

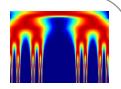
Multiscale Recurrence Analysis of Long-Term Nonlinear and Nonstationary Time Series

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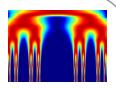
Relevant Publications



- □ H. Yang*, "Multiscale Recurrence Quantification Analysis of Spatial Vectorcardiogram (VCG) Signals," *IEEE Transactions on Biomedical Engineering*, Vol. 58, No. 2, p339-347, 2011, DOI: 10.1109/TBME.2010.2063704
- ☐ Y. Chen[†] and **H. Yang***, "Multiscale recurrence analysis of long-term nonlinear and nonstationary time series," *Chaos, Solitons and Fractals*, Vol. 45, No. 7, p978-987, 2012, DOI: 10.1016/j.chaos.2012.03.013
- H. Yang*, S. T. S. Bukkapatnam, and L. G. Barajas, "Local recurrence model for performance prediction and prognostics in nonlinear and nonstationary systems," *Pattern Recognition*, Vol. 44, No. 8, p1834-1840, 2011, DOI: 10.1016/j.patcog.2011.01.010
- ☐ Y. Chen[†], and **H. Yang***, "Wavelet packet analysis of disease-altered recurrence dynamics in the long-term spatiotemporal vectorcardiogram (VCG) signals", *Proceedings of 2013 IEEE Engineering in Medicine and Biology Society Conference (EMBC)*, p. 2595-2598, July 3-7, 2013, Osaka, Japan. DOI: 10.1109/EMBC.2013.6610071



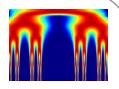
Outline



- ☐ Problem Statement
- ☐ Research Background
 - ➤ Wavelet transform
 - > Recurrence analysis
- ☐ Research Methodology
 - ➤ Multiscale recurrence analysis
 - > Feature selection
 - > Randomized classification experiments
- ☐ Experimental Designs & Results
- Conclusions



Problem Statement



☐ Challenges:

- > Data complexity: nonlinearity and nonstationarity
- > Enormous data torrents

☐ State of the Art:

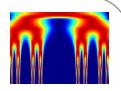
- > Conventional frequency-domain and linear system approaches
- ➤ Nonlinear stochastic dynamics under highly nonstationary conditions
- ➤ Nonlinear dynamic methods **computational expensive**

□ Goals:

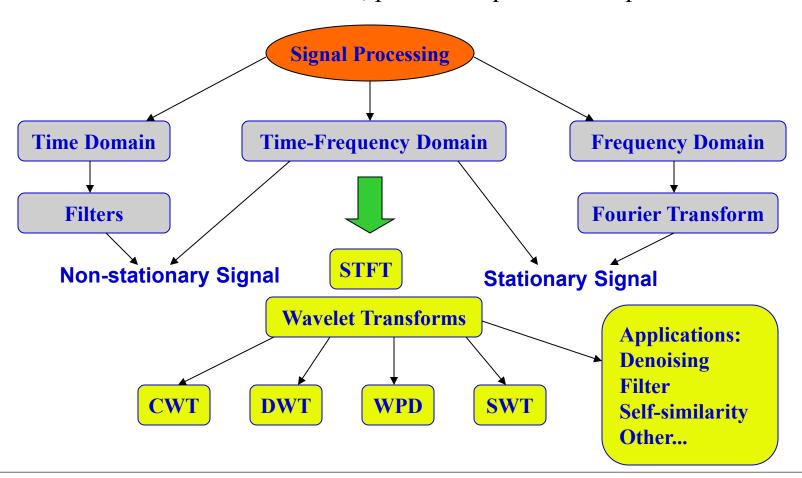
- ➤ Address the issues of nonlinearity, nonstationarity and large datasets
- > Extended and integrated into other nonlinear dynamic approaches
- ➤ Disease-altered nonlinear dynamics



Time-Frequency Representation

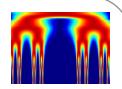


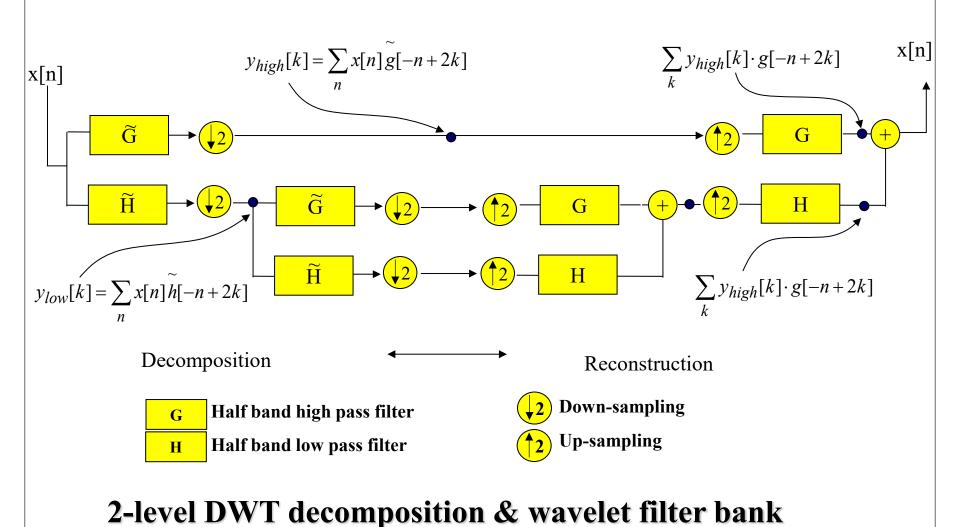
- ☐ Time info difficult to interpret in frequency domain
- ☐ Frequency info difficult to interpret in time domain
- ☐ Perfect time info in time domain, perfect freq. info in freq. domain





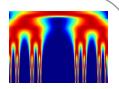
Discrete Wavelet Transform



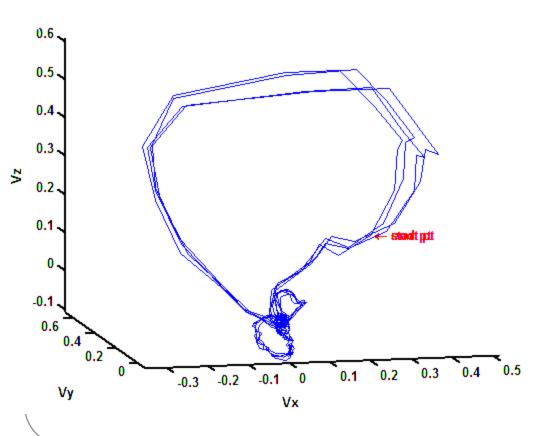


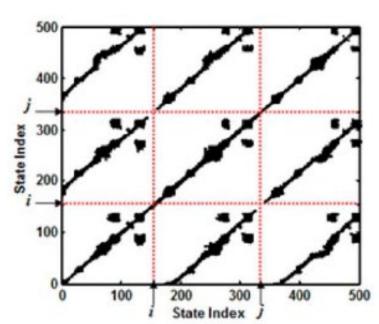


Recurrence Analysis



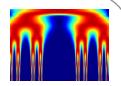
- ☐ Recurrence patterns of the dynamical systems
 - \triangleright Recurrence plot: $R(i,j) = \Theta(\varepsilon ||x(i) x(j)||)$

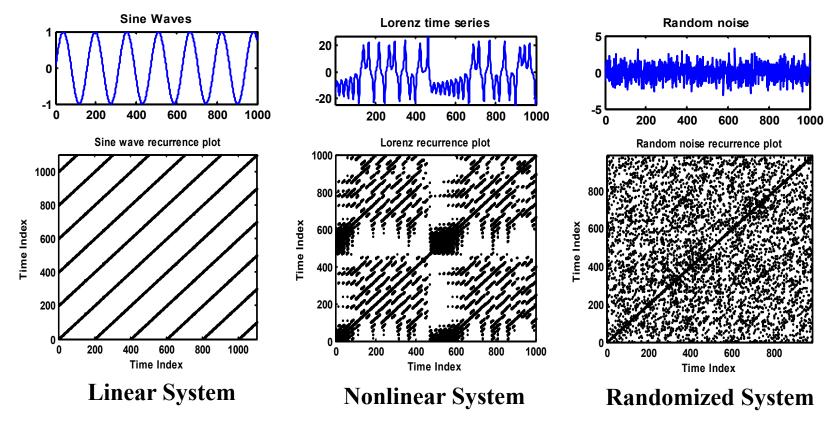






Structures in Recurrence Plots

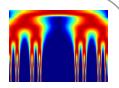




- **□Small-scale** structures
 - ➤ single dots, diagonal and vertical lines
- □ Large-scale structures
 - homogenous, periodic and disrupted visualization



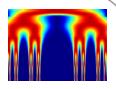
Recurrence Features



- ☐ Quantifying the *topological features of Recurrence Plots*
- Statistical features to quantify certain recurrence patterns from Threshold Recurrence Plot (Kantz, Marwan, and Kurths et al.):
 - ➤ Recurrence rate (%REC)
 - ➤ Determinism (%DET)
 - ➤ Linemax (LMAX)
 - > Entropy (ENT)
 - ➤ Laminarity (%LAM)
 - > Trapping time (TT)
- ☐ Diagonal structures (first four) and vertical structures (last two) in the threshold recurrence plot
- ☐ Computational complexity: square increase



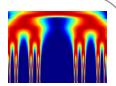
Outline

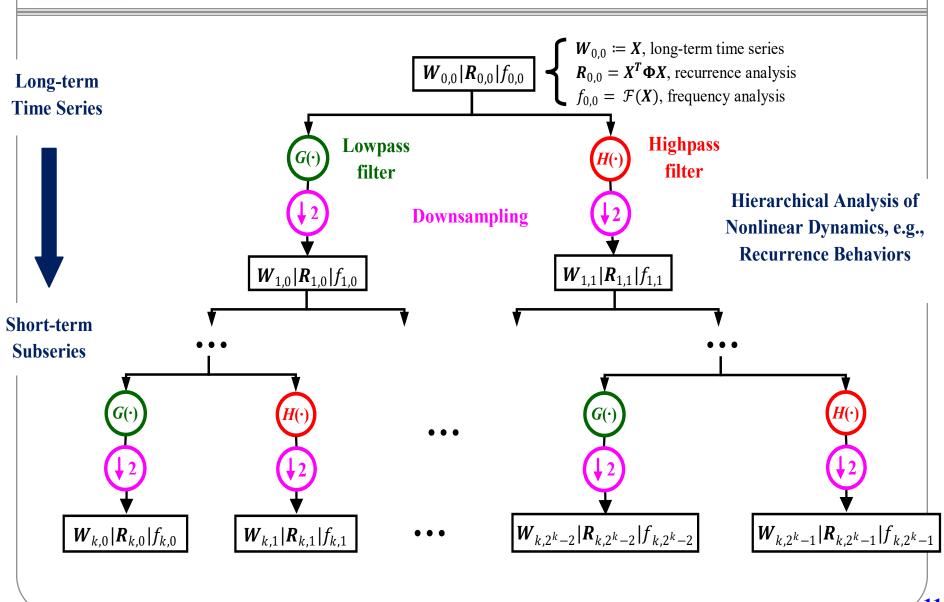


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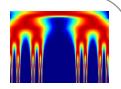
Hierarchical Nonlinear Dynamics







Completeness of MRA



- \square Given a time series $\boldsymbol{X} = \{x_1, x_2, \dots, x_N\}^T$
- \square Embedded state space $\mathbf{x}(i) = (x_i, x_{i+\tau}, \dots, x_{i+\tau(M-1)})$
- ☐ Recurrence distance matrix ← time series:

$$UR_{0,0}^{2}(i,j) = \|\mathbf{x}(i) - \mathbf{x}(j)\|^{2} = \sum_{m=0}^{M-1} |x_{i+m\tau} - x_{j+m\tau}|^{2}$$

$$=\sum_{m=0}^{M-1} (\mathbf{X}^T \Phi_{i+m\tau,j+m\tau} \mathbf{X})$$

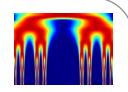
 $\Phi_{i,j}$ positive semidefinite, 1 in the ii^{th} and jj^{th} elements, -1 in the ij^{th} and ji^{th} elements and 0 otherwise.

☐ Recurrence distance matrix ← wavelet subseries:

$$UR_{0,0}^{2}(i,j) = [\boldsymbol{W}_{k,2^{k}-1}^{T} \cdots \boldsymbol{W}_{k,0}^{T}] \mathcal{W}_{k} \left(\sum_{m=0}^{M-1} \Phi_{i+m\tau,j+m\tau} \right) \mathcal{W}_{k}^{T} \begin{bmatrix} \boldsymbol{W}_{k,2^{k}-1} \\ \vdots \\ \boldsymbol{W}_{k,0} \end{bmatrix}$$

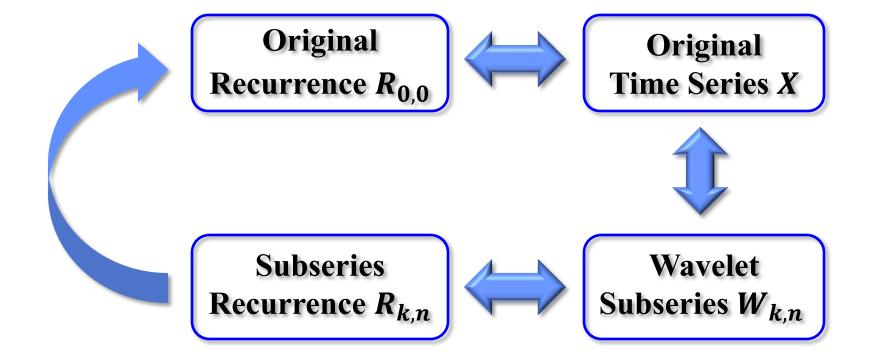


Multiscale Recurrence Analysis



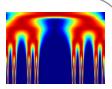
- ☐ Reconstruct time series from recurrence plot
 - > Y. Hirata et al. (2008); M. Thiel et al. (2004)

Recurrence Plot Time Series





Wavelet Preservation of Dynamics



- \square Time-delay state space: $\mathbf{w}(i) = (w_i, w_{i+\tau}, \dots, w_{i+\tau(M-1)})$
- □ Gram matrix: $G(i,j) \equiv w(i) \cdot w(j)$
- ☐ Multidimensional scaling

$$UR^{2}(i,j) = [w(i) - w(j)] \cdot [w(i) - w(j)]$$

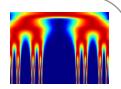
$$G(i,j) = -\frac{1}{2} \left[UR^{2}(i,j) - \frac{1}{N} \sum_{k=1}^{N} UR^{2}(i,k) - \frac{1}{N} \sum_{k=1}^{N} UR^{2}(k,j) + \frac{1}{N^{2}} \sum_{g=1}^{N} \sum_{h=1}^{N} UR^{2}(g,h) \right]$$

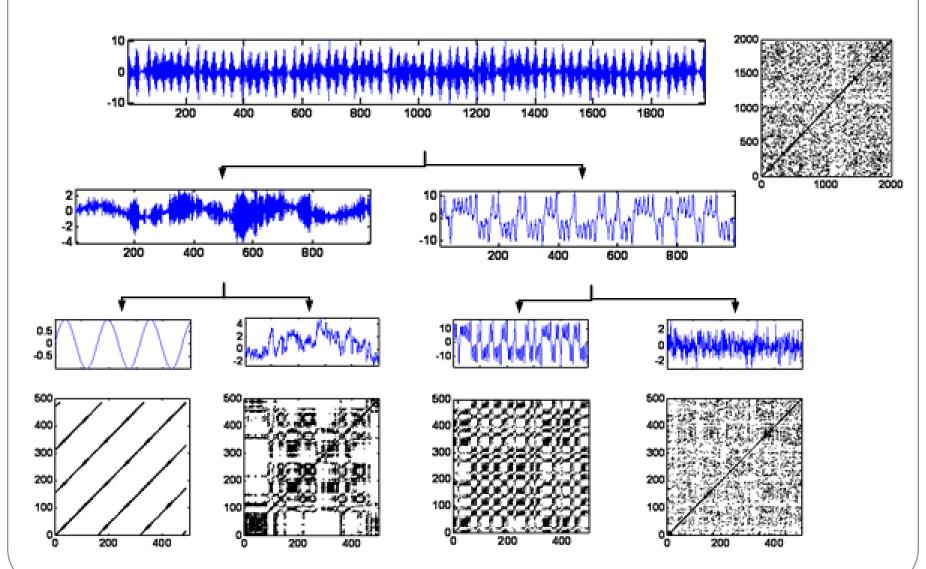
- \Box Gram matrix is a square matrix: $G = U\Lambda U^T$
 - \triangleright Λ is a diagonal matrix formed from the eigenvalues of G
 - \triangleright U is a matrix of the corresponding eigenvectors of G
- ☐ Gram matrix is positive semidefinite

 \square ISOMETRY: $U\sqrt{\Lambda}$ and w_i



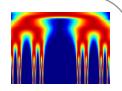
Multiscale Recurrence Analysis







Feature Selection

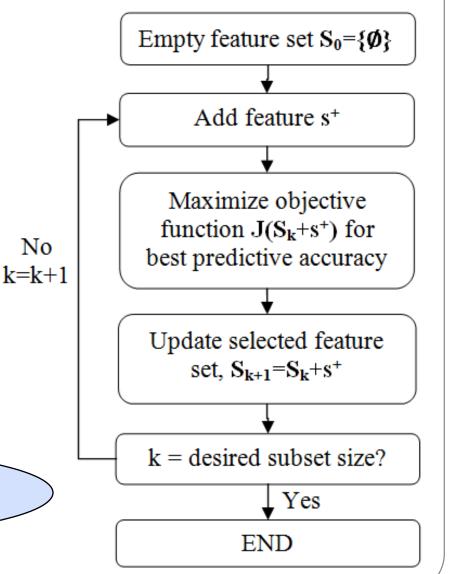


☐ Recurrence features

- > RR, DET, LMAX, ENT, LAM, TT are extracted for each of the wavelet subseries
- \triangleright k^{th} level: 2^k number of wavelet subseries
- > Selected level: *m* to *n*
- ☐ Total feature size:

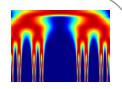
$$\sum_{k=m}^{n} 6 \times 2^{k}$$

Curse of dimensionality

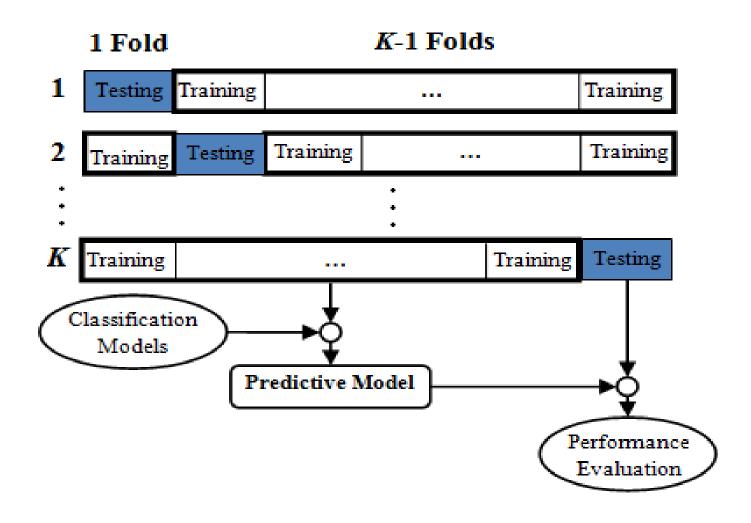




Cross-validation

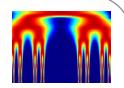


☐ K-fold cross-validation & Random sub-sampling

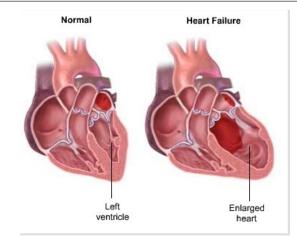


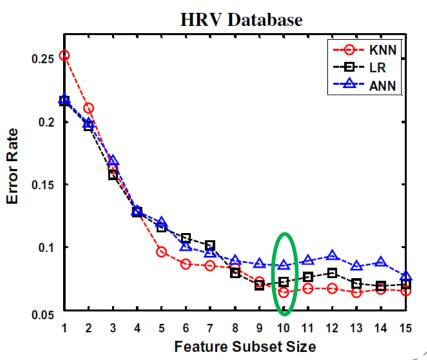


Dataset – Heart Rate Variability



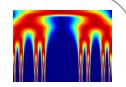
- □ Dataset 24-hour heart rate variability (HRV)
 - ➤ 54 Health control (HC)
 - 29 congestive heart failure(CHF)
- ☐ Classification models;
 - K-nearest neighbor (KNN)
 - ➤ Logistic regression (LR)
 - Artificial neural network(ANN)
- ☐ Feature selection
 - > Selected level: 6 to 9
 - ightharpoonup Total: $\sum_{k=6}^{9} 6 \times 2^k = 5760$
- Select 10 features in order to prevent overfitting.

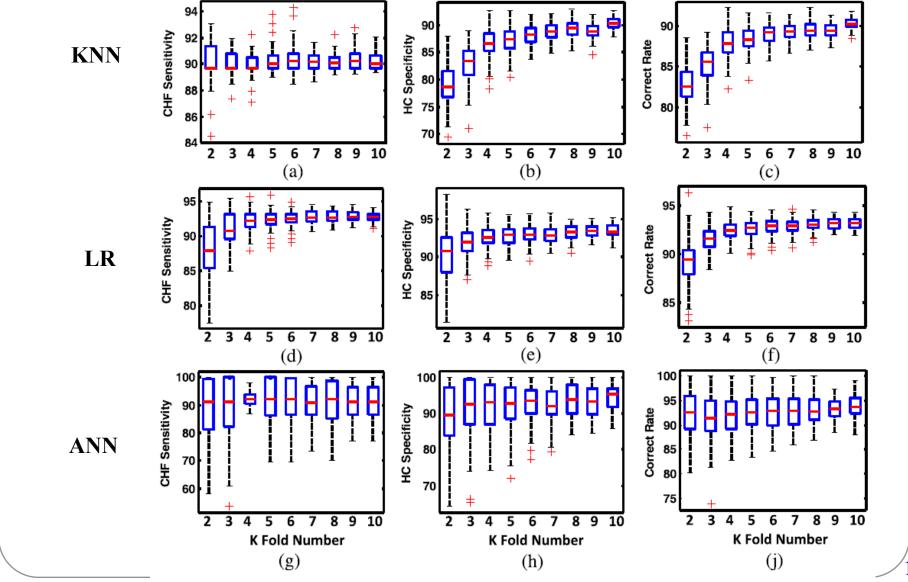






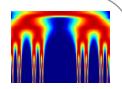
Performance Evaluation (1)



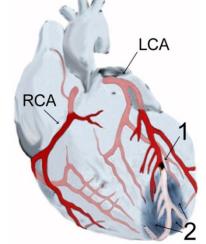




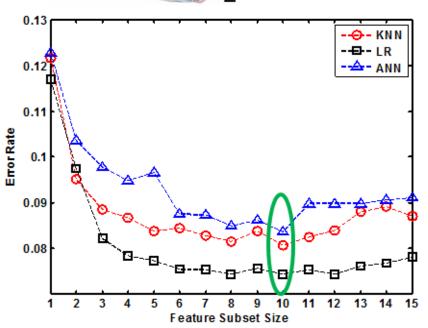
Dataset – Vectorcardiogram



- □ Dataset Vectorcardiogram(VCG)
 - > 80 Health controls (HC)
 - ➤ 368 myocardial infarctions (MI)
- ☐ Classification models:
 - ➤ K-nearest neighbor (KNN)
 - Logistic regression (LR)
 - > Artificial neural network (ANN)
- ☐ Feature selection
 - > Selected level: 4 to 5
 - ightharpoonup Total: $\sum_{k=4}^{5} 6 \times 2^{k} = 288$
- ☐ Select 10 features in order to prevent overfitting.

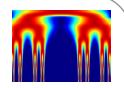


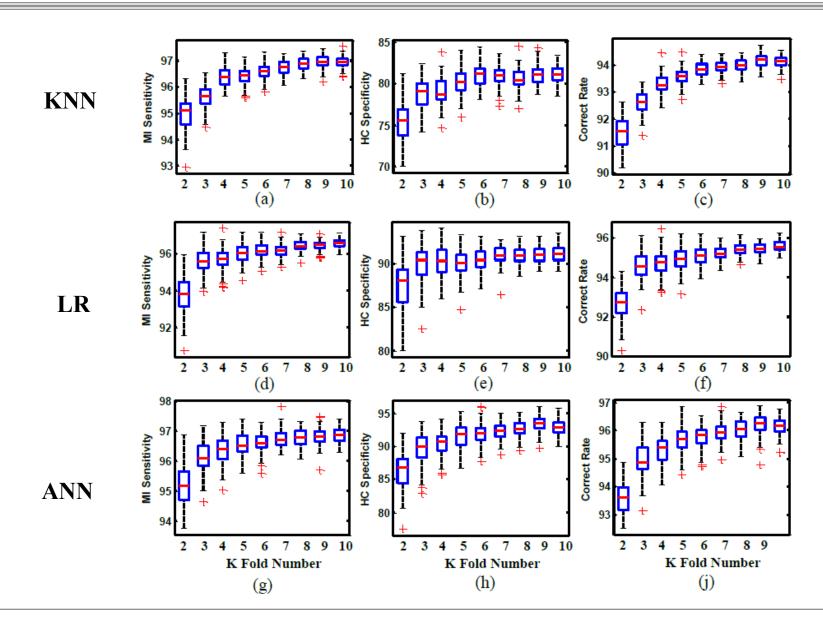
MI (2), after occlusion (1) of a branch of LCA, RCA





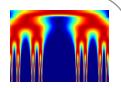
Performance Evaluation (2)



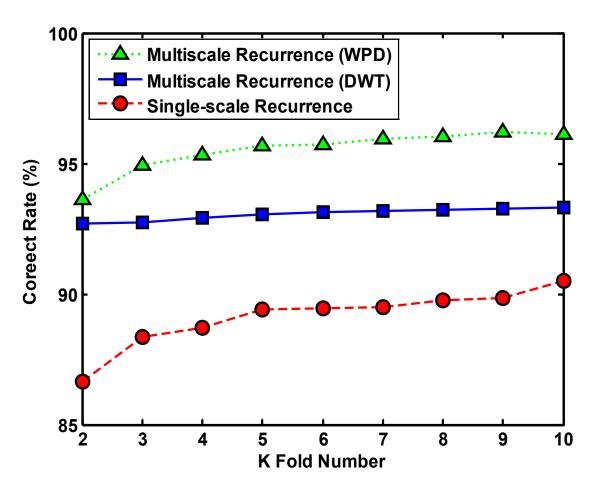




Single-scale VS. Multiscale

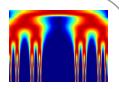


☐ Comparison of classification correct rates between single-scale and multi-scale (i.e., DWT and WPD) recurrence analysis



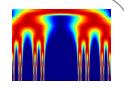


Conclusions



- **□** Challenges:
 - > Data complexity: nonlinearity and nonstationarity
 - Enormous data torrents
- ☐ Multiscale recurrence analysis
 - Large size of dataset dyadic subsampling
 - Nonstationarity wavelet decomposition
 - Nonlinearity recurrence analysis
- ☐ Discriminant analysis
 - > HRV database: 92.1% (sensitivity) and 94.7% (specificity)
 - > VCG database: 96.8% (sensitivity) and 92.8% (specificity)
- ☐ Single-scale vs. multiscale recurrence analysis





END Questions?