Visualizing the Invisibles: Micro Signals for Info. Forensics and Health Analytics

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, Hongmei Gou, Adi Hajj-Ahmad, Ravi Garg, Hui Su, Ashwin Swaminathan, Avinash Varna, Chau-Wai Wong, Qiang Zhu, C-H. Fu, X. Tian, M. Chen.

Min Wu: Bio-Sketch

minwu@umd.edu

1996: BSE (Automation) & BA (Economics), Tsinghua Univ.

2001: Ph.D. (EE), Princeton Univ. (advised by Prof. Bede Liu)

Since 2001: On faculty of Univ. Maryland, College Park

currently ECE/UMIACS Professor and Distinguished Scholar-Teacher

- Research: At intersection of image & signal processing, security/forensics, learning/statistical pattern recognition, and data science

- Past TC Chair, IEEE Tech. Committee on Info. Forensics and Security.

  Past Editor-in-Chief, IEEE Signal Proc. Magazine (top citation impact in EE)

- Patents cited by ~820+ other patents; 180 papers, h=54 (Google scholar)
- Won paper awards from IEEE, ACM & EURASIP; Google Scholar “Test of Time”.

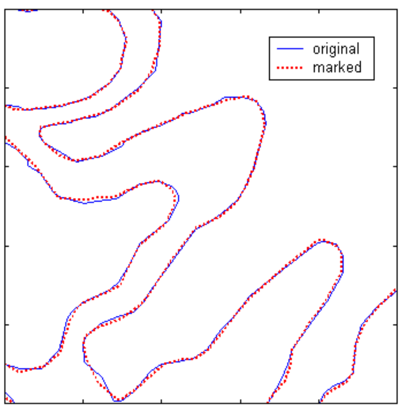
  AAAS & IEEE Fellow; IEEE Distinguished Lecturer;

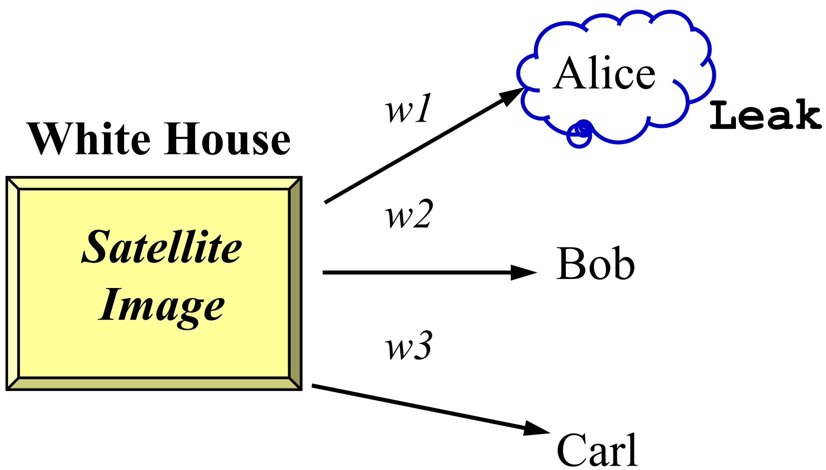
  Young Investigator Awards -- NSF CAREER, ONR YIP;

  Innovator Awards -- MIT TR100/TR35, Computer World “40 under 40”, Daily Record Innovator of the Year, UM Invention of the Year

Exploiting Micro-Signals

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



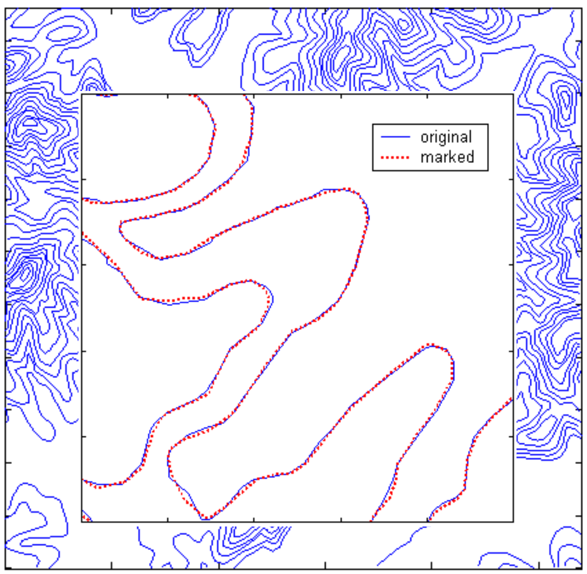


Embed invisible tracer

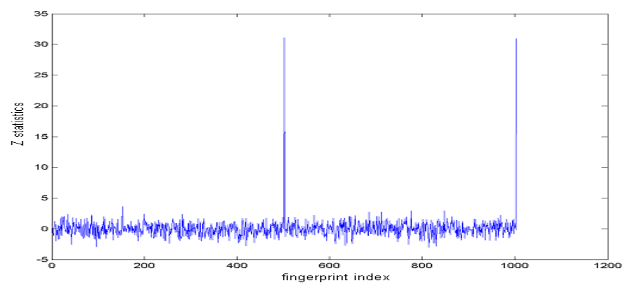
- *Label each copy*
- *Deter leak & illicit distribution*

Embedding Micro-Signals as Tracers

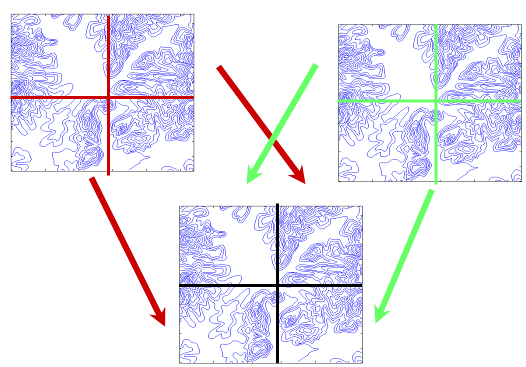
- Embedded FP (aka forensic watermark) is widely adopted to protect Hollywood media today
- Survive collusions and analog/physical channel:
  e.g. from hard copies

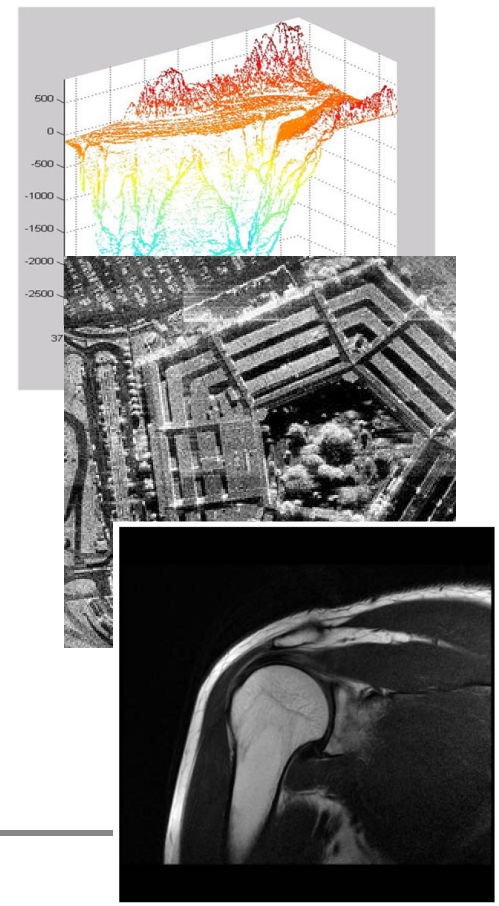


Fingerprinted Map



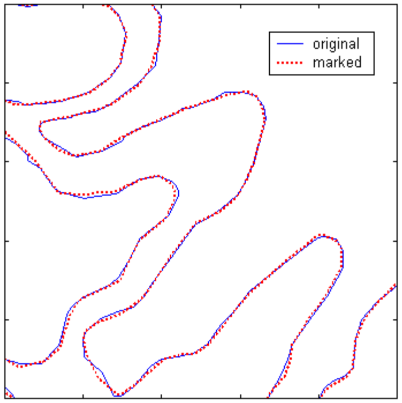
2-User Interleaving Attack





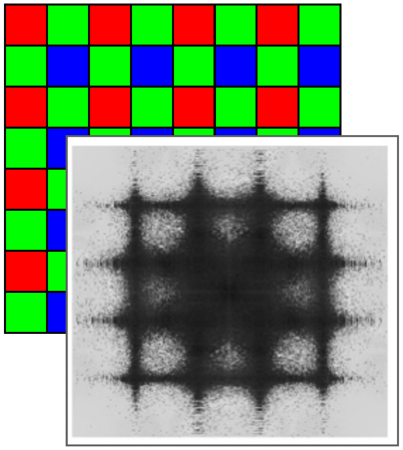
Exploiting Micro-Signals

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



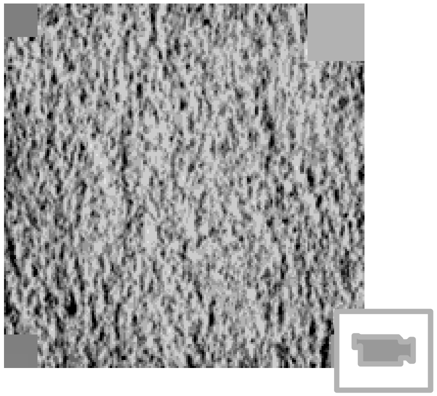
Embed invisible tracer

- *Label each copy*
- *Deter leak & illicit distribution*



Intrinsic from Device

- *How was an image generated? Tampered?*

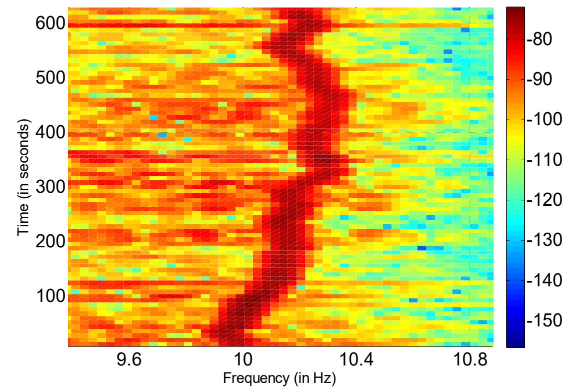


Unclonable object surfaces

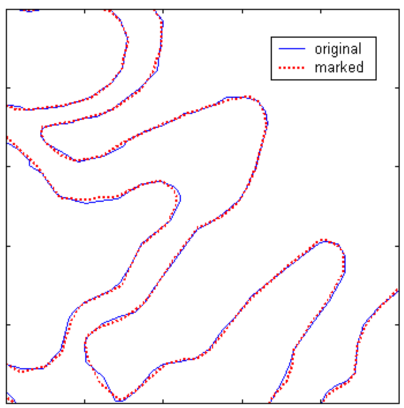
- *Verify by cellphone camera to detect counterfeit*

Exploiting Micro-Signals

Coming from environment

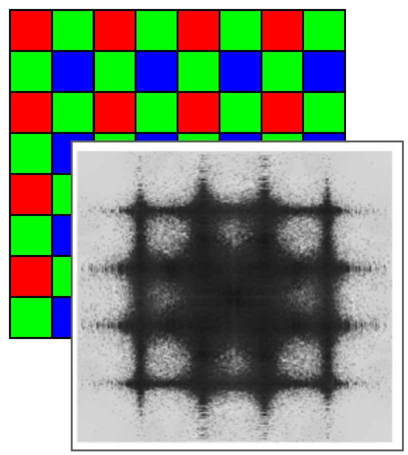


- "Micro signal" is small in terms of:
  - Amplitude than dominating signals (by 1+ order of magnitude)
  - Topological scale



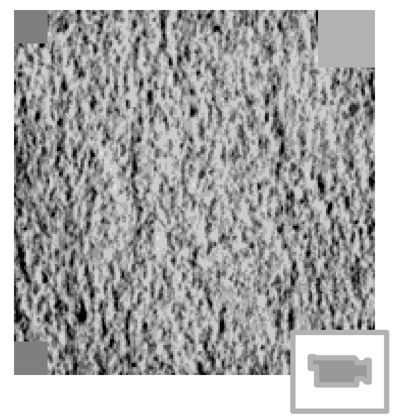
Embed invisible tracer

- *Label each copy*
- *Deter leak & illicit distribution*



Intrinsic from Device

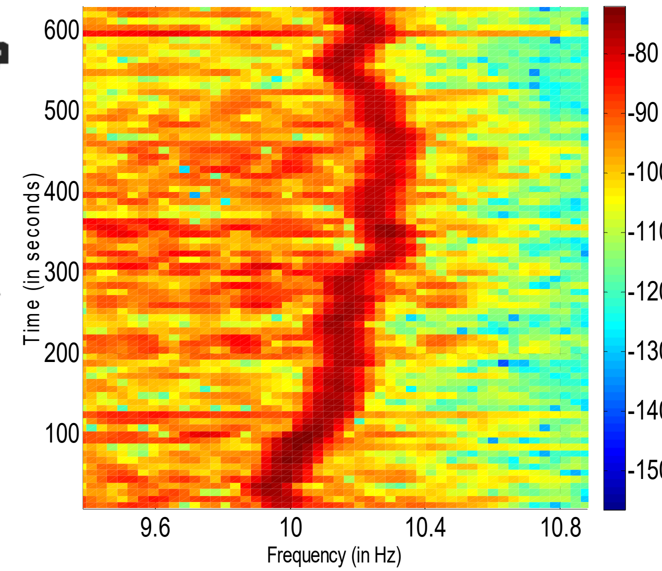
- *How was an image generated? Tampered?*



Unclonable object surfaces

- *Verify by cellphone camera to detect counterfeit*

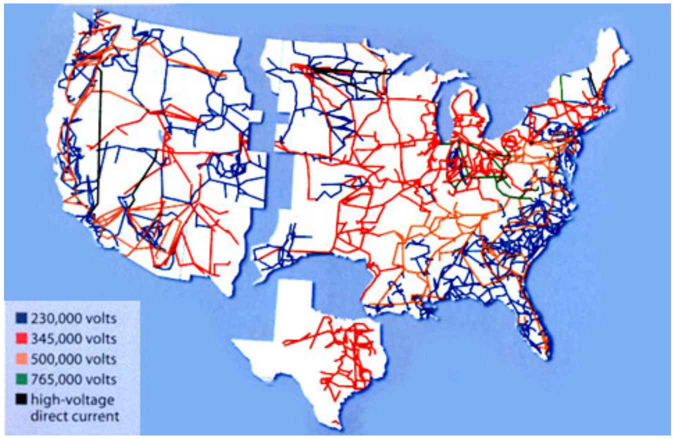
Micro Sig. E.g.: Forensic Ques. On "Time + Place"



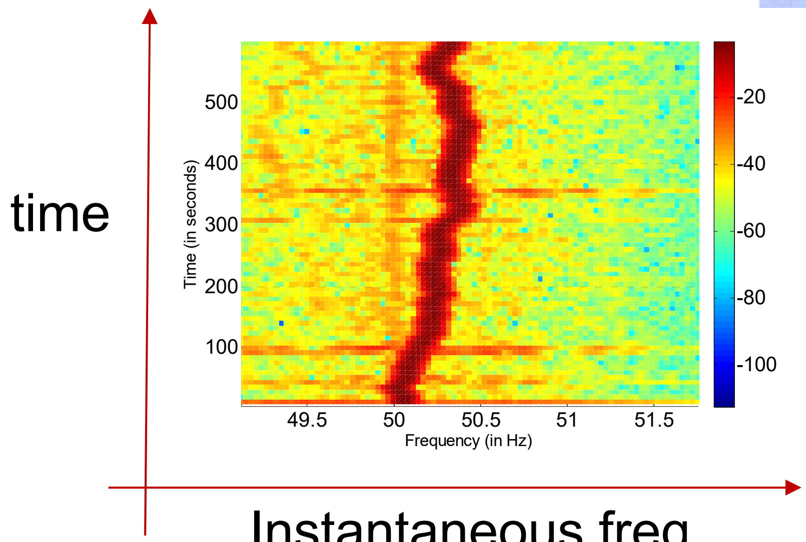
- When was the video actually shot? And where?
- Was the sound track captured at the same time as the picture? Or super-imposed afterward?
- Explore fingerprint influenced by power grid onto sensor recordings

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

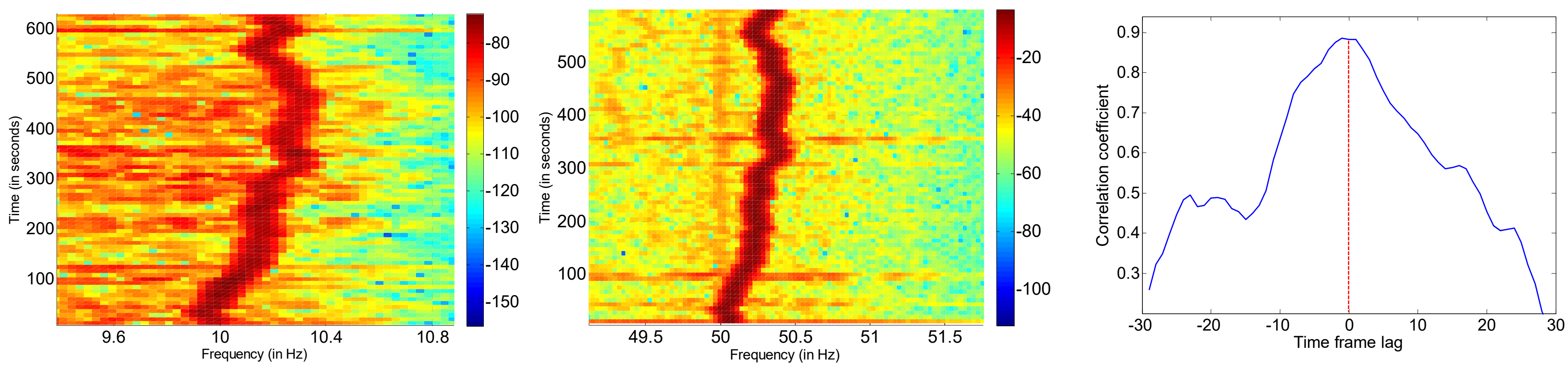


ENF signal *f(t)*



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
- 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.

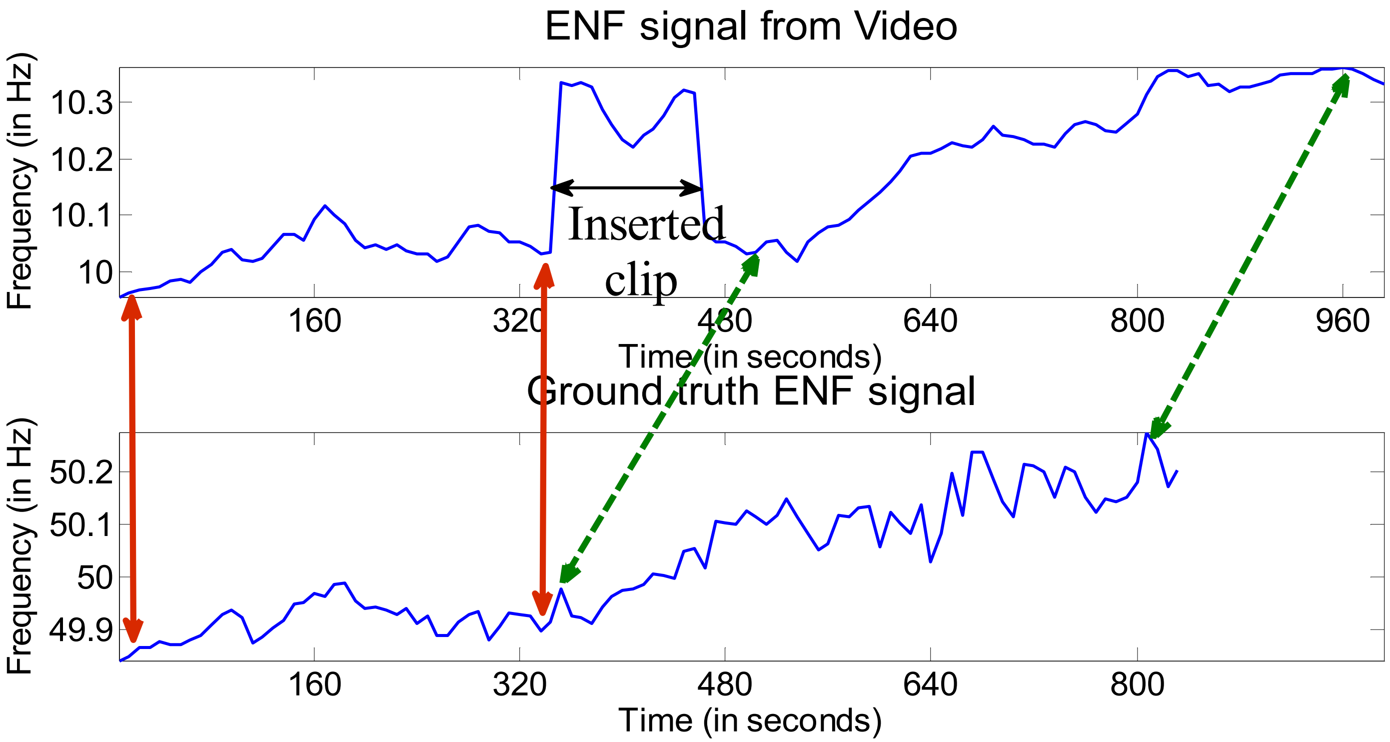


Video ENF signal | Power ENF signal | Normalized correlation

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

Tampering Detection

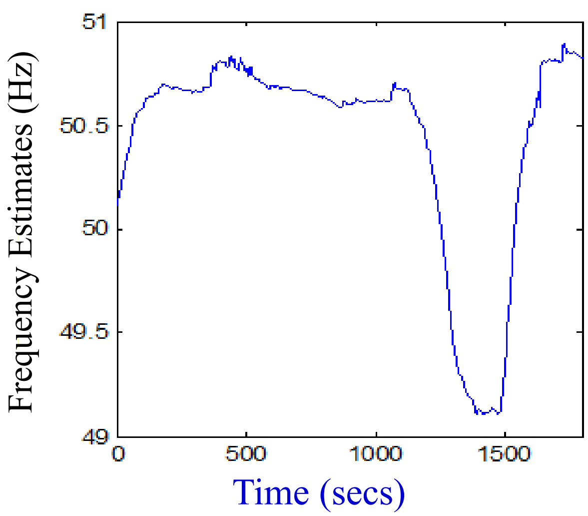
- Adding a clip into original video leads to discontinuity in ENF
  - Clip insertion can also be detected by comparing the video ENF signal with the power ENF at corresponding time



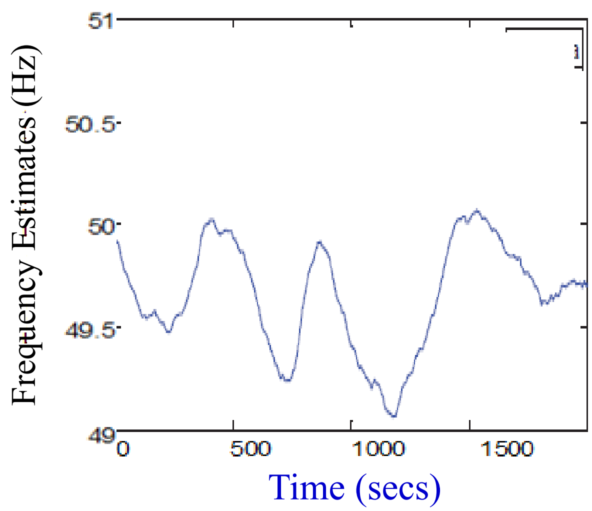
- Anti-forensics analysis and countermeasures [CCS/TIFS]

Infer Location from ENF

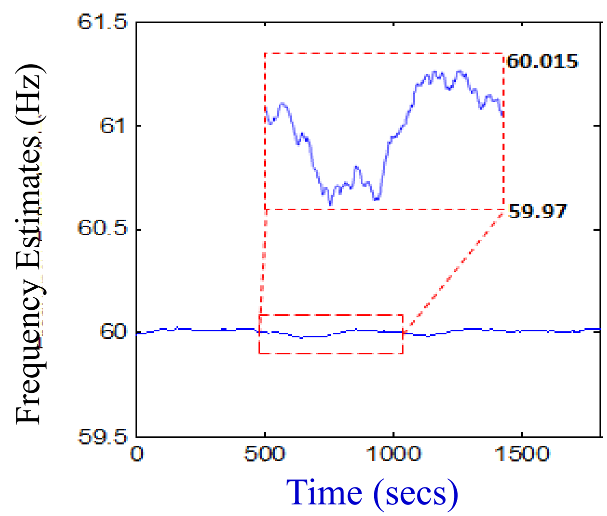
- Estimate grid location of a recording:
  - Support IoT location security and law enforcement A/V forensics
  - SP Cup 2016 as education and global outreach



LEBANON

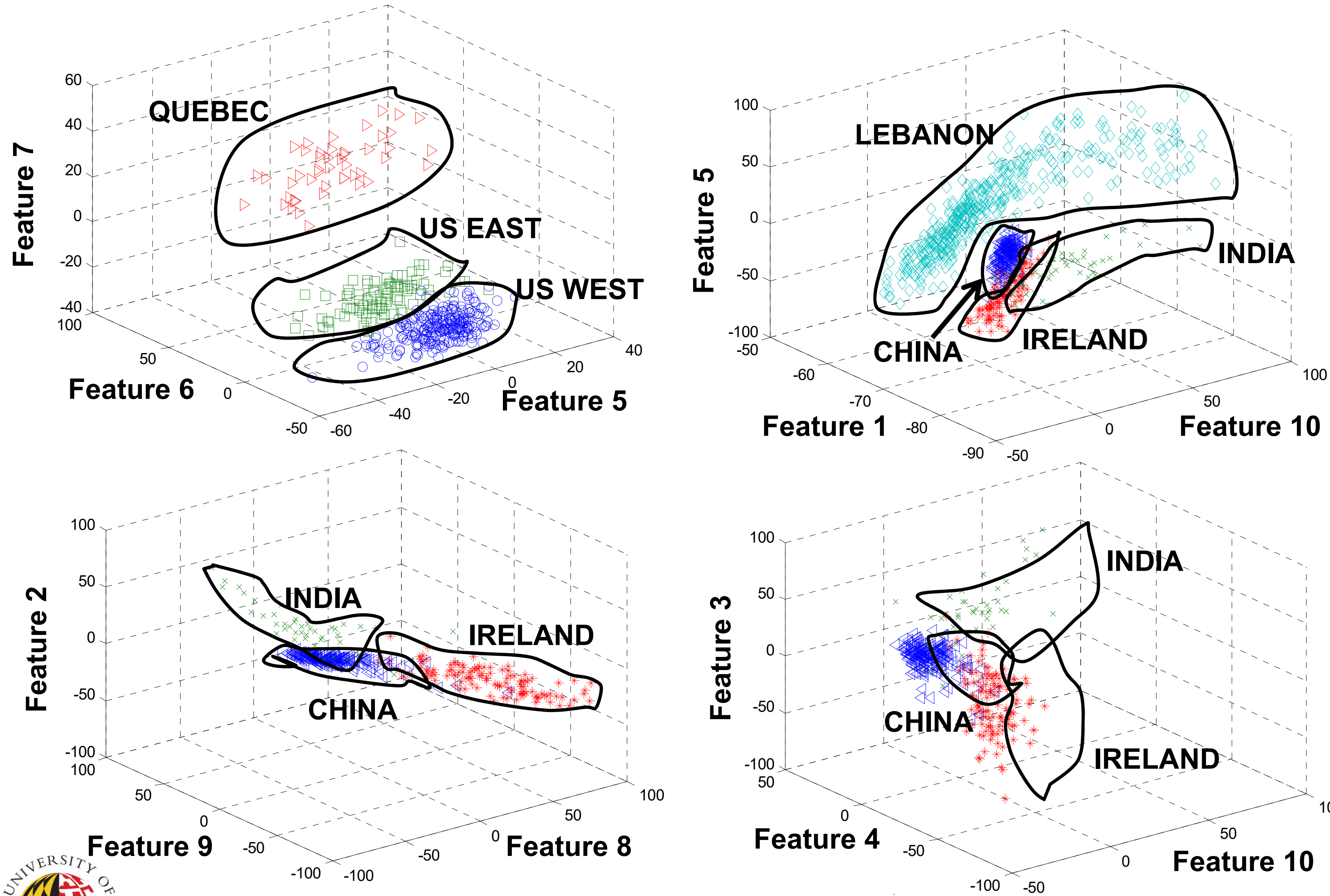


INDIA



Eastern US

ENF Feature Examples for Grid Locations



1. Mean of ENF segment;
2. log(range);
3. log(variance) of approx. after wavelet analysis

4-7. log(var.) of 4 high-freq subband sig.;

8-9. AR(2) modeling parameters;

10. log(var) of innovation sig.

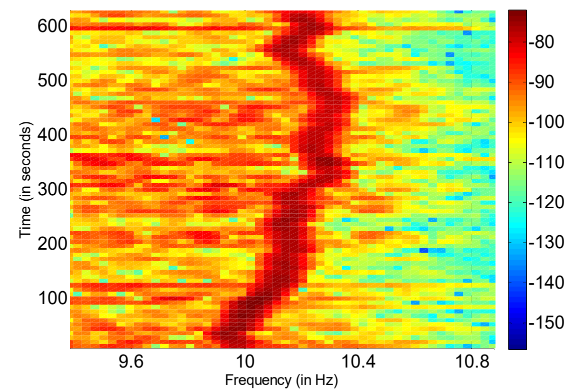
Adopted by IEEE SP Cup'16 Undergrad Competition

- 334 students registered in 52 teams ~ every continent covered
  - Final submissions by 33 teams from 23 countries
- 2 components: hardware and sensing; signal pattern classification

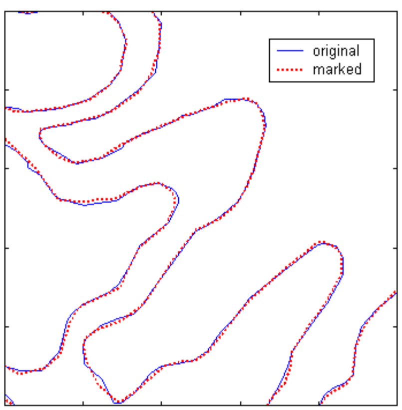
=> Read more in SPM 9/2016 issue; Check IEEE DataPort & SigPort for dataset

Exploiting Micro-Signals

Coming from environment

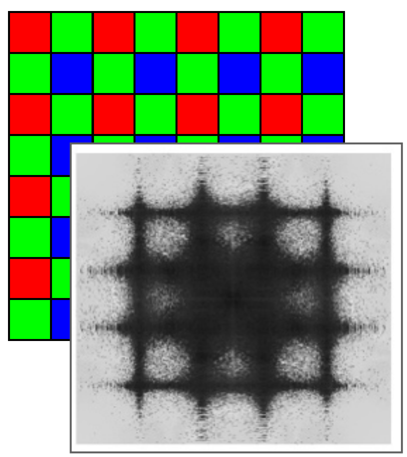


- "Micro signal" is small in terms of:
  - Amplitude than dominating signals (by 1+ order of magnitude)
  - Topological scale



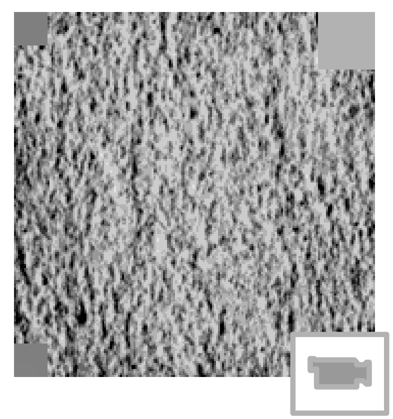
Embed invisible tracer

- *Label each copy*
- *Deter leak & illicit distribution*



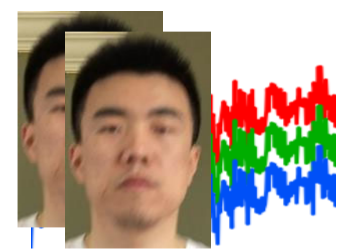
Intrinsic from Device

- *How was an image generated? Tampered?*

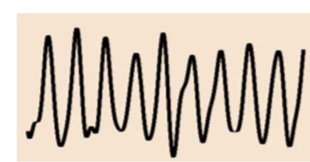


Unclonable object surfaces

- *Verify by cellphone camera to detect counterfeit*



Face color signal from motion video



Physiological monitoring

- *Heart rate, etc.*

Micro-Signal for Health: Heart Rate Monitoring

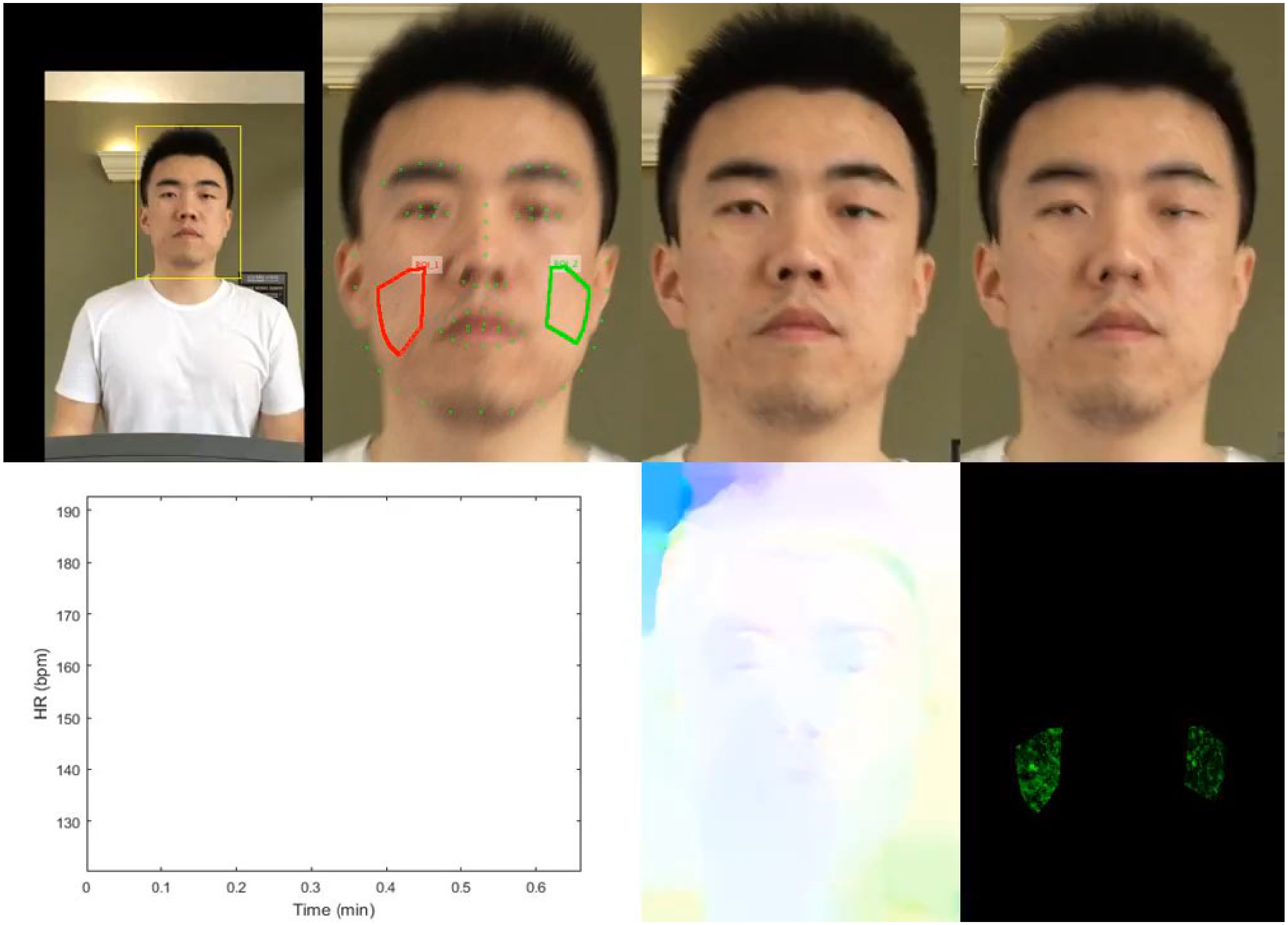
- Heart rate monitoring in home and fitness
  - Contact based: electrodes, chest belts, and finger clips.
  - Contact-free: more user-friendly, but challenging to design.

- Observation: face color changes in the same pace as heartbeat
  - Although naked eyes cannot see it
  - Prior work:
    "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.

Micro-Signal Examples: Heart Rate in Motion

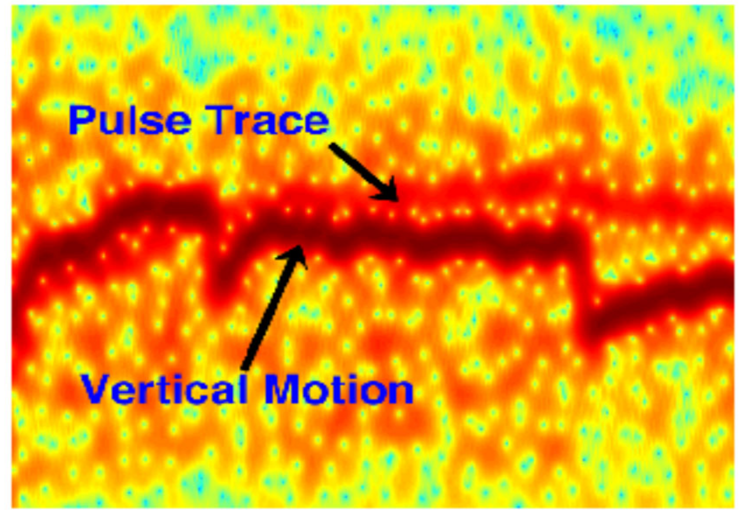


See video at <https://youtu.be/9njZ1fBq26g>

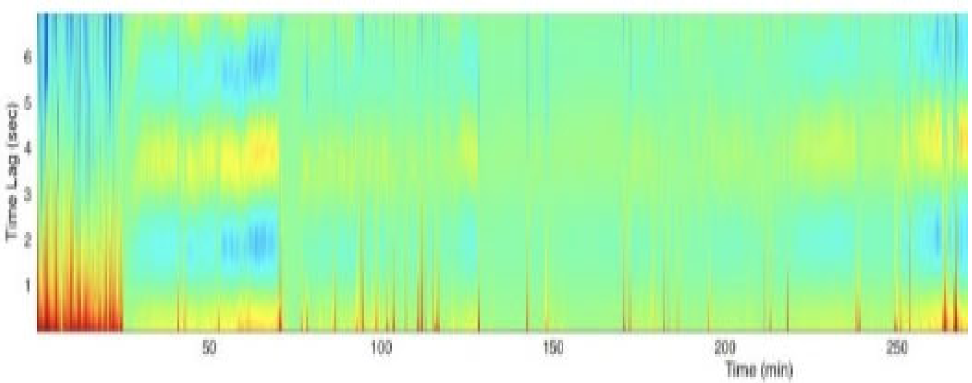
Robust Tracking of Weak Noisy Traces

- Challenges: very noisy + weak traces
  - Freq. tracking in many applications
  - Very low SNR; strong interference from other sources
  - Varying distortion types
  - Multiple freq. of interest
  - Need a good general/universal method

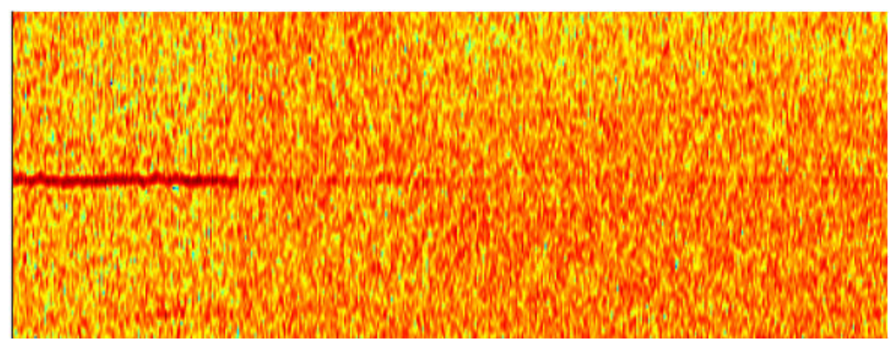
Spectrogram of a rPPG signal



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.**

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);

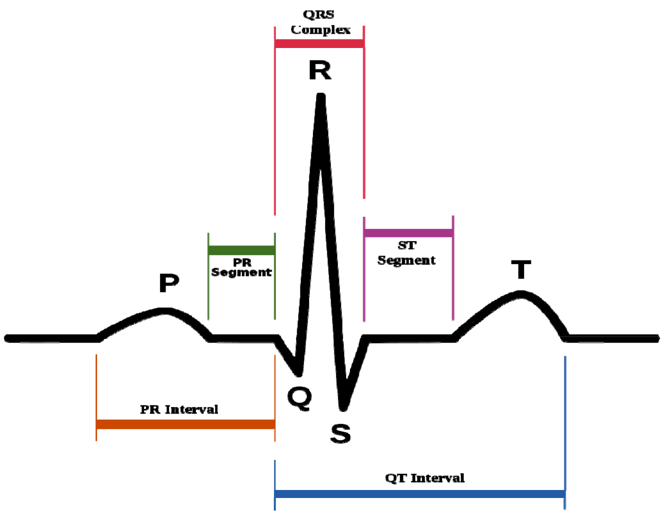
    Watches/bracelet (Apple Watch, Samsung Galaxy, FitBit, etc.)

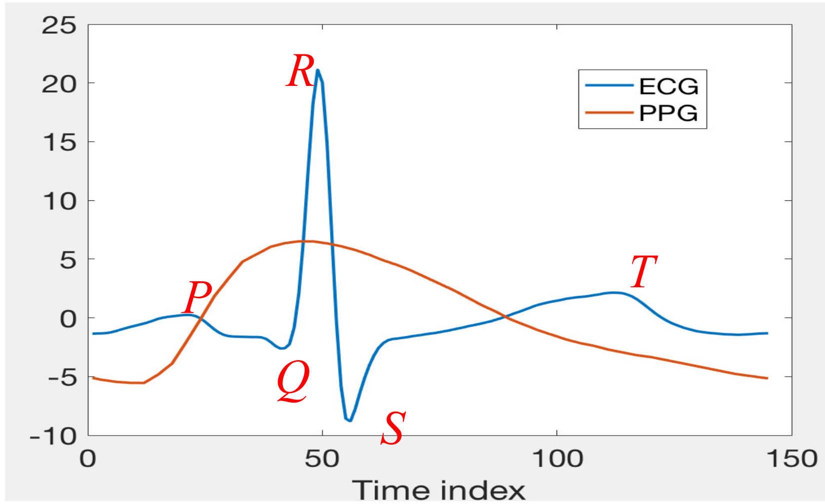
- ECG vs. PPG (photo-plethysmogram)

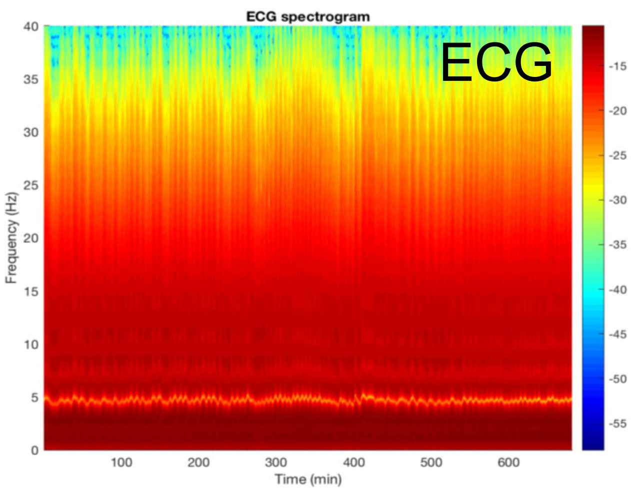
	ECG	PPG
What does it measure?	Electrical potential signal of cardio activities 	Optical measurement of the cardio-induced blood volume changes
Accuracy & knowledge base	Clinical gold standard; Rich knowledge base	Indirect to cardio function; Limited cardio knowledge from PPG directly; Prone to motion 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 etc.); skin irritation with 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



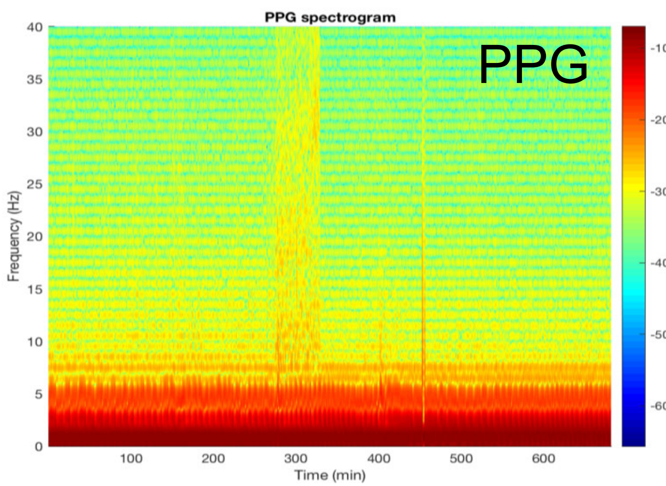




ECG

equiv. Filter

PPG



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

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?

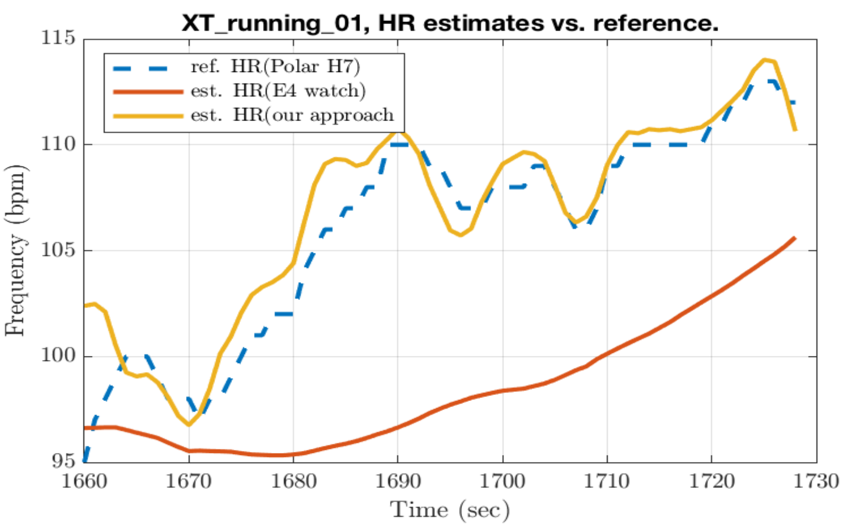
2. Can we clean up PPG due to movement etc.?

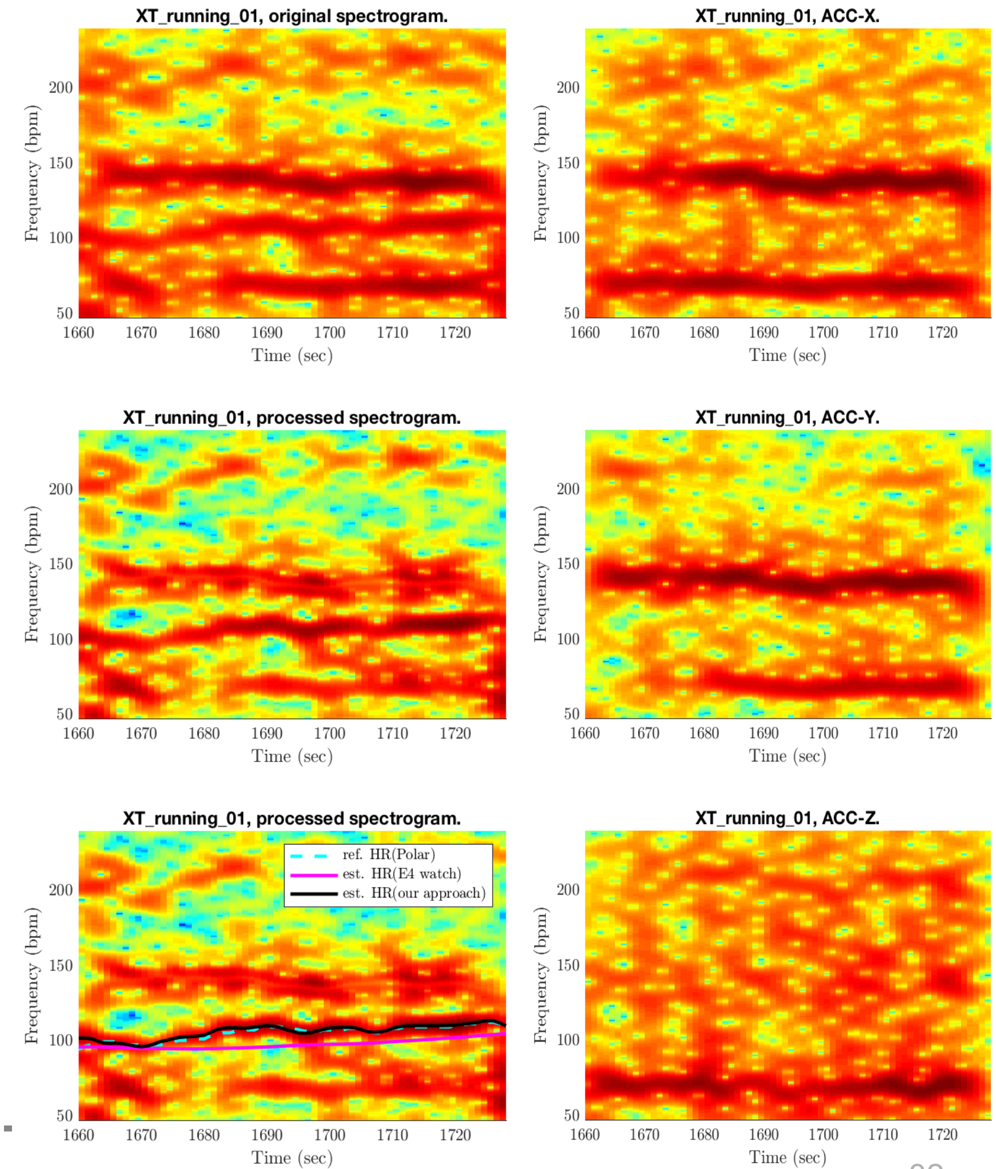
- Leverage multiple sensors (e.g. accelerometers)

Clean up PPG in Prep for Sig. Analytics (UMD E4 Dataset)

- Combined proc. from noisy PPG + accelerometer signals
- Improved heart rate (HR) accuracy than Empatica E4 under motion
  - Compared to gold standard for HR in fitness (Polar cheststrap)

e.g.1 Running (female subject)





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

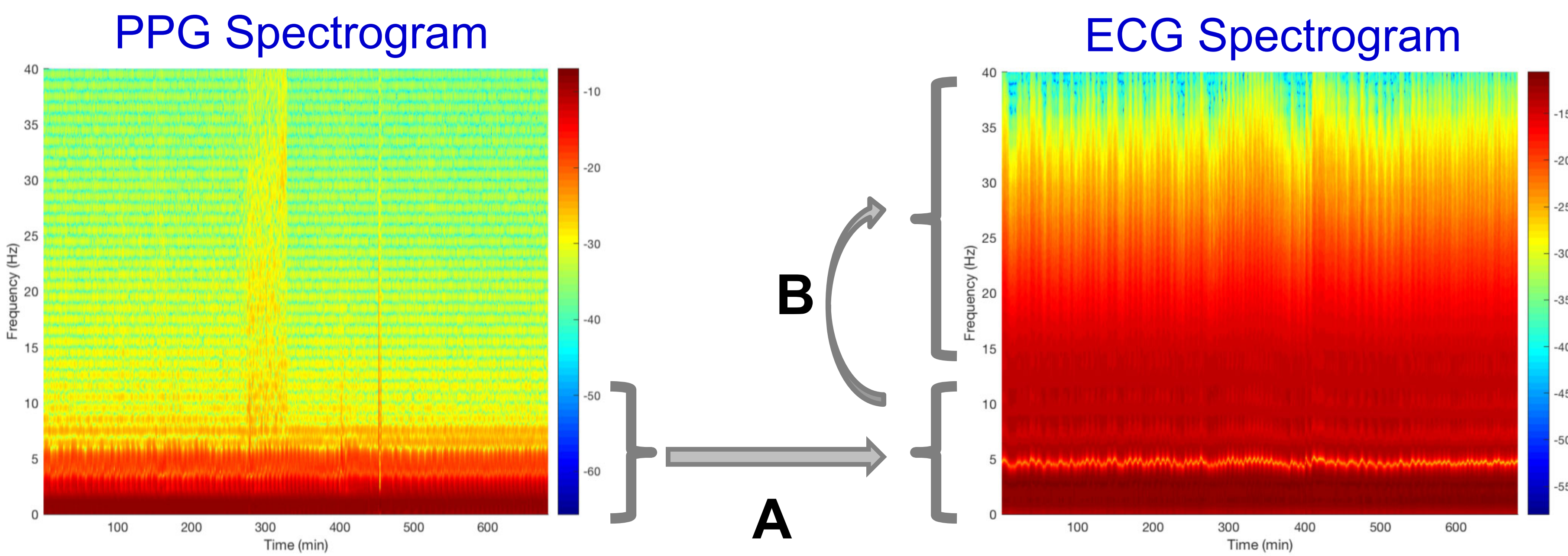
1. Can we infer ECG from a clean PPG? ← **most fundamental**

- 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)

PPG to ECG: Methodology At-a-Glance



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

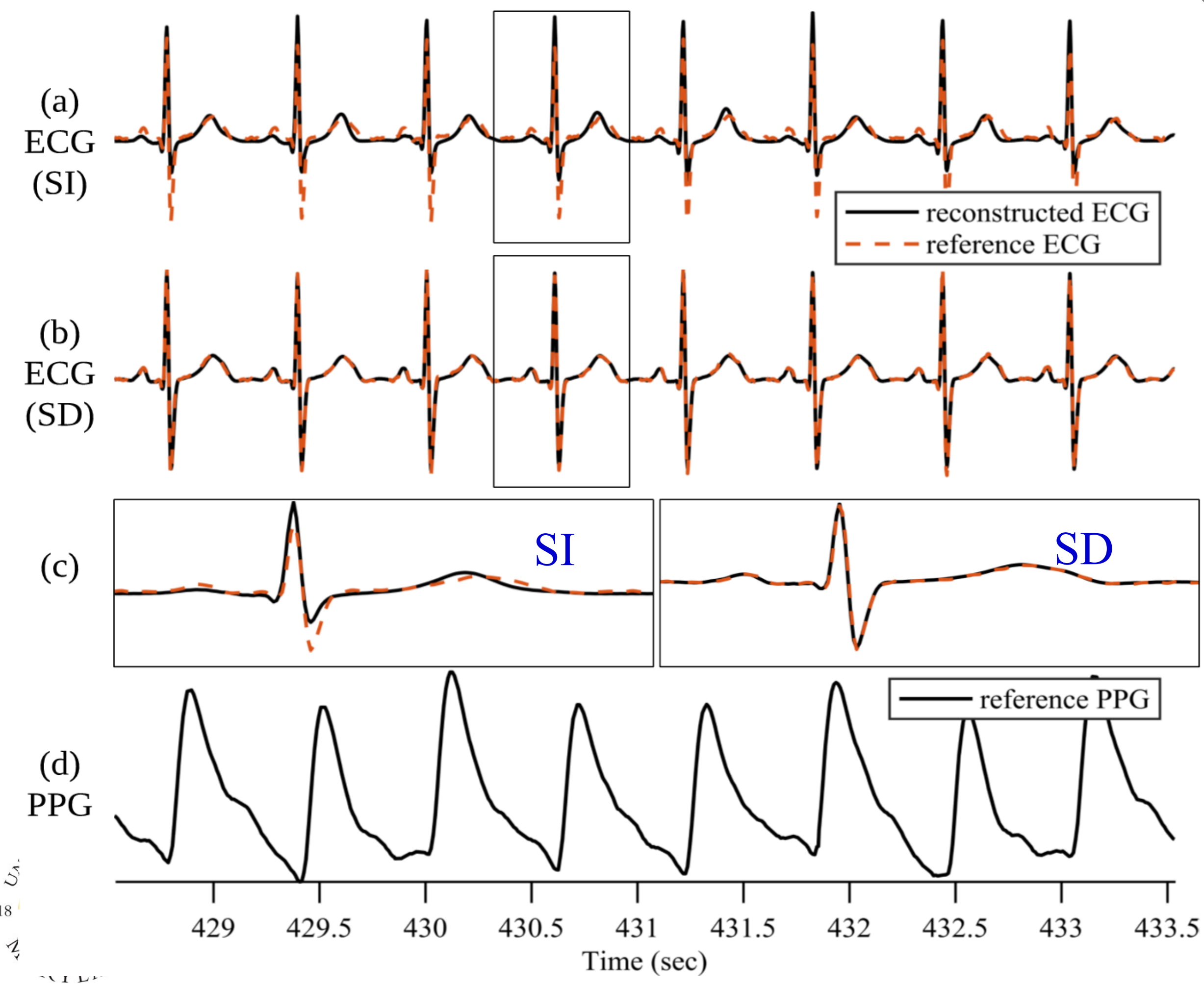
B. Reconstruct extended spectrum by exploiting correlation/sig. properties

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

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

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)

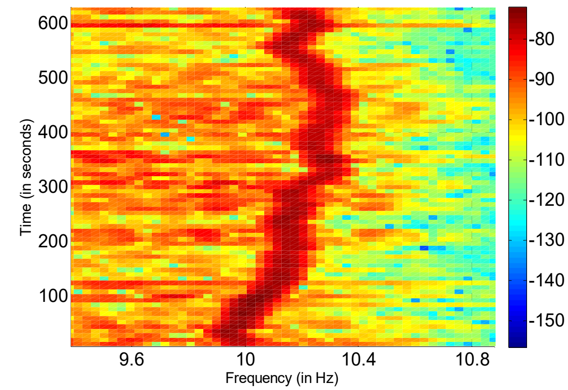
True Class \ Predicted Class	CHF	STMI	NSTMI	HYPO	CAD
CHF	81.5%	4.6%	9.2%	1.5%	3.1%
STMI	8.5%	83.1%	5.1%	3.4%	0.0%
NSTMI	22.5%	17.5%	55.0%	2.5%	2.5%
HYPO	1.8%	3.5%	1.8%	93.0%	0.0%
CAD	6.5%	22.6%	19.4%	0.0%	51.6%

Classification Accuracy:	Original ECG	ECG inferred from PPG	Original PPG
	99.6%	**99.3%**	76.6%

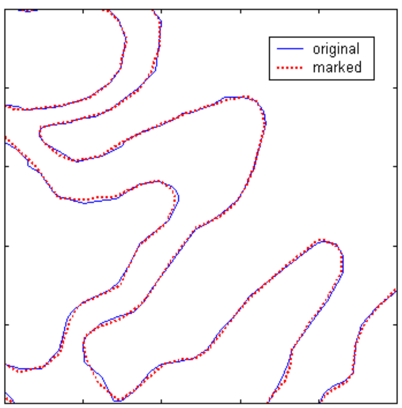
Our proposed inference shows promising benefit to **learn by physical model & biomedical knowledge + data** than PPG data alone

Recap: Exploiting Micro-Signals

Coming from environment

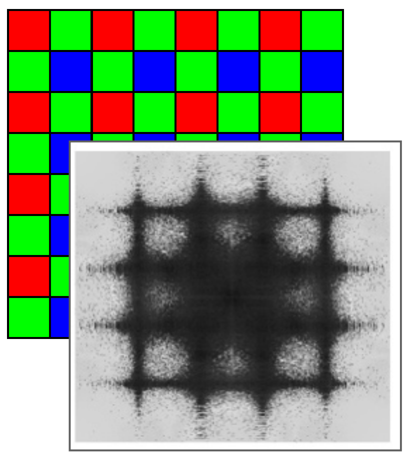


- Harnessing "Micro Signals" in media data: from forensics to health analytics
- Visual approach inspires an improved use of micro signals beyond the media domain



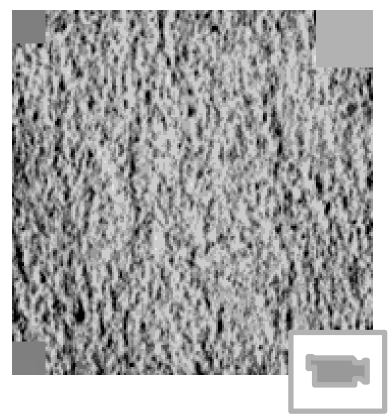
Embed invisible tracer

- *Label each copy*
- *Deter leak & illicit distribution*



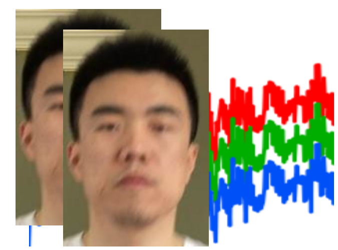
Intrinsic from Device

- *How was an image generated? Tampered?*

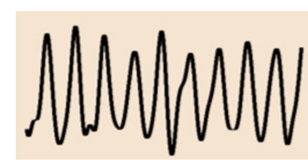


Unclonable object surfaces

- *Verify by cellphone camera to detect counterfeit*



Face color signal from motion video



Physiological monitoring

- *Heart rate, etc.*