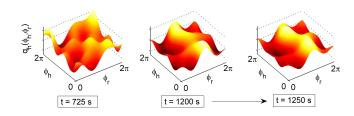
#### Interactions of Biomedical Oscillations

#### Tomislav Stankovski

Faculty of Medicine, Ss Cyril and Methodius University, Skopje, Macedonia Department of Physics, Lancaster University, UK

#### September 18, 2015



Oscillations

Oscillations

Theory

Oscillations

Theory

Methods

Oscillations

Theory

Methods

Applications and results

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0	Oscil	lations

Theory

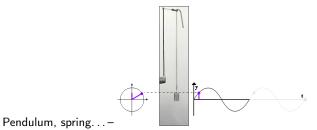
Methods

Applications and results

Ongoing projects

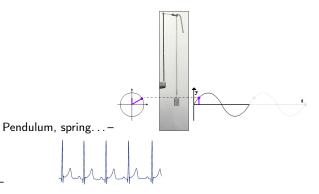
• Oscillation - repetitive, rhythmic and periodic dynamics

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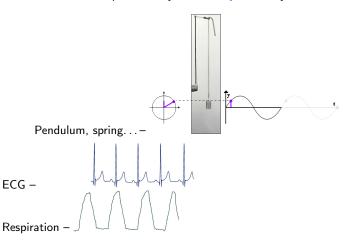


ECG -

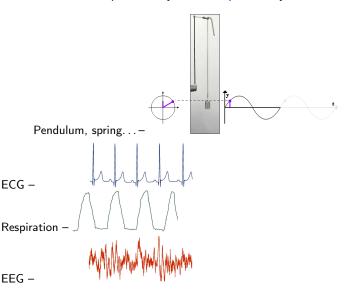
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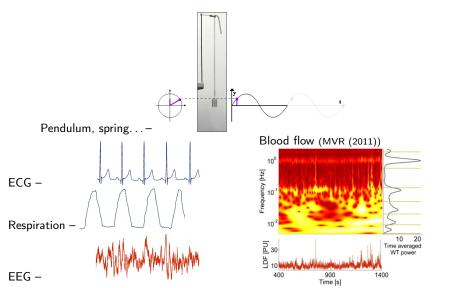
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Oscillation – repetitive, rhythmic and periodic dynamics



Ideal harmonic oscillator

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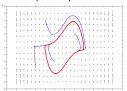
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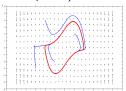


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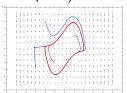
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Kuramoto, Springer 1984

• Interactions  $q_i(\phi_i, \phi_i)$  – Synchronization, Directionality, Coupling Function

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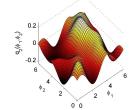
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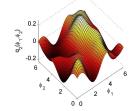
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- Additional dimension form of the function
- Prediction



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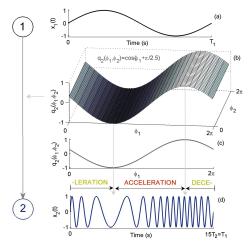
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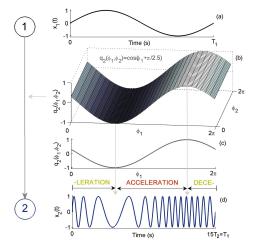
Unified and systematic way of describing mechanisms

Schematic example

#### Schematic example



Schematic example



• Increasing interest: chemistry, biomedicine, mechanics, encryption

• How to treat biomedical oscillations?

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- Time-varying dynamics

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- Three types of conectivity structural, functional and effective

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Time-series from noisy interacting systems

Bayesian inferential framework

Time-varying parameters



Synchronization Directionality Coupling function

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Oscilations

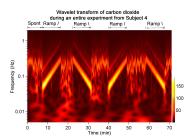
- Unknown model parameters  $\mathcal{M} = \{c_k, D_{ii}\}$  are to be inferred, two key 'ingredients' -
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Oscilations

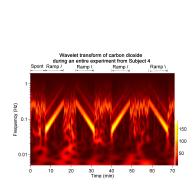
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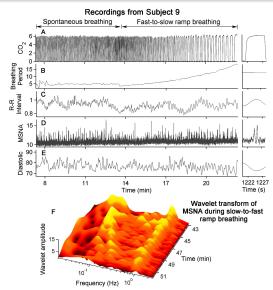
Details in: Stankovski et al. PRL (2012) Smelyanskiy et al, PRL (2005) Stankovski, Springer (2014)

# Ramp-breathing protocol



# Ramp-breathing protocol



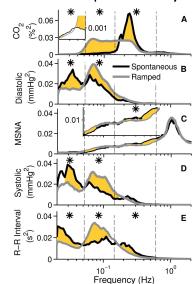


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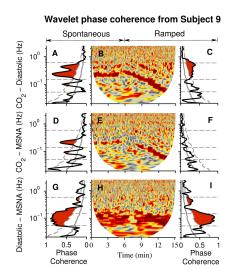
# Wavelet power

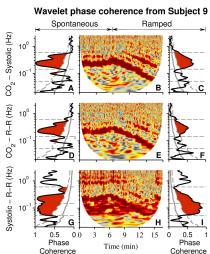
- spontaneous vs. ramp
- significant differences across broad frequency intervals
- large differences at very-low frequencies (bellow the ramps)
- cardiovascular coupled oscillators – possible reason

#### Median wavelet power for all subjects



#### Wavelet phase coherence

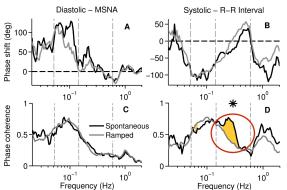




### Wavelet phase coherence - group results

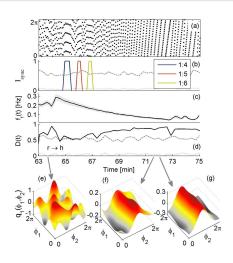
- MSNA-Diastolic high and not changed
- Systolic-RR changed around the breathing frequencies

#### Median wavelet phase shift and phase coherence for all subjects



## Cardiorespiratory interactions

- Human CR measurements with ramped breathing
- inferred ramped respiration frequency
- time-varying respiration-to-heart directionality
- intermittent synchronization transitions
- complex time-varying form of the coupling functions



## Cardiorespiratory interactions II

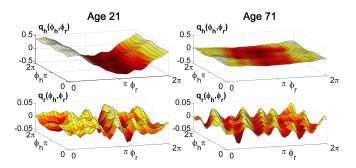
Video available on:

http://journals.aps.org/prl/supplemental/10.1103/PhysRevLett.109.024101

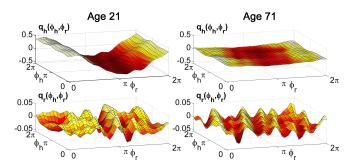
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Evolution of cardiorespiratory interactions with age

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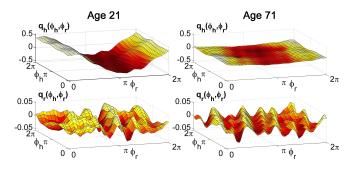
Evolution of cardiorespiratory interactions with age



• Direct coupling contribution of  $\phi_h$  dynamics, identified as RSA modulation, was found to decrease significantly with age

Oscilations

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# Neuronal cross-frequency coupling functions

Coupling functions and brain dynamics

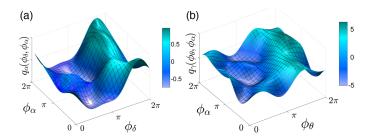
Applications

#### Neuronal cross-frequency coupling functions

- Coupling functions and brain dynamics
- Inference of multivariate 5-oscillator network including  $\delta, \theta, \alpha, \beta, \gamma$  EEG brain waves (anaesthesia)

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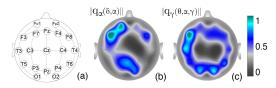
 $\delta$ - $\alpha$  coupling function;  $\theta$ - $\alpha$ - $\gamma$  triplet coupling function;

### Neuronal cross-frequency coupling functions II

- Analysis of coupling function from multi-channel EEG (autism)
- International EEG 10-20 system

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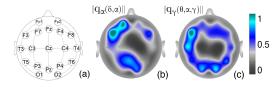
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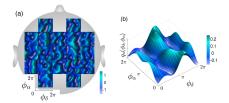
Coupling strength

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#### Coupling strength



Group and average coupling function

## Other (more purely physical) applications

• Theory and methods for coupled oscillators

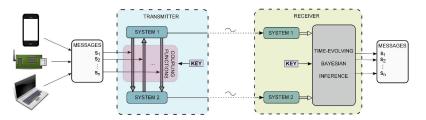
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Example - from cardiorespiratory interactions to secure communications



#### Secure communications

• Subject to patent application GB1314114.8, WO2015019054A1

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 Two small UK-EPRSC projects for implementation of hardware and software prototypes

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- Plans to link the work with images from nuclear medicine exploiting dynamical changes e.g. of the heart

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Thank you for the attention!