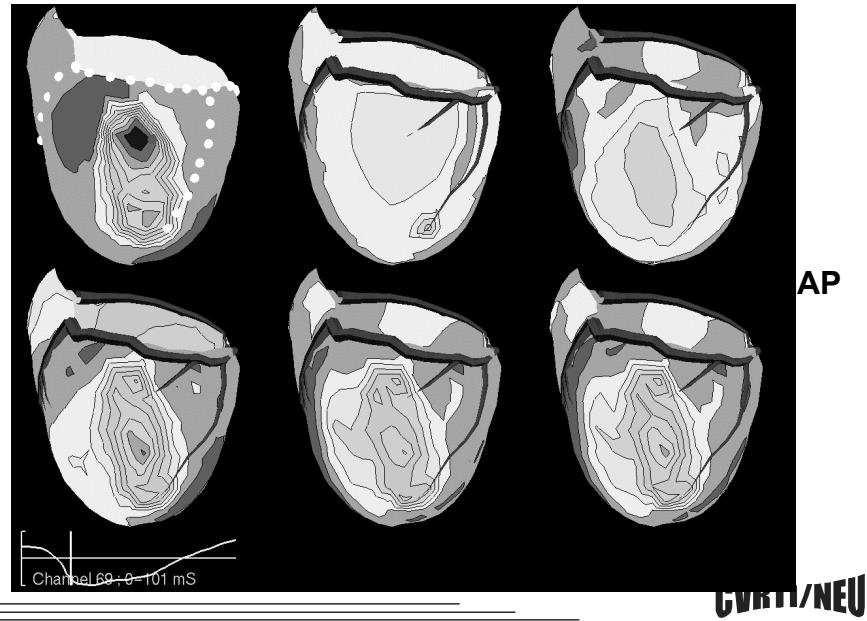


Mixed
Paced
Beats

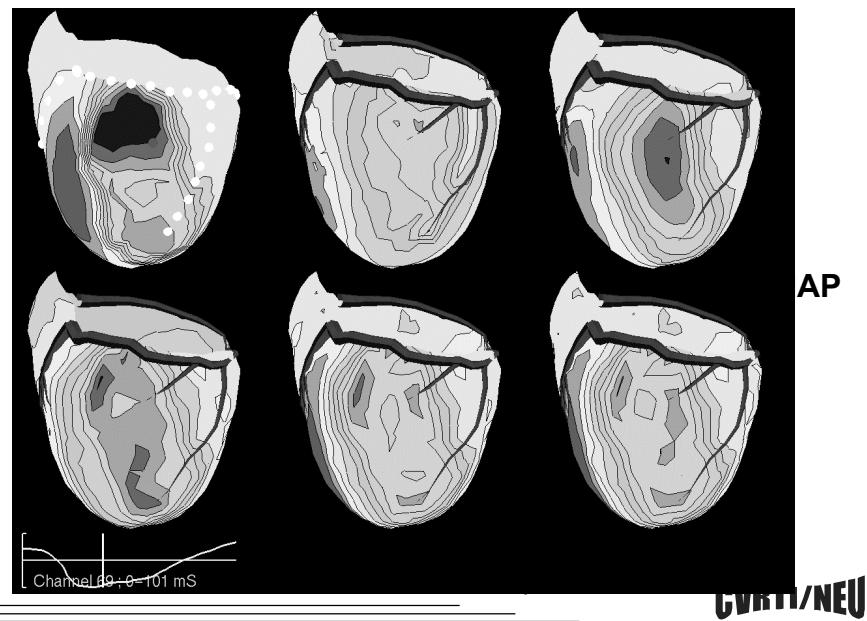


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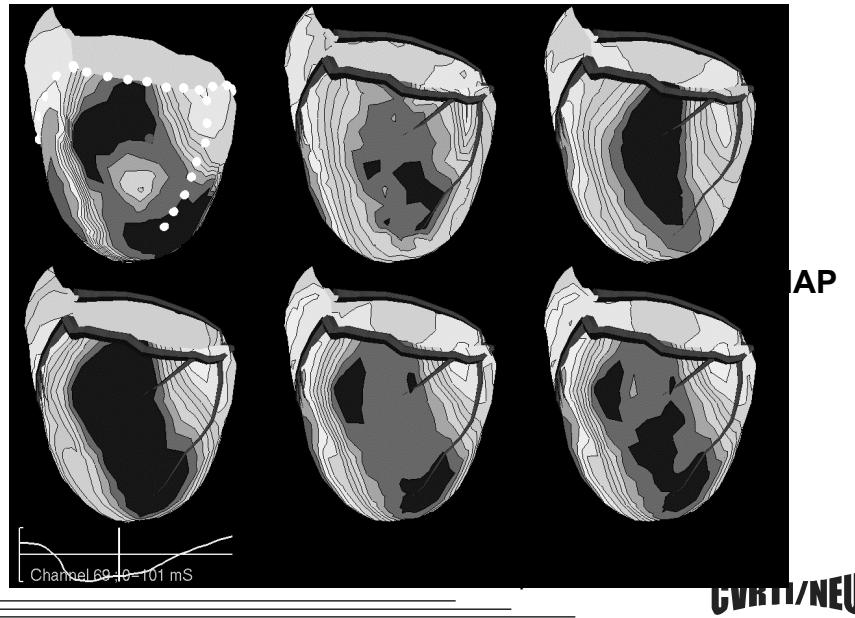
LV Pacing (LV-23 ms)



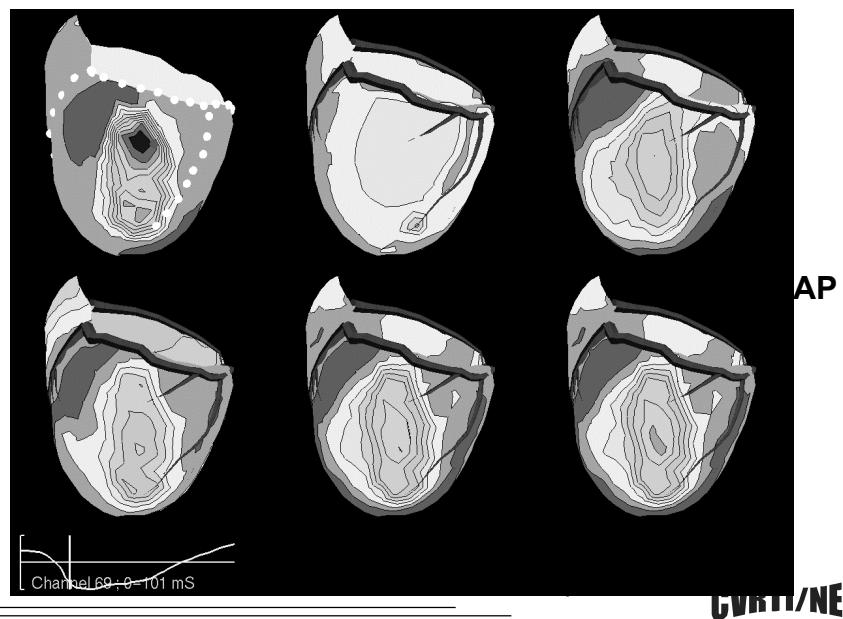
LV Pacing (LV-38 ms)



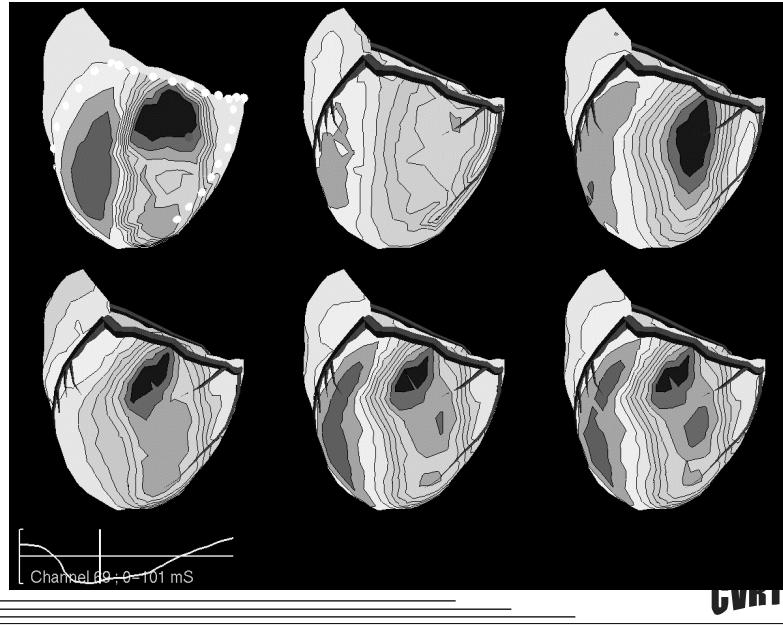
LV Pacing (LV-47 ms)



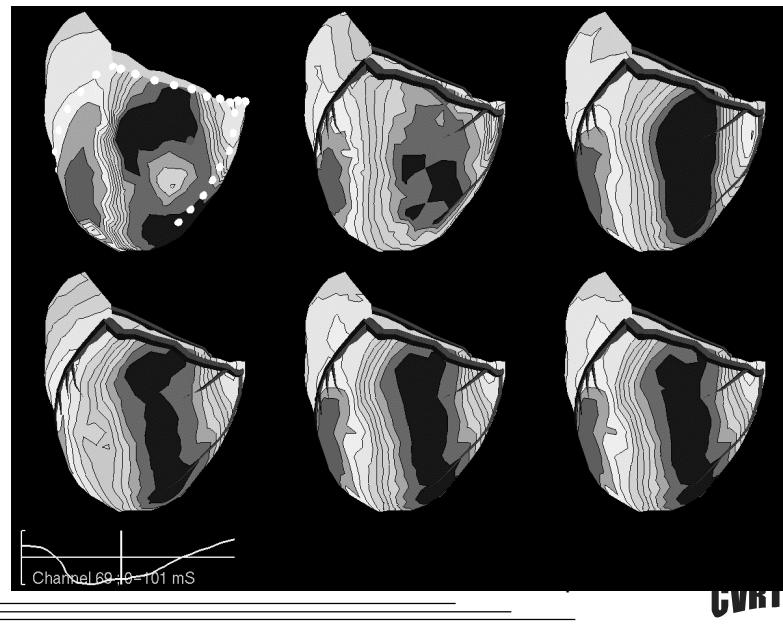
LV Pacing (Mixed-23 ms)



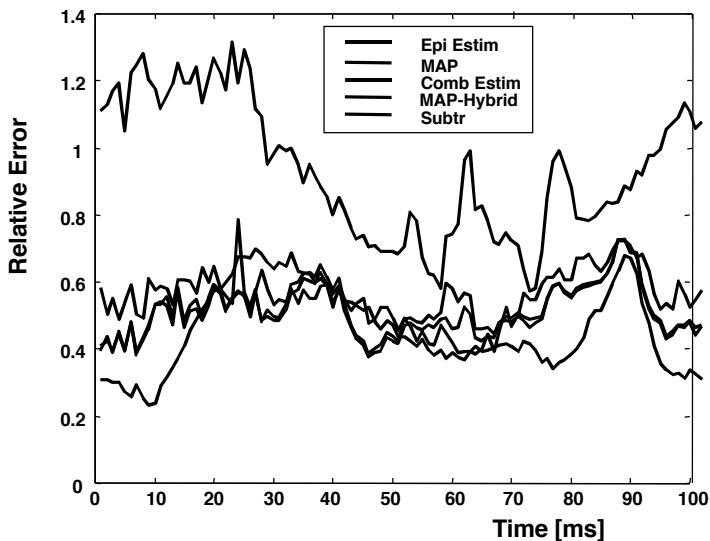
LV Pacing (Mixed-38 ms)



LV Pacing (Mixed-47 ms)

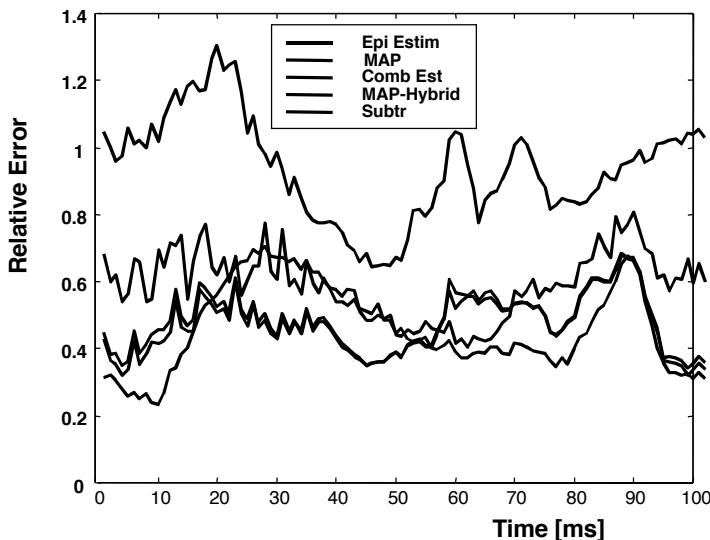


Relative Error (31-LV)



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Relative Error (31-Mixed)



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Estimation Findings

- **Estimation alone: noisy, unstable results**
- **Estimation + inverse: smoothing improves stability**



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Inverse Solution Findings

- **All solutions better than simple Tikhonov**
- **MAP usually improved with addition of catheter measurements (Hybrid MAP)**



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Role of Statistics (Training)

- **Generally helps**
- **But can add artifacts, e.g., spurious breakthroughs or wavefronts**
- **Torso potentials can reduce artifacts**



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Acknowledgements

- | | |
|---|---|
| <ul style="list-style-type: none">• CVRTI<ul style="list-style-type: none">– Bruno Taccardi– Rich Kuenzler– Bob Lux– Phil Ershler– Yonild Lian– Shibaji Shome– Lucas Lorenzo | <ul style="list-style-type: none">• CDSP<ul style="list-style-type: none">– Dana Brooks– Ghandi Ahmad |
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