Advances in Biomedical Signal Processing

Overview of our Current Research Interests

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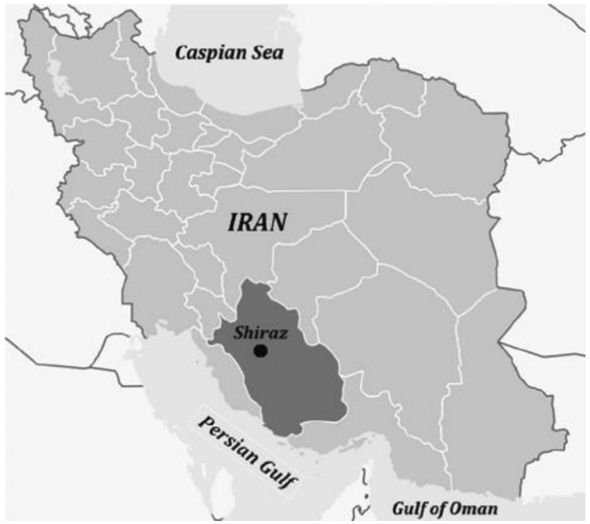
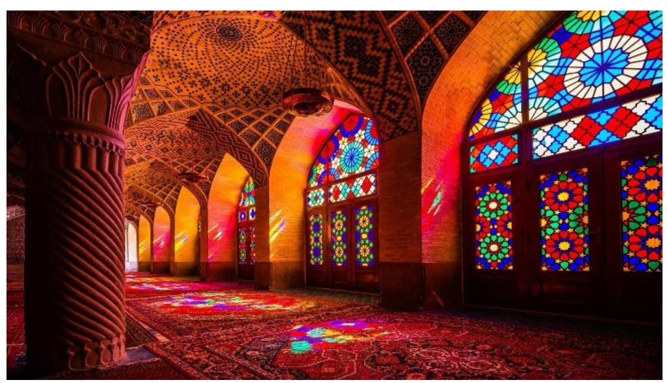
22 November, 2018, GIPSA-lab

Where I come from…





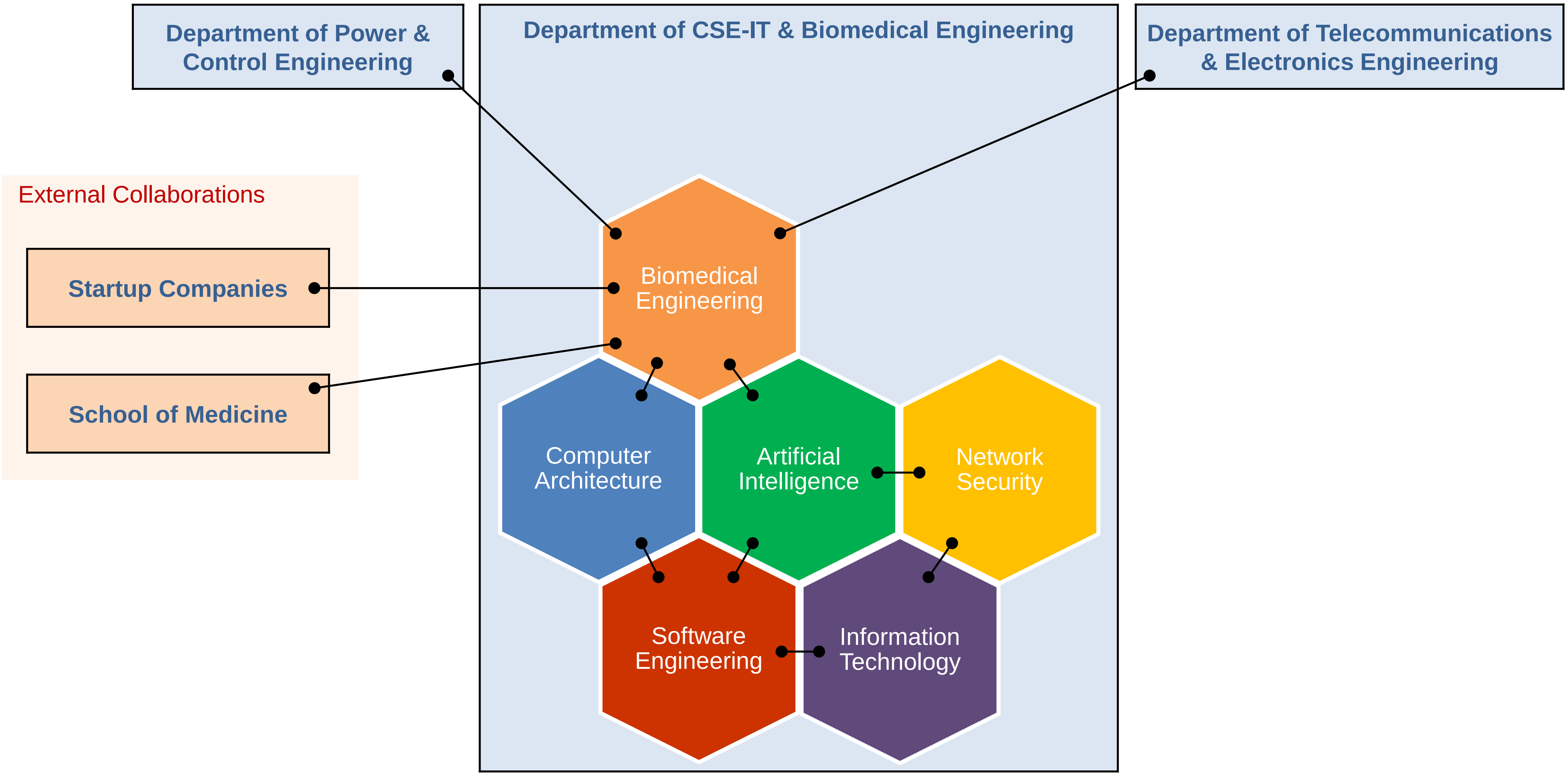
Shiraz University in a Glance

- Shiraz University is a comprehensive public university founded in 1946 (formerly known as Pahlavi University).
- Ranked among the first 5 to 8 universities of Iran (in different national/international rankings)
- The pioneer of doctoral programs in Iran
- Has the 2nd largest campus in Iran (after University of Tehran).
- Consists of 16 Schools in 80 Departments, over 700 faculty members, 19,000 students, with 200 Bachelor's degree programs (B.A. and B.Sc.), 300 Master's degree programs (M.A., M.Sc.), and 150 Ph.D. programs.

Shiraz University Schools

School of Agriculture	School of Economics, Management & Social Sciences	School of Law & Political Science	School of Sciences
School of Art & Architecture	School of Education & Psychology	School of Literature & Humanity Science	School of Theology & Islamic Studies
School of Chemical, Petroleum & Gas Engineering	School of E-Learning	School of Mechanical Engineering	School of Veterinary Science
School of Civil & Material Engineering	School of Electrical & Computer Engineering	School of New Science & Technology	Shiraz University International Division (SUID)

The School of Electrical & Computer Engineering



Overview

Currently Active Projects in SU Signal Processing Research Group

- Biomedical Signal Processing
  - Modeling, denoising and parameter extraction of electrocardiogram, phonocardiogram and electroencephalogram
- Hardware Design
  - Bio-potential signal acquisition systems (ECG and PCG)
  - Design and implementation of signal processing algorithms on FPGA

My research plan in GIPSA-lab

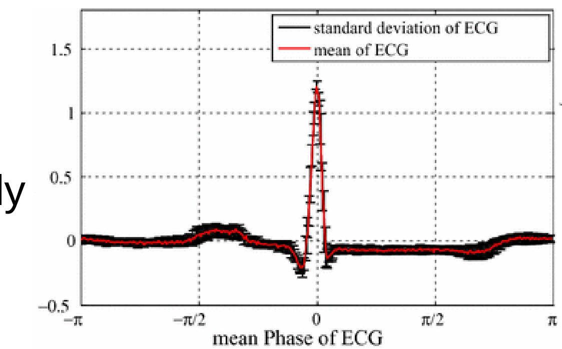
- Dynamic source separation
- Multimodal analysis of the electrocardiogram and the phonocardiogram

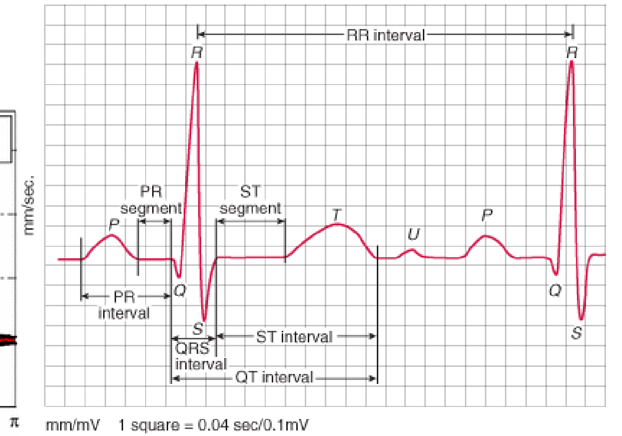
ELECTROCARDIOGRAPHY

adult and fetal electrocardiogram modeling and analysis

Statistical Performance Bounds on ECG Parameter Estimation

Objective: To find theoretical bounds for the performance of ECG parameter estimation (Heartrate, QT interval, ST-level, T/R ratio, etc.)



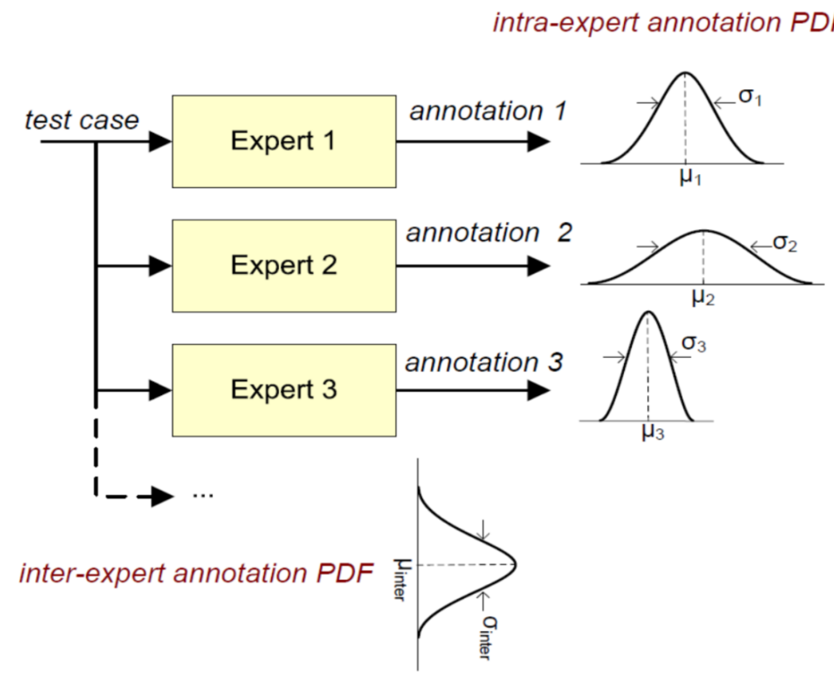


Facts:

- ECG parameter extraction is implicitly/explicitly model-based
- ECG parameters have intrinsic beat-wise variability ► *modeling errors*
- Measurements and expert annotations are always noisy, with inter-rater and intra-rater variabilities ► *observation noise*

Result: We derived Cramér–Rao Lower Bounds (CRLB) of ECG parameters for the most popular ECG models (orthogonal models, polynomial models, and sum of Gaussian models).

Apparently, the results do not depend on the parameter estimation method; but only rely on the presumed data model.



Ref:

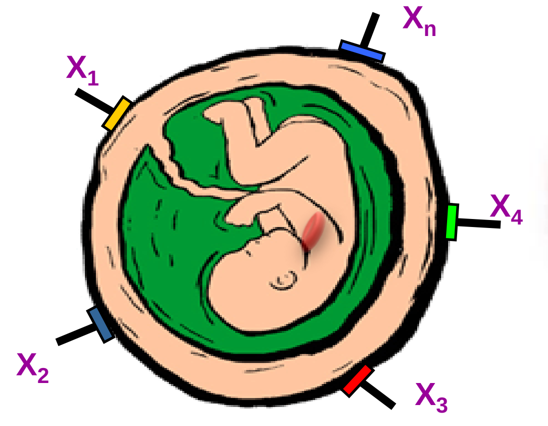
- Current research by D. Fattahi (PhD candidate) in Shiraz University
- Zhu, T., Johnson, A. E., Behar, J., & Clifford, G. D. (2014). Crowd-sourced annotation of ECG signals using contextual information. *Annals of biomedical engineering*, *42*(4), 871-884.

Noninvasive Fetal ECG Extraction

Objective: The noninvasive extraction of fetal ECG (fECG) from an array of maternal abdominal sensors

The problem is in the form of typical blind and semi-blind source separation:

$$\mathbf{x}(t) = \mathbf{H}_m\mathbf{s}_m(t) + \mathbf{H}_f\mathbf{s}_f(t) + \mathbf{H}_v\mathbf{v}(t) + \mathbf{n}(t)$$

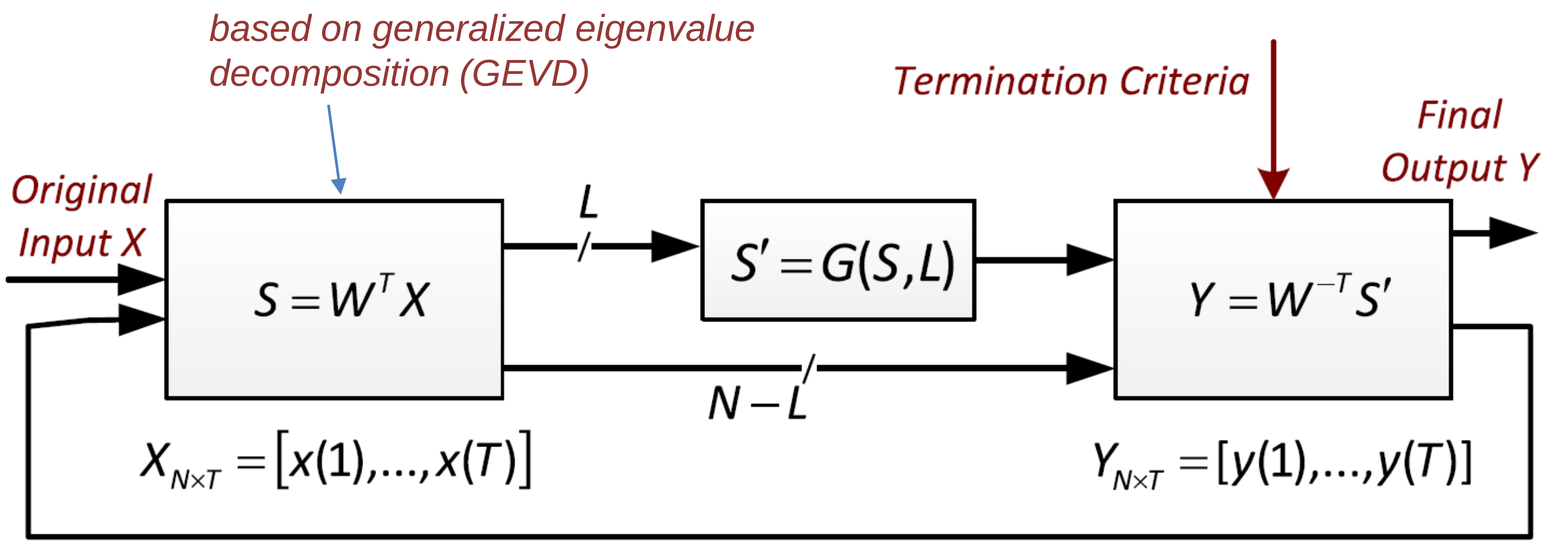


References:

- Sameni, R. (2008). *Extraction of fetal cardiac signals from an array of maternal abdominal recordings*, Doctoral dissertation, Institut National Polytechnique de Grenoble-INPG; Sharif University of Technology.
- Sameni, R., Jutten, C., & Shamsollahi, M. B. (2008). Multichannel electrocardiogram decomposition using periodic component analysis. *IEEE Trans. Biomed. Engineering*, *55*(8), 1935-1940.
- Sameni, R., Jutten, C., & Shamsollahi, M. B. (2010). A deflation procedure for subspace decomposition. *IEEE Transactions on Signal Processing*, *58*(4), 2363-2374.
- Sameni, R., Jutten, C., Shamsollahi, M. B., & Clifford, G. D. (2010). Extraction of fetal cardiac signals. *U.S. Patent No. 9,125,577*

Review of the Deflation Source Separation Algorithm

- A deflation procedure for subspace decomposition (closely related to wavelet shrinkage denoising)



Ref: Sameni, R., Jutten, C., & Shamsollahi, M. B. (2010). A deflation procedure for subspace decomposition. *IEEE Transactions on Signal Processing*, *58*(4), 2363-2374.

Industrial Contributions in Fetal ECG Extraction

- Our developed algorithm is patented and licensed to MindChild Medical Inc.
- We developed the fetal ECG extraction engine of the MERIDIAN™ software

mindchild

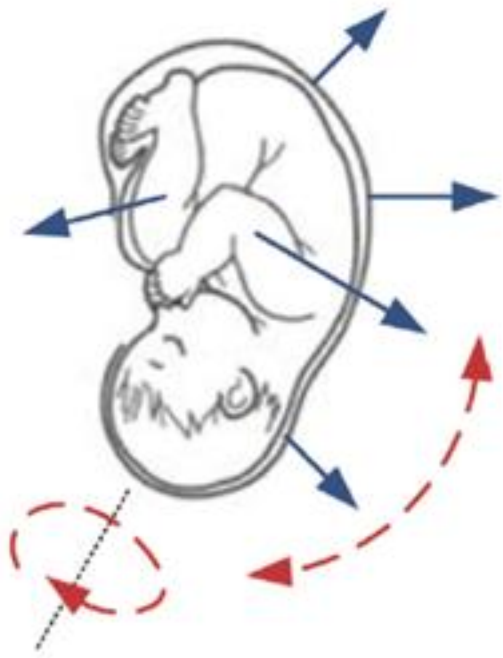
Making labor safer for women and their babies

Ref: www.mindchild.com

Recent Developments in Noninvasive Fetal ECG and Extraction

- **Fetal motion tracking** ► *use the extracted fetal ECG to estimate fetal motion/rotation with respect to the maternal body coordinates*
- **Online fetal ECG extraction** ► *use online diagonalization methods in a deflation fetal ECG extraction algorithm*
- **Low-rank and time-varying mixtures** ► *use a synthetic auxiliary maternal ECG channel for rank-deficiency compensation and single-channel fECG extraction*
- **Nonstationary background noise and irregular maternal beats** ► *use measures of nonstationary instead of periodicity for fetal ECG extraction*

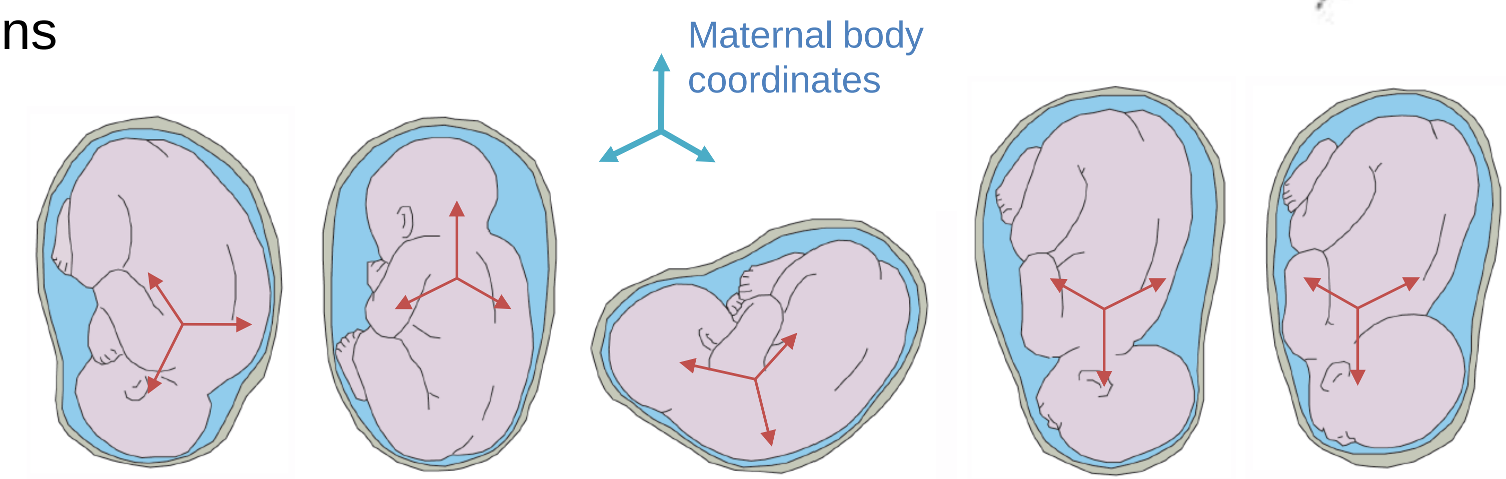
Online fECG Extraction and Fetal Motion Tracking from fECG



Fact: The fetal body coordinates varies with fetal movements, rotations, hiccups, with respect to the maternal body coordinates (and the surface leads).

Hence,

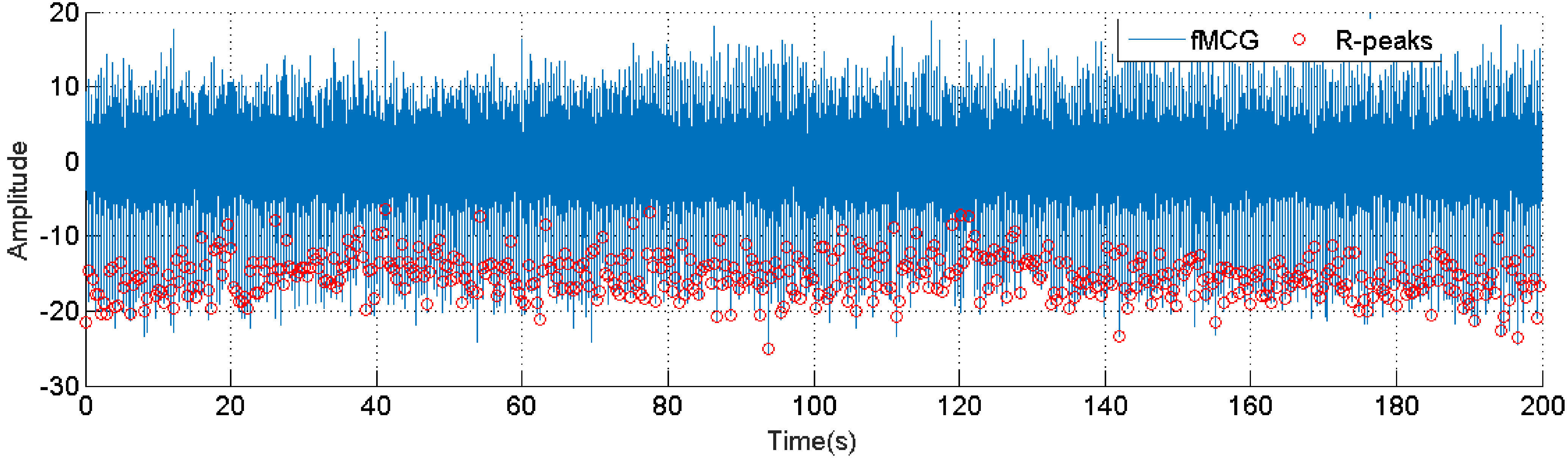
- The data-model is $\mathbf{x}(t) = \mathbf{A}(t)\mathbf{s}(t) + \mathbf{n}(t)$
- In this case: $\mathbf{y}(t) = \mathbf{B}\mathbf{x}(t) = \mathbf{B}[\mathbf{A}(t)\mathbf{s}(t) + \mathbf{n}(t)] \neq \mathbf{s}(t)$
- Online methods are required for extracting the fetal ECG
- $\mathbf{A}(t)$ conveys information regarding the fetal motions and positions



(a) Vertex 96.8 % (b) Breech 2.5 % (c) Shoulder 0.4 % (d) Face 0.2 % (e) Brow 0.1 %

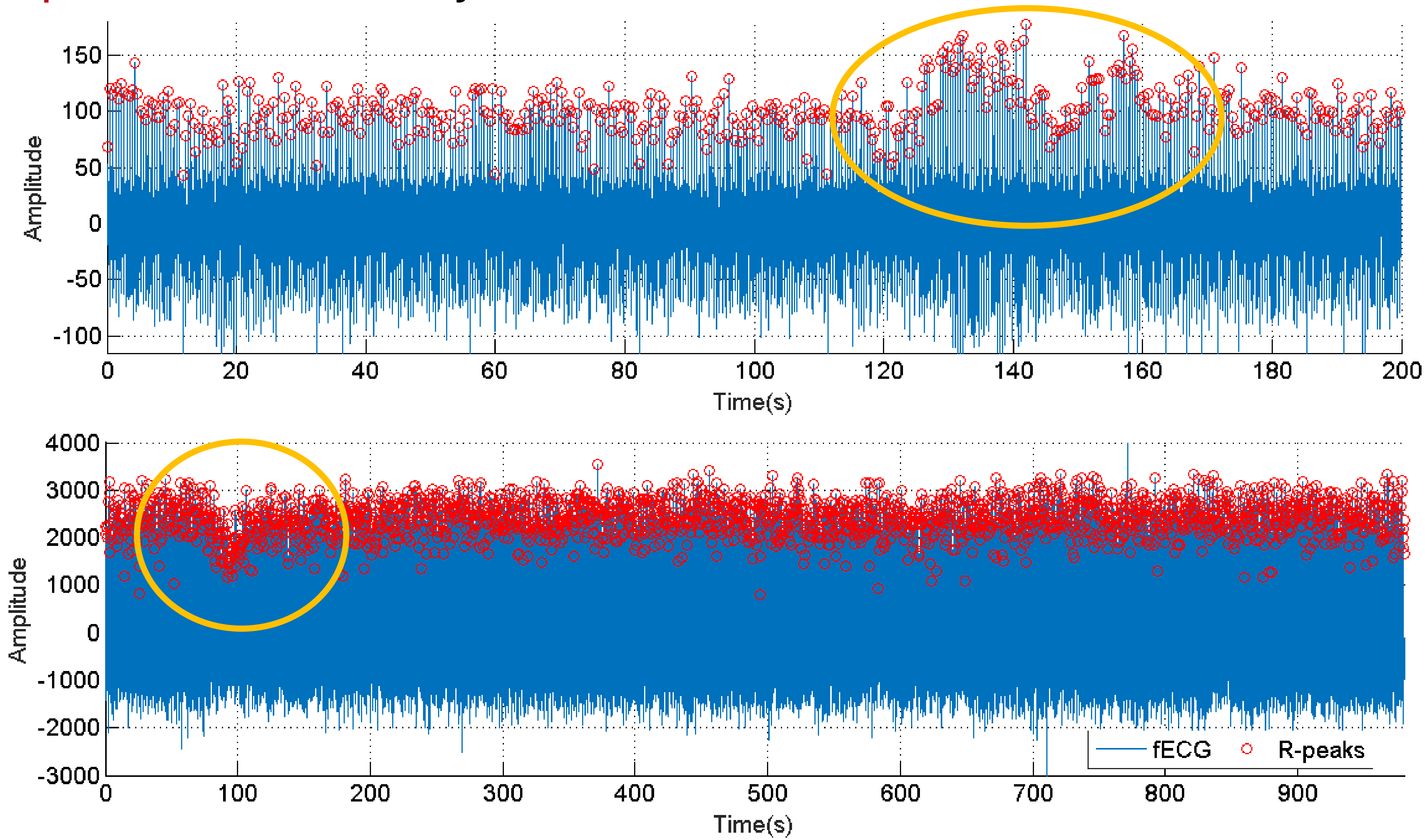
Time-Variant Scenarios

Example 1: Stationary case (for fetal MCG); no significant fetal motion observed



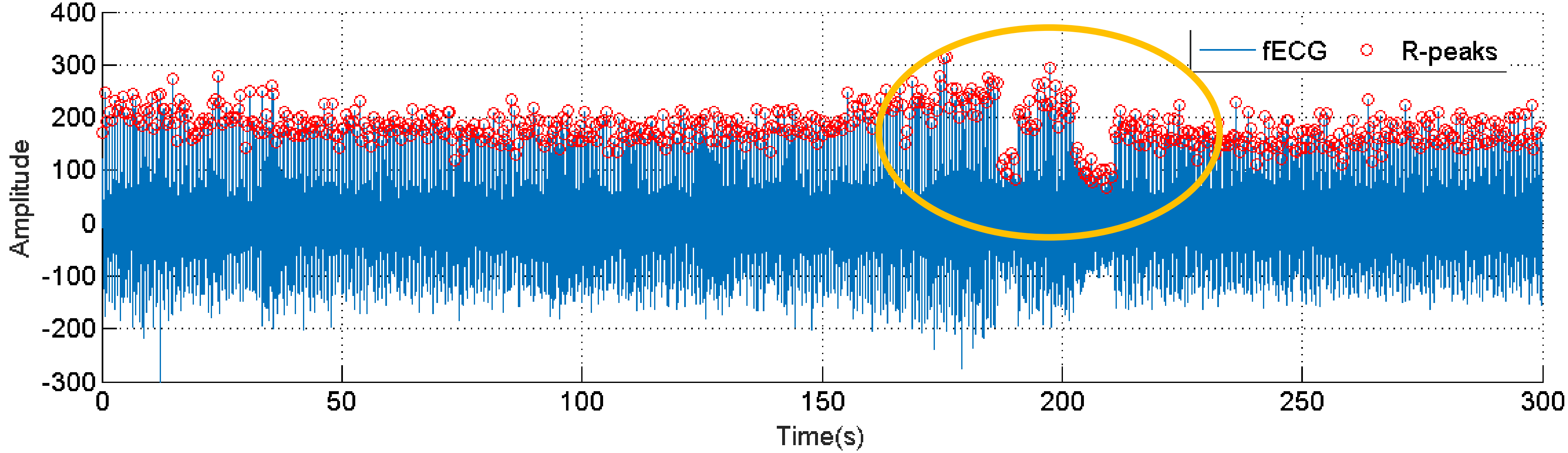
Time-Variant Scenarios

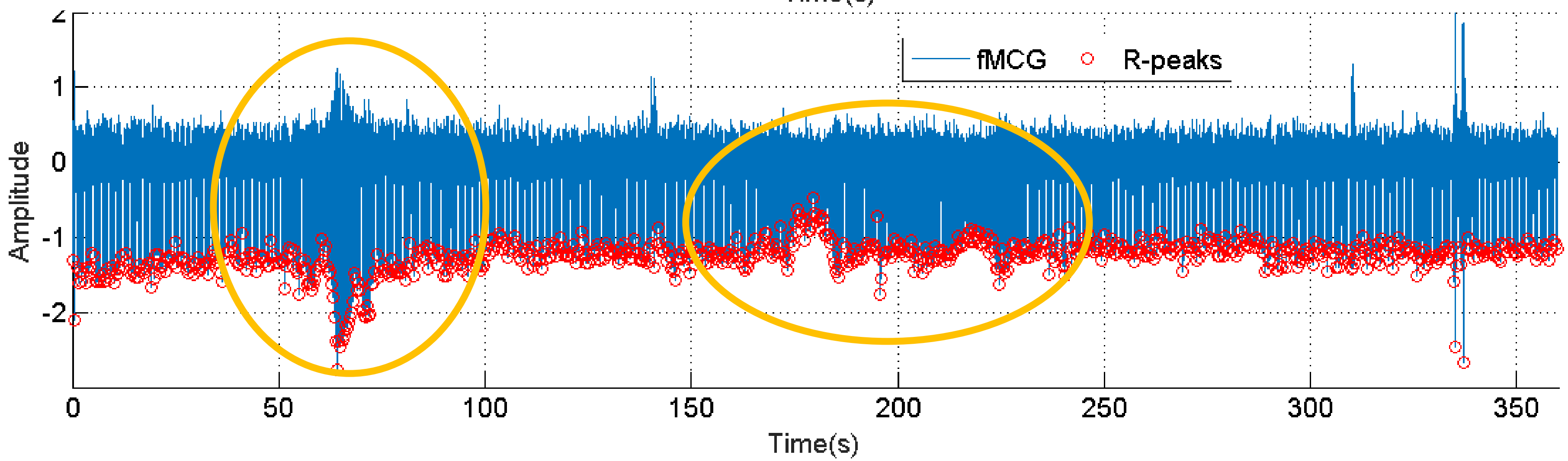
Example 2: Nonstationary case; minor fetal movement



Time-Variant Scenarios

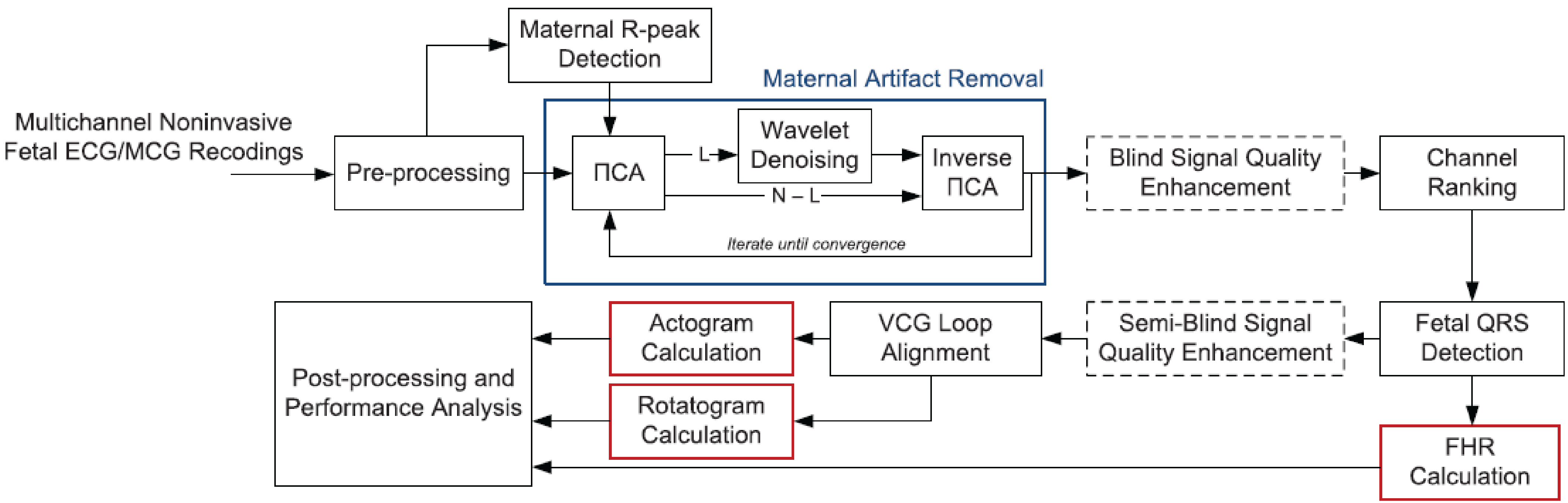
Example 3: Nonstationary case; fetal movements and/or hiccups





Fetal Motion Tracking from fECG

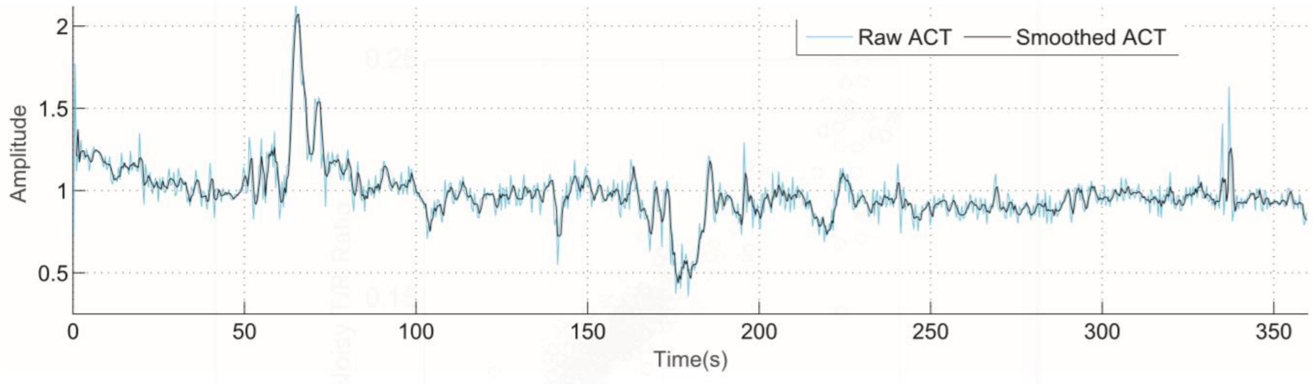
The notion of fetal actogram and rotatogram using fECG beat alignment:

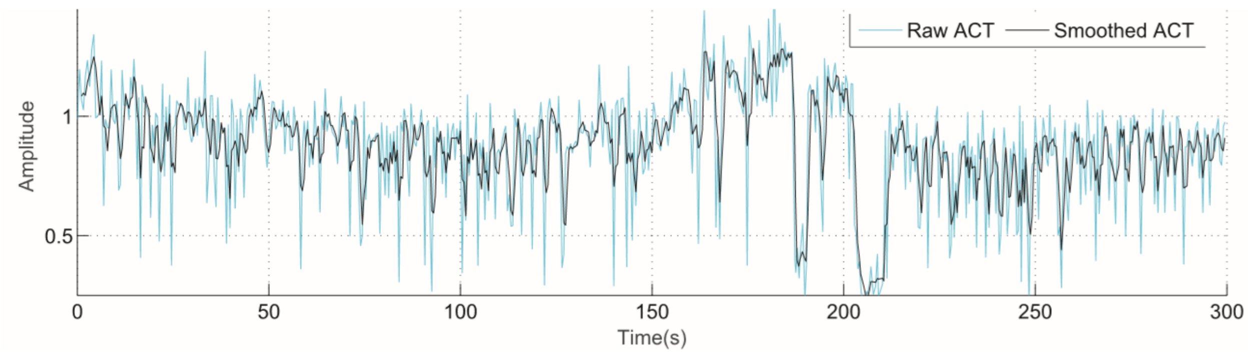


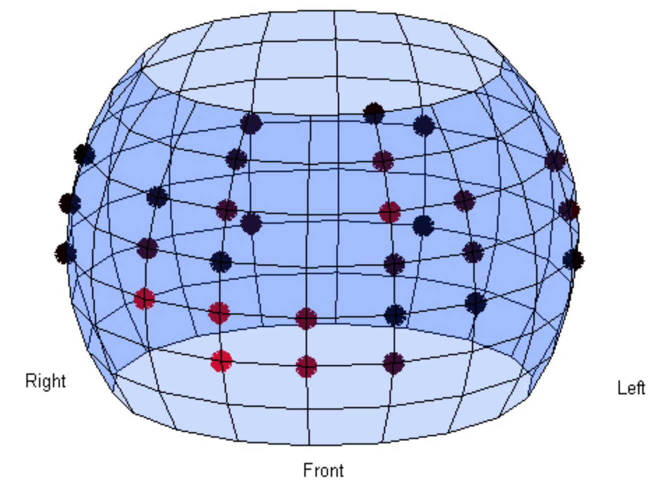
Ref: H. Biglari and R. Sameni, "Fetal motion estimation from noninvasive cardiac signal recordings," *Physiological Measurement*, vol. 37, no. 11, pp. 2003-2023, November 2016.

Fetal Motion Tracking from fECG (continued)

Example:



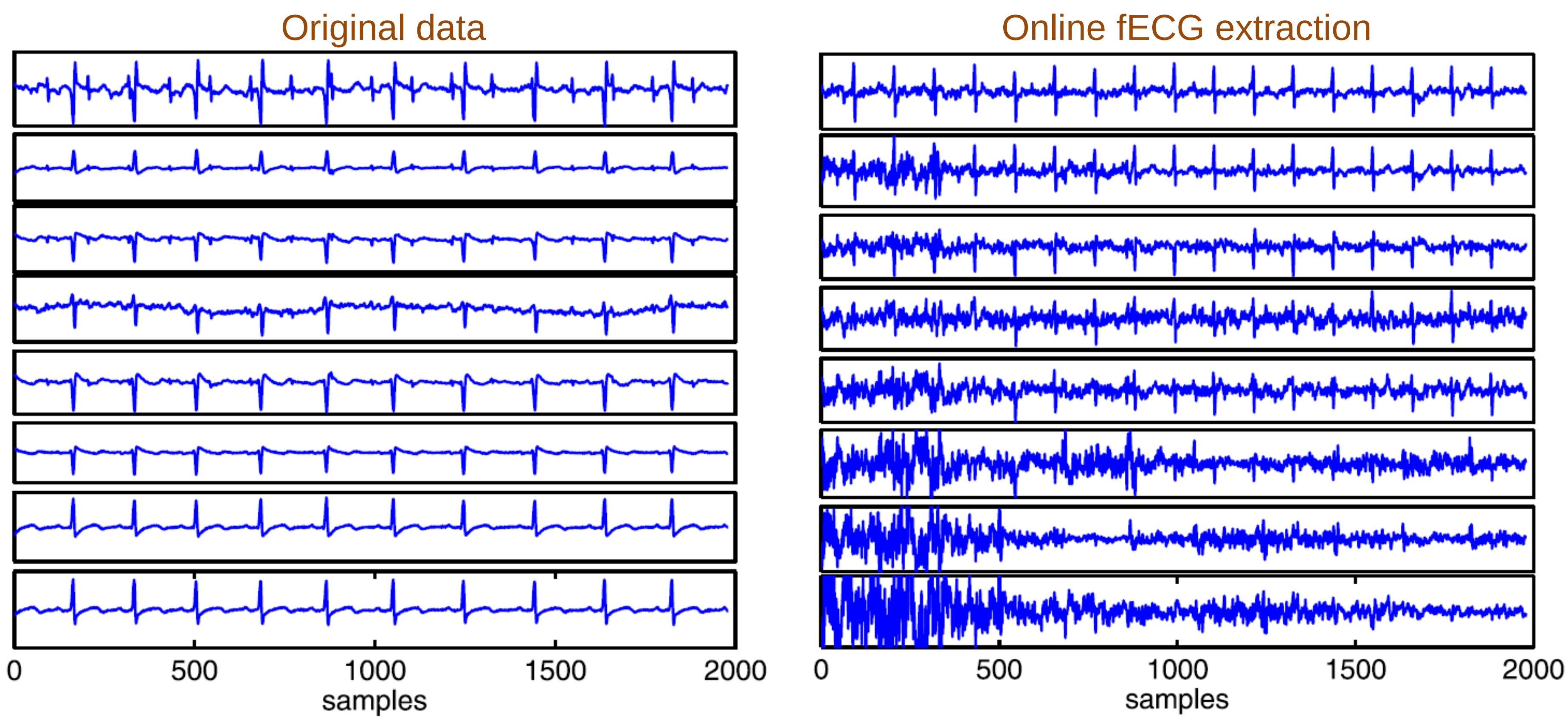




Ref: H. Biglari and R. Sameni, “Fetal motion estimation from noninvasive cardiac signal recordings,” *Physiological Measurement*, vol. 37, no. 11, pp. 2003-2023, November 2016.

Online fECG Extraction

Example:



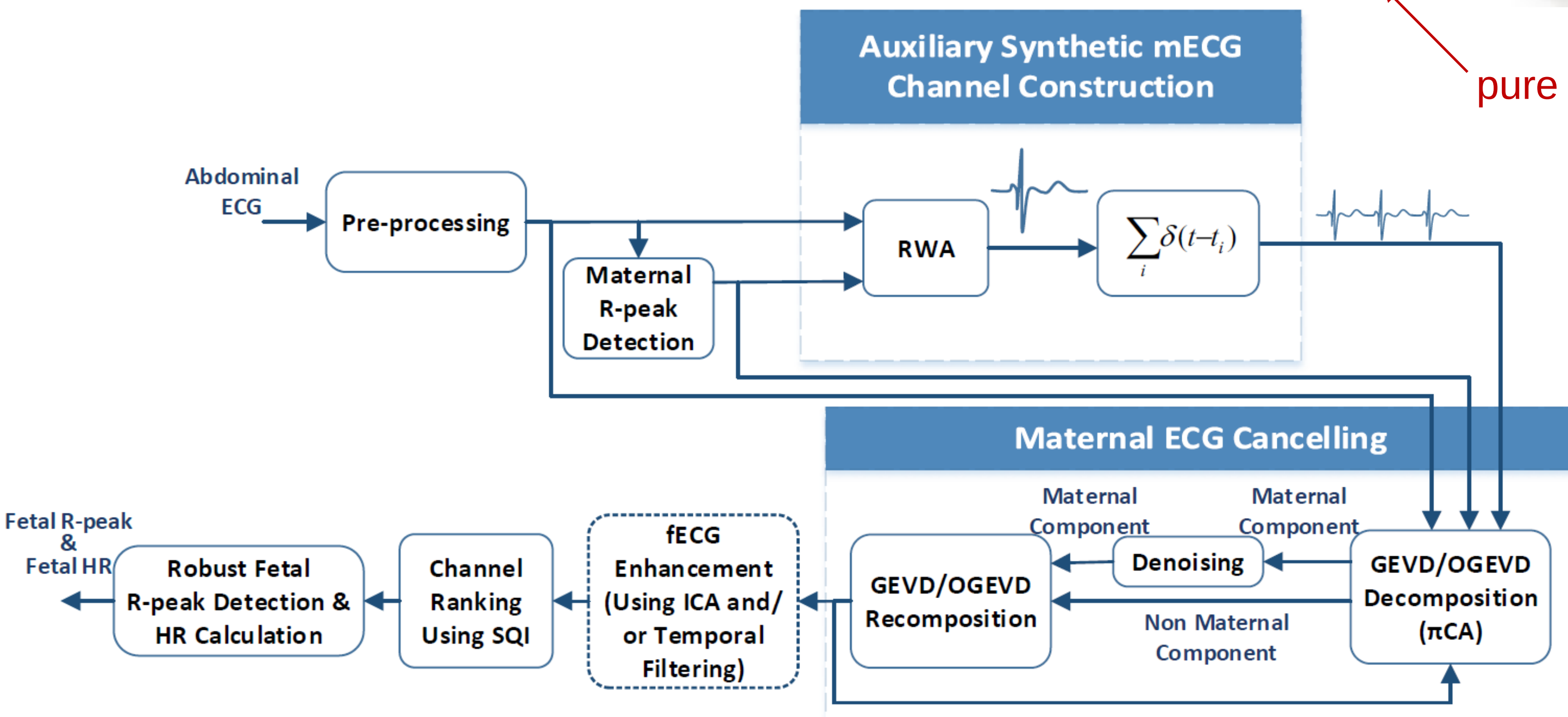
Ref: Fatemi, M., Sameni, R. (2017). An online subspace denoising algorithm for maternal ECG removal from fetal ECG signals. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, *41*(1), 65-79.

Low-Rank and Single-Channel fECG Extraction

Multichannel BSS techniques fail for (close to) singular mixtures or single-channel recordings

Solution: synthetic auxiliary channel augmentation: $\tilde{\mathbf{x}}(t) = \begin{bmatrix} \mathbf{x}(t) \\ \mathbf{x}_a(t) \end{bmatrix}$

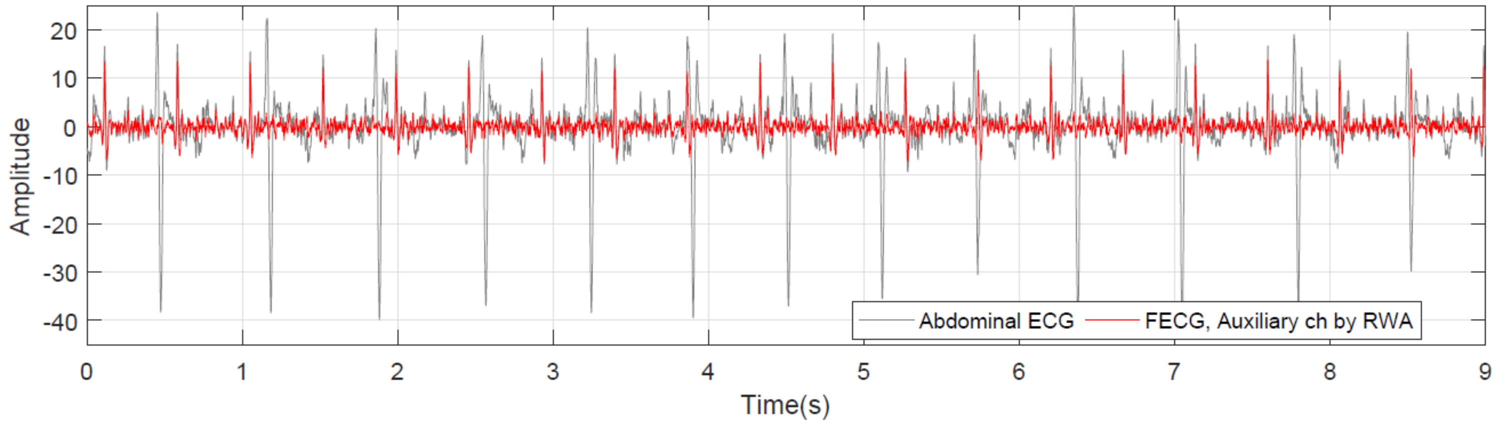
pure maternal ECG



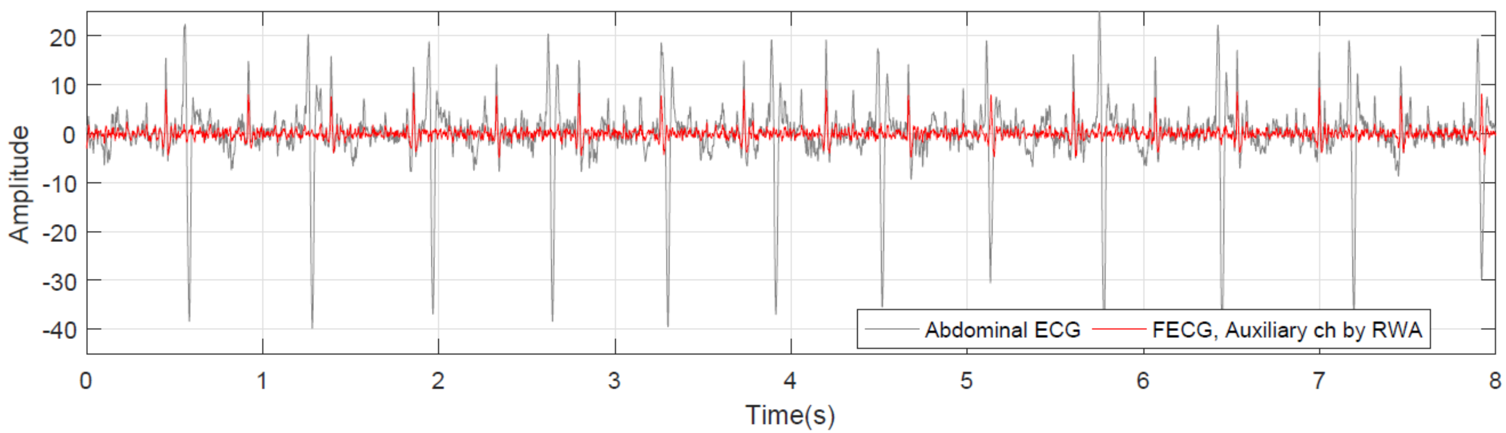
Ref: Jamshidian-Tehrani, F., Sameni, R (2019). Fetal ECG extraction from time-varying and low-rank noninvasive maternal abdominal recordings, *Physiological measurement,* [In Press]

Low-Rank and Single-Channel fECG Extraction (continued)

Example: single-channel fECG extraction



(a) A segment of the ADFECG database



(b) A segment of the NIFECG database

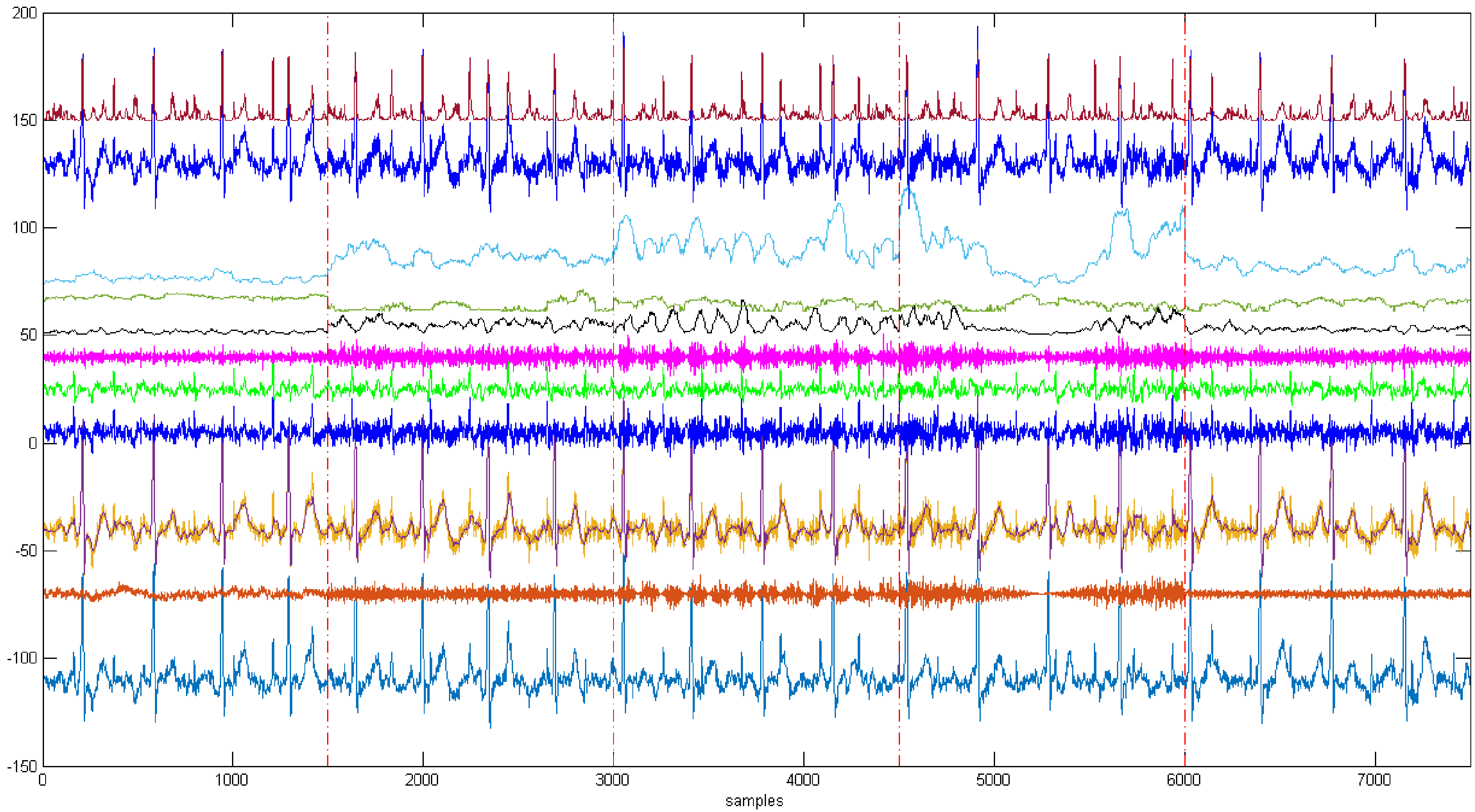
Nonstationarity Component Analysis (NSCA)

- Algebraic approaches to blind source separation are based on the (exact or approximate) diagonalization of a set of matrices:

$$\mathbf{W}^T\mathbf{C}_1\mathbf{W}=\mathbf{\Lambda}_1,\ \mathbf{W}^T\mathbf{C}_2\mathbf{W}=\mathbf{\Lambda}_2,\ldots,\ \mathbf{W}^T\mathbf{C}_n\mathbf{W}=\mathbf{\Lambda}_n$$

- Apart from the criteria used for defining and achieving diagonalization, the choice of the matrices $\mathbf{C}_1, \ldots, \mathbf{C}_n$ is crucial in the performance.
- For temporally nonstationary components we can select $\mathbf{C}_i=E_{\theta_i}\{\mathbf{x}(\theta_i)\mathbf{x}(\theta_i)^T\}$, and the problem reduces on how to choose the nonstationary time epochs θ_i
- Choosing θ_i requires prior knowledge, e.g.,
  - Stimulation times in event related potentials
  - Ocular artifacts recorded from a reference EOG channel for EEG denoising
  - The QRS peaks of the ECG
  - Local energy thresholding for speech and EMG signals
  - …
- In a recent research, we utilized the variations in the dynamics of the background/foreground ECG signals using the innovation process of a Kalman filter to identify the nonstationary epochs for GEVD and JADE source separation

Fetal and Adult ECG Extraction using Temporal Nonstationarity (continued)



Advantage: The method does not assume the ECG to be periodic

Ref: Jamshidian-Tehrani, F., Sameni, R (2019). Nonstationary Component Analysis; Application to Fetal Electrocardiogram Extraction

MULTI-MODAL CARDIAC ANALYSIS

simultaneous phonocardiogram and electrocardiogram acquisition, modeling and analysis

Multimodal ECG-PCG Analysis

- A rather new trend of research is to use a combination of different and simultaneously acquired modalities for adult/fetal cardiac monitoring
- The ultimate objective is to study the electro-mechanical coupling of the heart

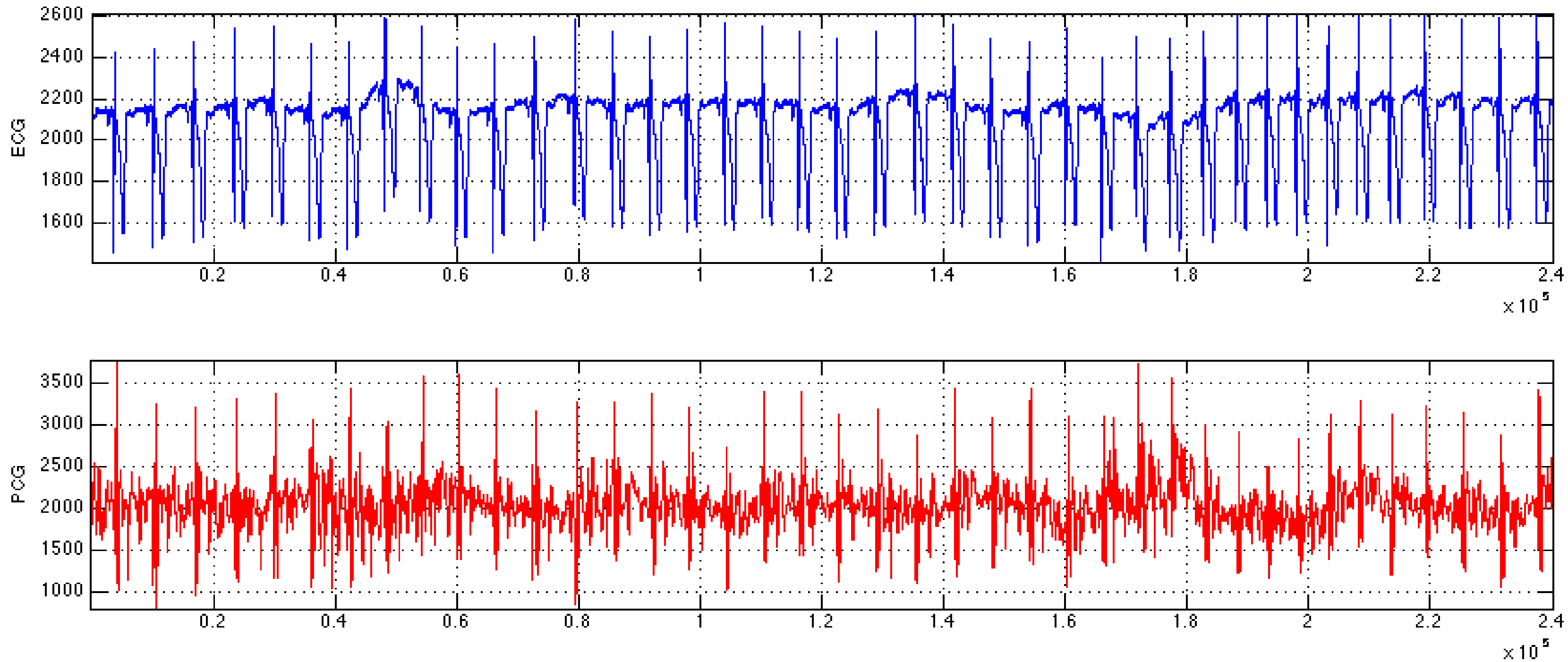
Example: simultaneous adult /fetal ECG and PCG

Ref:
• Samieinasab, M., & Sameni, R. (2015, May). Fetal phonocardiogram extraction using single channel blind source separation. In Electrical Engineering (ICEE), 2015 23rd Iranian Conference on (pp. 78-83). IEEE.
• Shiraz University Fetal Heart Sounds Database (SUFHSDB), Physionet. Available Online: https://physionet.org/physiobank/database/sufhsdb/

Current research in Shiraz University, Shiraz, IRAN

Multimodal ECG-PCG Analysis (continued)

- We have acquired a simultaneous ECG and PCG database with 50 subjects during physical activity
- Findings: There are meaningful differences between the heartrate parameters extracted from the ECG and the PCG during rest, walking, and sports.



Ref: Arsalan Kazemnejad (2018), Simultaneous electrocardiogram and phonocardiogram acquisition and analysis, Master's thesis, Shiraz University.

ELECTROENCEPHALOGRAPHY

Robust phase estimation

Robust Electroencephalogram Phase Calculation

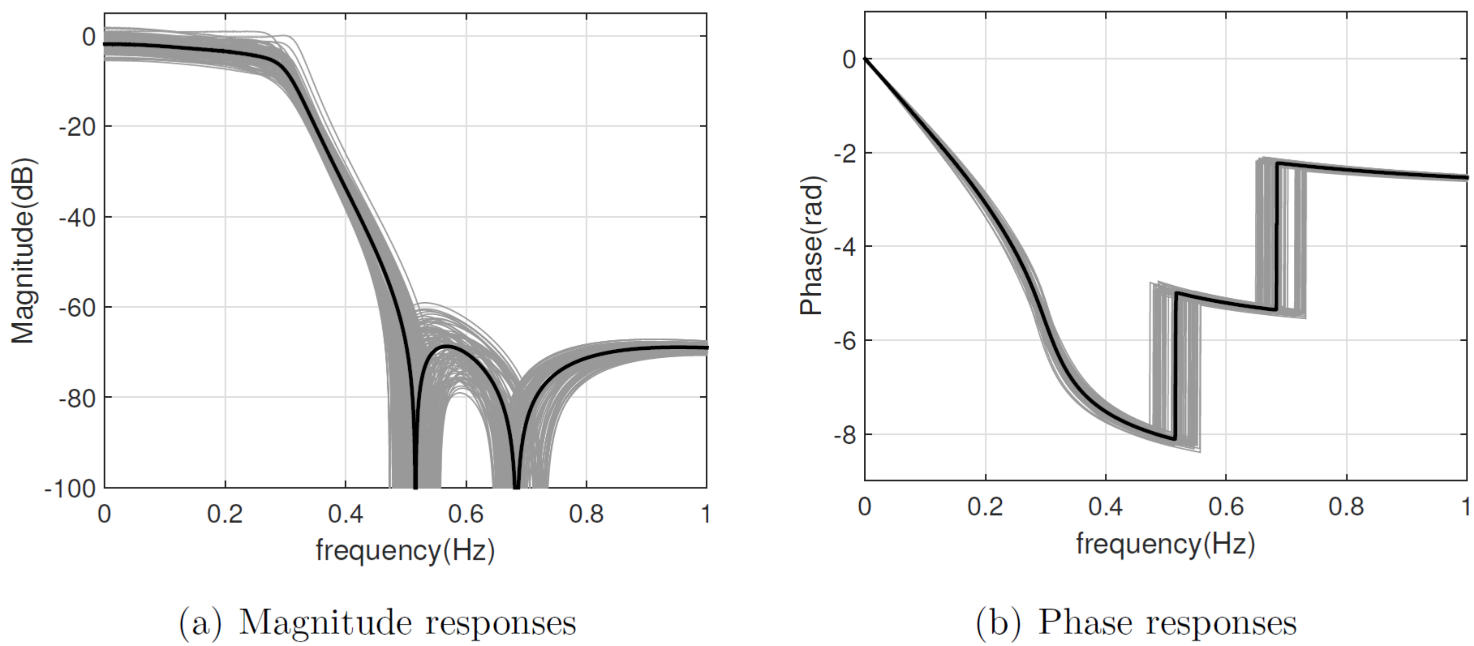
- In recent years, the EEG phase is extensively used as a complementary source of information in cerebral signal analysis
- Various phenomena have been introduced and studied in the literature: phase resetting, phase synchrony, phase locking, etc.
- However, the notion of EEG phase highly depends on the calculation method
- The conventional approach for calculating the EEG phase is based on the analytic form of the signal:
  1. $x(t) = s(t) * h_{BP}(t)$
  2. $x_a(t) = x(t) + jH\{x(t)\}$
  3. $A(t) = \sqrt{Re\{x_a(t)\}^2 + Im\{x_a(t)\}^2}$, $\varphi(t) = \mathrm{atan}[\frac{Im\{x_a(t)\}}{Re\{x_a(t)\}}]$ and $f(t) = \frac{1}{2\pi}\frac{d}{dt}\varphi(t)$

     (envelope) *(phase)* *(instantaneous frequency)*
- The above definition has a singular point for EEG at small amplitudes, which means that the phase is highly susceptible to changes in algorithm parameters and background noise

Robust Electroencephalogram Phase Calculation (continued)

Theoretical results: Using a statistical framework, we have derived the pdf of EEG envelope and phase

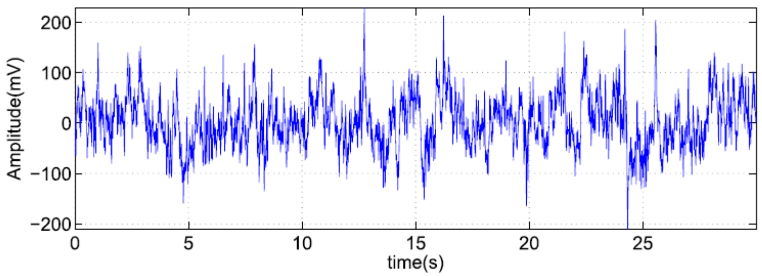
Proposed algorithm: The EEG phase should be calculated by performing a Monte-Carlo sweep over the narrow-band filter parameters and dithering the background noise



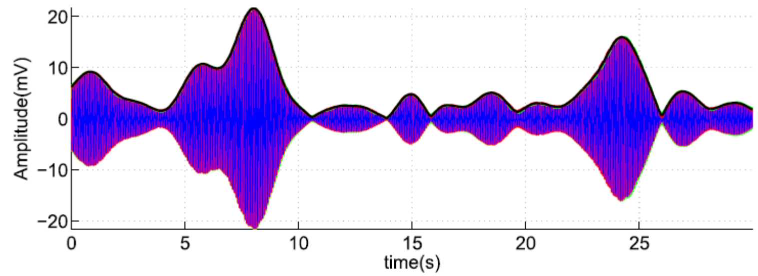
A typical lowpass filter prototype used for EEG phase extraction

Robust Electroencephalogram Phase Calculation (continued)

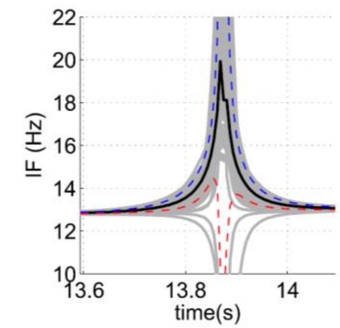
Results:

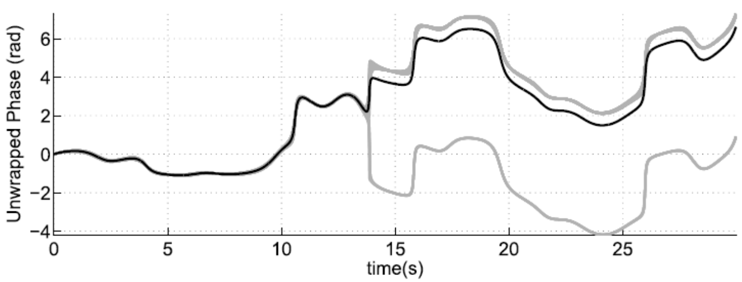


(a)

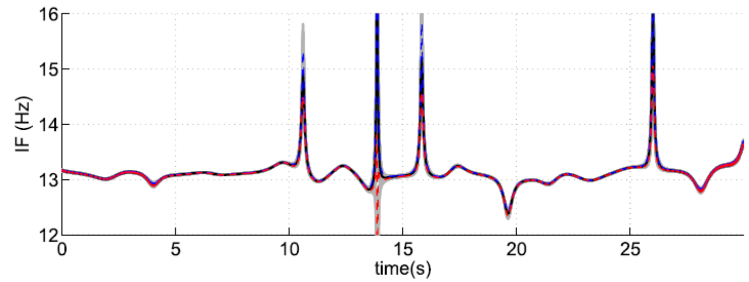


(b)

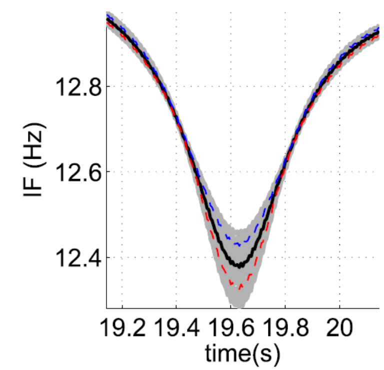


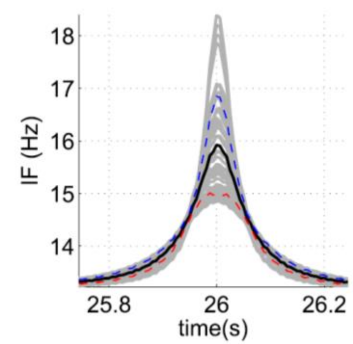


(c)



(d)





Refs:

- R. Sameni and E. Seraj, “A robust statistical framework for instantaneous electroencephalogram phase and frequency estimation and analysis,” *Physiological Measurement*, vol. 38, no. 12, pp. 2141-2163, 2017
- E. Seraj and R. Sameni, “Robust electroencephalogram phase estimation with applications in brain-computer interface systems,” *Physiological Measurement*, vol. 38, no. 3, p. 501, 2017.
- F. Karimzadeh, R. Boostani, E. Seraj, and R. Sameni, “A distributed classification procedure for automatic sleep stage scoring based on instantaneous electroencephalogram phase and envelope features,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 2, pp. 362-370, Feb 2018.

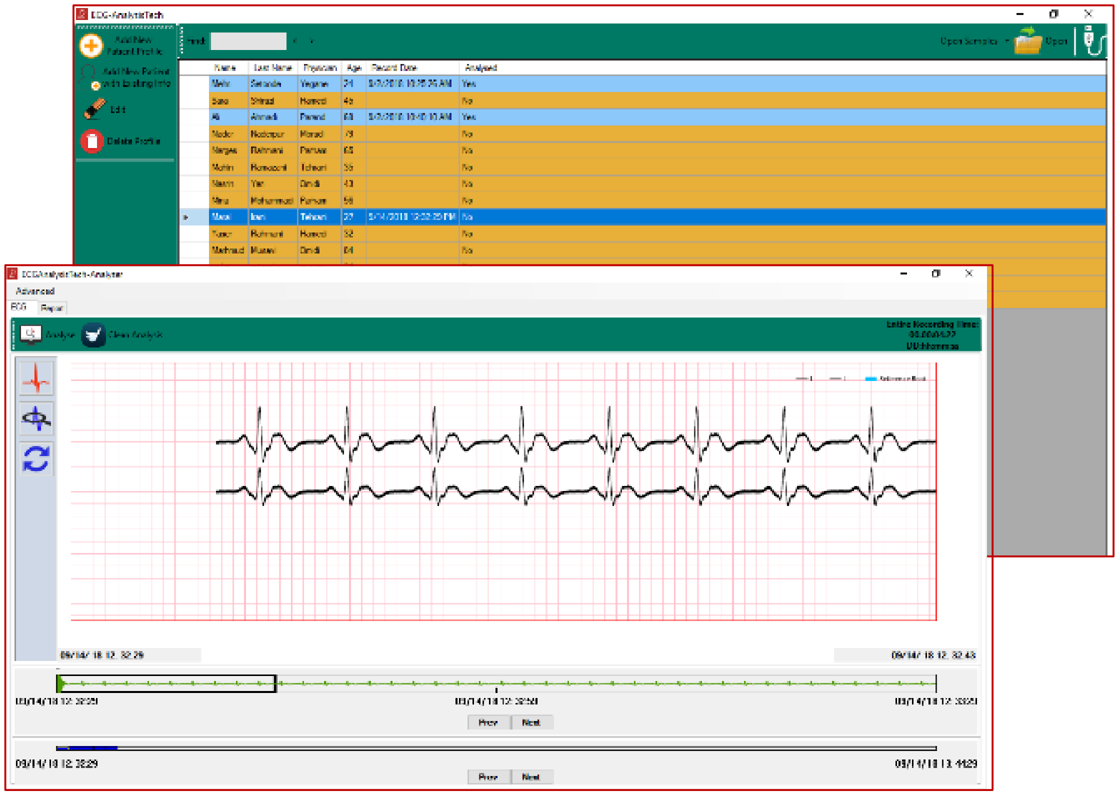
PRODUCTION & INDUSTRIALIZATION

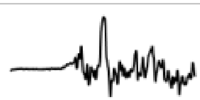
Hardware and software manufacturing for education and research

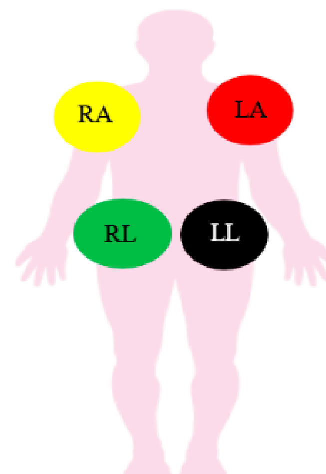
The Open-Source Electrophysiological Toolbox (OSET)

- OSET (www.oset.ir) is a collection of electrophysiological data and open source codes for biological signal generation, modeling, processing, and filtering, originally released in 2006.
- It is distributed under the GNU General Public License and may be freely used or modified under the specified terms of use.
- The source codes have been mainly developed in Matlab and partially in C++; but contributions in other languages are welcome.
- Starting from Version 3.14 (the π version), OSET is accessible and will be updated on a Git repository (https://gitlab.com/rsameni/OSET.git)

Holter Monitors and ECG Analysis Software



Reference Beat	Label	# Total Beats	# Detected Beats	Ratio
	Abnormal	98201	90386	92.04 %
	Normal	98201	90800	92.46 %

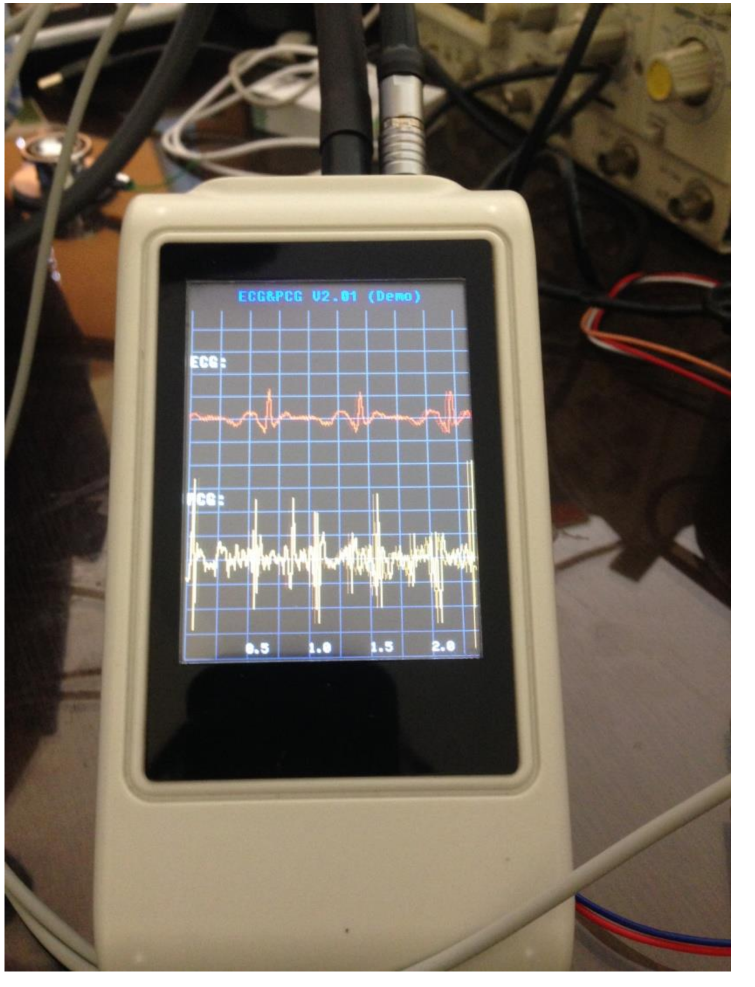


RA Right Arm
LA Left Arm
RL Right Leg
LL Left Leg

Simultaneous ECG-PCG system

Features:

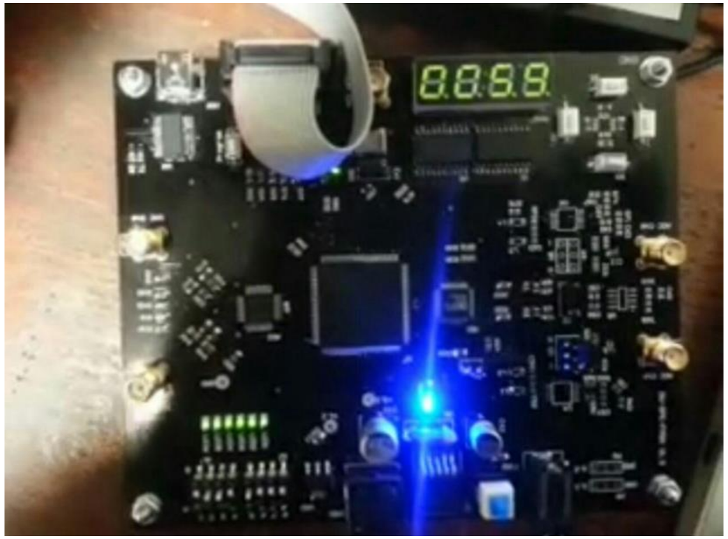
- Single-channel three-lead ECG
- Single and two-channel PCG
- Sample-wise synchronous ECG and PCG
- Sampling frequency of 8kHz
- Internal active noise canceller for environmental noise

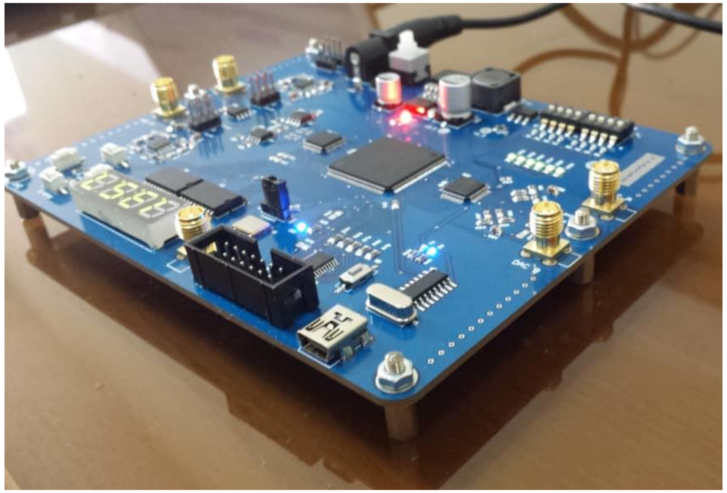


Design and Implementation of Digital Signal Processing Algorithms on Embedded Systems and FPGA

Algorithms implemented on FPGA in our research group:

- A toolbox for linear algebra (low-level matrix-vector operations)
- Algorithms for subspace decomposition and tracking
- Neural networks for deep learning applications





FPGA boards made in Shiraz University Signal Processing Group, 2018

DYNAMIC COMPONENT ANALYSIS

A problem statement

(Semi-) Blind Source Separation

We're all familiar with the classical problem of blind source separation:

$$\boldsymbol{x}_t = \boldsymbol{h}(\boldsymbol{s}_t) + \boldsymbol{n}_t$$

Objective: retrieve the sources $\boldsymbol{s}_t$ from the observations $\boldsymbol{x}_t$ in presence of noise $\boldsymbol{n}_t$, with minimal assumptions on the source and the unknown mixture model $\boldsymbol{h}(\cdot)$

Common assumptions leading to possible solutions:

- Linearity of the mixture
- Statistical independence and non-gaussianity of the sources
- Sparsity
- Nonstationarity and temporal correlation
- Periodicity or pseudo-periodicity in time
- …

Dynamic Source Separation

- Problem definition: We are focusing on a special class of semi-blind source separation problems, for which the sources are independent; but follow a presumed dynamics:

$$\boldsymbol{s}_{t+1} = \boldsymbol{f}(\boldsymbol{s}_t, \boldsymbol{w}_t)$$
$$\boldsymbol{x}_t = \boldsymbol{h}(\boldsymbol{s}_t) + \boldsymbol{n}_t$$

- Assumptions:
- $\boldsymbol{w}_t \in \mathbb{R}^{\boldsymbol{M}}$ is a vector of M white independent sources of model noise
- $\boldsymbol{n}_t \in \mathbb{R}^{\boldsymbol{N}}$ is the observation noise, independent from $\boldsymbol{w}_t$
- $\boldsymbol{f}(\cdot)$ is known (or presumed)
- $\boldsymbol{h}(\cdot)$ is unknown
- $\boldsymbol{s}_t \in \mathbb{R}^{\boldsymbol{P}}$ is the state vector of interest
- $\boldsymbol{x}_t \in \mathbb{R}^{\boldsymbol{N}}$ is the observation vector

- Objective: Retrieve the sources $\boldsymbol{s}_t$ by implicit or explicit inversion of $\boldsymbol{h}(\cdot)$

Dynamic Source Separation (continued)

Why is this problem interesting?

1. It represents a finite-order Markovian process
2. Many problems can be formulated with this model
3. The assumptions are realistic in many applications: slowly varying sources, periodic sources, sources with spectral priors…
4. It is in state-space form; a huge body of literature exist for it from different perspectives: observability, identifiability, stability, etc.
5. State-space forms are very flexible and non-unique
6. Many algorithms exist for it: Kalman Filters, Extended Kalman Filters, Dual Kalman Filters, Unscented Kalman Filters, Particle Filters, H-Infinity Filters, etc.

Dynamic Source Separation Methodology

- $\boldsymbol{r_t} = \boldsymbol{x_t} - \boldsymbol{h}(\boldsymbol{\hat{s}_t})$ is known as the innovation process.
- *The innovation process is the only useful part of the observations*, which could not be estimated from the system's dynamics or previous observations.
- In a healthy Kalman filter (linear or nonlinear), the innovation process should be white noise with the presumed covariance matrix.

- Methodology: We are focusing on the properties of the innovation process to design source separation algorithms for random processes

- Applications: Single and multi-modal data (e.g. the ECG and PCG)

Thank you for your attention!

Appendix

Online Version of the Deflation Algorithm for fECG Extraction

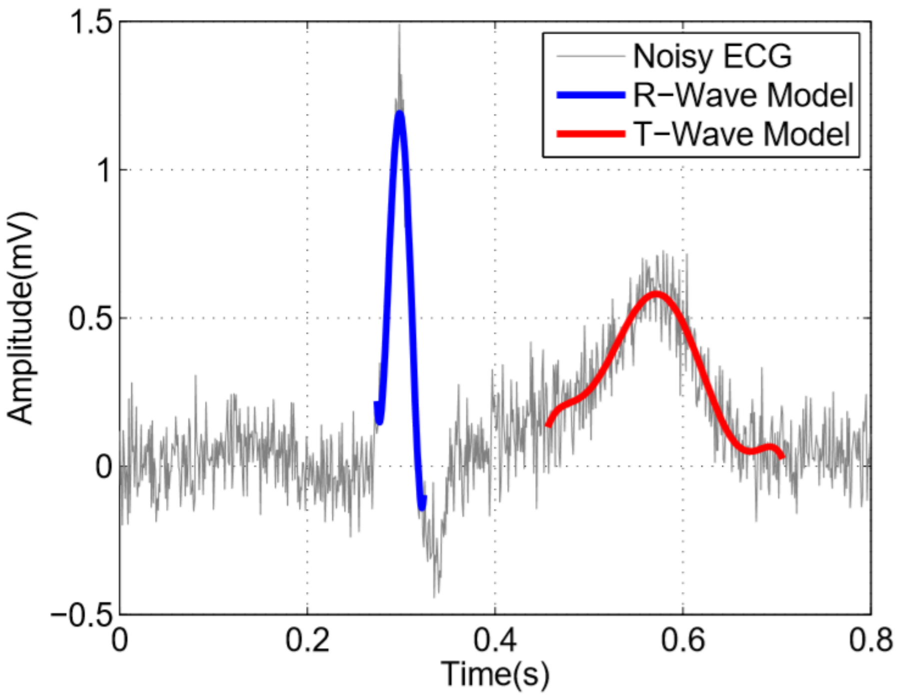
Algorithm 1 Online denoising by deflation (ODEFL)

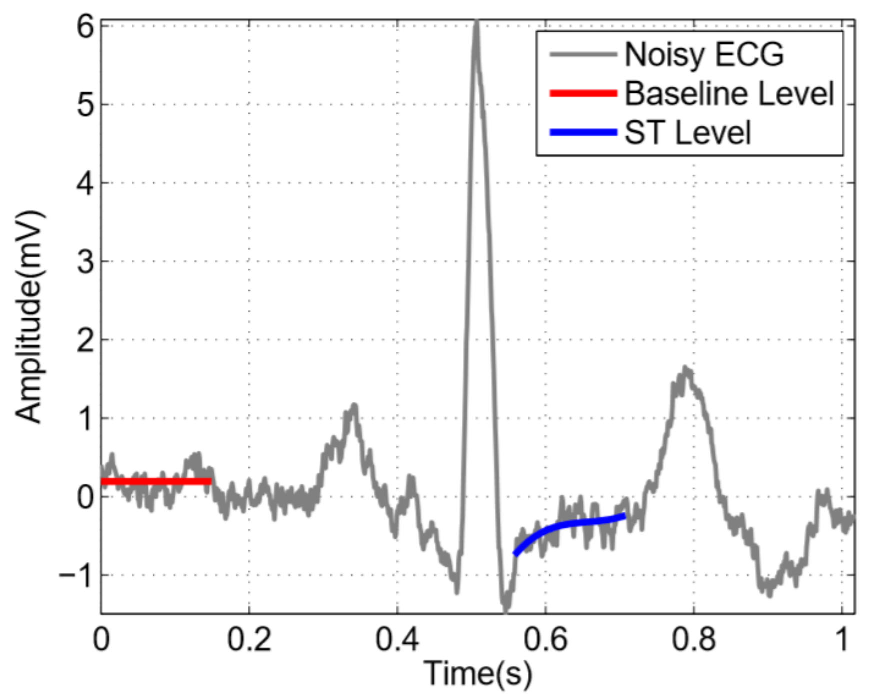
$\mathbf{x}_1(t) \leftarrow \mathbf{x}(t)$ ▷ Initialize with the input data
for $i = 1, \dots, K$ **do** ▷ In each of the parallel stages of ODEFL
 $\mathbf{C}_i(0) \leftarrow \mathbf{I}_N$ ▷ Initialize with identity (or random unitary) matrices
 $\mathbf{C}_{\tau,i}(0) \leftarrow \mathbf{I}_N$
 $\mathbf{W}_i(0) = [\mathbf{w}_{i1}(0), \dots, \mathbf{w}_{iN}(0)] \leftarrow \mathbf{I}_N$
 for $t = 1, \dots, T$ **do** ▷ Repeat for all samples of the data
  $\mathbf{C}_i(t) \leftarrow \beta \mathbf{C}_i(t-1) + \mathbf{x}_i(t)\mathbf{x}_i(t)^T$ ▷ Covariance matrix update
  $\mathbf{C}_{\tau,i}(t) \leftarrow \gamma \mathbf{C}_{\tau,i}(t-1) + \mathbf{x}_i(t)\mathbf{x}_i(t+\tau_t)^T$ ▷ Lagged covariance matrix update
  $\mathbf{C}_i(t) \leftarrow [\mathbf{C}_i(t) + \mathbf{C}_i(t)^T]/2$ ▷ Covariance matrix symmetrization
  $\mathbf{C}_{\tau,i}(t) \leftarrow [\mathbf{C}_{\tau,i}(t) + \mathbf{C}_{\tau,i}(t)^T]/2$ ▷ Lagged covariance matrix symmetrization
  $\mathbf{C}_{\tau,i}^{-1}(t) \leftarrow \gamma^{-1}\mathbf{C}_{\tau,i}^{-1}(t-1) - \dfrac{\gamma^{-1}\mathbf{C}_{\tau,i}^{-1}(t-1)\mathbf{x}_i(t)\mathbf{x}_i(t+\tau_t)^T\mathbf{C}_{\tau,i}^{-1}(t-1)}{\gamma + \mathbf{x}_i(t)^T\mathbf{C}_{\tau,i}^{-1}(t-1)\mathbf{x}_i(t+\tau_t)}$ ▷ Matrix inversion lemma
  $\tilde{\mathbf{C}} \leftarrow \mathbf{C}_i(t)$
  for $j = 1, \dots, N$ **do** ▷ Perform Online GEVD of $(\tilde{\mathbf{C}}, \mathbf{C}_\tau(t))$ over all channels
   $\mathbf{w}_{ij}(t) \leftarrow \dfrac{\mathbf{w}_{ij}^T(t-1)\mathbf{C}_{\tau,i}(t)\mathbf{w}_{ij}(t-1)}{\mathbf{w}_{ij}^T(t-1)\tilde{\mathbf{C}}\mathbf{w}_{ij}(t-1)}\mathbf{C}_{\tau,i}^{-1}(t)\tilde{\mathbf{C}}\mathbf{w}_{ij}(t-1)$ ▷ Incremental CSP update
   $\mathbf{w}_{ij}(t) \leftarrow \mathbf{w}_{ij}(t)/\|\mathbf{w}_{ij}(t)\|$ ▷ Normalization
   $\tilde{\mathbf{C}} \leftarrow \left[\mathbf{I}_N - \dfrac{\tilde{\mathbf{C}}\mathbf{w}_{ij}\mathbf{w}_{ij}^T}{\mathbf{w}_{ij}^T\tilde{\mathbf{C}}\mathbf{w}_{ij}}\right]\tilde{\mathbf{C}}$ ▷ Deflation procedure
  end for
  $\mathbf{W}_i(t) = [\mathbf{w}_{i1}(t), \dots, \mathbf{w}_{iN}(t)]$
  $\mathbf{s}(t) \leftarrow \mathbf{W}_i^T(t)\mathbf{x}_i(t)$ ▷ Go to transform space
  Estimate L ▷ The number of effective mECG dimensions
  $\tilde{\mathbf{s}}(t) \leftarrow \mathbf{G}_i(\mathbf{s}(t), L)$ ▷ Apply denoising operator over the first L channels
  $\mathbf{y}_i(t) \leftarrow \mathbf{W}_i^{-T}(t)\tilde{\mathbf{s}}(t)$ ▷ Return to original space
  $\mathbf{x}_{i+1}(t) \leftarrow \mathbf{y}_i(t)$ ▷ Use output as input for next stage
 end for
end for

Ref: Fatemi, M., Sameni, R. (2017). An online subspace denoising algorithm for maternal ECG removal from fetal ECG signals. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, *41*(1), 65-79.

Model-Based Parameter Extraction

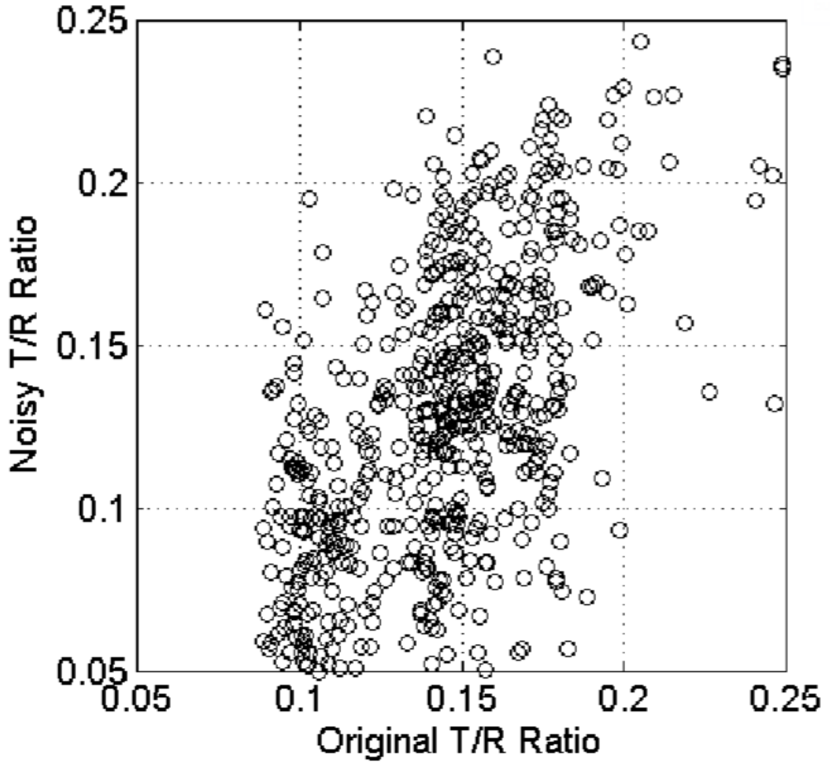
By fitting polynomial (or other) models over ECG segments (or over average beats), more accurate and robust parameters are obtained



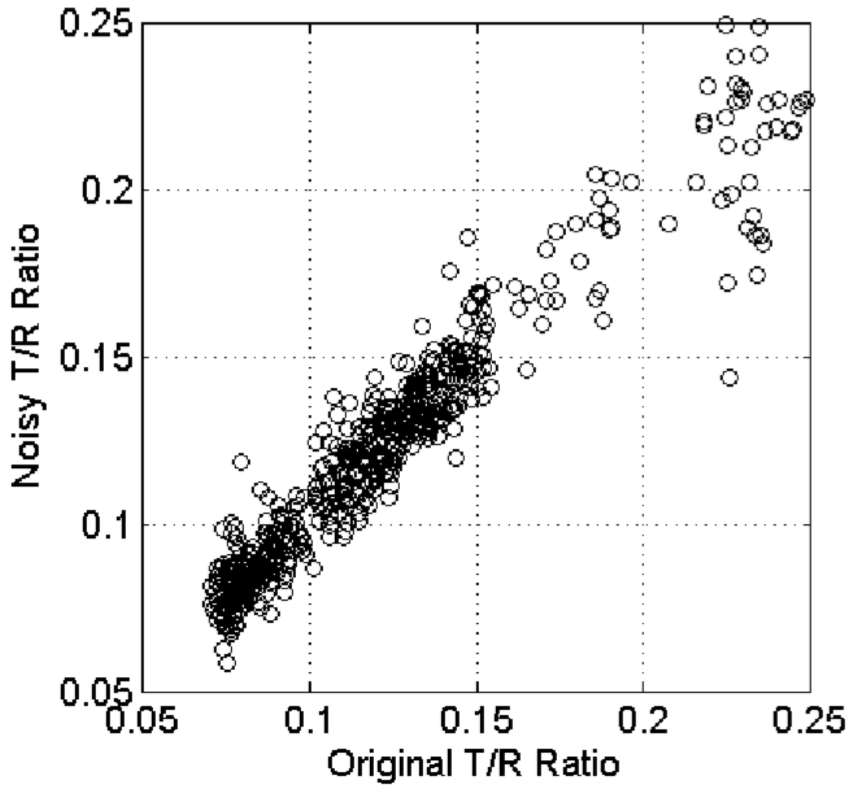


Model-Based Parameter Extraction (continued)

Example 1: T/R ratio calculation with and without model fitting (adult ECG samples)



without model fitting



with model fitting

Semi-Blind Source Separation for Biomedical Signals

- Biomedical signal extraction and processing has been among the most common applications for BSS; why?
  - We are interested in noninvasive (in vivo) techniques and we don't have many alternatives
  - In many cases, the prior assumptions can be assessed by physical or biological facts (e.g., linearity/nonlinearity of the model, existence of temporal correlation, instantaneous/convolutive mixtures, etc.)
  - The output performance can be assessed versus experts' annotations

  - Reservation: It's not always easy to evaluate/challenge the results (not many reference solutions exist).

Example: Deep Neural Networks on FPGA