Wavefront-based models for inverse electrocardiography



Alireza Ghodrati (*Draeger Medical*) Dana Brooks, Gilead Tadmor (*Northeastern University*)

Rob MacLeod (University of Utah)



Inverse ECG Basics

Forward

Inverse

- Problem statement:
 - Estimate sources from remote measurements
- Source model:
 - Potential sources on epicardium
 - Activation times on endo- and epicardium
- Volume conductor
 - Inhomogeneous
 - Three dimensional
- Challenge:
 - Spatial smoothing and attenuation
 - An ill-posed problem













WBCR Formulation

$$c_{n+1} = f(c_n) + u_{n+1}$$
$$u_{n+1} = Aq(c_{n+1}) + w_{n+1}$$

- *n* : time instant
- c : activation wavefront which is state variable (continuous curve)
- y : measurements on the body
- *f* : state evolution function
- g : potential function
- *u* : state model error (Gaussian white noise)
- w : forward model error (Gaussian white noise)







Setting Model Parameters

- Goal : Find rules for propagation of the activation wavefront
- Study of the data
 - Dog heart in a tank simulating human torso
 - 771 nodes on the torso, 490 nodes on the heart
 - 6 beats paced on the left ventricle & 6 beats paced on the right ventricle

Filtering the residual (Extended Kalman Filter)

- Error in the potential model is large
- This error is low spatial frequency
- Thus we filtered the low frequency components in the residual error

$$\min \|U_k^T(y_n - Ag(c_n))\|$$

 $A = USV^T$

 U_k contains column k+1 to N of U

Implementation

- Spherical coordinate (θ, ϕ) to represent the curve.
- B-spline used to define a continuous wavefront curve.
- Distance from the wavefront approximated as the shortest arc from a point to the wavefront curve.
- Torso potentials simulated using the true data in the forward model plus white Gaussian noise (SNR=30dB)
- Filtering : k=3
- Extended Kalman Filtering



Wavefront-based Potential Reconstruction Approach (WBPR)

Tikhonov (Twomey) solution:

$$\hat{x}_{x} = argmin \|Ax_{k} - y_{k}\|_{2}^{2} + \lambda^{2} \|R(x_{k} - \bar{x}_{k})\|_{2}^{2}$$
$$\hat{x}_{x} = \bar{x}_{k} (A^{t}A + \lambda^{2}R^{t}R)^{-1} A^{t} (y_{k} - A\bar{x}_{k})$$

- Previous reports were mostly focused on designing R, leaving $\overline{x}_k = 0$



WBPR Algorithm

Step 1:
$$c_k = f(\hat{x}_{k-1})$$
 Wavefront from thresholding
previous time step solution
Step 2: $\bar{x}_k = g(c_k)$ Initial solution from wavefront curve
Step 3: $\hat{x}_k = \bar{x}_k + (A^T A + \ddot{e}^2 I)^{-1} A^T (y_k - A \bar{x}_k)$

Simulation study

- 490 lead sock data (Real measurements of dog heart in a tank simulating a human torso)
- Forward matrix : 771 by 490
- Measurements are simulated and white Gaussian noise was added (SNR=30dB)
- The initial wavefront curve: a circle around the pacing site with radius of 2cm







Conclusions

- High complexity is possible and sometimes even useful
- WBCR approach reconstructed better activation wavefronts than Tikhonov, especially at early time instants after initial activation
- WBPR approach reconstructed considerably better epicardial potentials than Tikhonov
- Using everyone's brain is always best

Future Plans

- Employ more sophisticated temporal constraints
- Investigate the sensitivity of the inverse solution with respect to the parameters of the initial solution
- Use real torso measurements to take the forward model error into account
- Investigate certain conditions such as ischemia (the height of the wavefront changes on the heart)
- Compare with other spatial-temporal methods