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

Min Wu
Media and Security Team (MAST)
ECE Department / UMIACS
University of Maryland, College Park
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.

Micro-Signals for Forensics

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

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: (Verkruysse 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

**Skin Model of Remote PPG (photo-plethysmogram)**

PPG through pulse oximeter

- Optical sensing
- Instrument measuring (blood) volume change

![Diagram of skin model and light source](image)

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])


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**“Seeing” Heart Rate in Motion: No Touch Needed**

- **Original video frame**
- **Reference face**
- **Aligned face**
- **Green channel**

**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

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**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

**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)

**Align Visual Streams using ENF Row Signals**

- Video signal: combination of visual component and ENF component.
  - Estimate visual component
  - Subtract visual component
  - Take row averages as source signal
  - Frequency estimation from source signal

- Can we exploit row sampling to overcome ENF aliasing?

**ENF matching result demonstrating similar variations in the ENF signal extracted from video and from power signal recorded in India**
**Synchronize Multiple Videos by Power Trace**

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

- Lag by manual alignment: 60.80 sec

**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
    - “Detrending” takes domain knowledge & synergistic expertise for micro signal
  - Improve micro signal SNR

- **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/9njZ1fBq26g]
- 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

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**Seam-Carving Inspired Weak-Trace Tracking**

\[ f^* = \arg\max_f \left( E(f) + \lambda P(f) \right), \quad \lambda > 0 \]

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**Experimental Result (HR using remote PPG)**

- Fitness pulse signal using video-based rPPG method

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**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)

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### Performance of various methods on ENF data

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE in Hz</th>
<th>Pearson’s ( \rho )</th>
</tr>
</thead>
<tbody>
<tr>
<td>QL</td>
<td>0.24</td>
<td>0.18</td>
</tr>
<tr>
<td>Particle Filter</td>
<td>0.04</td>
<td>0.07</td>
</tr>
<tr>
<td>YAAPT</td>
<td>0.16</td>
<td>0.12</td>
</tr>
<tr>
<td>AMTC</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

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

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**Typical Pattern: Waveforms & Spectrograms**

**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)

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

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**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

- **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)

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Support & promote public health and more

not just blackbox data-driven AI but medically explainable
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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  1. Can we infer ECG from a clean PPG?  \[\rightarrow\text{most fundamental}\]
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     - Role of disease types on the inference model?
  2. Can we clean up PPG due to movement etc.?  \[\rightarrow\text{Can combine the two steps with model+data supported learning}\]

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

Support & promote public health and more not just blackbox data-driven AI but medically explainable
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.

Min Wu (UMD) - GlobalSIP 2019: Micro-Signals for Health & Forensics

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

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

<table>
<thead>
<tr>
<th>Class</th>
<th>Original ECG (reference)</th>
<th>ECG inferred from PPG (proposed idea)</th>
<th>Original PPG (direct learning from wearables)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CHF</td>
<td>100.0%</td>
<td>100.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>STI</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>NSTEMI</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
<tr>
<td>HYPO</td>
<td>0.0%</td>
<td>0.0%</td>
<td>96.2%</td>
</tr>
<tr>
<td>CAD</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

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

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

**Include joint work with colleagues, graduate & REU students**

Wei-Hong Chuang, Adi Hajj-Ahmad, Ravi Garg, Hui Su, Avinash Varna; Chau-Wai Wong, Qiang Zhu, Chang-Hong Fu, Xin Tian, Mingliang Chen, Yuenan Li, J. Su, Michael Luo (MERIT REU), Maggie Xiong (REU), J. Luo (REU).