Photoplethysmography Imaging
- Signal, Model & Cognitive States -

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Content

- PPGI & History
- Motion artefacts
- Robust features
- A stochastic oscillator model
- PPGI and the cognitive states

Sensing PPGI from human face under real world conditions!

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Photoplethysmography Imaging (PPGI)

- Greek "plethysmos" (increasing, enlarging, becoming full), and "graphein" (to write).
- A non-contact measurement of blood volume changes based on the optical absorption properties of skin (caused by HbO2).

Wu et al., Eulerian Video Magnification for Revealing Subtle Changes in the World, SIGGRAPH 2012
History

- Molitor and Kniazuk, 1936:
  - Peripheral circulatory changes in animals.
- Hertzman, 1937:
  - Photoelectric plethysmography
  - Analog device
- Blazek, 1985:
  - Photoplethysmography Imaging
  - Semiconductor: Opto-electronics
- Today: Ongoing name debate
  - PPGI, IPPG, RPPG, DPPG
Factors influencing accuracy

- **Endogenous:**
  - Age
  - Health

- **Exogenous:**
  - Sensor:
    - Quantum efficiency vs. Wavelength
    - Molar extinction coefficients: HbO2 (Peak: 420nm)
  - Illumination
  - Motion

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Classical Signal Processing

- Expectation of pixel intensities over a fixed skin region (Green channel)
- Filtering/ Detrending
- Spectral Analysis (FFT)
- Heuristic Peak-Search
Classical Signal Processing

- Works great
  - under laboratory conditions
    - with controlled static lighting and without subject motions
  - but less in real life!
Motion

- causes a change of illumination under natural (inhomogenous) lighting
- and the signal is not continuously differentiable anymore.

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How to incorporate invariance to the measurements with respect to motion forces
Wiener algebra

- The Fourier series of a periodic function converges to the given function $f$ only if
  \[ \|f\|_A := \sum_{n=-\infty}^{\infty} |\hat{f}(n)| < \infty \]
  and $f$ satisfies
  \[ |f(x) - f(y)| \leq C\|x - y\|^\alpha \]
- The function $f$ needs to be a Riemann/Lebesgue-integral.
Local Group Invariance

- Let be $G$ a transformation group acting on a manifold $M$.
- An invariant of $G$ is a real valued function
  \[ I : M \rightarrow \mathbb{R} \]
- which satisfies
  \[ I(g \cdot x) = I(x) \]
- for all transformations $g \in G$.
Local Group Invariance
Local Group Invariance

- Interaction between bright and dark during motion
- Translation of pixel intensities
Local Group Invariance

- We want to minimize over the group of all translations

\[ \frac{\partial}{\partial T} \bigg|_{T=0} = f(L_T, \bar{x}(t)) = 0 \]

- with

\[ \vec{p} \in \mathbb{R}^n = \{ R, G, B \}, n = 3 \]

- and

\[ \bar{x}(t) = \int_0^\infty \mathbb{E}[\{\vec{p} \mid s(\vec{p})\}] dt \]
Local Group Invariance

- For the expected group action
  \[ \frac{1}{l} \sum_{i=1}^{l} (\frac{\partial}{\partial T}|_{T=0} f(\mathcal{L}_T, \vec{x}_i))^2 \quad \{\vec{x}_i : i = 1, ..., l\} \]

- with covariance
  \[ C := \frac{1}{l} \sum_{i=1}^{l} (\frac{\partial}{\partial T}|_{T=0} \mathcal{L}_T, \vec{x}_i)(\frac{\partial}{\partial T}|_{T=0} \mathcal{L}_T, \vec{x}_i)^\top \]

- and the corresponding symmetric eigenvalue problem
  \[ CV = V\Lambda \]
We’ll find a projection operator

\[ \lim_{l \to \infty} P = I - VV^\top \]

with corank \( k = 1 \)

and the feature map

\[ \tilde{x} = P \cdot \vec{x} \]

with the hyperplane

\[ \mathcal{H} = \mathcal{N}(P) \]
Local Group Invariance

- The operator $P$ carries out
- an orthogonal projection to the
- blood volume changes complementary space.

- The emphasis is put
- to the features which
- vary less under the
- group action $\mathcal{L}_T$. 

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Local Group Invariance

- This implies a reduction of the spectral radius of the observation
- of the observation $X := \{x_i : i = 1, \ldots, l\}$

$$\rho(\tilde{X}) < \rho(X)$$

- with

$$\rho(X) := \max\{|\lambda|, \lambda \text{ eigenvalue of } X\}$$
The Riemannian submanifold

- Mapping to unit sphere

\[ \rho(X) \leq \|X\| \]

\[ \vec{x}_\mathcal{M}(t) = \int_0^\infty \mathbb{E}\left[ \left\{ \frac{\vec{p}_{ij}}{\|\vec{p}_{ij}\|} \mid s(\vec{p}_i) \right\} \right] dt \]

\[ \rho(X_\mathcal{M}) < \rho(X) \Rightarrow \rho(X_\mathcal{M}) \equiv \rho(\tilde{X}) \]

\[ \mathbb{S}^2 = \{ \vec{x}_\mathcal{M} \in \mathbb{R}^3 \mid \|\vec{x}_\mathcal{M}\| = 1 \} \]
The Riemannian submanifold

- Spherical coordinates

\[ r = \sqrt{x_1^2 + x_2^2 + x_3^2} = \|\mathbf{x}_M\| = 1 \]

\[ \varphi = \arctan \frac{x_2}{x_1} \]

\[ \theta = \arccos \frac{x_3}{r} = \arccos \mathbf{x}_M_3 \]

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Diffusion Process

- **Physics**
  - Deterministic process
    \[ \frac{d\mathbf{x}(t)}{dt} = F \mathbf{x}(t) \]

- **Physiological Signals**
  - Stochastic process
    \[ \frac{d\mathbf{x}(t)}{dt} = F \mathbf{x}(t) + L \mathbf{w}(t) \]

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Diffusion Process

- Truncated Fourier series
  - for a stationary frequency $f$
    - with harmonic components as multiple of their base $n*f$

$$c(t) = \sum_{n=1}^{N} a_n \cos(2\pi n ft) + b_n \sin(2\pi n ft)$$
Diffusion Process

- The perfusion phenomena is not stationary:
  - varying fundamental frequency $f(t)$
  - small changes in amplitude and phase $e(t)$

\[
c(t) = \sum_{n=1}^{N} a_n \cos(2\pi n f(t) t) + b_n \sin(2\pi n f(t) t) + e_n(t)
\]
Diffusion Process

- However, this representation is sensitive to changes in the frequency:
  - for large \( t \), any change in frequency causes a large change in the signal \( c(t) \)
  - and discontinuities in the frequency will also cause the signal \( c(t) \) to be discontinuous

\[
c(t) = \sum_{n=1}^{N} a_n \cos(2\pi n f(t) t) + b_n \sin(2\pi n f(t) t) + e_n(t)
\]

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Diffusion Process

- The classical mechanics of circular motion
  - as 2nd order differential equation

\[
\frac{d^2 c_n(t)}{dt^2} = -(2\pi nf)^2 c_n(t)
\]

- with the solution

\[
c_n(t) = a_n \cos(2\pi nf t) + b_n \sin(2\pi nf t)
\]
Diffusion Process

- As stochastic differential-equation
  - for the quasi-periodic nature of heart rate

\[
\frac{d^2 c_n(t)}{dt^2} = -(2\pi n f(t))^2 c_n(t) + e_n(t)
\]
Diffusion Process

- Even when the frequency is discontinuous
- the signal remains continuous

\[
\frac{d^2 c_n(t)}{dt^2} = -(2\pi n f(t))^2 c_n(t) + e_n(t)
\]
Diffusion Process

- The stochastic state-space representation for the oscillator yields to a Kalman-Filter for known frequencies.

\[
\frac{dx(t)}{dt} = F_0(f(t))x(t) + Le(t),
\]

\[
c(t) = Hx(t).
\]
Diffusion Process

- Since the frequency is unknown, the state space depends on an additional latent variable
  \[ \frac{dx(t)}{dt} = F_0(\theta)x(t) + Le(t), \]
  \[ c(t) = H(\theta)x(t). \]

- such that \( \theta \in \Omega = \{\theta^1, \ldots, \theta^S\} \)
- forming a Markov chain with transition matrix
  \[ P(\theta^i_t | \theta^j_{t-1}) = \Pi_{ij}. \]
Diffusion Process

- A closed form solution to such kind of switching state space representation is given by the Interactive Multiple Model (IMM) algorithm.

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Diffusion Process

- The diffusion term is usually modeled by a Wiener process

\[ \frac{d^2 x(t)}{dt^2} = w(t), \]
\textbf{Diffusion Process}

- Any violation of the smoothness criterion modeled as 2D Poisson-Process (Jump-Diffusion) with unknown jump magnitude and frequency.

\[ X(t) = X_0 + \sum_{i:s_i \leq t} \xi_i \]
LGI-Multi-Session Database

25 User – 4 Sessions - over 200 min total duration

Camera: Logitech HD C270
Reference PPG Device: Contec CMS50E

Session 1 (S1): Resting
Session 2 (S2): Head Rotation
Session 3 (S3): Bicycle Ergometer
Session 4 (S4): Urban Conversation

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LGI-Multi-Session Database

- Comparison against:
  - Green Channel, Hülsbusch/ RWTH, 2008
  - ICA, Picard/ MIT, Optical Express, 2011
  - Spatial Subspace Rotation (SSR), Wang&DeHaan/ TUE, IEEE, 2016
  - Algorithmic principles of remote-PPG (POS), Wang&DeHaan/ TUE, IEEE, 2017
LGI-Multi-Session Database

- Spectrogram
  - Resting
  - Head Rotation
  - Bicycle
  - Talk

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LGI-Multi-Session Database

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PPGI Matlab Toolbox

- [https://github.com/partofthestars/PPGI-Toolbox](https://github.com/partofthestars/PPGI-Toolbox)

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Predicting Brainwaves from Face Videos

- We measured the face dynamics and the vegetative nervous system activity (HRV) with a camera (PPGI), and
- the central nervous system activity (vigilance) with an EEG.
Predicting Brainwaves from Face Videos

- We found a strong correlation between the brain activity, the heart and face dynamics

- High EEG alpha activity indicates a deactivation of the brain region
- High sympathetic activity, heart is pumping stronger
- High entropy, non-deterministic facial dynamics
Predicting Brainwaves from Face Videos

- We formulated the process as inverse problem of the underlying stochastic nature.
Predicting Brainwaves from Face Videos

- 100 users performed different tasks over a period of three hours.
- All users played computer games and participated in alertness and sustained attention tests and provided their sleepiness.

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Predicting Brainwaves from Face Videos

- Using the video based features we predicted:
  - the EEG vigilance (alpha activity in the visual cortex)
  - the Karolinska Sleepiness Score (KSS)
  - the Reaction Time (RT) and
  - Tap errors
  - during the psychomotoric
  - vigilance tests (PVT)
Conclusion

- Under invariant PPGI represenation moderate subject motion can be tolerated.
- However under fully uncontrolled environmental conditions it is still very difficult.
Conclusion

- PPGI and facial dynamics are good surrogate measurements for brain arousal states.
- This impacts a broad range of applications:
  - Transport sector: Driver Assistent Systems
  - Health sector: Monitoring of Affective Disorders
  - HMI: Affective Computing