Disentangling respiratory, cardiogenic and vasomotor rhythms from dynamic infrared thermogram signals

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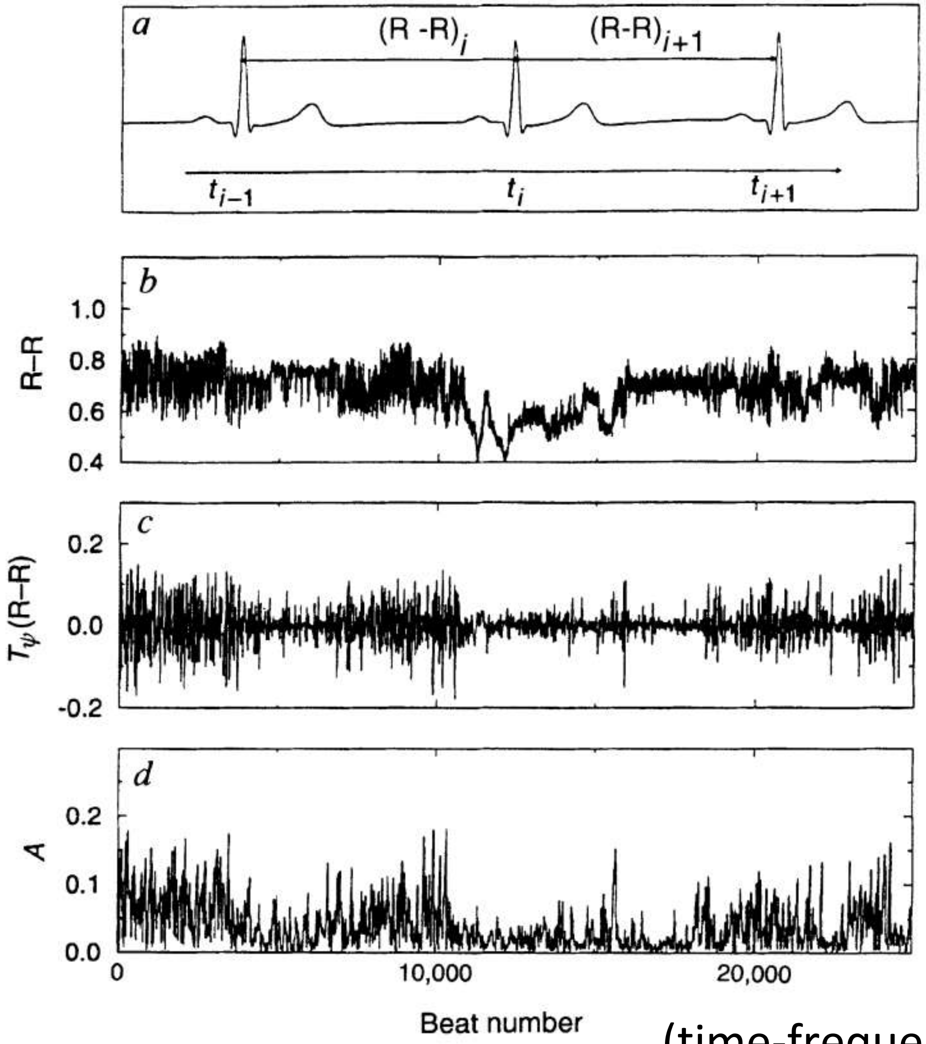
E. Gerasimova et al., EPL 104 (2013) 68011
E. Gerasimova et al., Frontiers in Physiology 5 (2014) 176

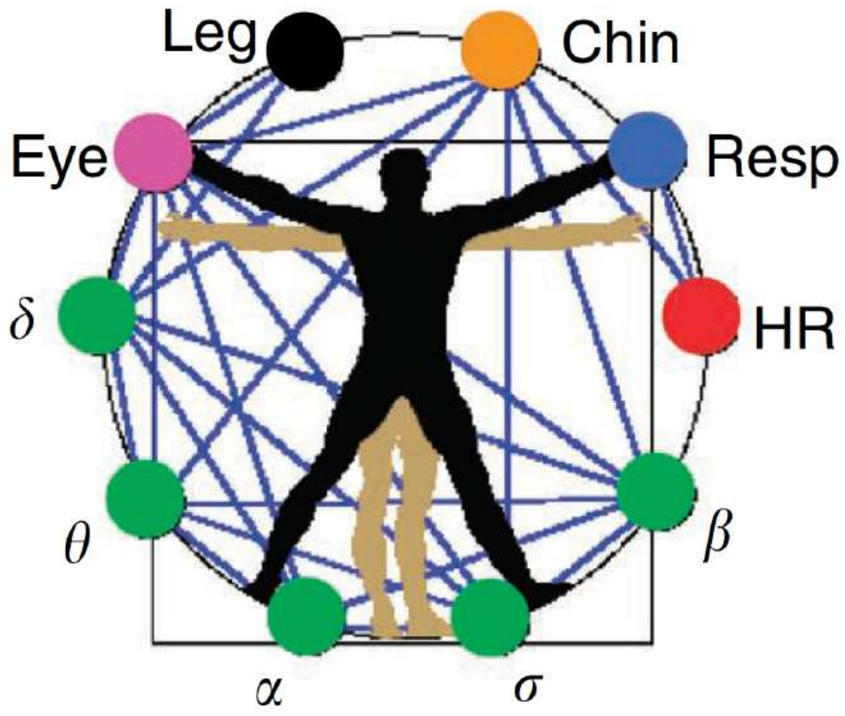
Physiological networks : the inter-node dynamics complexity is the issue

Scaling behavior of heartbeat intervals
Ivanov et al. Nature ***1996***



(time-frequency analysis)

Network Physiology *->*
Network Topology <-> Physiological Function
Bashan Nature Communications ***2012***

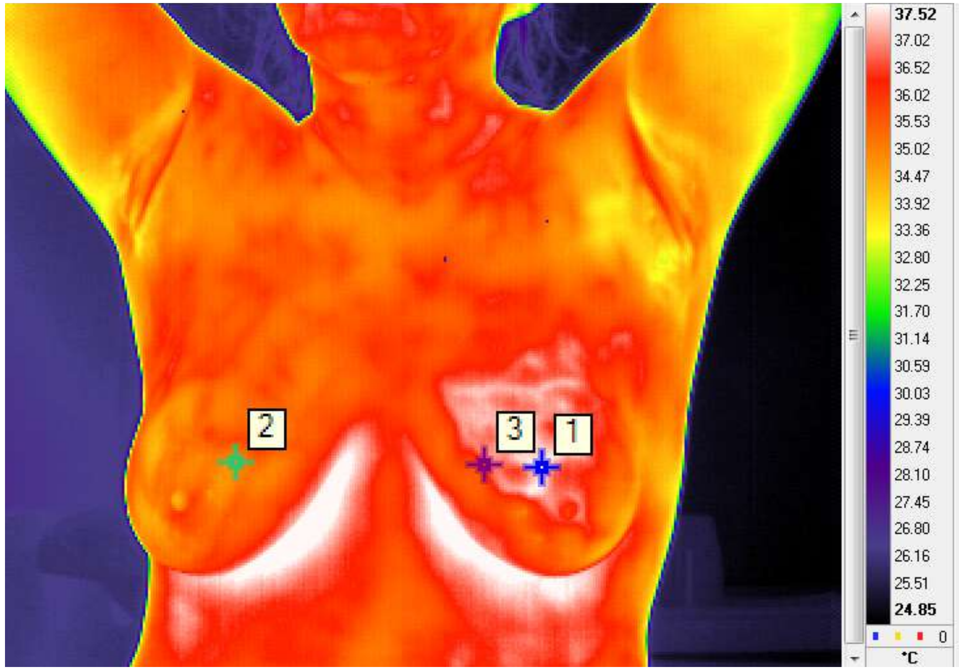


Disentagling respiratory, cardiogenic and vasomotor rhythms from dynamic infrared thermogram signals

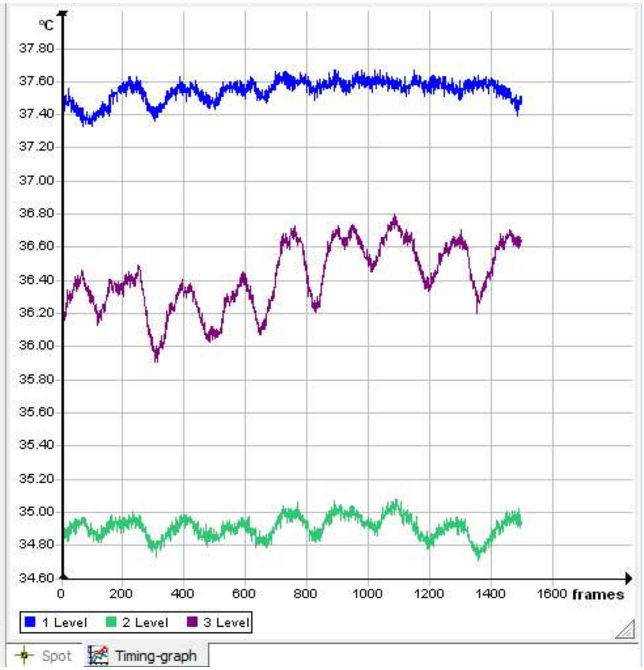
IR thermography to assist cancer diagnosis

Infrared camera

Breast thermogram



Temperature time series



...... -> **IR thermography video film**

E. Gerasimova et al., EPL 104 (2013) 68011
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PLAN OF THE PRESENTATION

- Characterization of the physiological noise of thermogram signals
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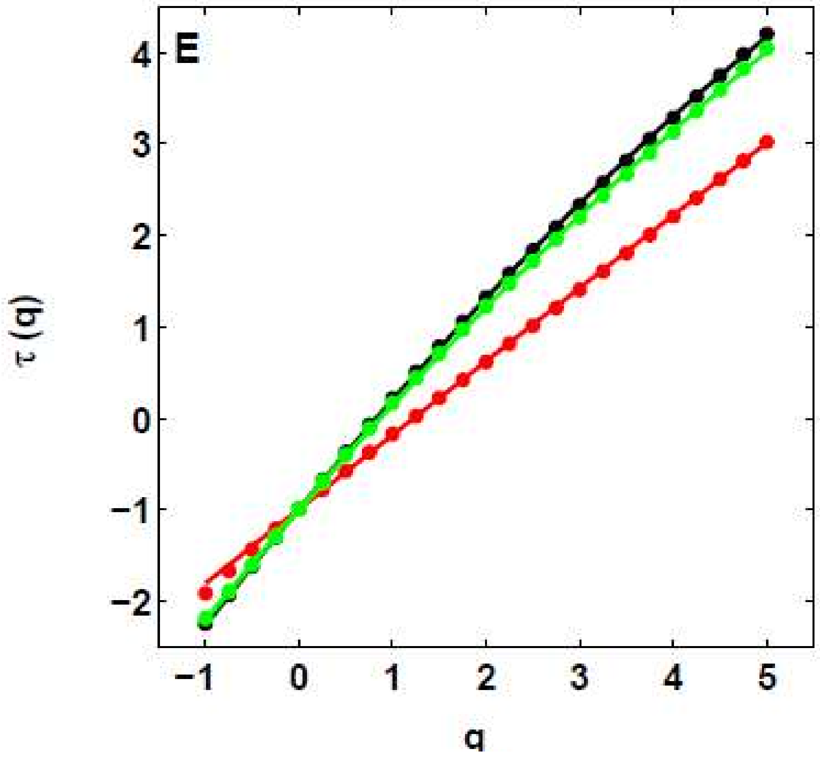
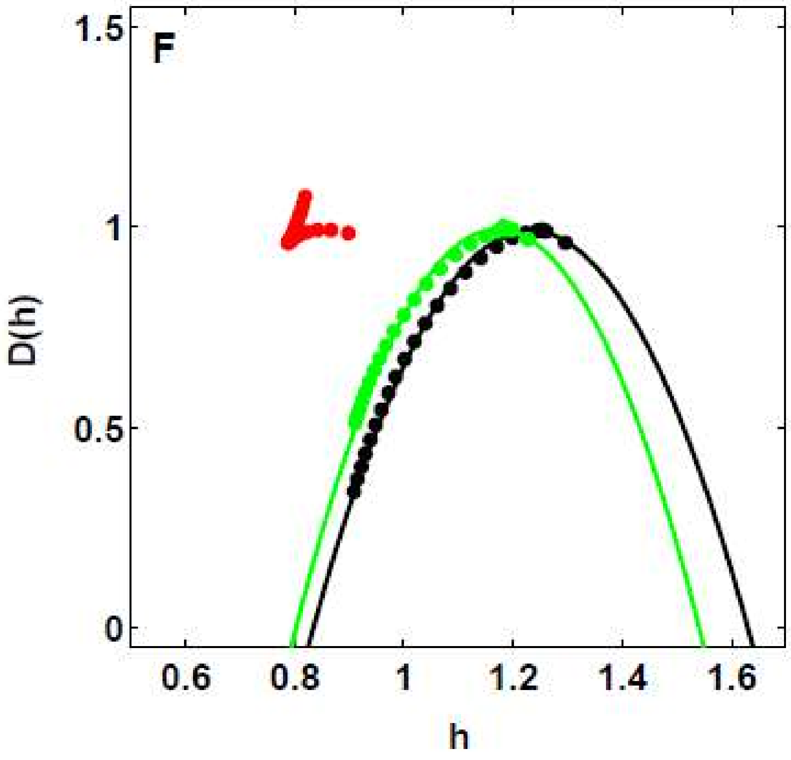
Multifractal spectra of cumulative IR temperature time series

Average over 8x8 pixel^2





$$\tau(q) = -c_0 + c_1 q - c_2 q^2 / 2$$

$$D(h) = c_0 - (h - c_1)^2 / 2c_2$$

Cancer	[c0, c1, c2]=[0.99, 0.81, 0.0044]
Opposite	[c0, c1, c2]=[0.99, 1.23, 0.080]
Healthy	[c0, c1, c2]=[0.99, 1.171, 0.069]

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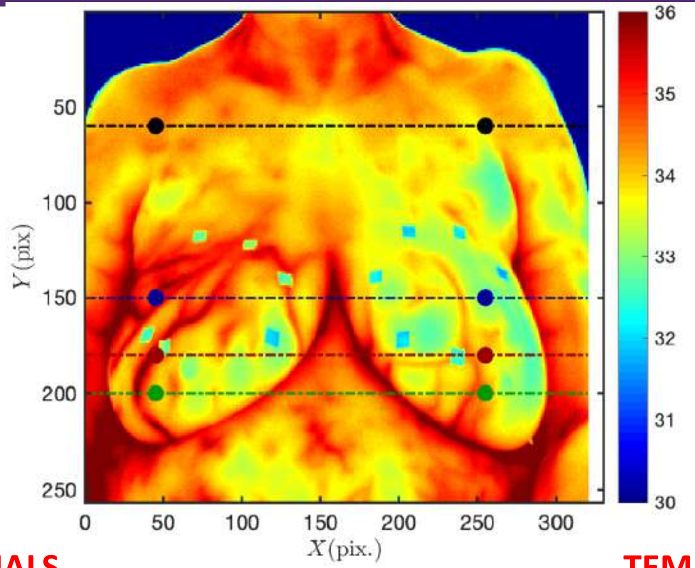
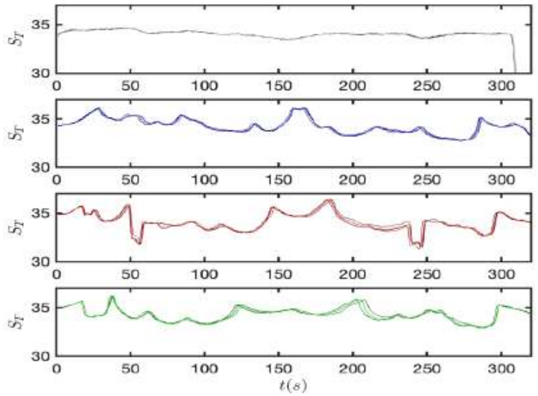
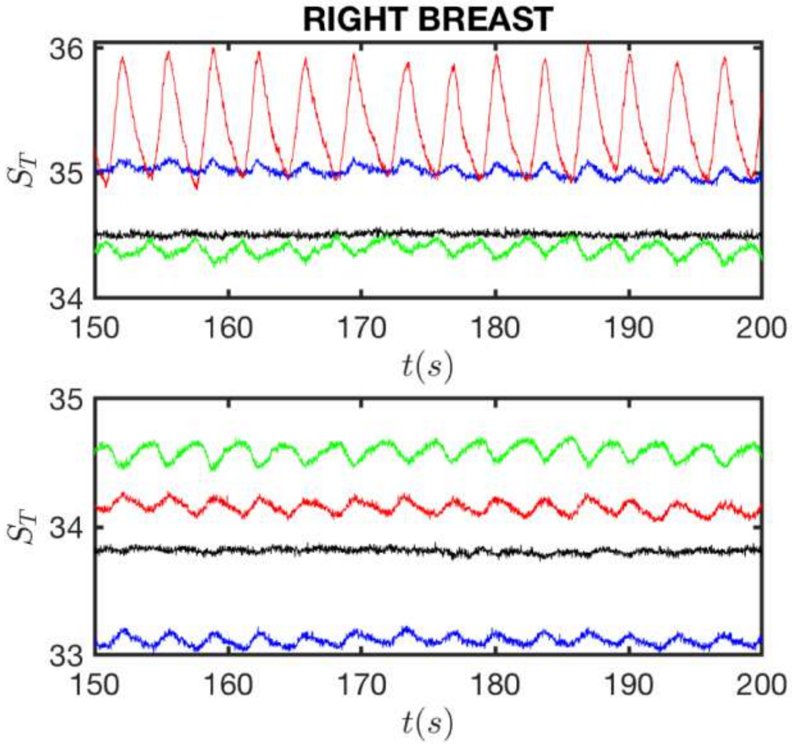
Respiratory and cardiogenic functions impact both the spatial tissue position and skin temperature



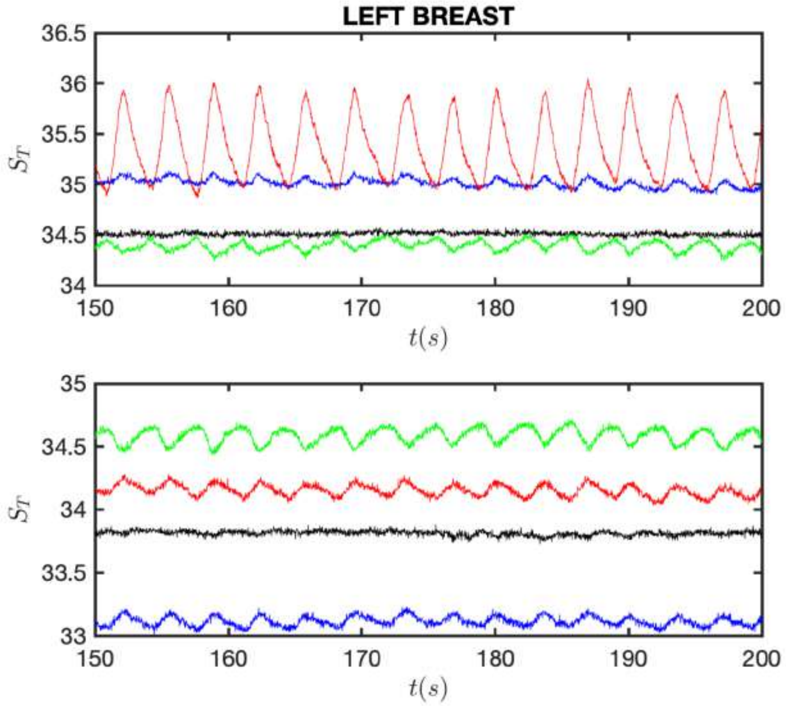
HORIZONTAL SECTIONS



TEMPERATURE SIGNALS

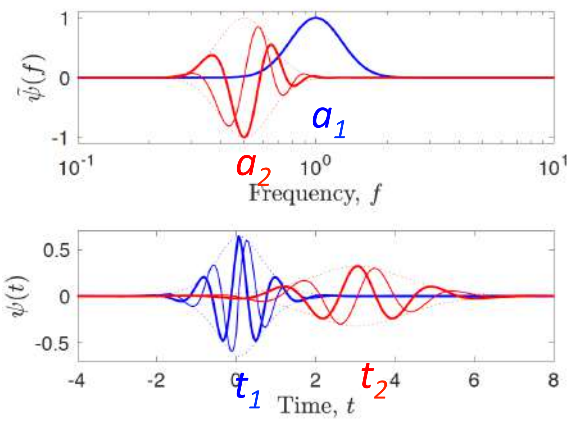


TEMPERATURE SIGNALS



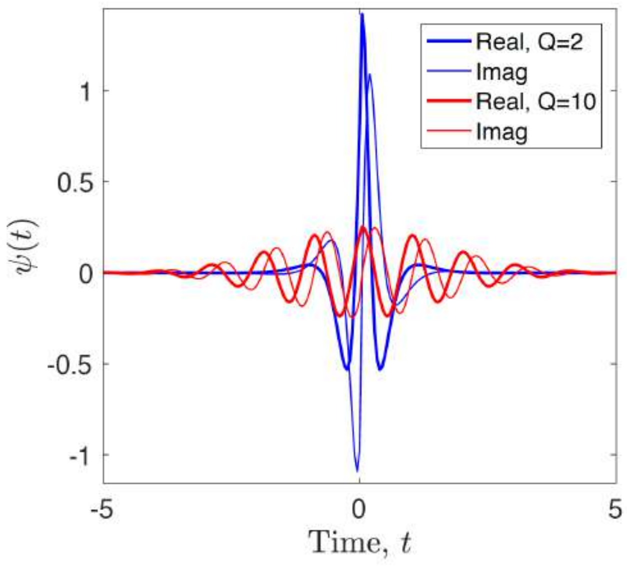
Wavelet transform for time-frequency analysis of rhythmic signals

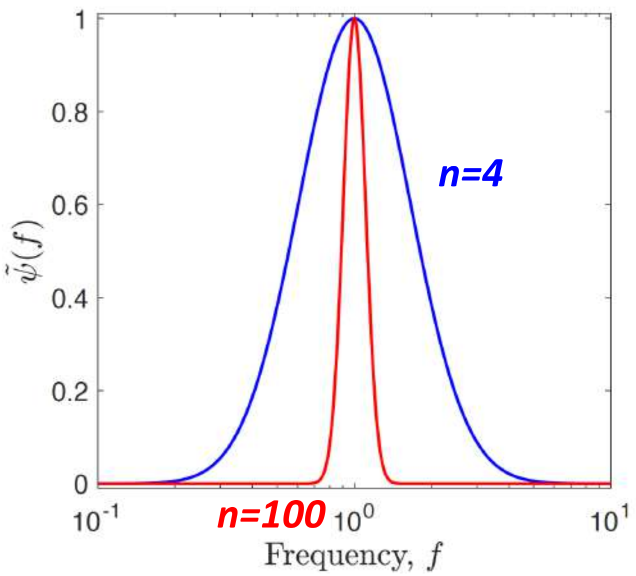
$$\mathcal{W}_\psi[s](a,t;p) = \int_{-\infty}^{+\infty} s(t')a^{-\frac{1}{p}}\overline{\psi}\left(\frac{t'-t}{a}\right)dt'$$



- ψ *Wavelet function (in time variable)*
  (the bar corresponds to the complex conjugate)
- t *translation parameter*
- a *scale parameter ($a = f_0/f$)*
- p *normalization exponent*

Morse wavelet $\tilde{\psi}_{n,\gamma}(f) \propto f^n e^{-f^\gamma} \quad \forall f > 0$; *0 if f<0*

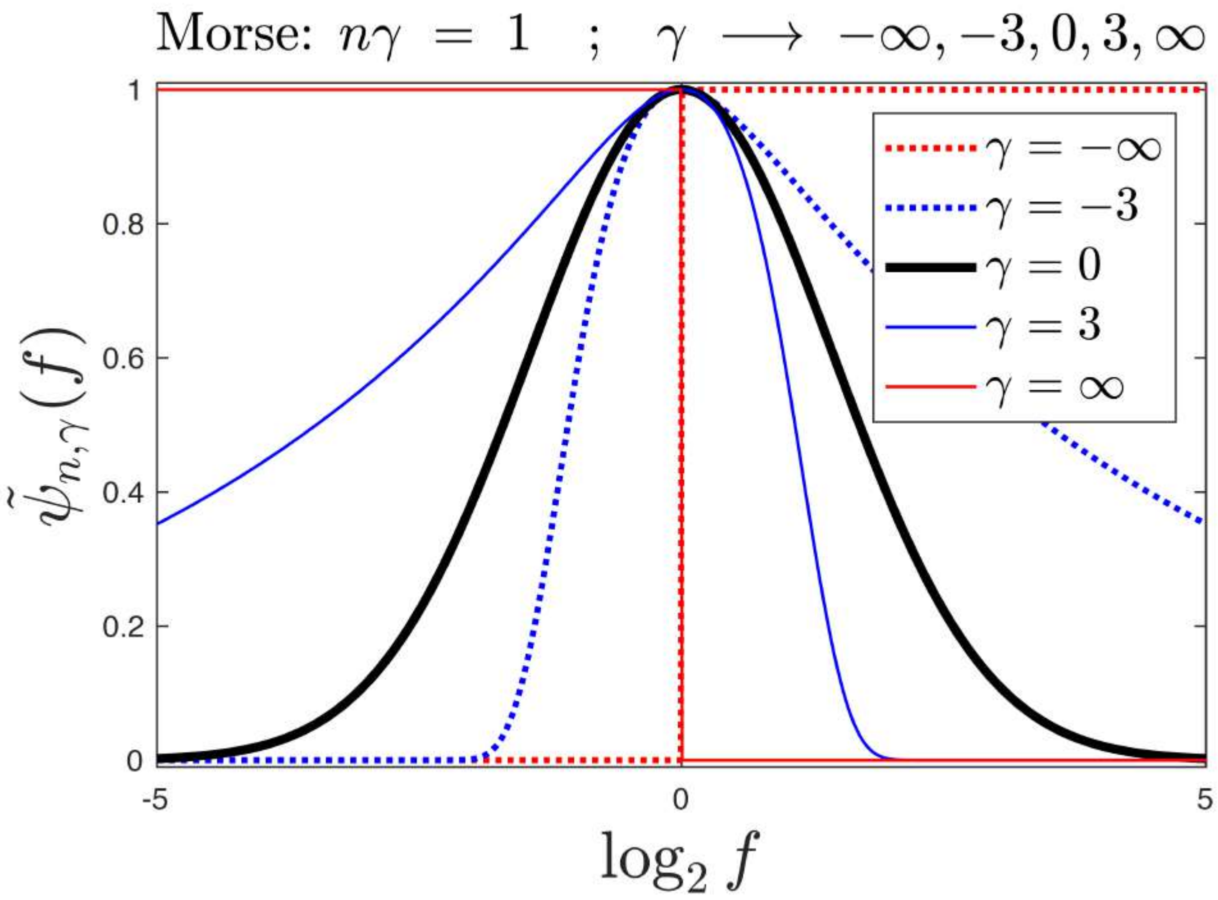




$Q = (n\gamma)^{1/2}$ quality factor

The larger Q, the sharper the wavelet in frequency domain

Wavelet transform for time-frequency analysis of rhythmic signals



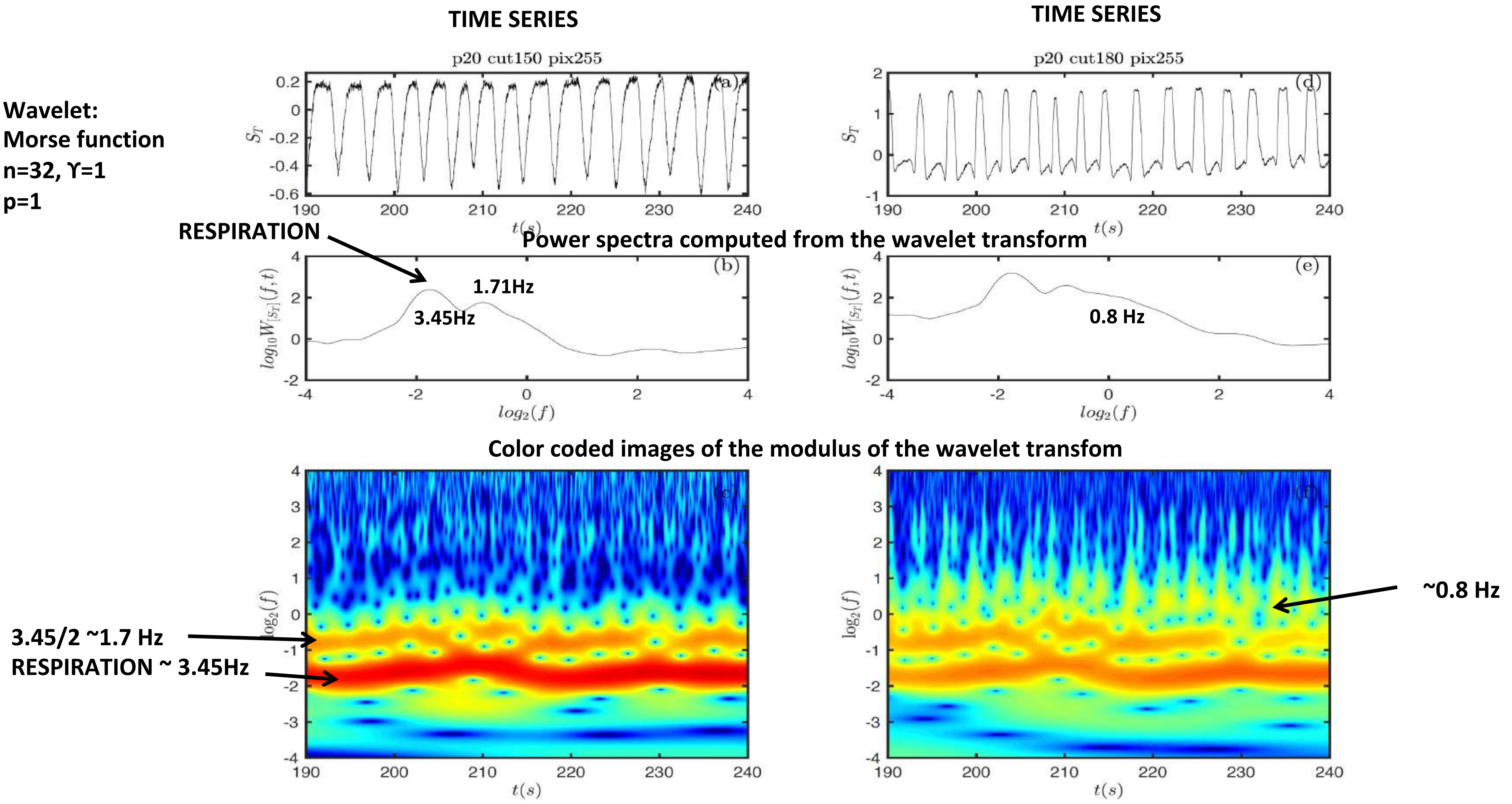
Log-normal Morse wavelet: γ = 0, nγ = 1

$$\tilde{\psi}_Q(f'/f) = e^{-\frac{1}{2}(Q \log f'/f)^2}$$

This wavelet is symmetric in frequency space
It is parametrized by the quality factor Q

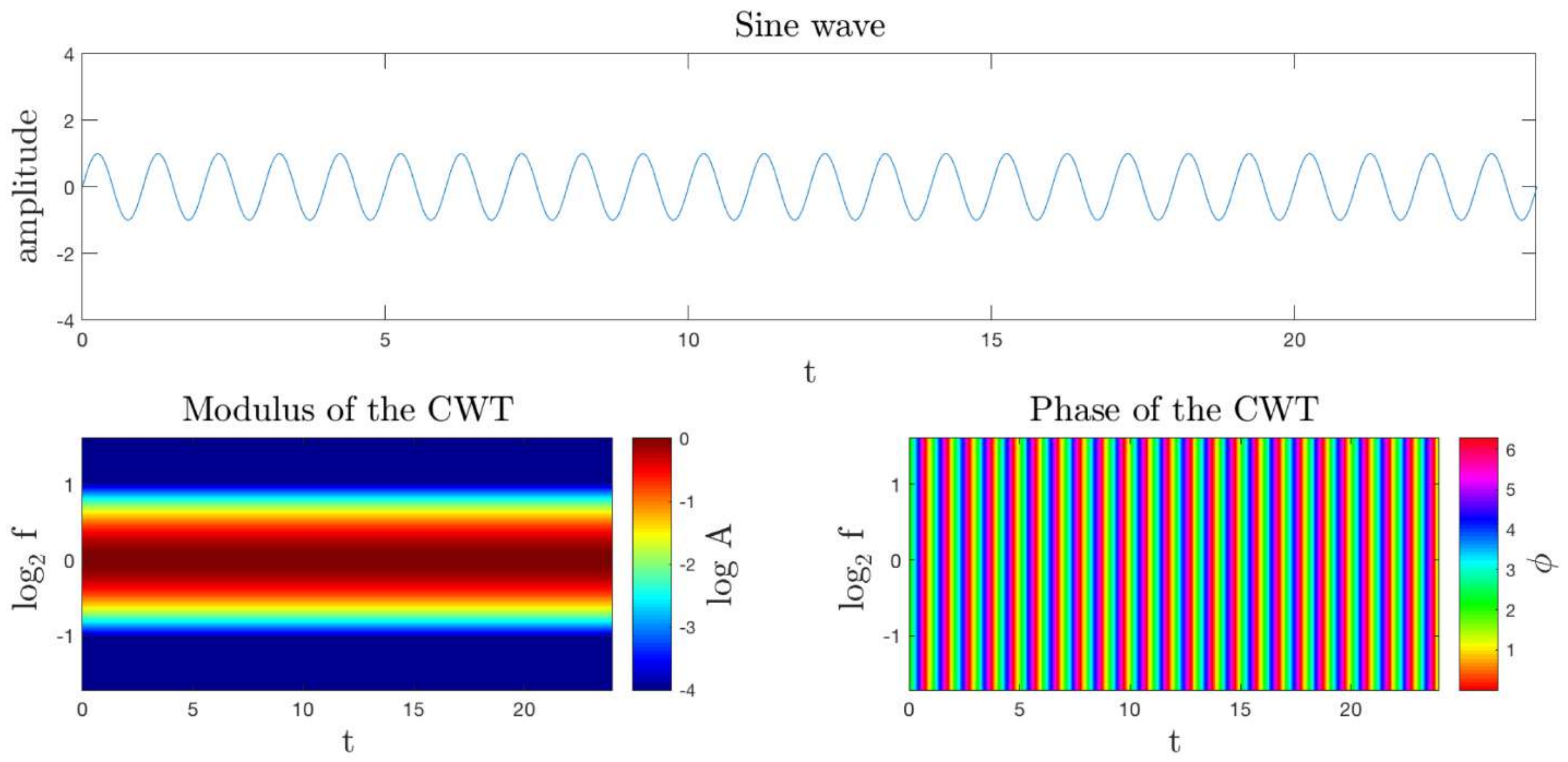
Wavelet transform for time-frequency analysis of rhythmic signals

Wavelet:
Morse function
n=32, ϒ=1
p=1



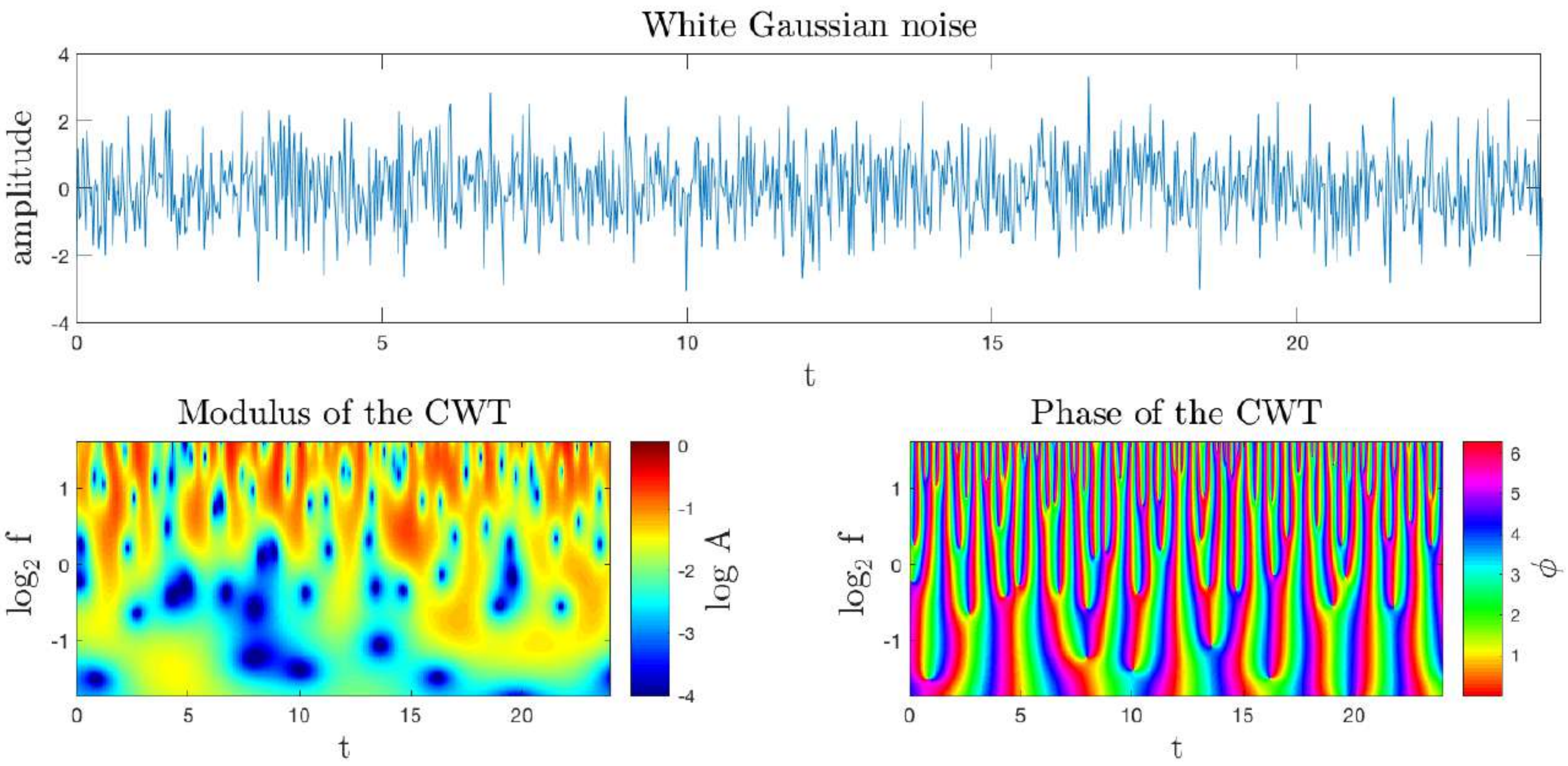
Wavelet transform analysis of model signals

PERIODIC SIGNAL (pure sinus)

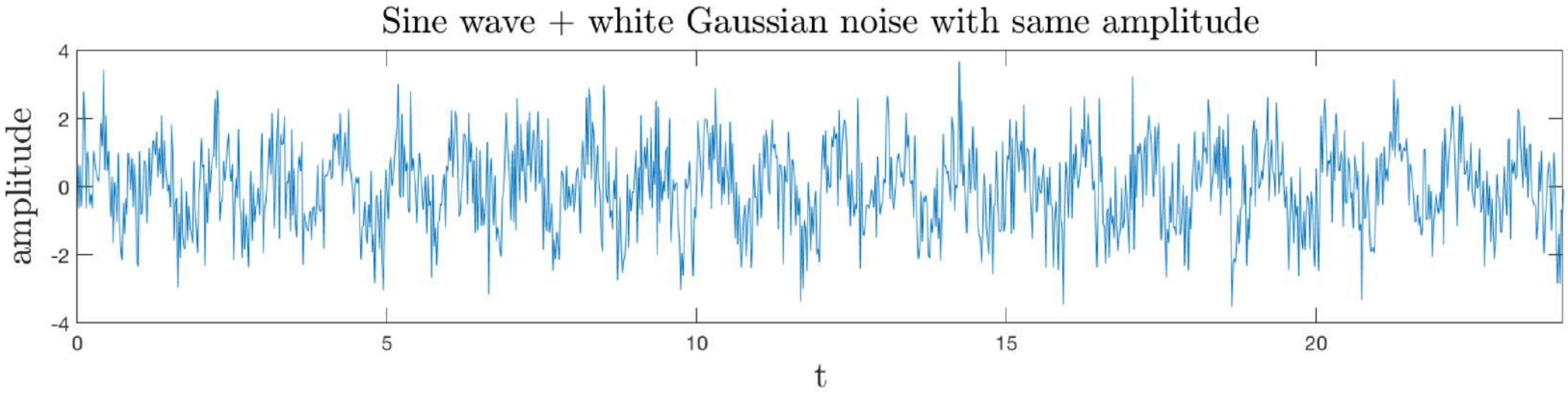


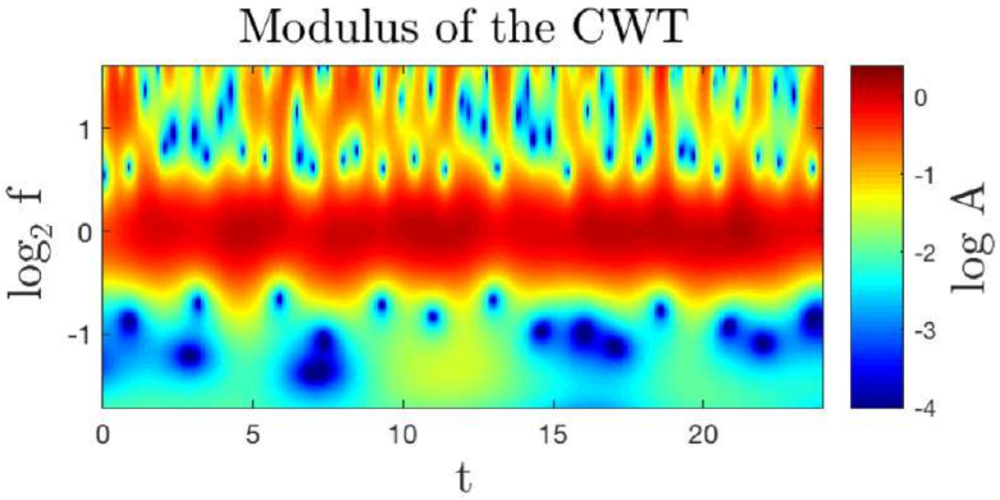
Wavelet transform analysis of model signals

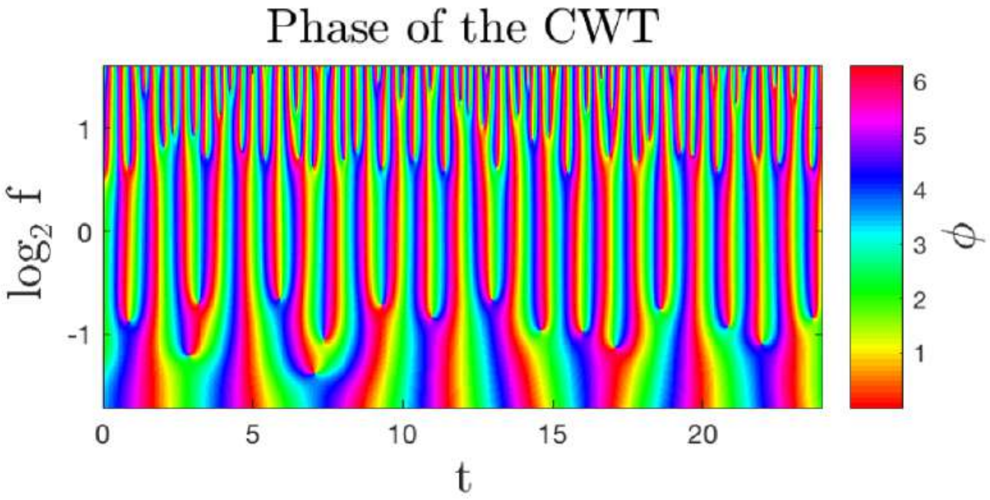
RANDOM SIGNAL (no rhythms)



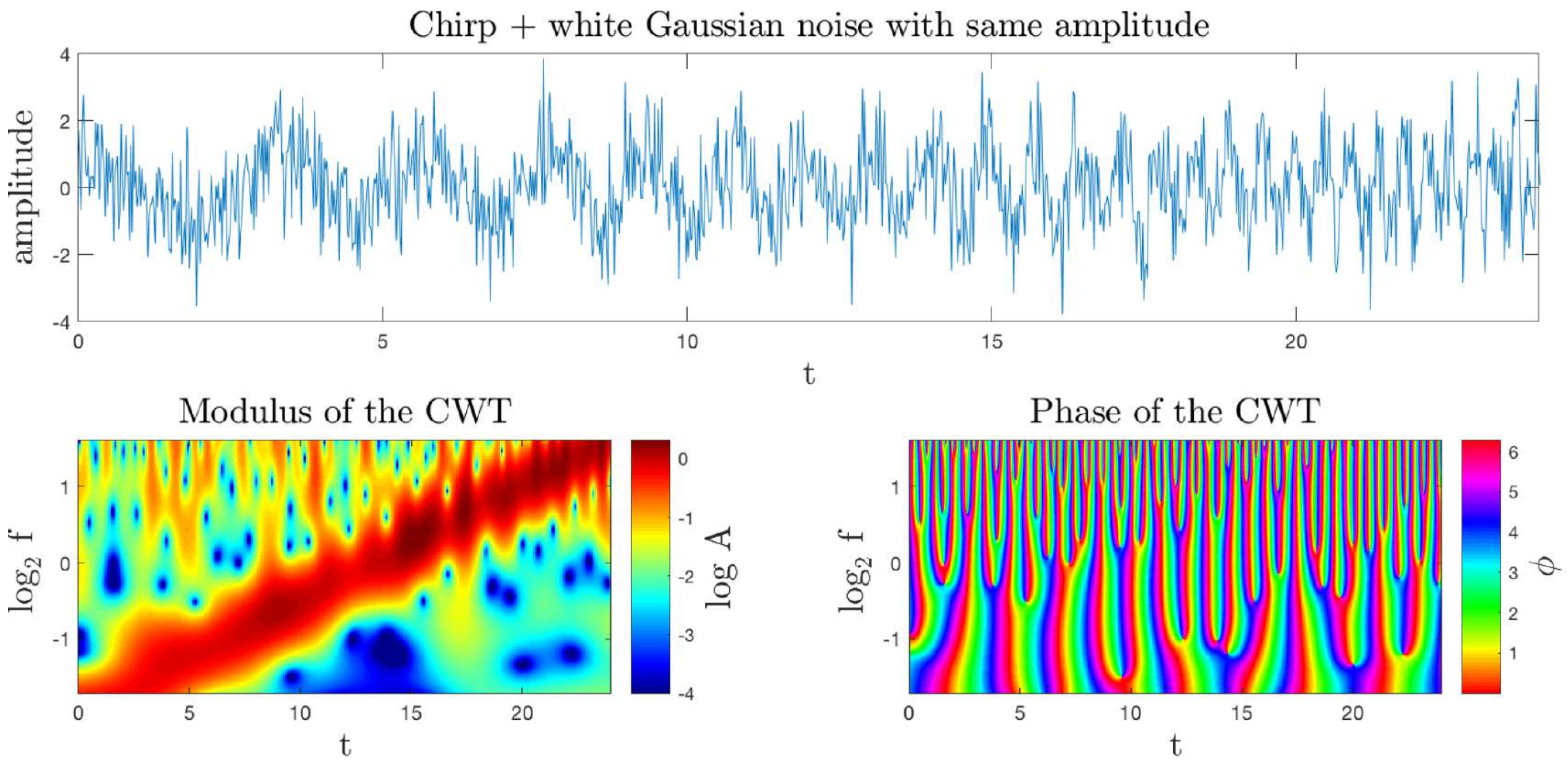
Wavelet transform analysis of model signals





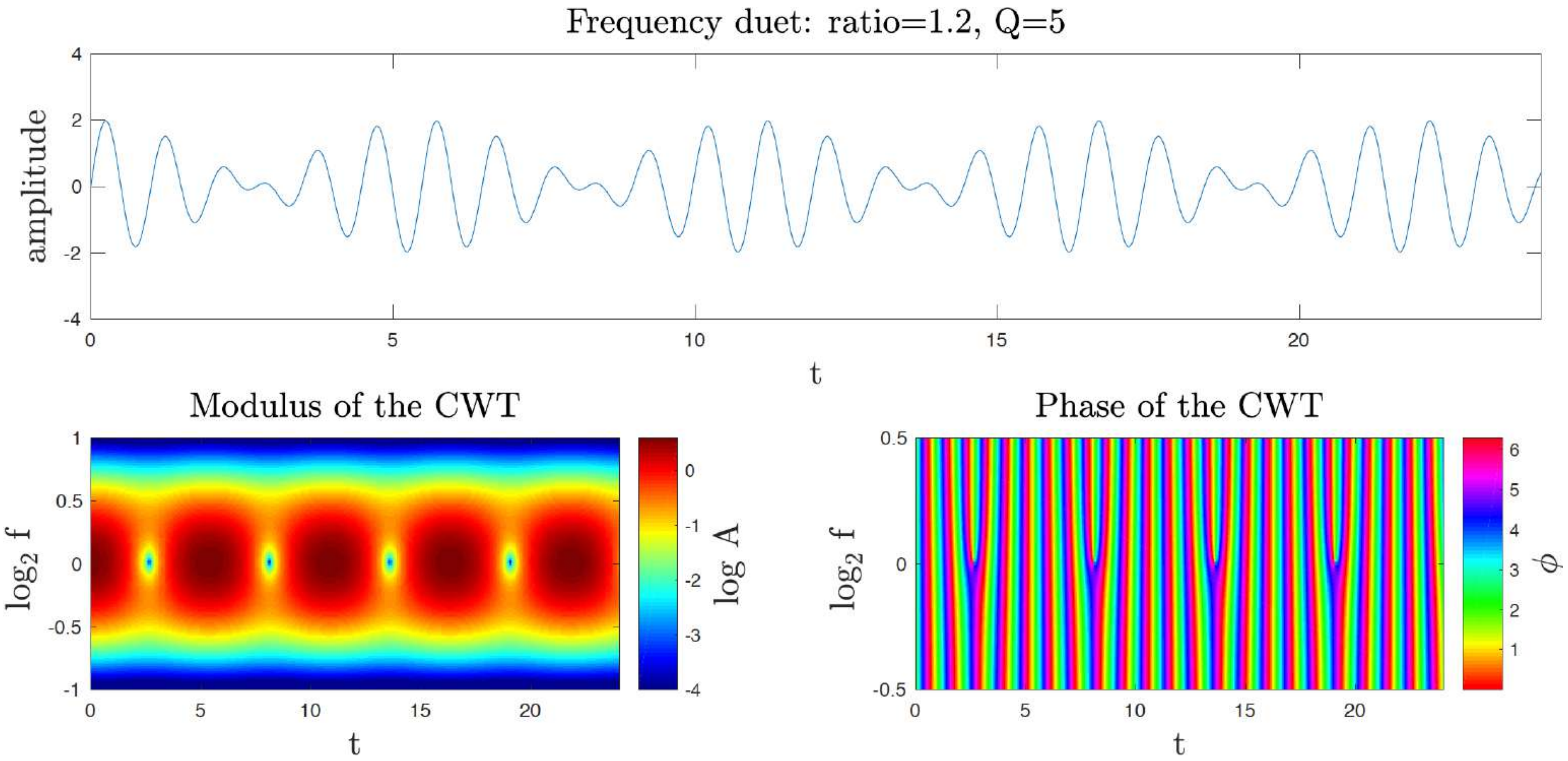


Wavelet transform analysis of model signals



Wavelet transform analysis of model signals: frequency duets

$$S(t) = \sin(ft) + \sin((f+\delta f)t)$$



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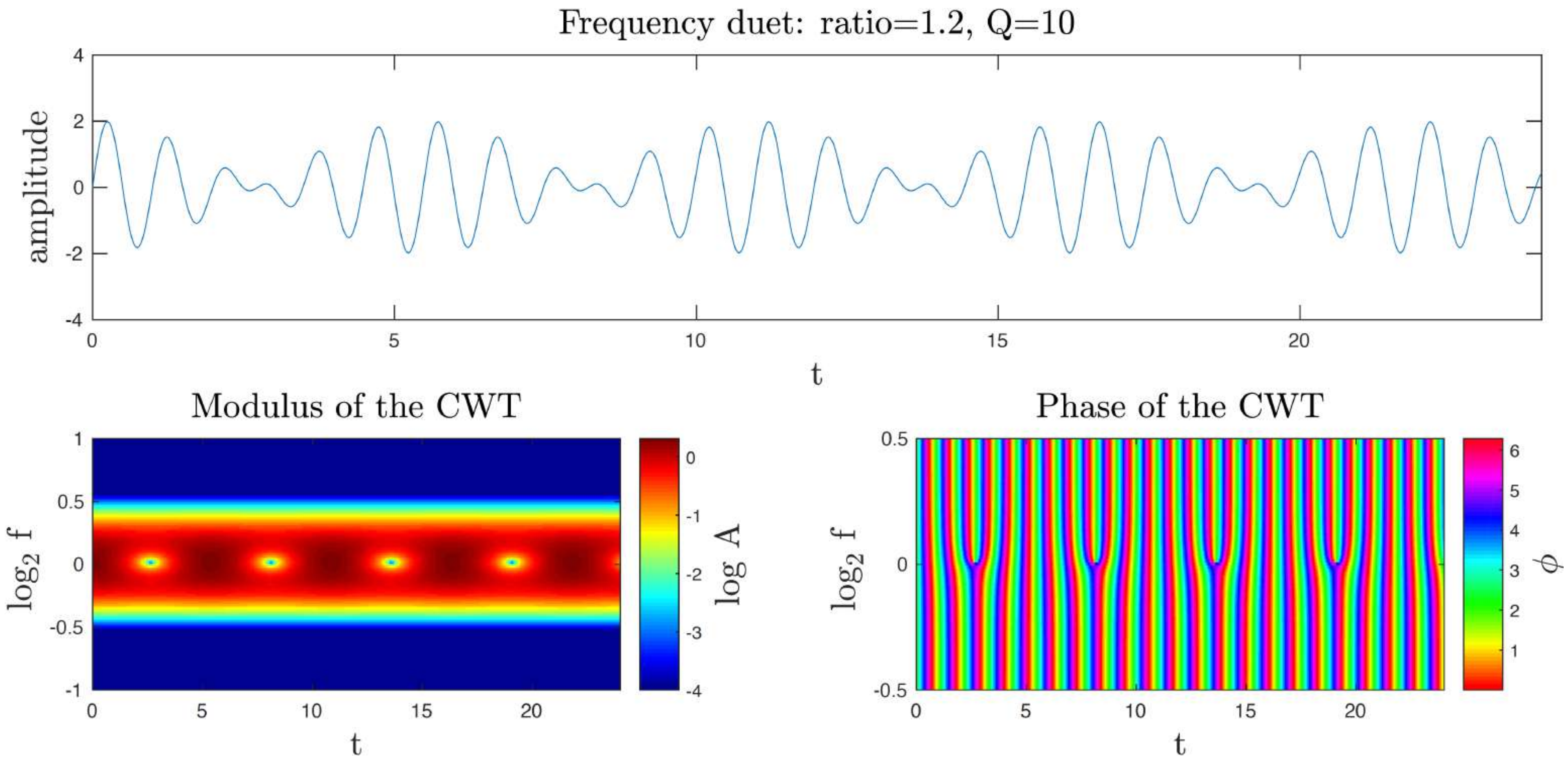

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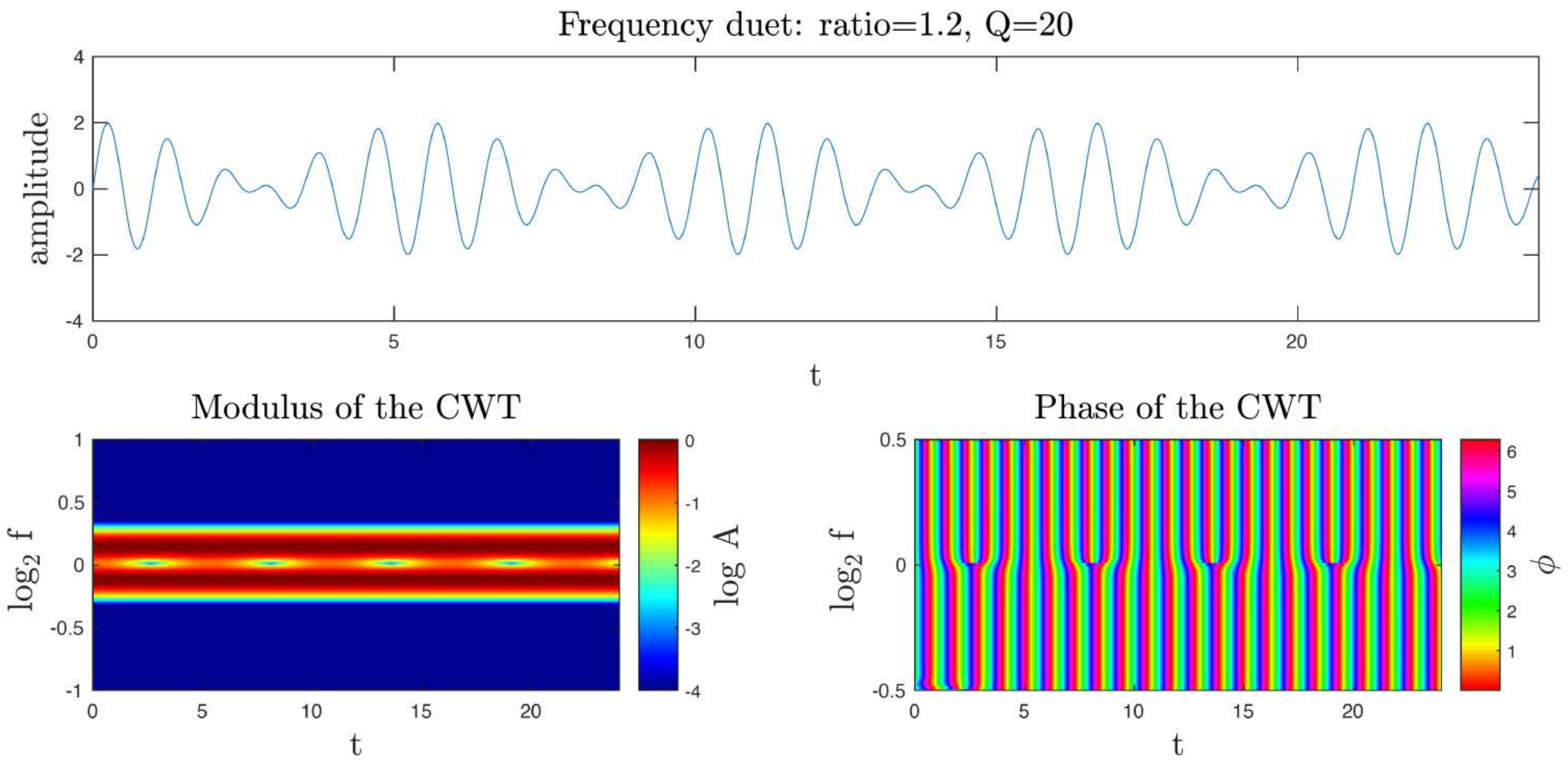

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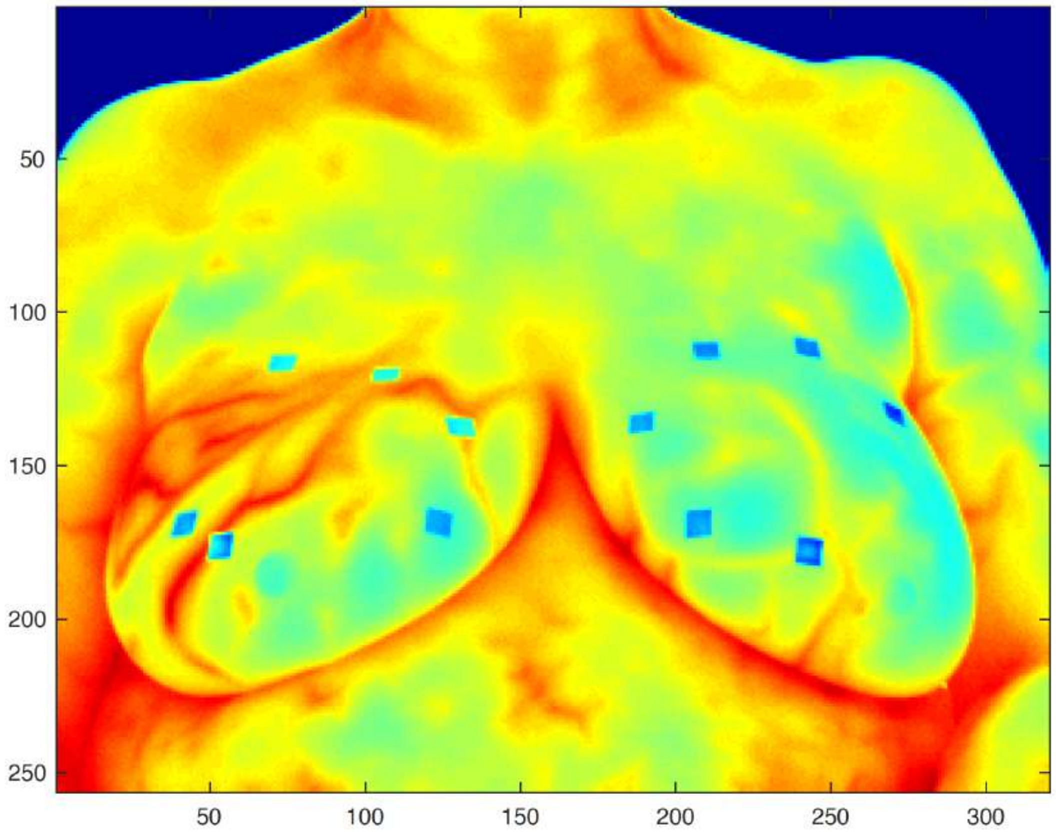
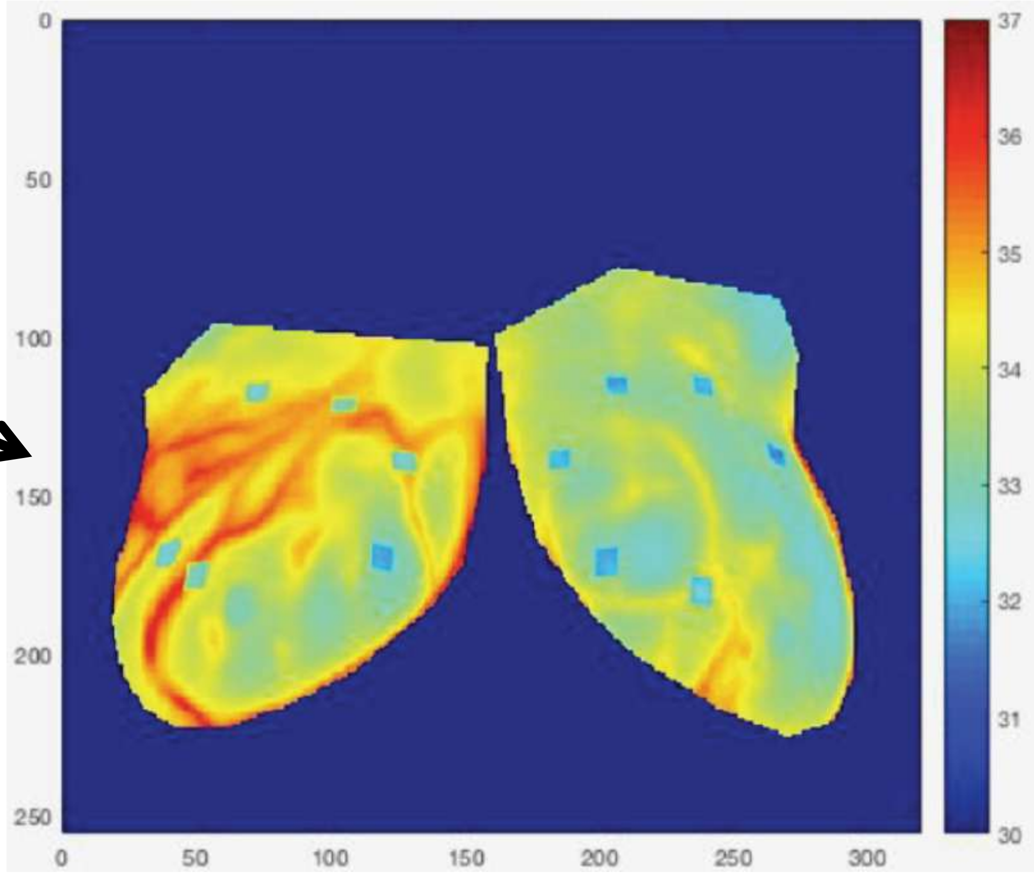
Global selection of the two breasts (R − L) with ellipse-like shapes

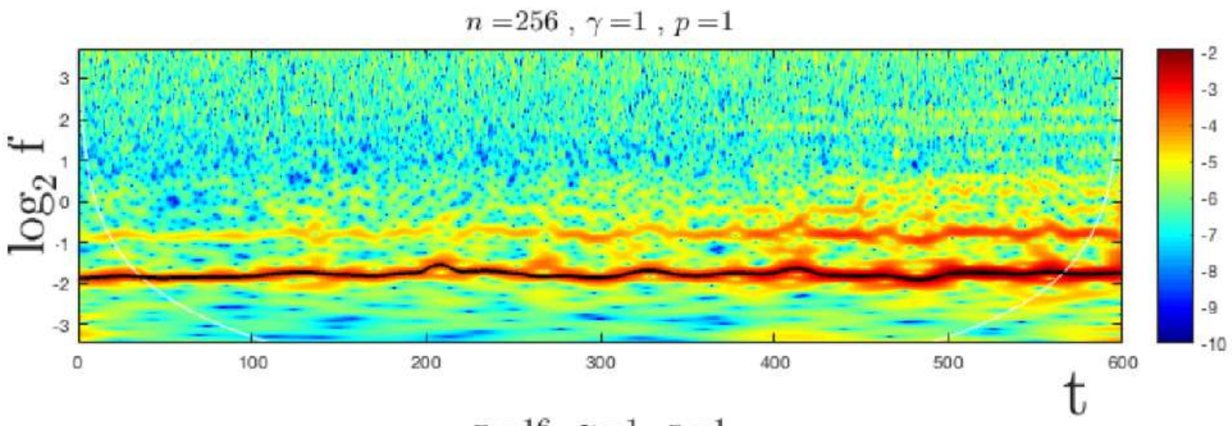




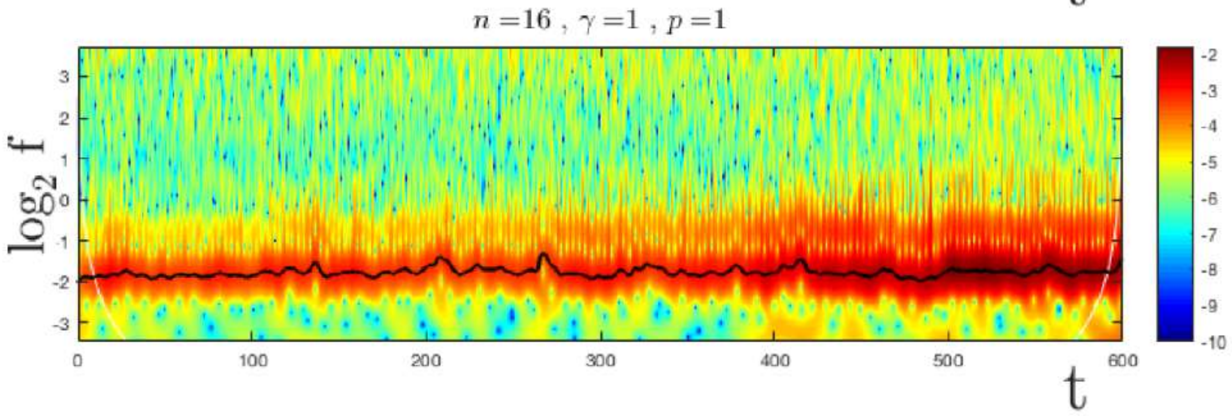
Influence of the quality factor Q on the detection of the rhythms

$Q = (n\gamma)^{1/2}$ quality factor

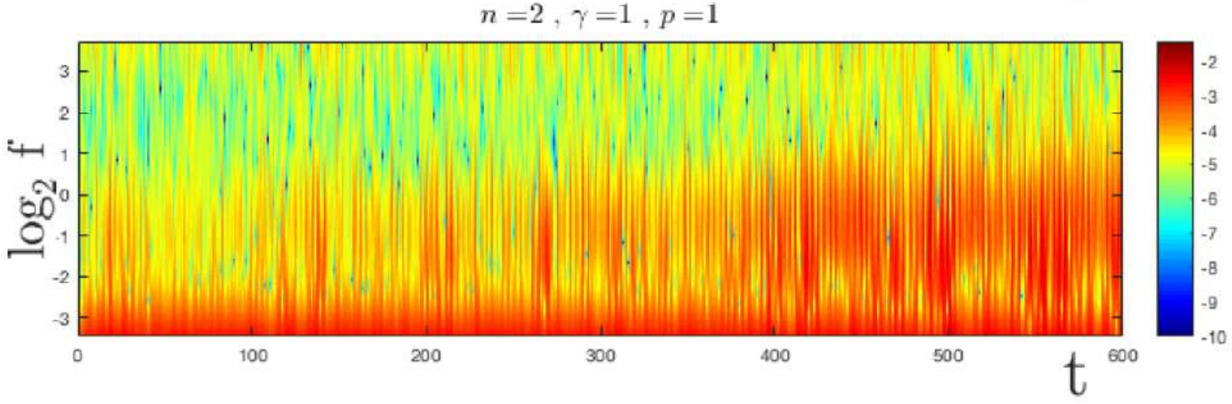
The larger Q, the sharpest the wavelet in frequency domain



High quality factor
Q = 16

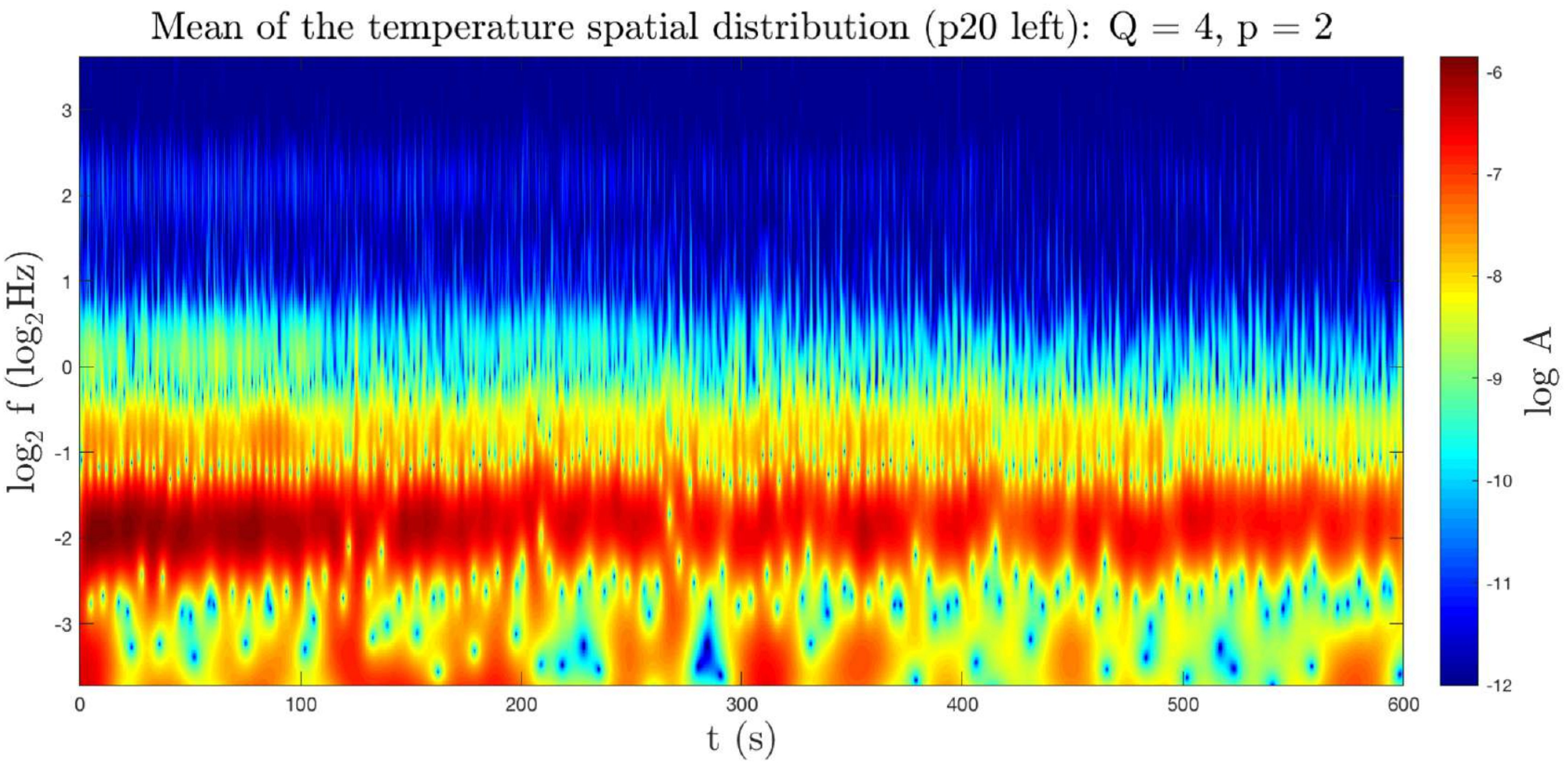


medium quality factor
Q = 4

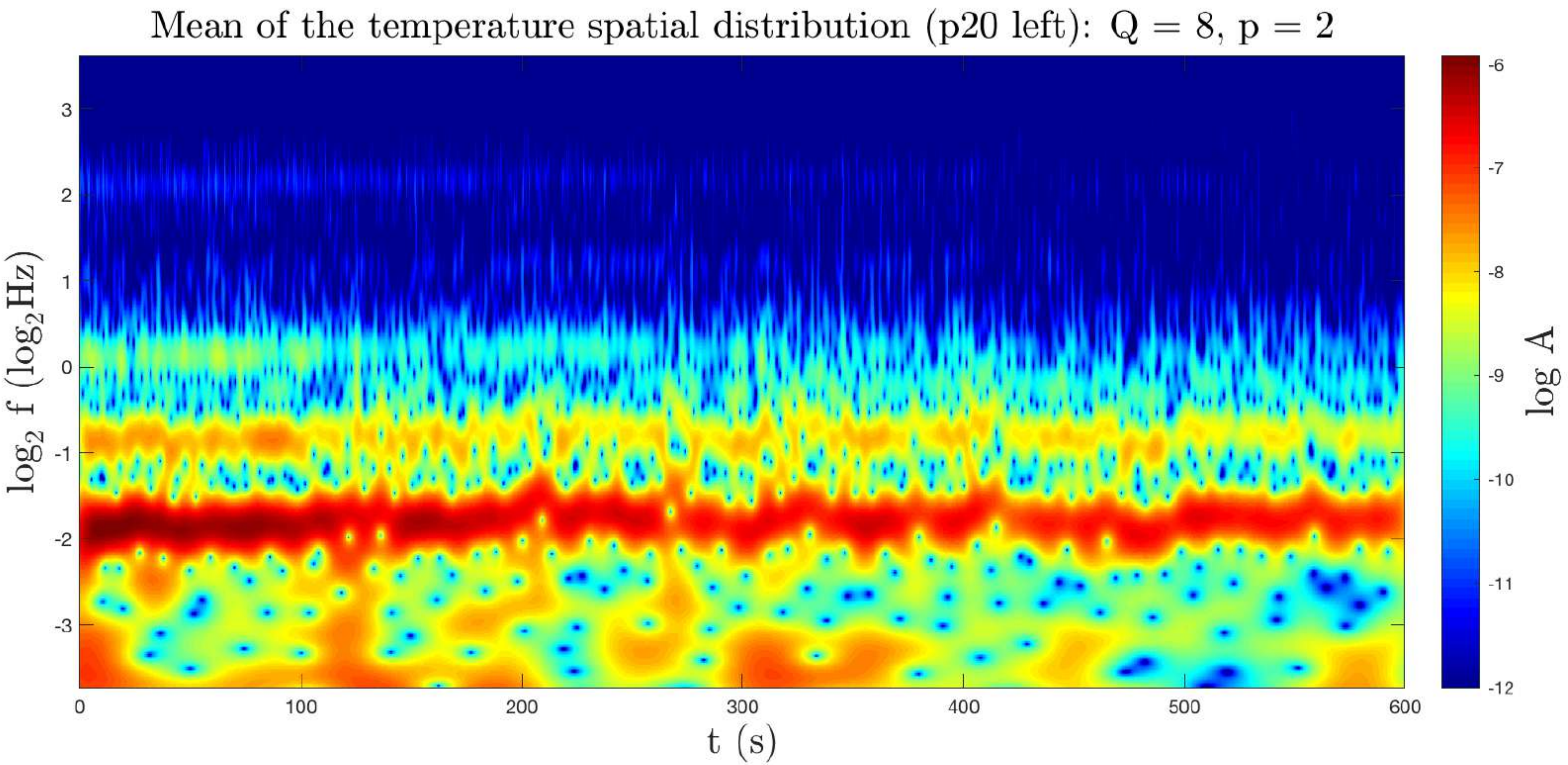


Low quality factor
Q = 1.4

Playing on the wavelet function parameters to reveal both respiratory and cardiac rhythms



Playing on the wavelet function parameters to reveal both respiratory and cardiac rhythms



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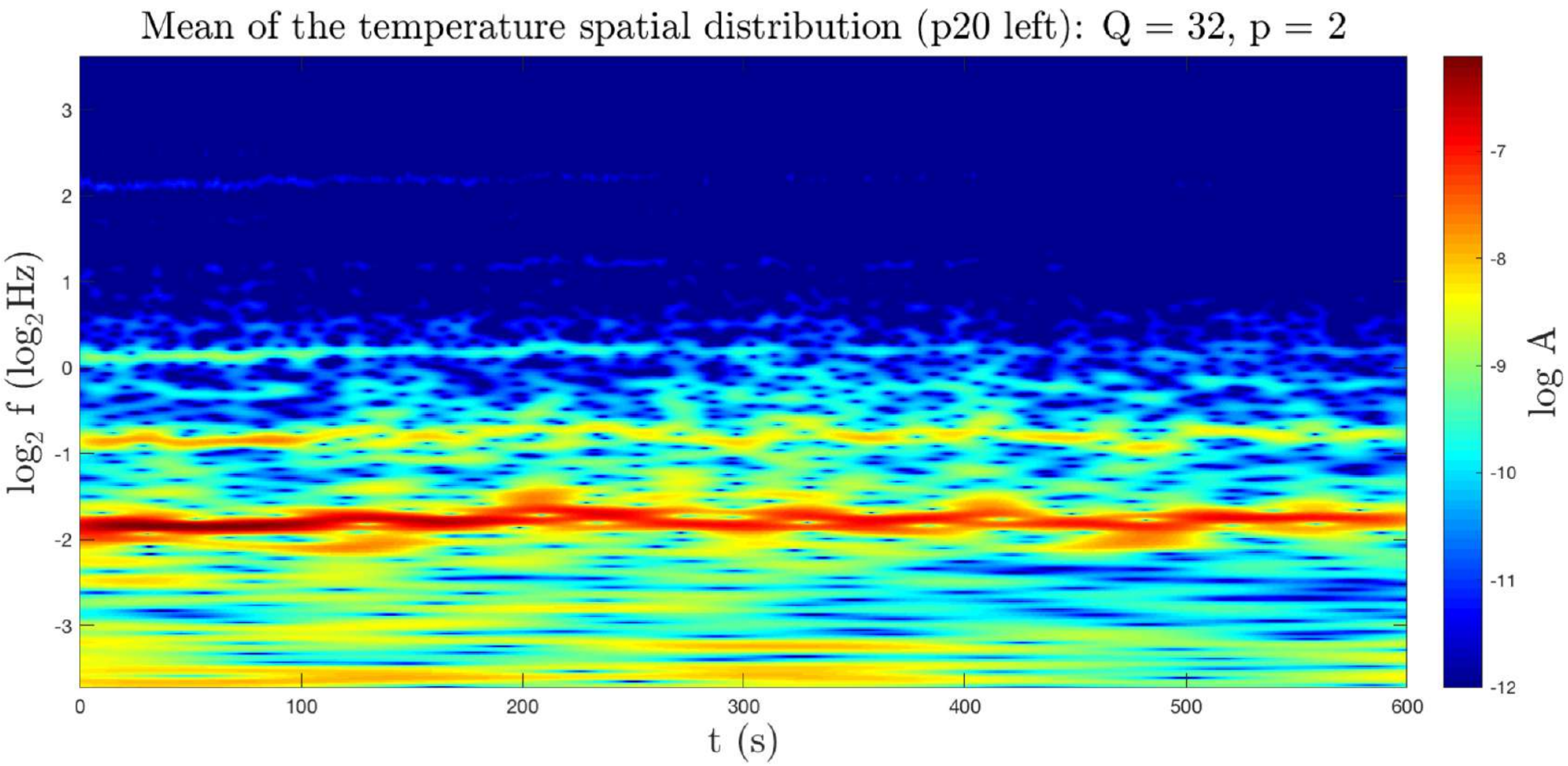

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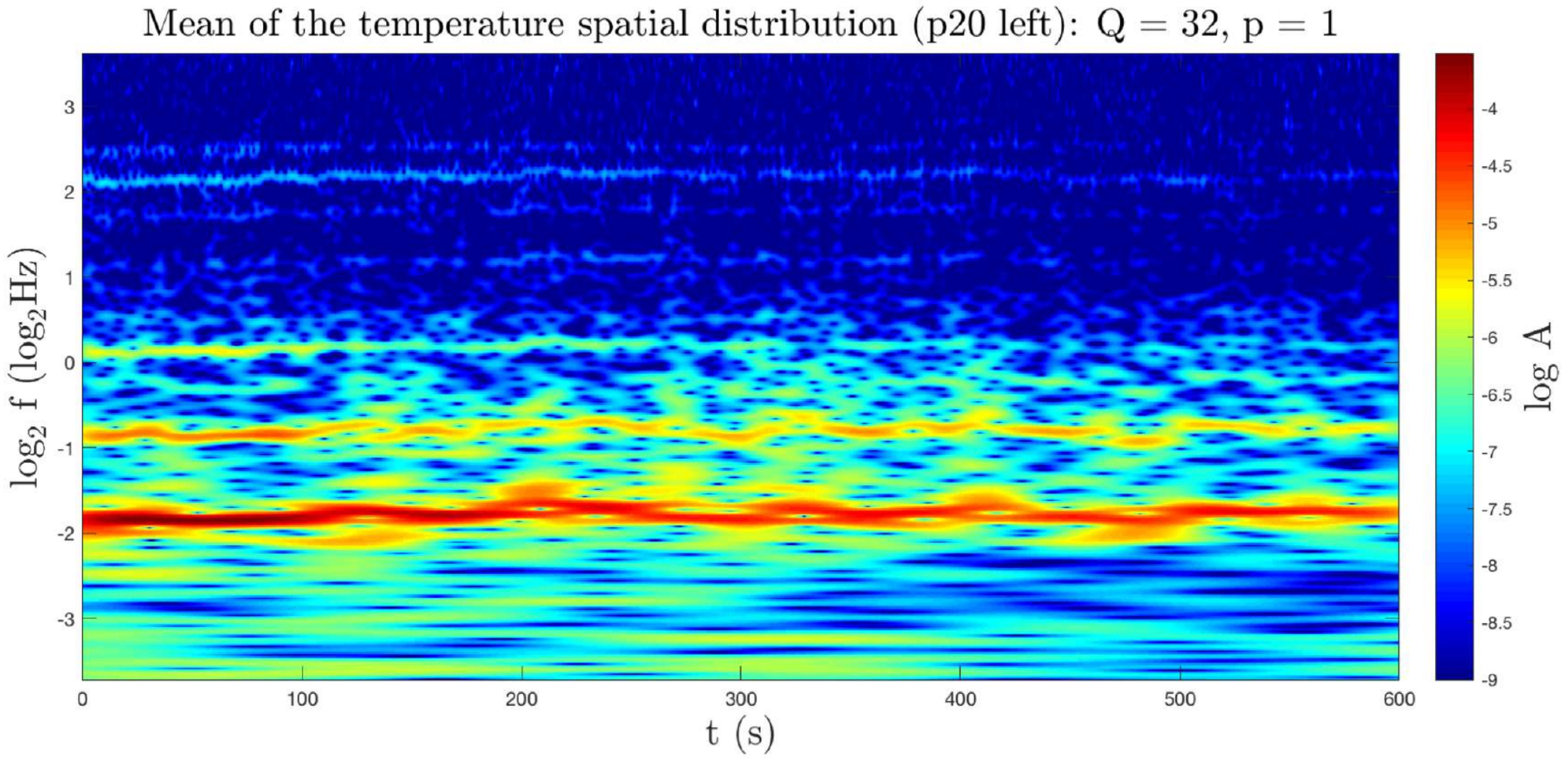

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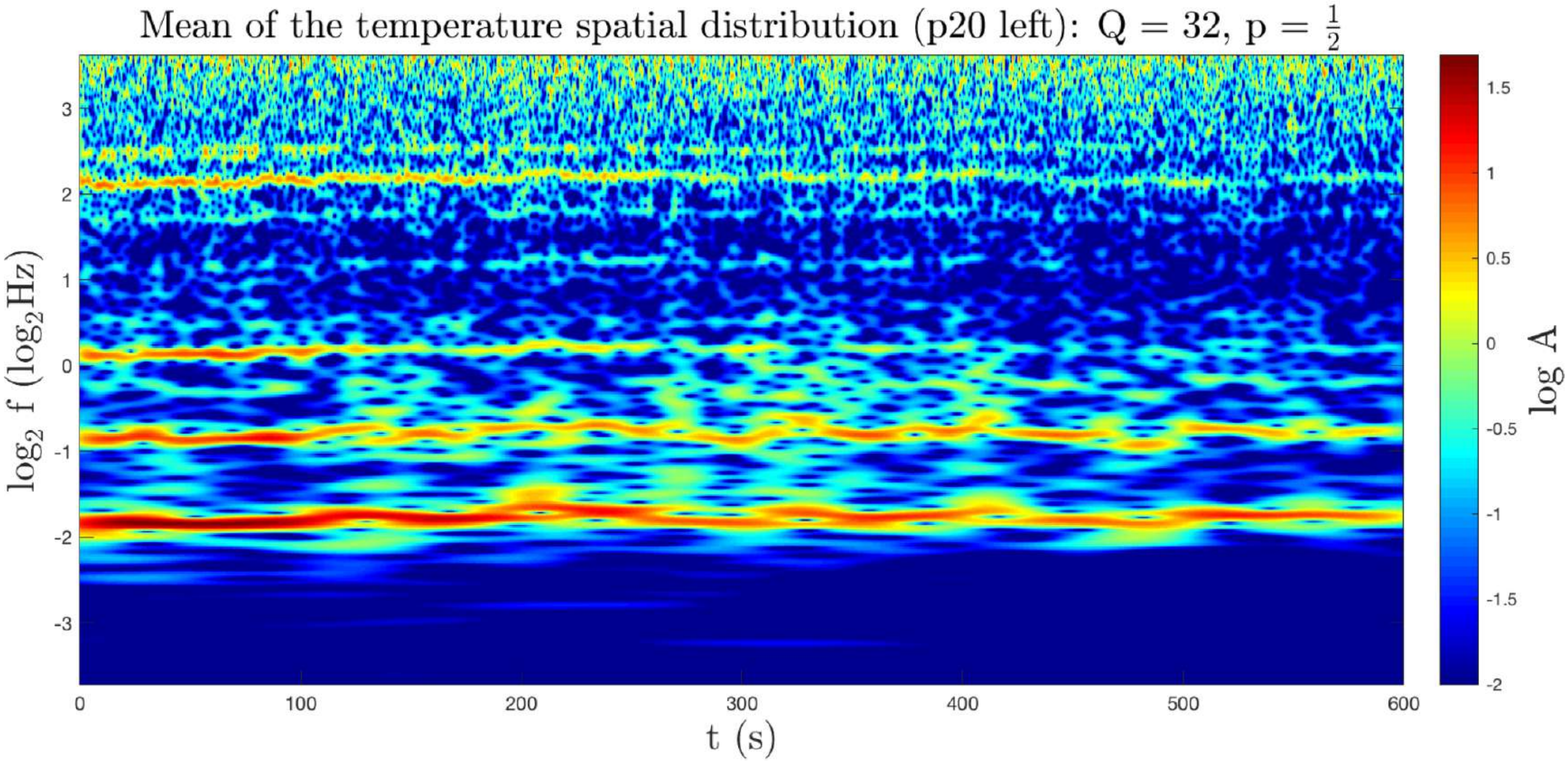
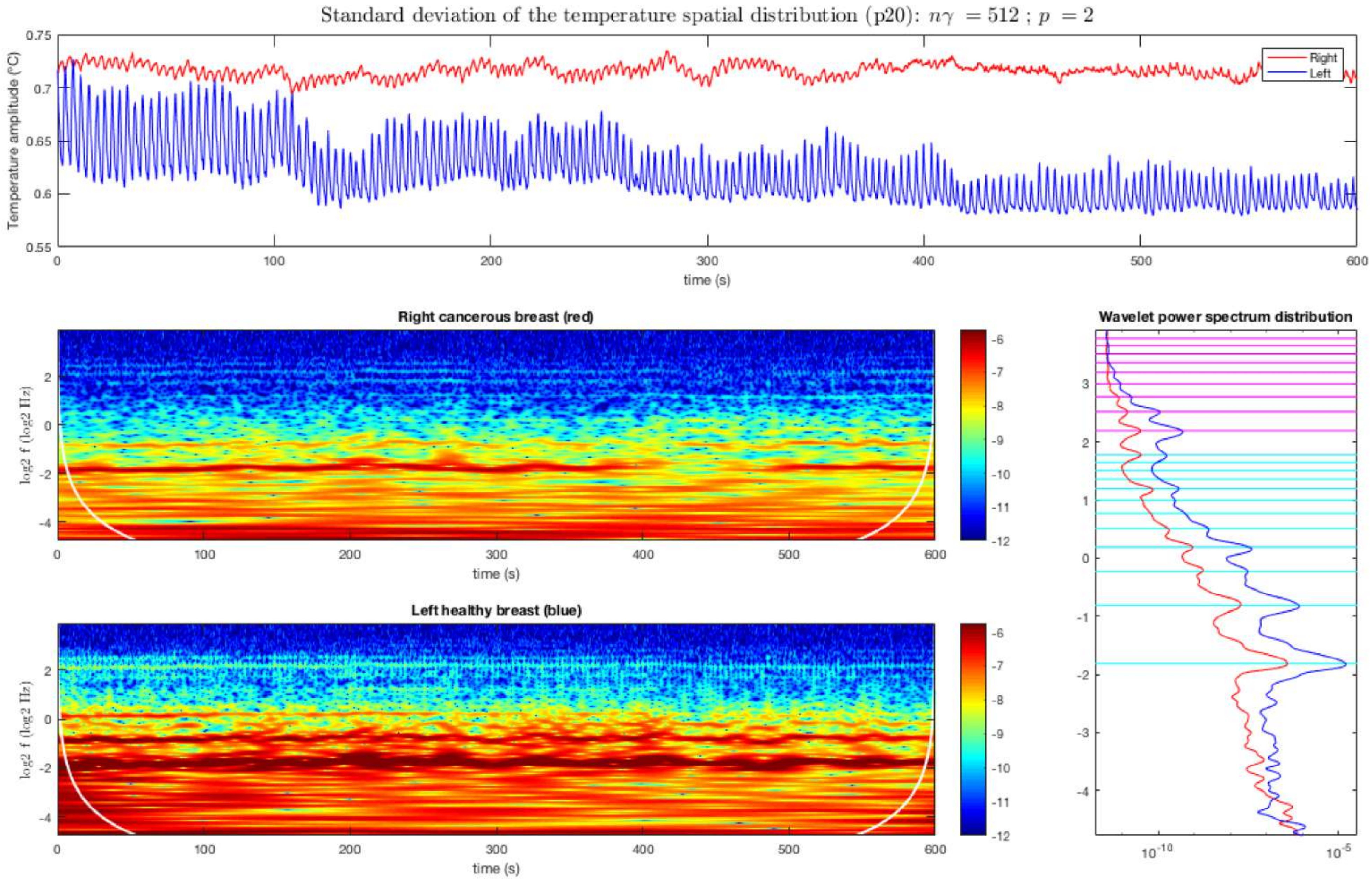


Comparison of right (cancerous) and left (healthy) breast global temperature signals

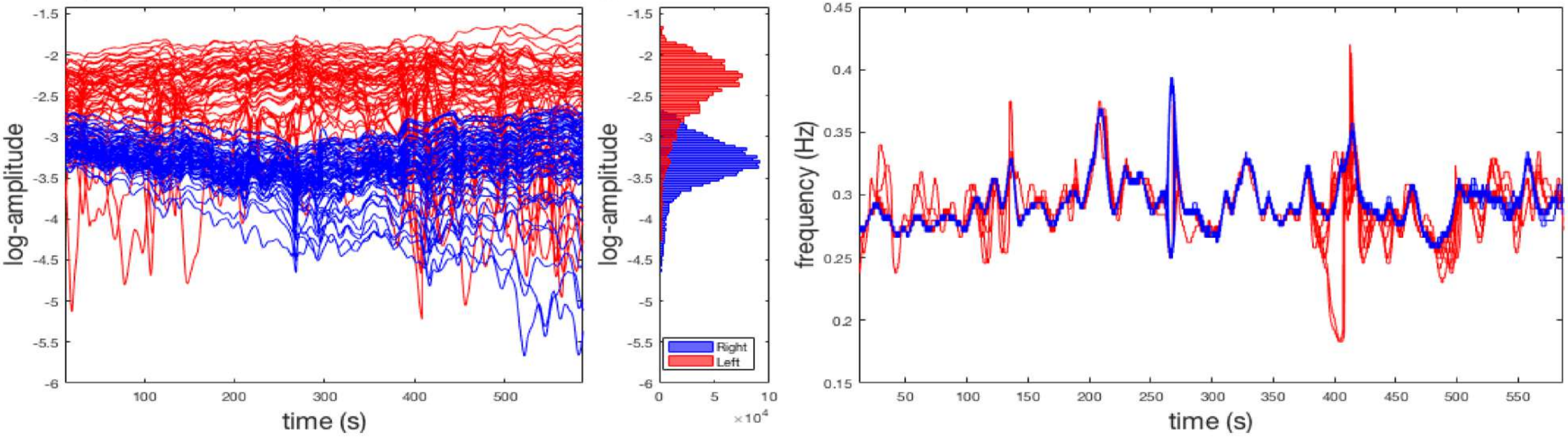


Comparison of right (cancerous) and left (healthy) breast global temperature signals

Focusing on the respiratory rhythm fundamental on the same patient (red: cancer breast, blue healthy)

Wavelet transform amplitude modulus

Temporal evolution of the instantaneous frequency



Skewed distributions (long tails)

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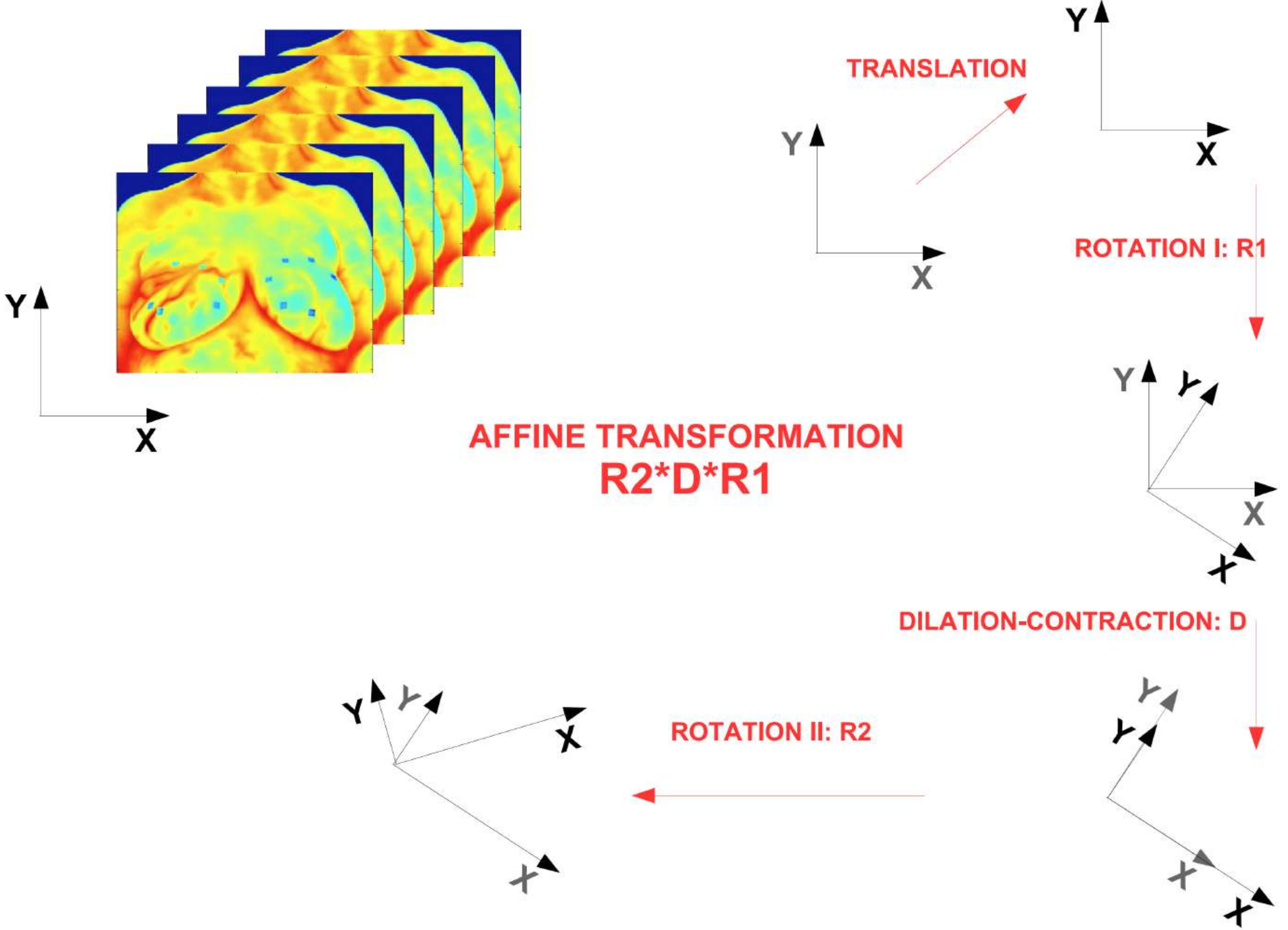
Translation and Affine algorithm to extract these displacements



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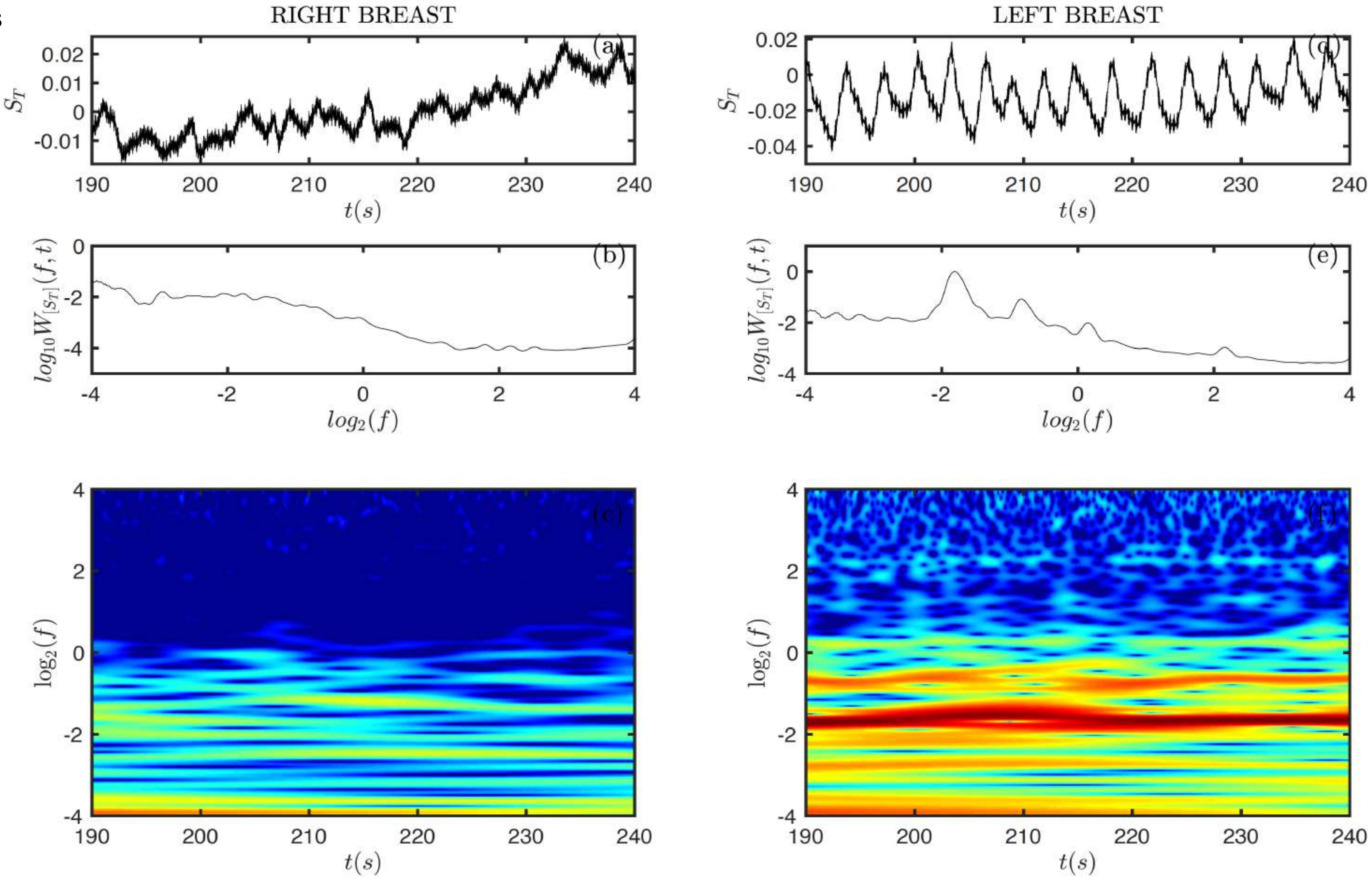
Comparison of time-frequency decomposition of uncorrected and corrected signals

Uncorrected signals
N=256
p=1



Comparison of time-frequency decomposition of uncorrected and corrected signals

Corrected signals
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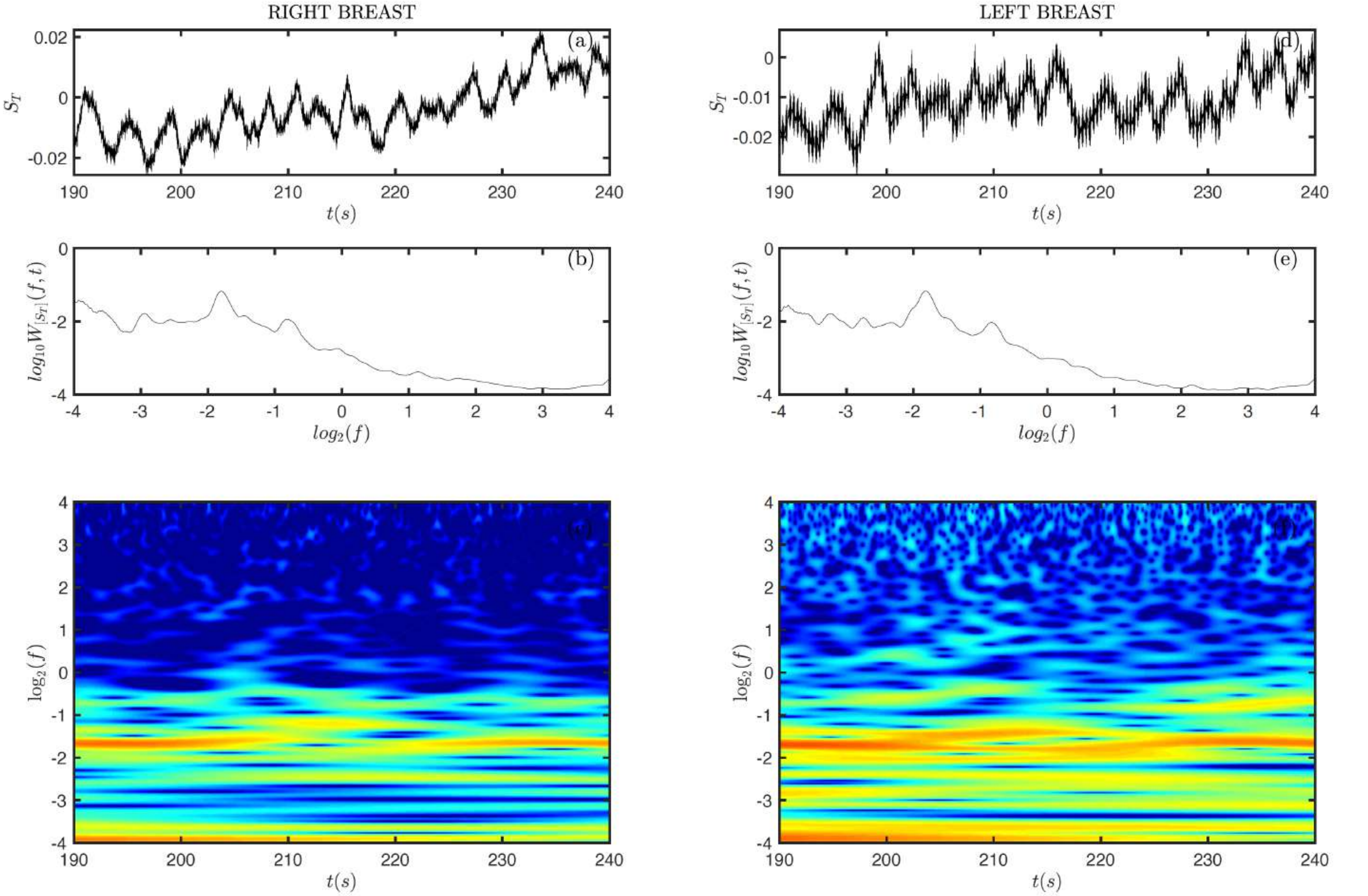
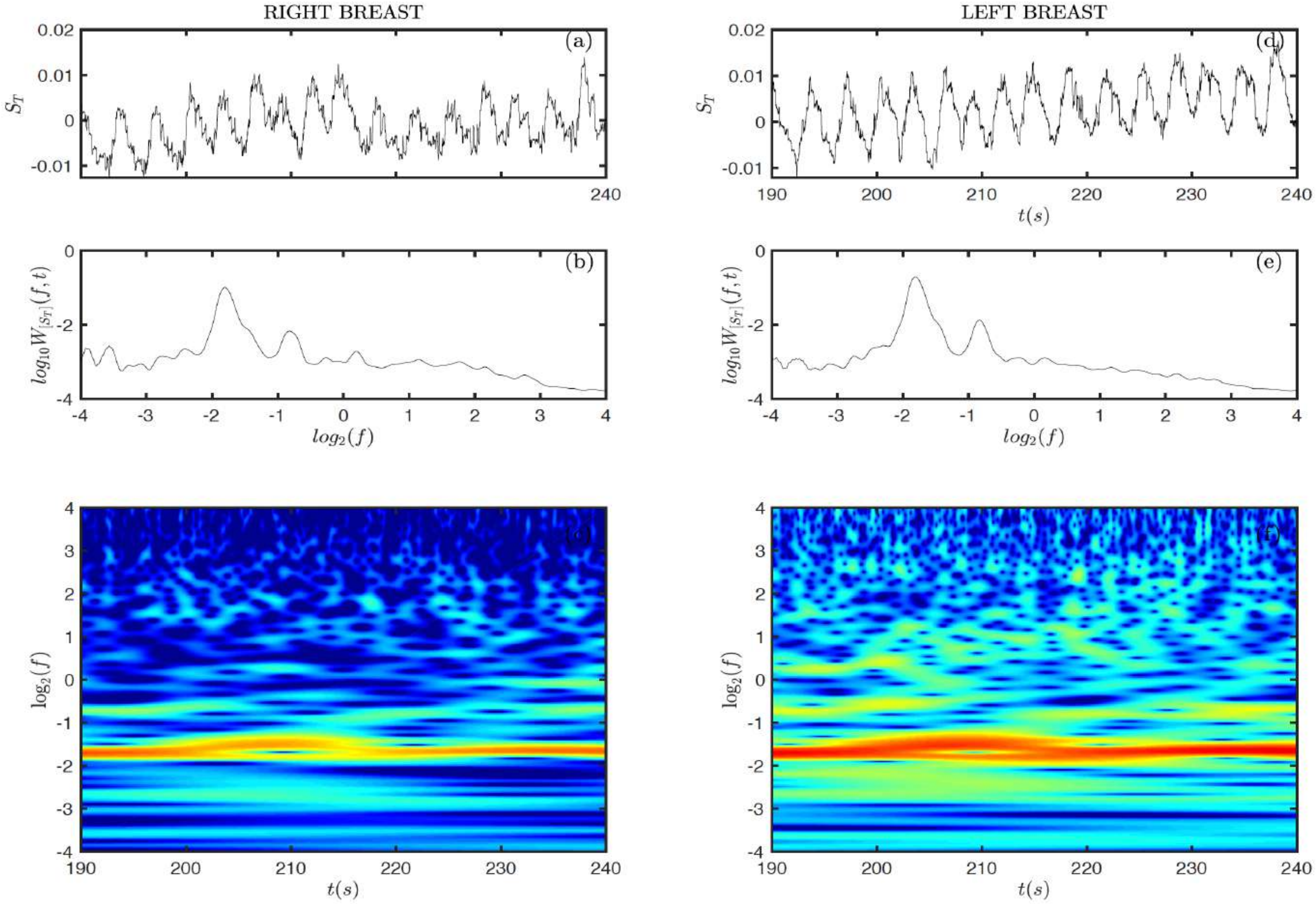


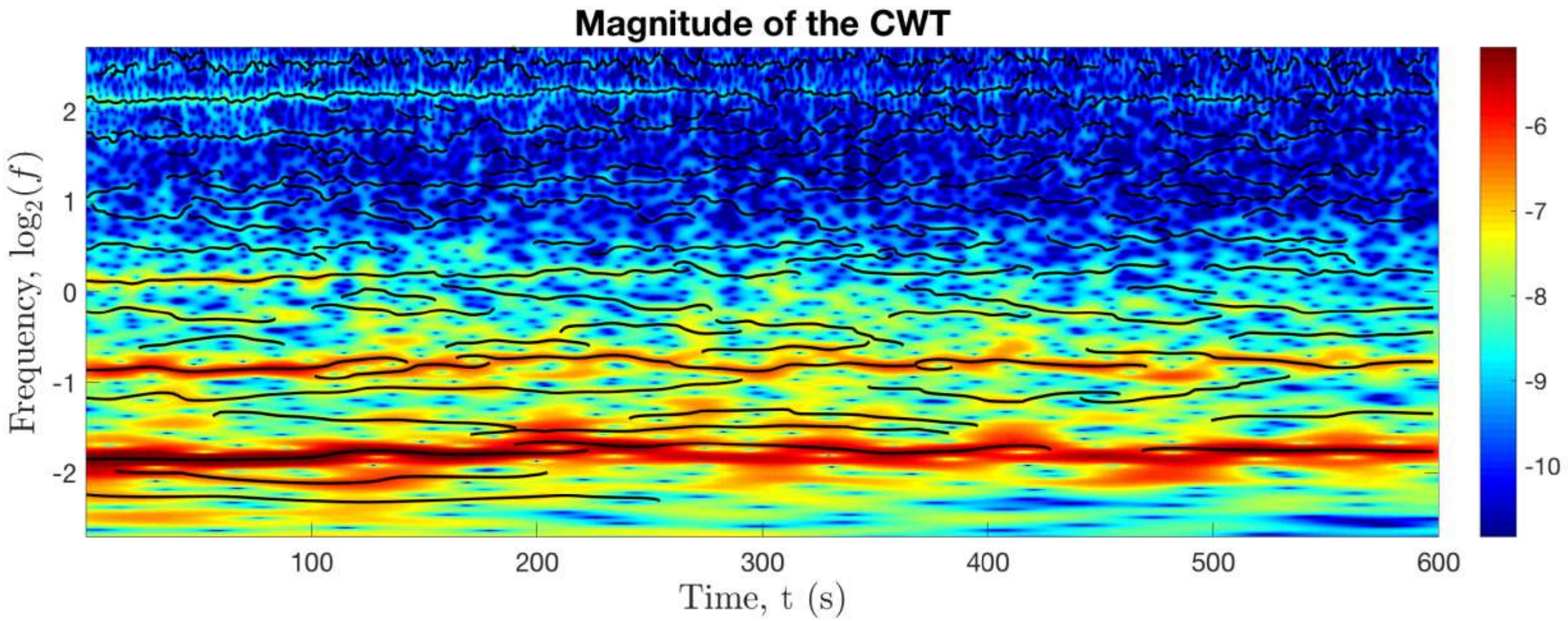
Comparison of time-frequency decomposition of uncorrected and corrected signals

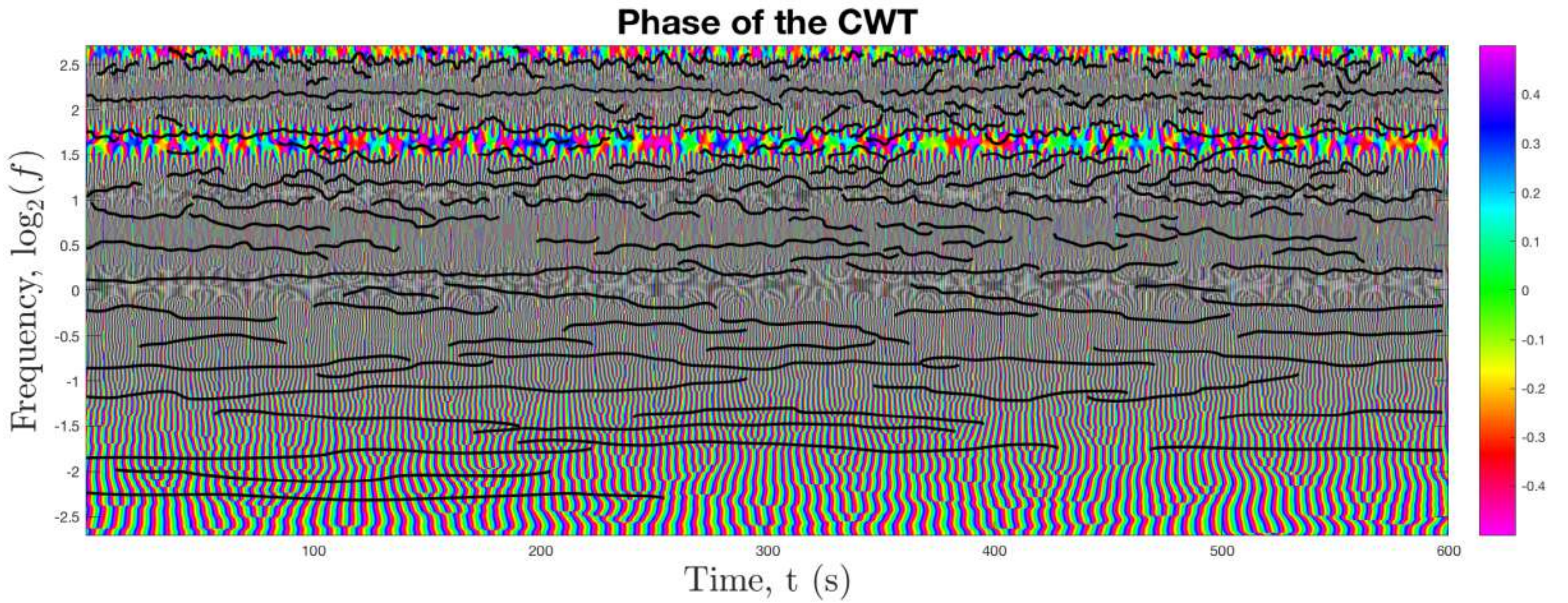
Transformation
Affine matrix
determinant
N=256
p=1



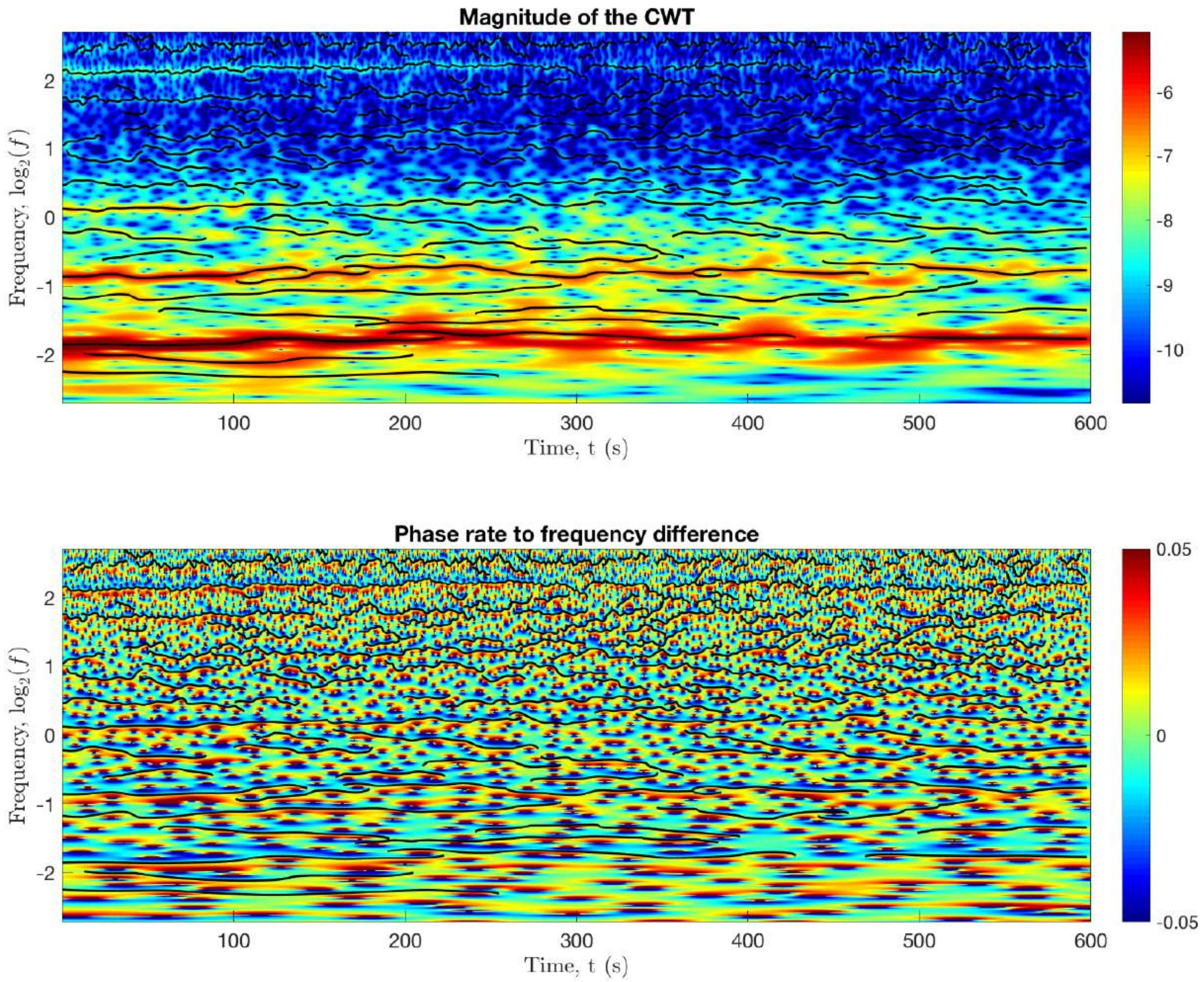
Detection of the ridges of the CWT (from the magnitude or modulus of the CWT)

Q=32





Detection of the ridges of the CWT (comparing modulus and phase difference methods)



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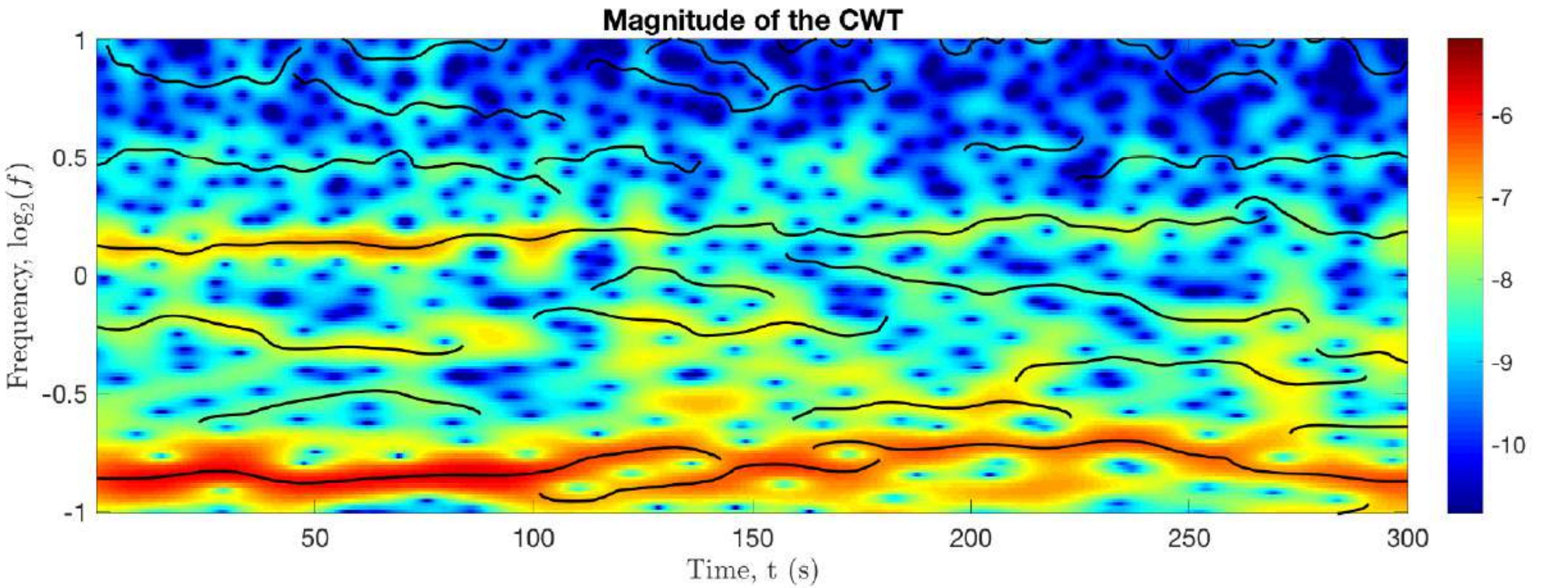

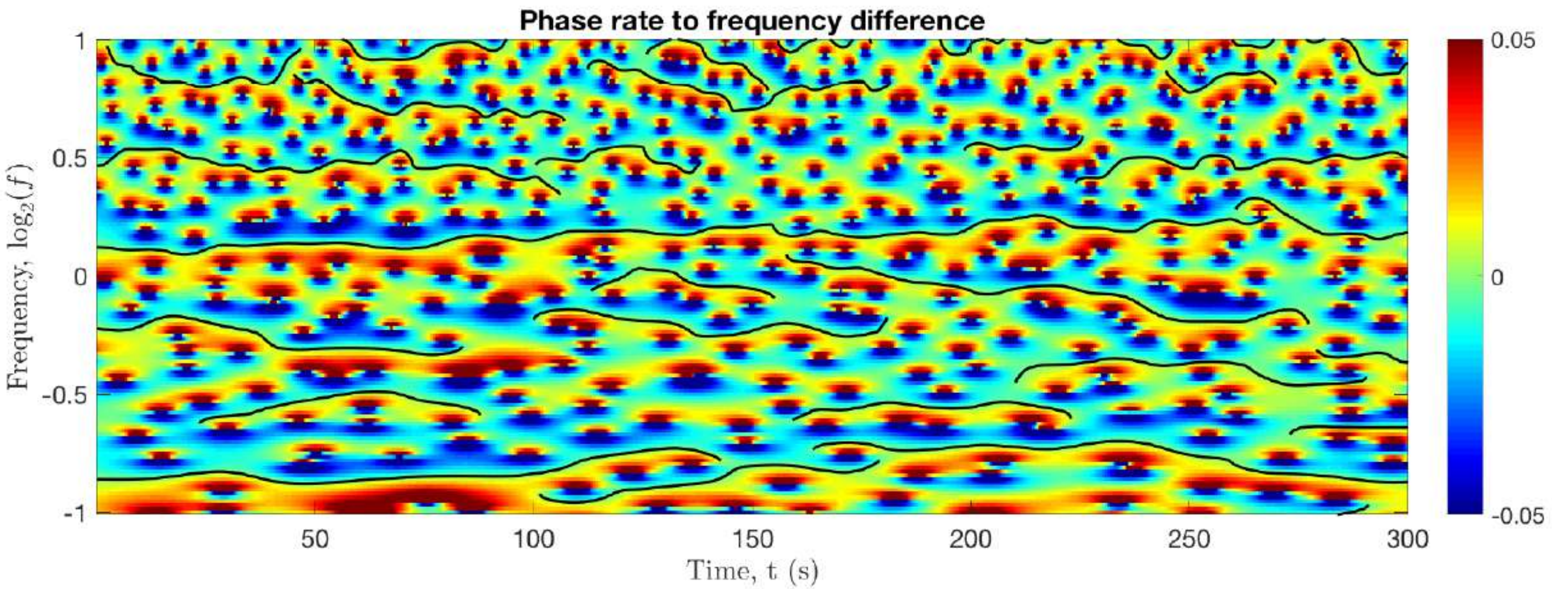

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Disentangling respiratory from cardiogenic rhythms

Recognition of the presence of two (or more rhythms) inside the signal: multiplicative cross-correlation of the modulus of the CWT in the frequency variable f (the integral is performed in log(f) scales)

Here we take $s_1 = s_2$, the log-frequency variable for s_2 is shifted by log(q)

$$R_\psi[s_1, s_2](q,t) = C_{\psi,\psi}^{-1} \int_0^\infty |W_\psi[s_1](f,t) W_\psi[s_2](qf,t)| \mathrm{d}f/f \quad ,$$

where $C_{\psi,\psi} = \int_0^\infty |\tilde{\psi}(f)|^2 \mathrm{d}f/f$.

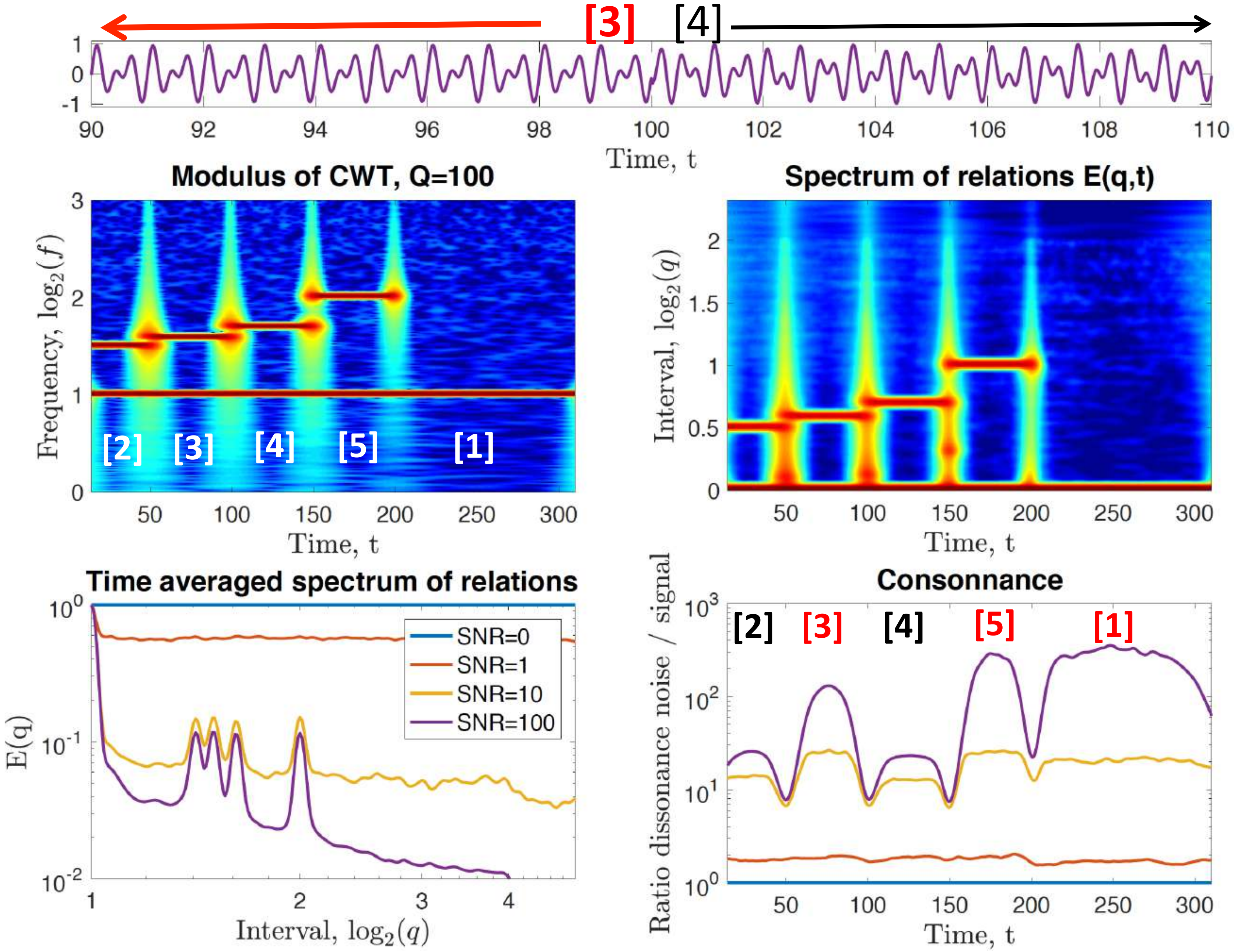
$E(q,t) = R_\psi[s_1, s_2](q,t)$ *is the spectrum of relations of the two signals s_1 and s_2*

*Identification of irreducible fractions of the frequency ratios occuring in the spectrum of relations of the signal with itself -> **« consonance of the rhythms »***

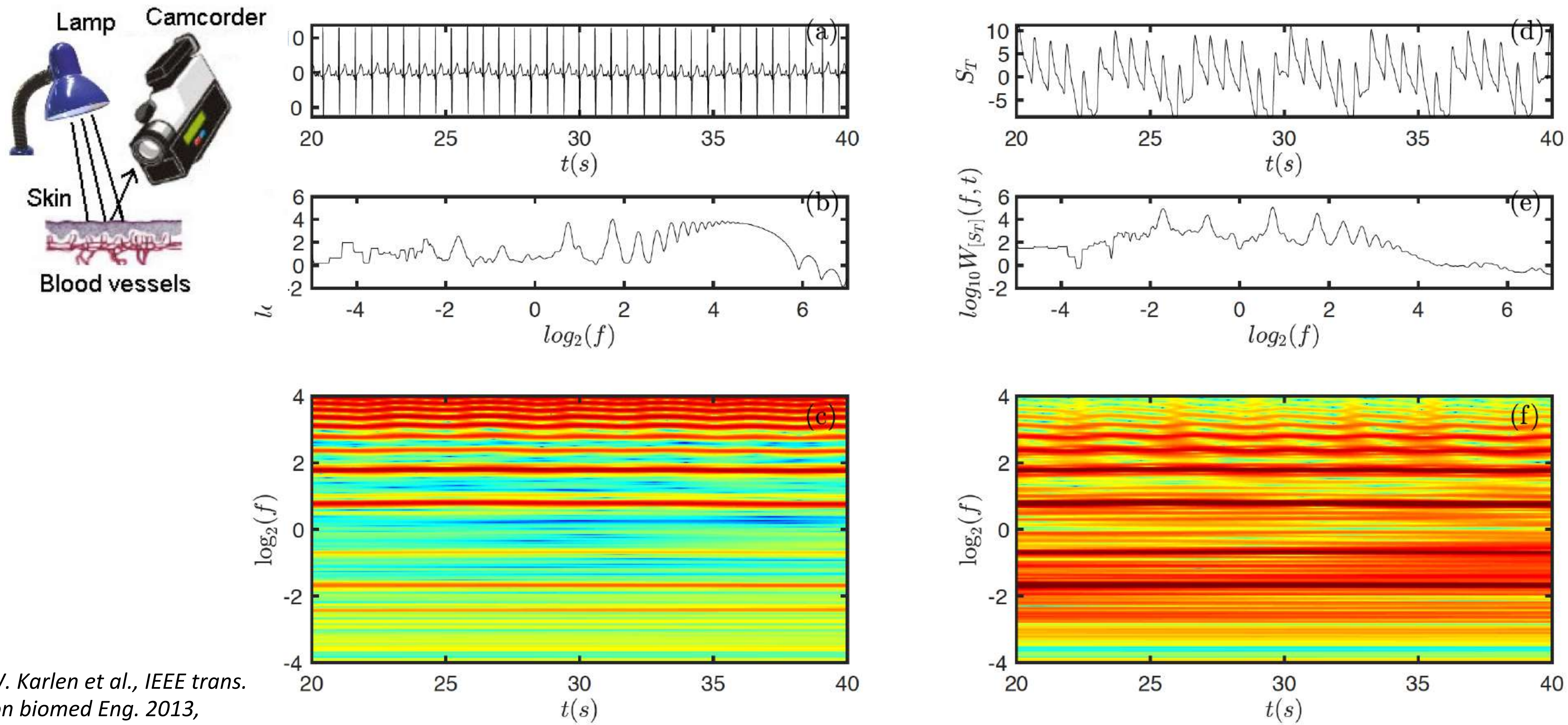
Searching for the “consonance” of a synthetic signal

Rhythm ratios

[1] **1**
[2] √2
[3] **3/2**
[4] (√5 +1)/2 (golden)
[5] **2**



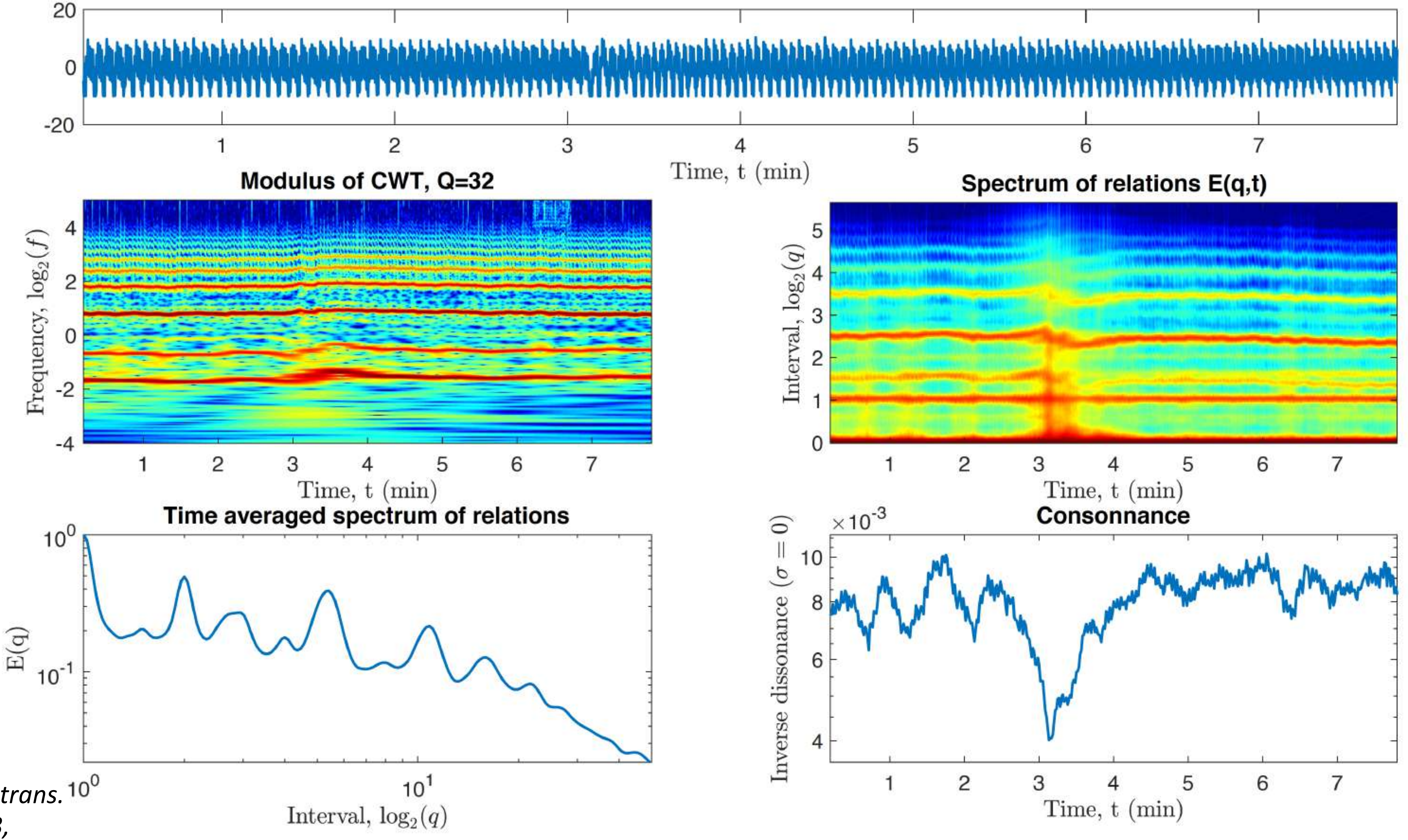
CWT analysis of photoplethysmogram signals



W. Karlen et al., IEEE trans. on biomed Eng. 2013,

Signals downloaded from http://www.capnobase.org/index.php?id=857

Wavelet based computation of consonance of photoplethysmogram signals



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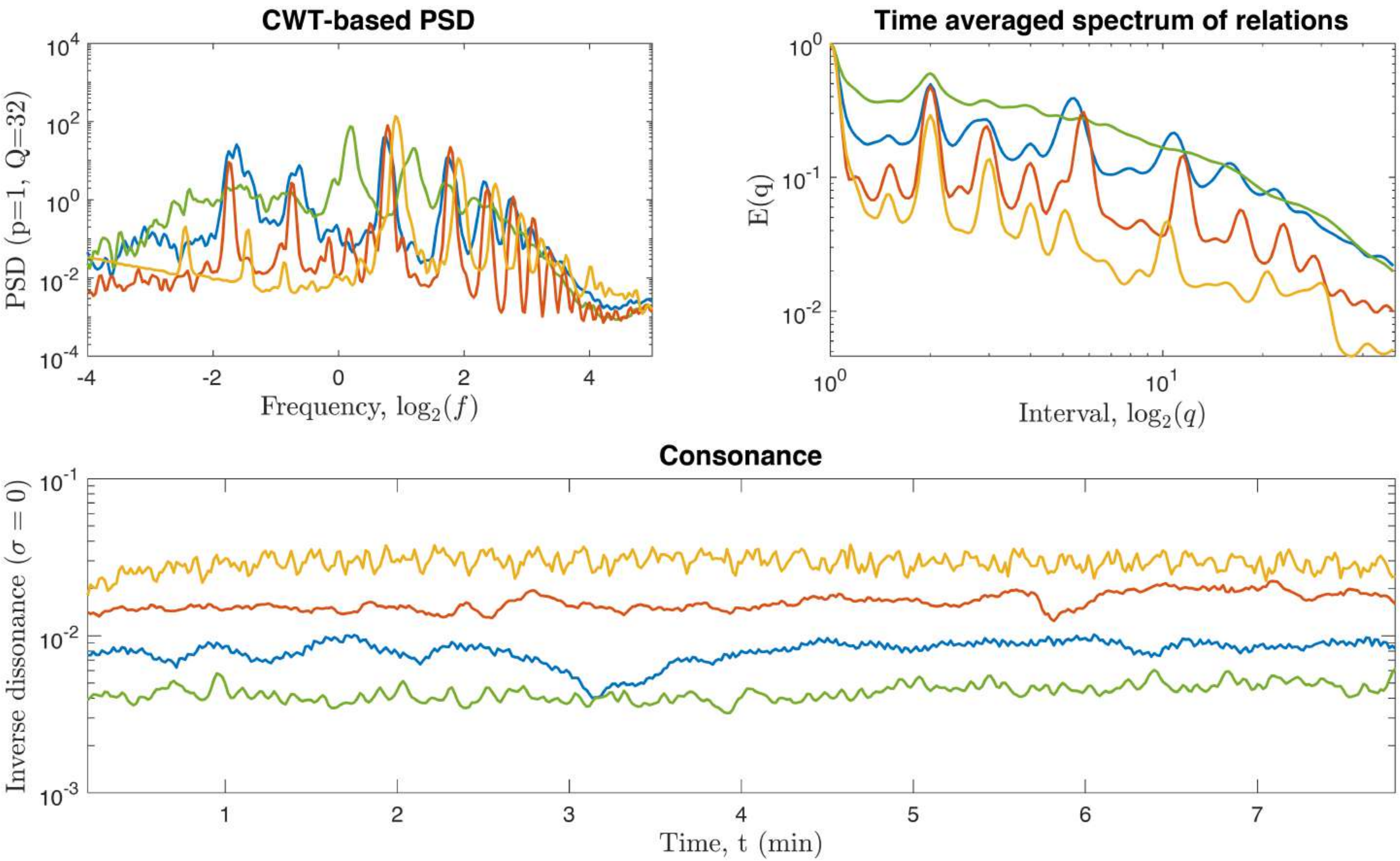

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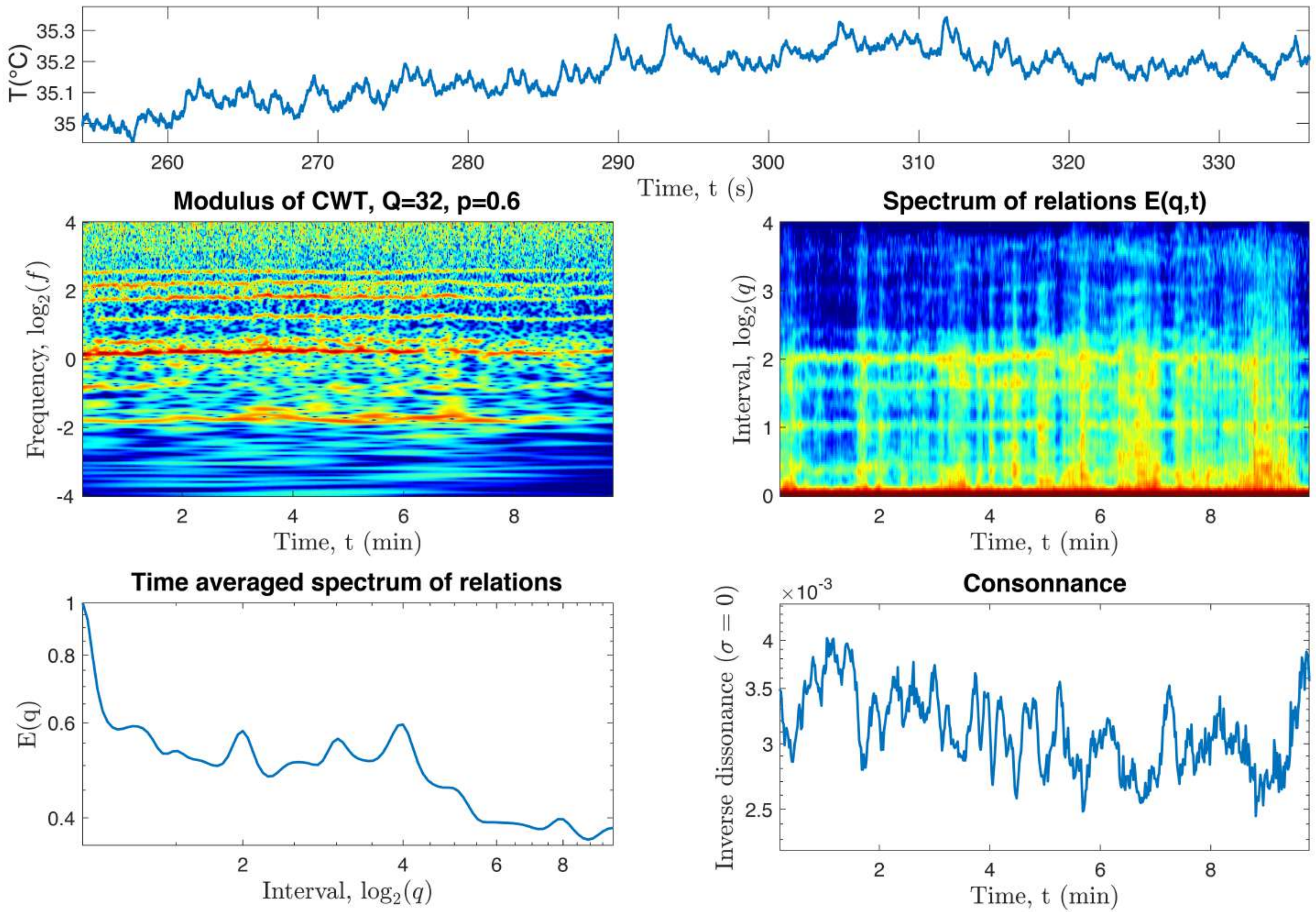
Signals downloaded from http://www.capnobase.org/index.php?id=857

Wavelet based computation of the consonance of a thermogram signal



CONCLUSIONS

Time-frequency decomposition allows a complete characterization of the intertwining of rhythms in physiology

The introduction of consonance (or disonance) of rhythm ratios and its temporal change (or variability) as a marker of the dynamical adjustement of the body

Can this quantity be used as a ‘dynamical’ hint for assisting clinician diagnosis?

Statistical tests on large data sets need to be performed

A statistical physics formalism accounting for the spectrum of rhythm ratios is currently under progress (in the same line as the singularity spectrum has be elaborated for fractal signals)