Harnessing Noise and Invisibles: Micro-Signal Analytics for Healthcare and Physiological Forensics

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http://www.ece.umd.edu/~minwu/research.html

Include joint research with Wei-Hong Chuang, Adi Hajj-Ahmad, Ravi Garg, Hui Su, Avinash Varna, Chau-Wai Wong, Qiang Zhu, C-H. Fu, Xin Tian, Mingliang Chen, and Yuenan Li.

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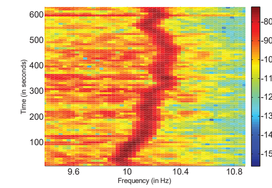
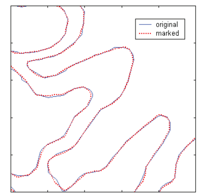
Micro-Signals for Forensics

- "Micro signal" is small in terms of:
  - Amplitude than dominating signals (by 1+ order of magnitude)
  - Topological scale

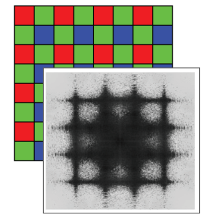
Coming from environment:

- synch multi sensing streams

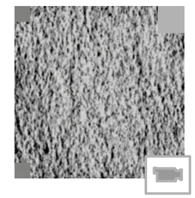




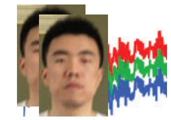
Embed invisible tracer
- *Label each copy*
- *Deter leak & protect privacy/sensitive info*



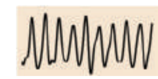
Intrinsic from Device
- *How was an image generated? Tampered?*
- *Emerging use in bio/med research integrity*



Unclonable object surfaces
- *Verify by cellphone camera to detect counterfeit*



Face color signal from motion video



Physiological monitoring
- *Heart rate, etc.*

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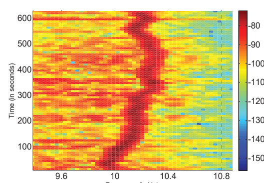

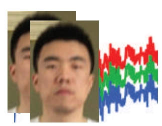

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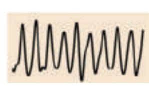


Physiological monitoring
- *Heart rate, etc.*

Micro-Signal Meets Health: Physiology Forensics

- Heart rate monitoring in home and fitness
  - Contact based: electrodes, chest belts, and finger clips.
  - Contact-free: more user-friendly, but challenging to design.

- Observation: face color changes in the same pace as heartbeat
  - Although naked eyes cannot see it
  - Prior work: (Verkruyesse et al OptExp'08 etc.) "rest case" with little or small motions

- Challenging cases: videos with significant motions
  - Fitness/athletic training (running on treadmill, …); Driving;
  - Contact-free monitoring for children in special needs; Surveillance

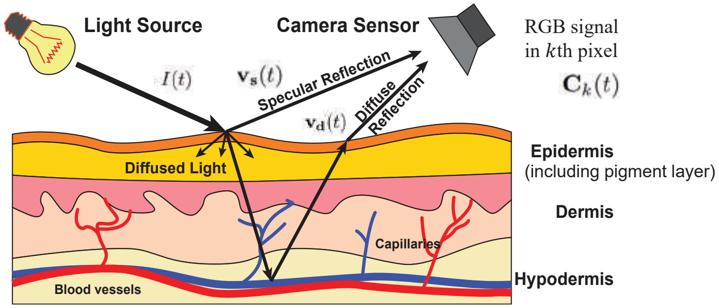
Video Source: M. Rubinstein, N. Wadhwa, F. Durand, W. T. Freeman, "Revealing invisible changes in the world," *Science*, vol.339(6119), Feb. 2013.

Skin Model of Remote PPG (photo-plethysmogram)

PPG through pulse oximeter

Optical sensing

Instrument measuring (blood) volume change

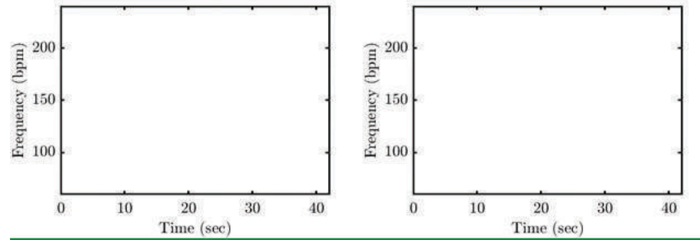


Anatomical cross-section structure of human skin tissues and the specular and diffuse reflections captured by a RGB sensor when the skin is illuminated by a light source.

(Revised from [1])

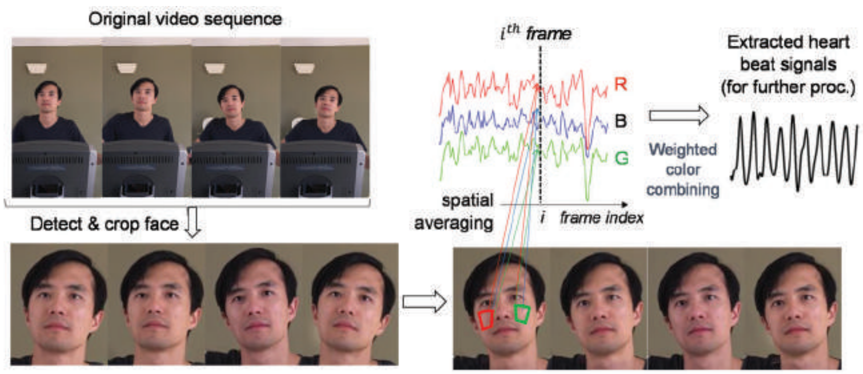
[1] Wang, W., et al. (2016). Algorithmic principles of remote PPG. *IEEE TBME*, *64*(7), 1479-1491.

"Seeing" Heart Rate in Motion: No Touch Needed



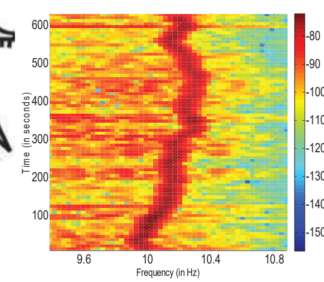
 See video at <https://youtu.be/WVBD4srQduE>

High-Res Motion Compensation & Face Alignm.



- Face color signal: by spatial averaging over Regions of Interest (ROI)
- Pre-processed signal is achieved by a suitable linear combination of three color channels
  - Detailed study by Philips Research on various ways of color combining

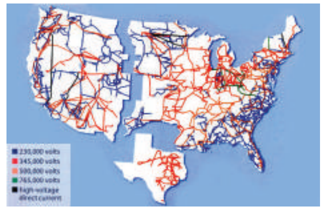
A Forensics Detour: Finding "Time + Location"

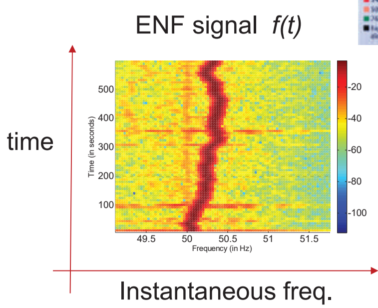


- When was the video actually shot? And where?
- Was the sound track captured at the same time as the picture? Or super-imposed afterward?
- Explore fingerprint influenced by power grid onto sensor recordings

Ubiquitous Forensic Fingerprints from Power Grid

- Electric Network Frequency (ENF): 50 or 60 Hz nominal
  - Change slightly due to demand-supply
  - Main trends consistent in same grid





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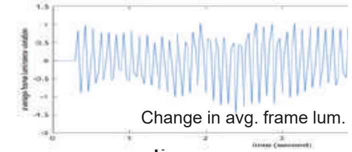
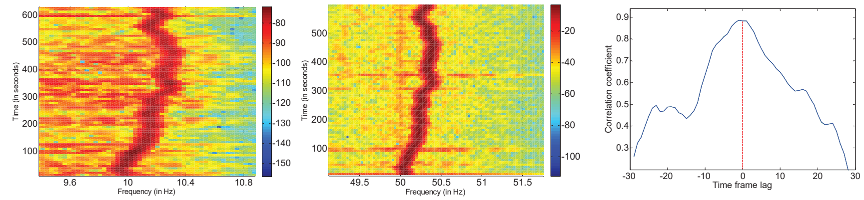


- ENF can bee "seen" or "heard" in sensor recordings
  - Power grid influences electronic sensing (E/M interference, vibration etc)
  - Help determine recording time/location, detect tampering, etc.

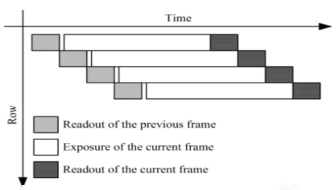


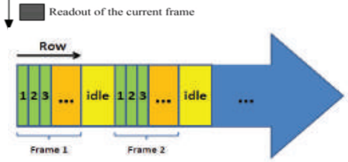
Video ENF signal | Power ENF signal | Normalized correlation

ENF matching result demonstrating similar variations in the ENF signal extracted from video and from power signal recorded in India

Overcome ENF Aliasing: CMOS Rolling Shutter

- CMOS imaging sensors: Low cost; low power
- Rolling shutter in CMOS sensor: sequential row readout
  - Different rows exposed at different time
  - Often considered bad: distortions on fast moving scenes (see wiki)



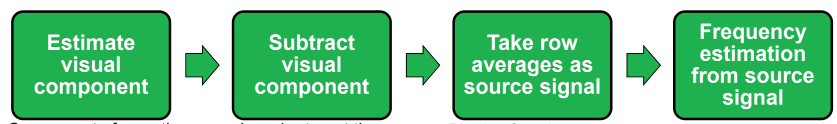


Wikipedia Example: Artifacts of rolling shutter under motion

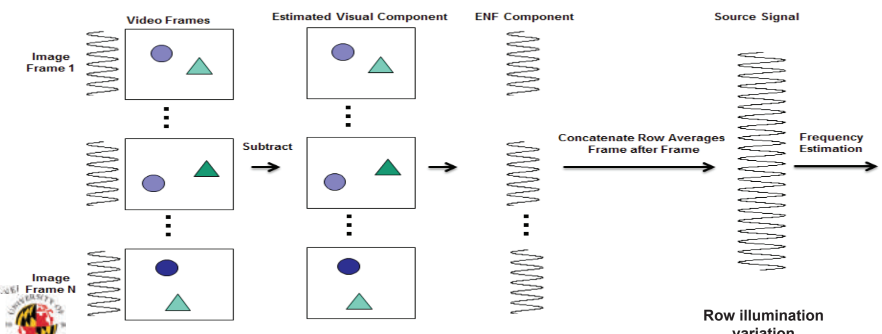
- Can we exploit row sampling to overcome ENF aliasing?

Align Visual Streams using ENF Row Signals

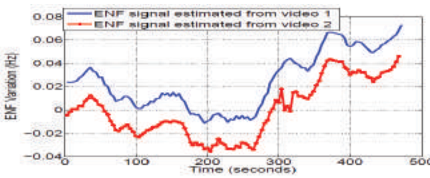
- Video signal: combination of visual component and ENF component.

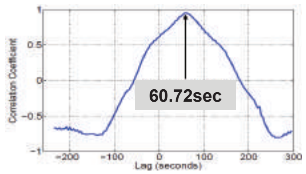


Compensate for motion, brightness changes, etc. | In order to get the ENF component. | Pixels of each row are recorded at same time.



Synchronize Multiple Videos by Power Trace



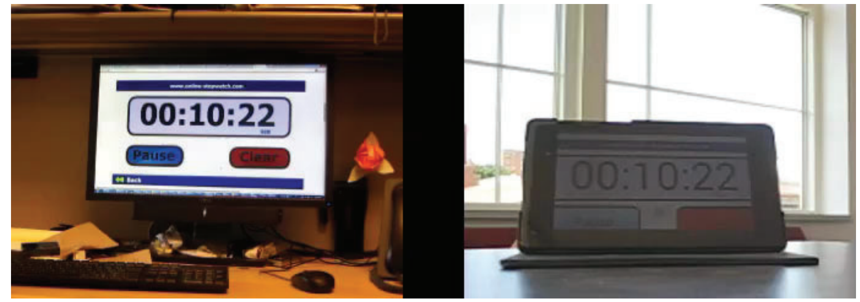


- Align ENF estimated from rolling-shutter videos
- Hallway video with motion & auto brightness change.

Lag by manual alignment: 60.80sec

Synchronize Video by Intrinsic Power Trace

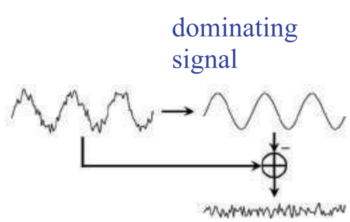
- Demo-1: With disappearing objects & different viewing angles
  - After synch by ENF in visual tracks
- Demo-2: Videos at different locations
  - After synch by ENF in audio tracks

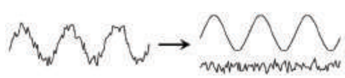


Extraction Strategies of Micro Signal

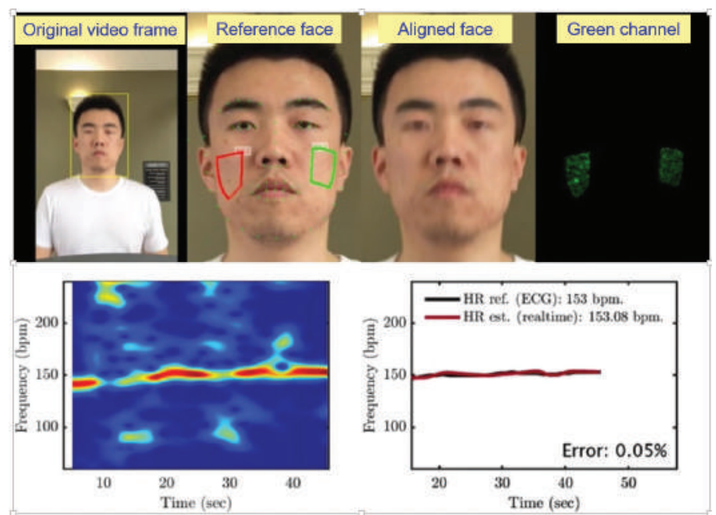
- **Residue analysis**
  - Dominant signals disguise micro signals (overall lighting, motion, etc.)
  - Estimate and compensate dominant signals to reveal residues

    => Improve micro signal SNR
  - "Detrending" takes domain knowledge & synergistic expertise for micro signal
- **Statistical source separation:**
  - Apply ICA to isolate components
  - PCA or Singular Spectrum Analysis (SSA)
- **Physical model/properties help**
  - E.g. sinusoidal model in power sig. analytics





Return from Detour: "Seeing" Heart Rate in Motion

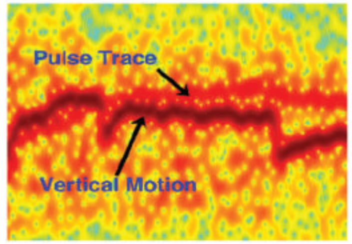


See video at <https://youtu.be/WVBD4srQduE>

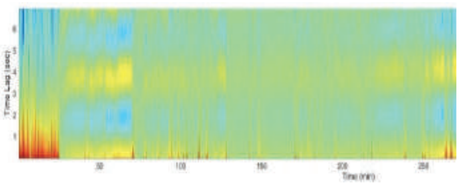
Robust Tracking of Weak Noisy Traces

- Trace tracking in many applications
- Challenges: very noisy + weak traces
  - Very low SNR; strong interference from other sources
  - Varying, unforeseen distortions
  - Multiple frequencies of interest
  - Need a good general/universal method: esp. with limited instances to learn

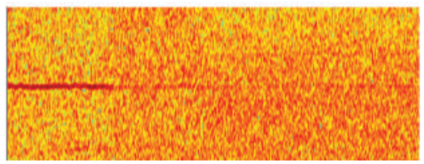
Spectrogram of a rPPG signal



Preproc. Visualization from Radio Analytics *

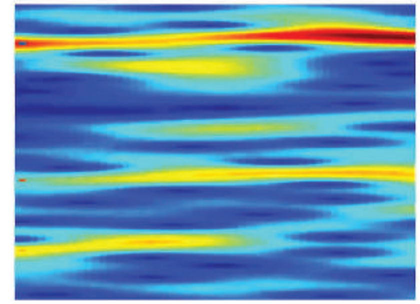


Spectrogram of an audio ENF signal



* Radio Analytics data: courtesy of Dr. Ray Liu and Feng Zhang @ Origin Wireless Inc.

Seam-Carving Inspired Weak-Trace Tracking



Experiment: 3 synthetic signals (-10dB)

Spectrogram energy function

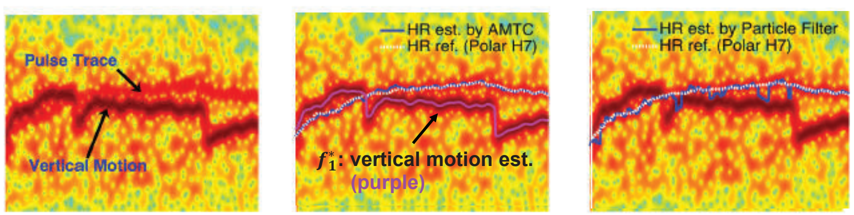
Regularize with trace Markovian dynamics

$$\boldsymbol{f}^* = \underset{\boldsymbol{f}}{\operatorname{argmax}}\, E(\boldsymbol{f}) + \lambda P(\boldsymbol{f}), \qquad \lambda > 0$$

Ref.: Zhu et al. Asilomar'18

Experimental Result (HR using remote PPG)

- Fitness pulse signal using video-based rPPG method



(a) (b) (c)

(a) Weak heart pulse embedded in a strong trace induced by vertical motion running on a elliptical machine. (b) Heart rate estimation after compensating first trace estimate using AMTC. (c) Heart rate estimation using motion spectrogram notching and particle filter method.

Method	RMSE in bpm		ECOUNT		ERATE	
	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\mu}$	$\hat{\sigma}$
MN+PF	5.29	5.51	9.41%	14.13%	2.20%	2.24%
AMTC	2.11	1.11	3.16%	6.04%	1.02%	0.56%

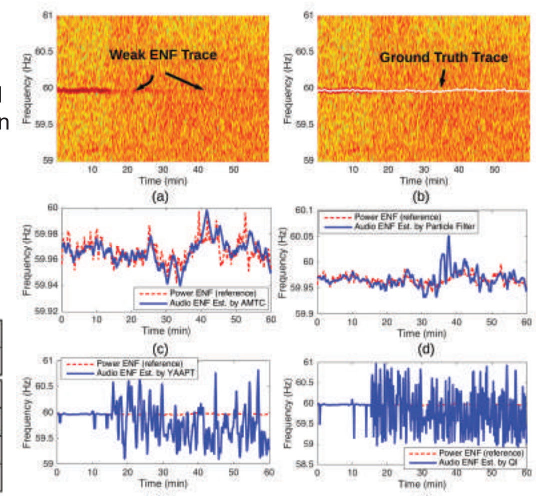
Performance of *AMTC* and *Motion Notching + Particle Filter* methods

Experimental Result (ENF from audio)

- Audio ENF data
  - 27 pairs of 1-hour power grid signal and audio signal from a variety of locations in North America (Nominal ENF: 60 Hz)
  - Recorder: Olympus Voice Recorder WS-700M (f_s=44.1 kHz)

Performance of various methods on ENF data

Method	RMSE in Hz		Pearson's ρ	
	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\mu}$	$\hat{\sigma}$
QI	0.24	0.18	0.18	0.26
Particle Filter	0.04	0.07	0.55	0.37
YAAPT	0.16	0.12	0.23	0.28
AMTC	0.01	0.01	0.85	0.18



(a) (b) (c) (d) (e) (f)

ENF data: 03:03am to 04:03am PT, 20121031 San Diego, CA

Pushing the Envelope:

Can we "see" ECG?

An Enabling Step …

Relation of ECG vs. PPG?

Measure electric potentials

Optical sensing of blood volume change

Promising or Skeptical: Cardio from Wearables?

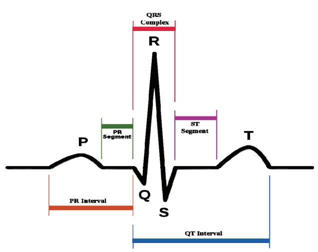
- Wearables for heart rate monitoring in home & fitness
  - Chest belt (related to 1-lead ECG) ~ gold standard in sports
  - Most wearables measure PPG: Finger clips (oximeter); Watches/bracelet (Apple Watch, Samsung Galaxy, FitBit, etc.)

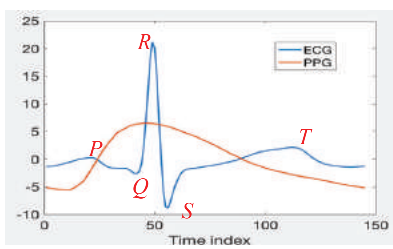
- ECG vs. PPG (photo-plethysmogram)

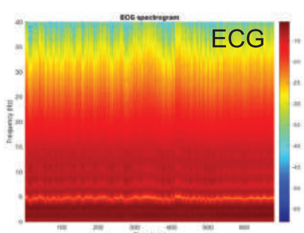
	ECG	PPG
What does it measure?	Electrical potential signal of cardio activities	Optical measurement of the cardio-induced blood volume changes
Accuracy & knowledge base	+ Clinical gold standard; Rich knowledge base	– Indirect to cardio function; Limited cardio knowledge from PPG directly; Prone to motion artifacts due to loose contact etc.
Comfort	– Restrictive on user activities and uncomfortable	+ More user friendly; possible to be contact-free by video etc.
Cont's long-term use	– Specialized equipment (Holter, Zio etc.); skin irritation w/ adhesive wear	+ Long-term wear possible w/o constant user intervention

Image source: https://www.indiamart.com/proddetail/ecg-machine-leads-11806445962.html, http://helowearables.world/helo-wristband-products-science-behind-helo/

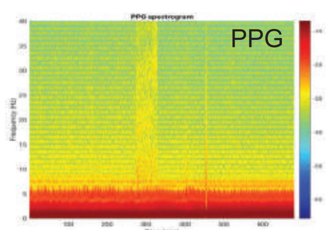
Typical Pattern: Waveforms & Spectrograms







ECG → equiv. Filter → PPG



Spectrograms based on data from CapnoBase, Subject #3, age 2, 500th cycle

ECG PQRST image: https://en.wikipedia.org/wiki/Electrocardiography

Can we obtain ECG from PPG?

- Benefits if this could be done:
  - Enable user-friendly, low-cost, long-term & continuous cardio monitoring
    - *Facilitate studies on patients w/ special needs (autism, etc.)*
  - Leverage rich ECG knowledge and "transfer" it to build knowledge base for PPG and data from wearables

Support & promote public health and more

not just blackbox data-driven AI but medically explainable

- Two major research issues

1. Can we infer ECG from a clean PPG? ← **most fundamental**

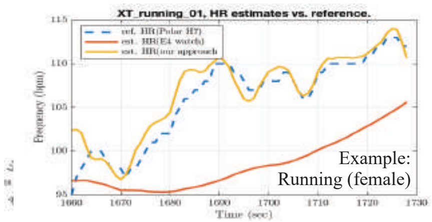
- Patient independent (inference for a group of patients, e.g. by age, gender etc.) vs. Patient specific (refine with specific patient info.)
- Role of disease types on the inference model?

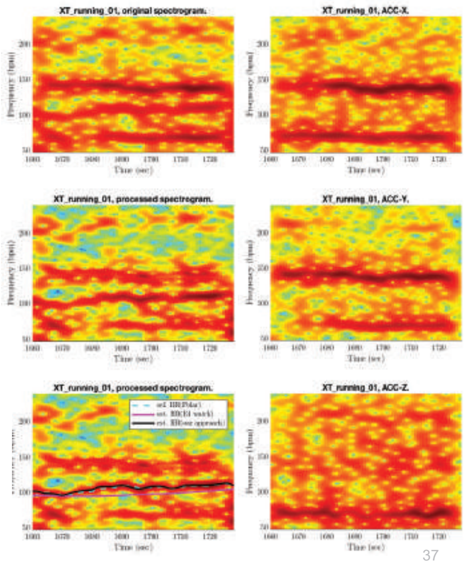
2. Can we clean up PPG due to movement etc.?

- Leverage multiple sensors (e.g. accelerometers)

Clean up PPG in Prep for Signal Analytics

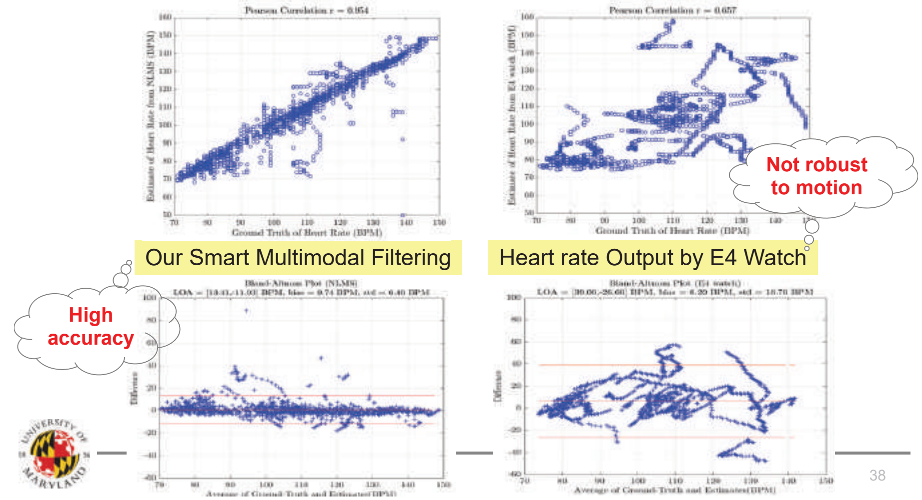
- Combined proc. from noisy PPG + accelerometer signals
  - SP Cup 2015 Heart rate (Zhang@ Samsung; Schack et al.@TU Darmstadt)
- Joint adaptive sp + robust trace tracking (on UMD E4 Dataset)
  - Improved heart rate accuracy than Empatica E4 under motion
  - Compared to gold standard for HR in fitness (Polar cheststrap)





Accuracy Comparison of PPG Clean-up (UMD E4 Dataset)

- Heart rate estimates: 22 sessions total of 5 subjects; jump, walk, run, row, still
- Pearson correlation (w.r.t. chest-strap ref.); Bland-Altman plot 95%



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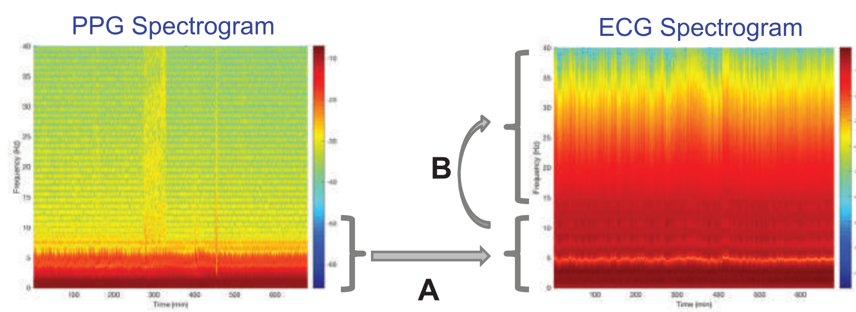
PPG to ECG: Methodology At-a-Glance

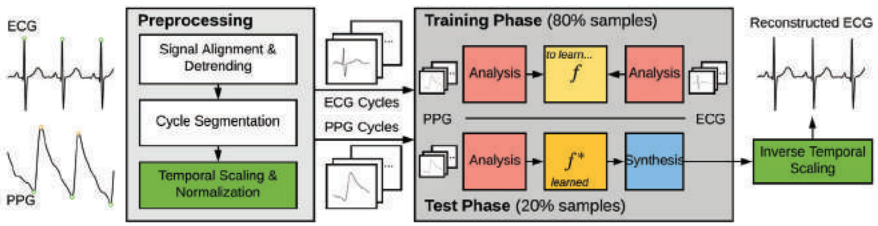


A. Reconstruct lower-freq. spectrum via inverse filtering type of operation

B. Reconstruct extended spectrum by exploiting correlation/sig. properties

➔ *Can combine the two steps with model+data supported learning*

A Cycle-level Learning Framework

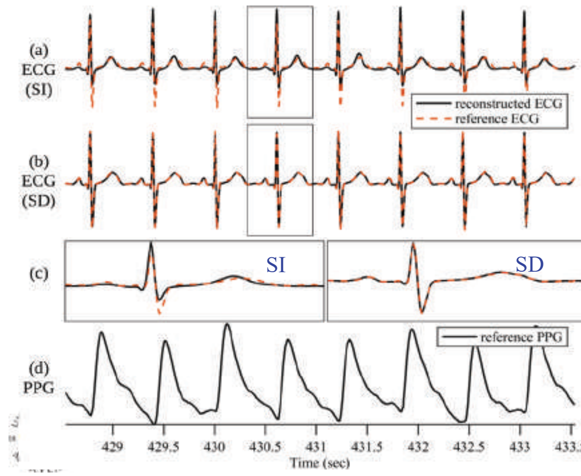


Framework and Generalization:

- The mapping *f* can be a linear transform (first tries, BHI'19), and generalized to nonlinear mappings or transforms (e.g., learnt from data via neural networks).
- The analysis mechanism can be DCT (BHI'19) or other mapping/transform, e.g. learned with *f* via dictionary learning or neural networks.
- By further exploring (big) data with detailed patient profiles, a more complex model may be learned based on biomedical, statistical, and physical meanings of the signals to better capture the relation of PPG and ECG.

Subject Dependent (SD) vs. Independent (SI) Model

- SD: training and testing on different data from the same subject
- SI: one model trained with all training data from multiple subjects



SI is more challenging to be accurate; may explore by age, gender, etc.

PPG-to-ECG example (on CapnoBase)

- 4 years old, weight 18 kg

Pearson's correlation coeff. of inferred ECG from PPG:

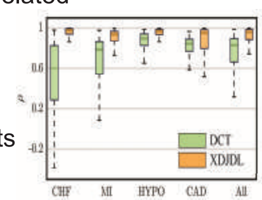
0.991 in SD mode

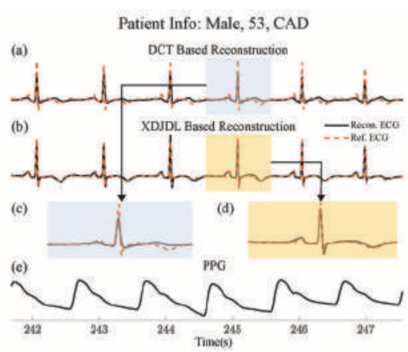
0.883 in SI mode

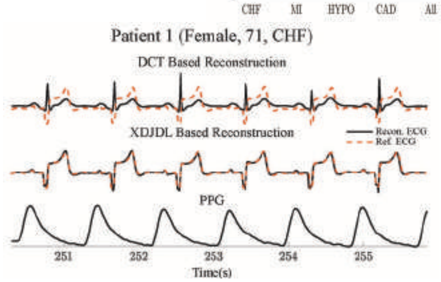
See BHI'19 paper, slides at <http://sigport.org/4558>

DCT Based vs. Joint Dictionary Learning

- DCT: near-optimal data-independent for highly correlated data => focus on learning PPG-ECG relations
- Dictionary learning w/ improved inference
  - Jointly learn ECG/PPG representations & their relation from data, esp. useful for disease patients



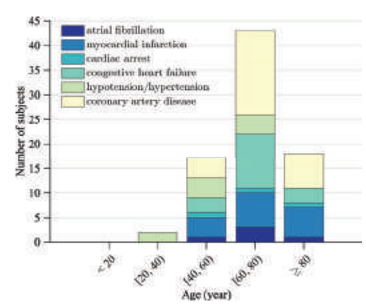




patient-wise rho: DCT:0.19; XDJDL:0.94

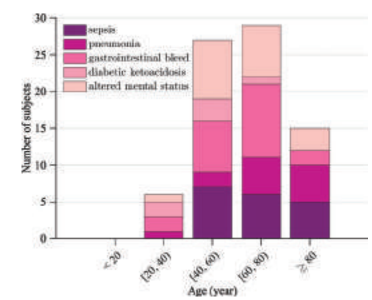
patient-wise rho: DCT:0.80; XDJDL:0.85

Mini-MIMIC Database: ICU Patient Profile



Total # of cardiac patients: 80

- Atrial fibrillation: 5
- Myocardial infarction: 17
- Cardiac arrest: 3
- Congestive heart failure: 17
- Hypotension/hypertension: 10
- Coronary artery disease: 28



Total # of non-cardiac patients: 77

- Sepsis: 18
- Pneumonia: 13
- Gastrointestinal bleed: 21
- Diabetic ketoacidosis: 6
- Altered mental status: 19

Prelim Results: Cardio Disease Classification

- Confusion matrices & classification accuracy of SVM (w/ polynomial kernel) on 3 types of data: original ECG vs. inferred ECG vs. original PPG

Confusion matrix from number of PCs = 100

Original ECG (reference)

True Class \ Predicted Class	CHF	STMI	NSTMI	HYPO	CAD
CHF	100.0%	0.0%	0.0%	0.0%	0.0%
STMI	0.0%	100.0%	0.0%	0.0%	0.0%
NSTMI	0.0%	0.0%	100.0%	0.0%	0.0%
HYPO	0.0%	1.8%	0.0%	98.2%	0.0%
CAD	0.0%	0.0%	0.0%	0.0%	100.0%

ECG inferred from PPG (proposed idea)

True Class \ Predicted Class	CHF	STMI	NSTMI	HYPO	CAD
CHF	100.0%	0.0%	0.0%	0.0%	0.0%
STMI	0.0%	100.0%	0.0%	0.0%	0.0%
NSTMI	4.3%	0.0%	95.7%	0.0%	0.0%
HYPO	0.0%	0.0%	0.0%	100.0%	0.0%
CAD	0.0%	0.0%	0.0%	0.0%	100.0%

Original PPG (direct learning from wearables)

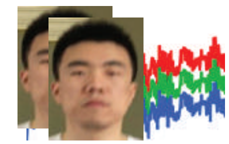
True Class \ Predicted Class	CHF	STMI	NSTMI	HYPO	CAD
CHF	81.5%	4.6%	9.2%	1.5%	3.1%
STMI	8.5%	83.1%	5.1%	3.4%	0.0%
NSTMI	22.5%	17.5%	55.0%	2.5%	2.5%
HYPO	1.8%	3.5%	1.8%	93.0%	0.0%
CAD	6.5%	22.6%	19.4%	0.0%	51.6%

Classification Accuracy:	Original ECG (reference)	ECG inferred from PPG (proposed idea)	Original PPG (direct learning from wearables)
	99.6%	**99.3%**	76.6%

Promising "**Explainable AI**" benefit from our inference to **learn by physical model & biomedical knowledge + data** than PPG data alone

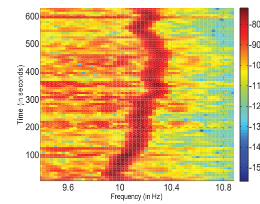
Recap: Exploiting Micro-Signals

- Harnessing "Micro Signals" for health analytics and physiological forensics
- Cross-cutting Synergy of multiple SPS tech areas
- Benefits and cautions:
  - Physio. w/o needing active user involvement
  - Privacy implications: e.g. in surveillance

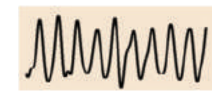


Face color signal from motion video

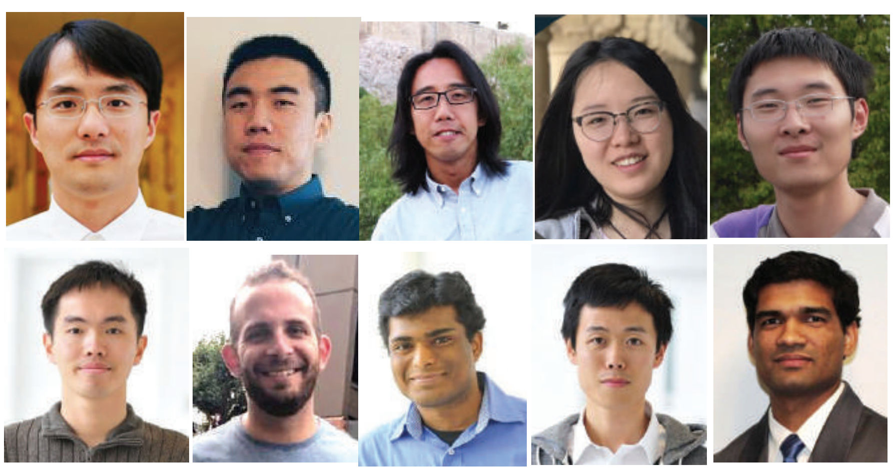
- Outlook: promising use of physiological micro-signals in detecting fake media



Coming from environment



Physiological monitoring
- *Heart rate, breathing, etc.*



Include joint work with colleagues, graduate & REU students

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