VIRGINIA TECH
TRANSPORTATION INSTITUTE

COLLEGE OF ENGINEERING
BRADLEY DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING
VIRGINIA TECH

TUTORIAL PRESENTATION

UBIQUITOUS HEALTH MONITORING AND ASSESSMENT OF HUMAN PSYCHOPHYSIOLOGY USING REMOTE MEASUREMENT AND AI

ABHIJIT SARKAR AND LYNN ABBOTT

AHFE 2025 International Conference
July 26-30, 2025 - Orlando, Florida

INTRODUCTION

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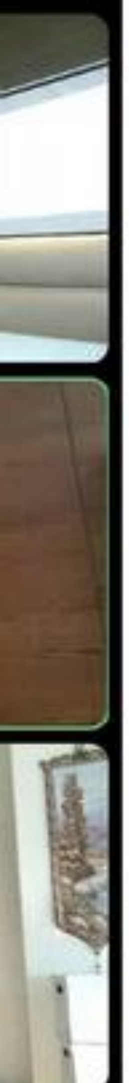


PURPOSE OF THIS TUTORIAL

- To describe new technologies for measuring vital signs, particularly noncontact ("remote") methods
- Current state and challenges in ubiquitous health monitoring
- To describe how measurement of vital signs can be useful for diverse applications
- How AI is changing the landscape of health monitoring?

A. LYNN ABBOTT, PHD

PROFESSOR, DEPARTMENT OF ECE, VIRGINIA TECH

ABOUT VIRGINIA TECH

- Virginia Polytechnic Institute and State University
- Founded in 1872
- 38,800 students
- 2,580 instructional faculty members (both full-time and part-time)
- $590 million in sponsored research expenditures (ranks 35th among public universities in the National Science Foundation's annual survey of higher education research expenditures)
- Departments represented here:
  - Electrical and Computer Engineering
  - Computer Science

VIRGINIA TECH

RESEARCH TEAM

- Abhijit Sarkar
- Lynn Abbott
- Yogesh Deshpande (G)
- Surendrabikram Thapa (G)
- Fulan Li
- Ishtiaque Khan
- Gayatri Bhatambarekar
- Jonathan Tyler
- Zeeshan Karamat
- Ayush Sadekar
- Shreyas Bhat










ABHIJIT SARKAR, PHD

SENIOR RESEARCH ASSOCIATE, TEAM LEADER
VTTI

With a legacy of innovation and pioneering approaches, we are the global destination for mobility research.

300+	researchers dedicating their lives to saving lives
$1B	of infrastructure accessible to VTTI and partners
$150M	in infrastructure managed by VTTI
$50M	annual research portfolio supporting 100s of sponsors
70M	miles of naturalistic driving data
>1M	hours of car naturalistic driving data
3,000	studies completed
4,000	instrumented vehicles
30,000	hours of data collected on Virginia Smart Roads

VIRGINIA TECH
TRANSPORTATION INSTITUTE

For VTTI, innovation is a team sport.

For a more complete list of our 200+ partners, check out our website at: https://www.vtti.vt.edu/about/partners-sponsors.html

Facilities & Resources

Virginia Smart Roads

- Opened in 2000; co-sponsored with VDOT and operated by VTTI
- First road built specifically with research in mind
- Nearly 14 miles of closed test track among the combined sections
- DGPS; 8 DSRC and 4 C-V2X / 5G RSUs

Other Test Track Resources

- Virginia International Raceway (Alton, VA)
- Several of our strong partners have world-class test tracks and proving grounds available to support task order research

Surface Street
(urban)
Intersections, merging areas, roundabouts, ADS compatible pavement markings (temporary)

Highway
Weather-making capabilities (rain, snow, and fog), variable lighting, full DGPS

Rural Roadway
Built to older standards with more challenging roadway environments

Smart Roads Capabilities

Rural Roadway



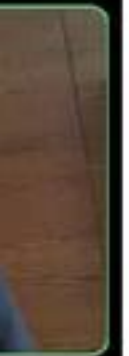

Highway




TUTORIAL AGENDA

UBIQUITOUS HEALTH MONITORING

- Ubiquitous health monitoring: 15 minutes (Sarkar, Abbott)
- Scope: 15 min (Abbott)
- Applications: 15 min (Sarkar)
- Existing methods (Non – Camera based): 25 min (Abbott)
- Camera based rPPG methods: 35 min (Sarkar)
- Resources, conclusion, and discussion: 10 mins


UBIQUITOUS HEALTH MONITORING

SESSION 2

WE ARE INCREASINGLY AWARE OF OUR HEALTH

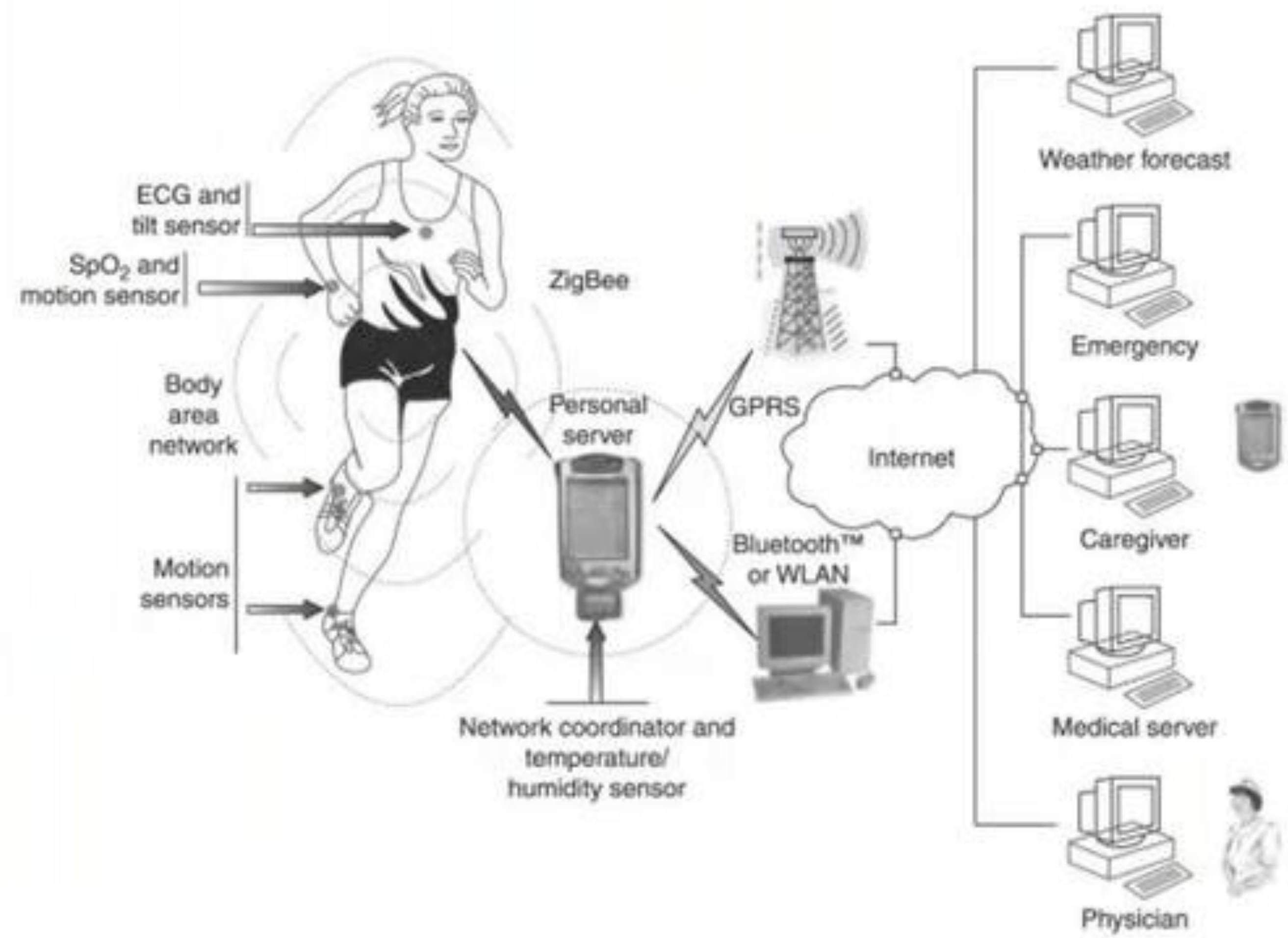
COGNITIVE AND PHYSICAL LOAD

- Monitor psychophysiology
  - Improve performance
  - Improve safety
  - Improve lifestyle
- How to measure them?
  - Individually
  - Collectively
  - Continuously

Images from: amazon.com, flickr.com

UBIQUITOUS HEALTH MONITORING

- Connecting multiple technology and service providers
- Use the power of data
- Use the power of AI
- Use the power of connectivity



Crean, C., Mcgeouge, C., & O'kennedy, R. (2012). Wearable biosensors for medical applications. In *Biosensors for Medical Applications* (pp. 301-330). Woodhead publishing.

WEARABLES ARE GREAT SOURCE OF INFORMATION ABOUT OUR HEALTH AND LIFESTYLE

WHAT CAN WE MEASURE?

- Heart rate
- Pulse rate
- Breathing rate
- Galvanic skin response
- Electrical activity in brain
- Heart rate variability
- Sleep
- Stress
- Step counts
- SpO2
- Gyroscopic data
- Blood glucose level
- Blood pressure
- ...

Non Invasive measurement – greater usability

UBIQUITOUS HEALTH MONITORING

WHAT IS IT?

Integration: Devices and technologies used are seamlessly integrated into everyday objects, such as wearable devices, smartphones, and even household items like beds or chairs.

Constant Monitoring: It allows for continuous monitoring of health indicators such as heart rate, blood pressure, glucose levels, and more, without the need for active user engagement.

Real-Time Data: Provides real-time feedback and data to both users and healthcare providers, enabling immediate response to potential health issues and facilitating timely medical intervention.

Predictive Analytics: Utilizes AI and machine learning to analyze the vast amount of data collected, predicting potential health issues before they become critical.

Personalization: The data collected can be used to tailor health and wellness strategies to the individual's specific needs, bring awareness, optimizing personal health outcomes.

UBIQUITOUS HEALTH MONITORING

KEY COMPONENTS?

- Wearables
- Mobile applications
- Vital signs monitors
- Internet of things
- Other appliances
- Demographics and history
- Medical records
- AI and data analysis
- Cloud Computing
- Privacy
- Video streaming
- Social media
- Voice/ text communications
- Lifestyle logs

UBIQUITOUS HEALTH MONITORING

APPLICATIONS

- Elder care
- Child care
- Special needs (Autism)
- Remote patient monitoring
- Recovery tracking
- Pandemic prediction
- Resource allocations
- Efficient scheduling
- Lifestyle coaching
- Workplace stress monitoring
- Work-life balance

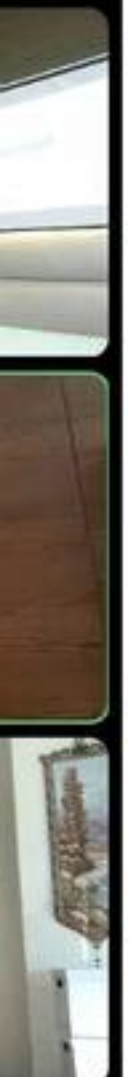
ONE MOTIVATION FOR UBIQUITOUS HEALTH MONITORING:

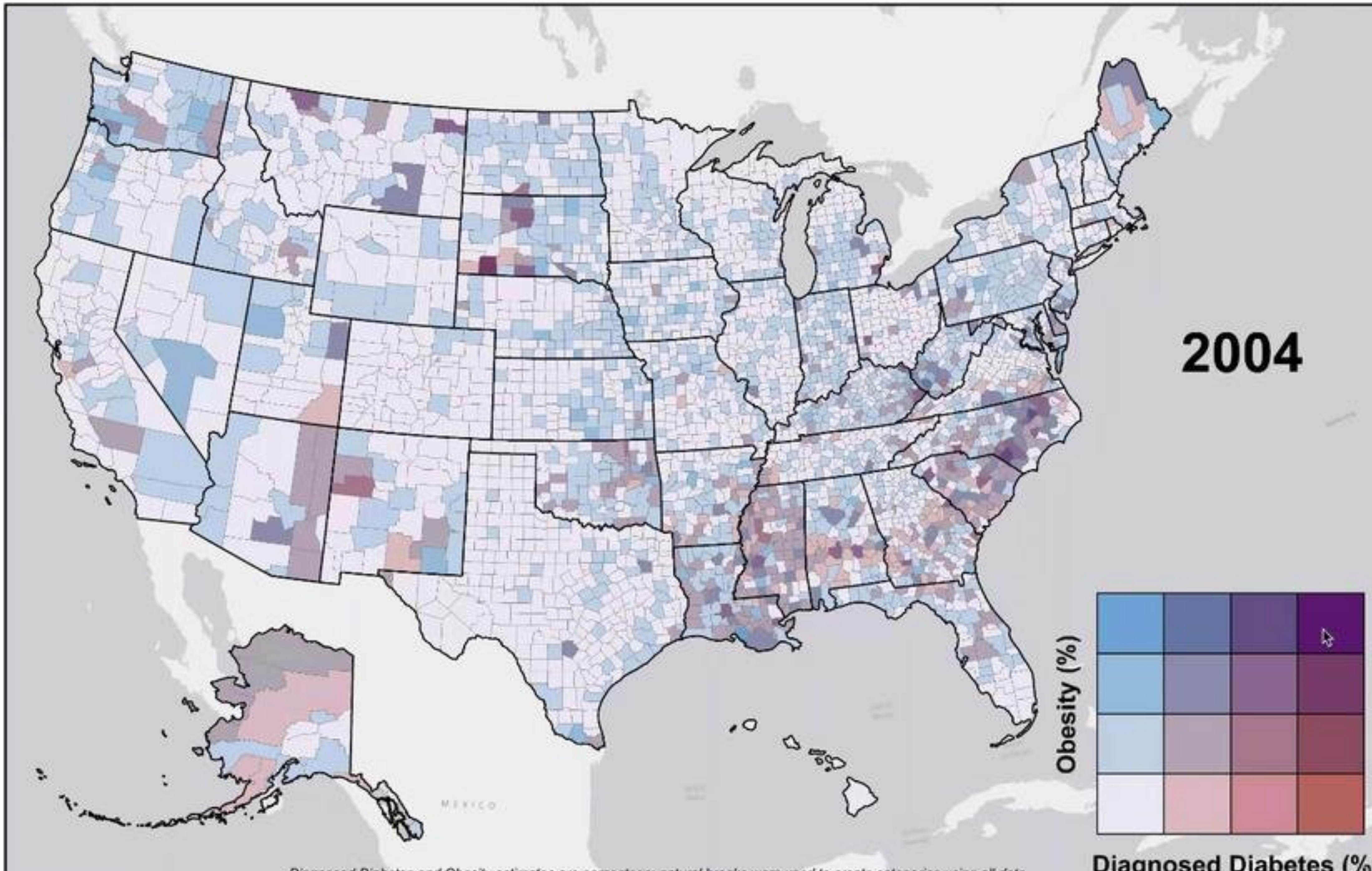
INCREASING PREVALENCE OF DIABETES AND OBESITY

- The following slides were prepared by the US Centers for Disease Control (CDC)

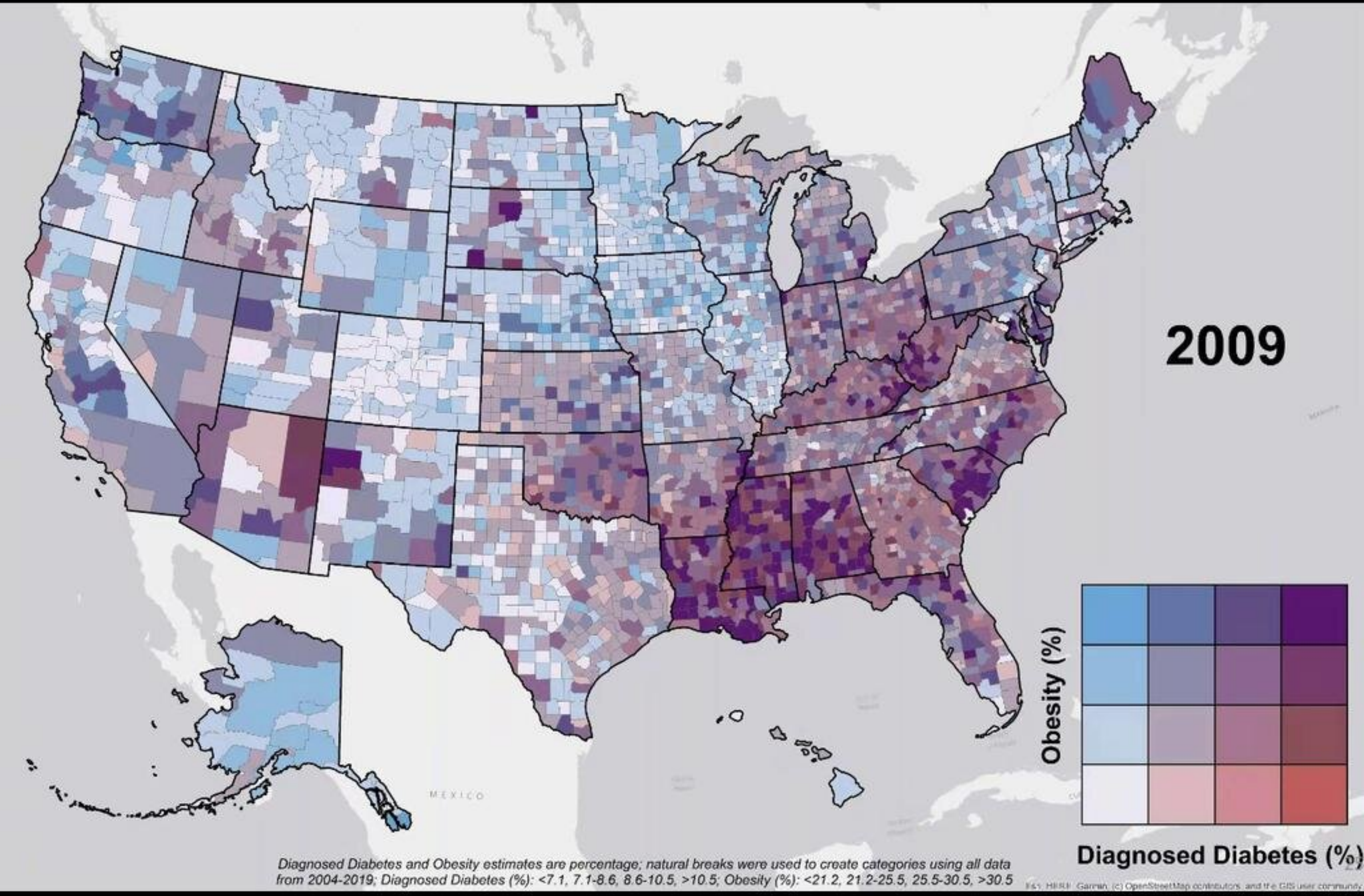
CDC's National Center for Chronic Disease Prevention and Health Promotion

Age-Adjusted Prevalence of Diagnosed Diabetes and Obesity Among Adults, by County, United States (2004, 2009, 2014, 2019)

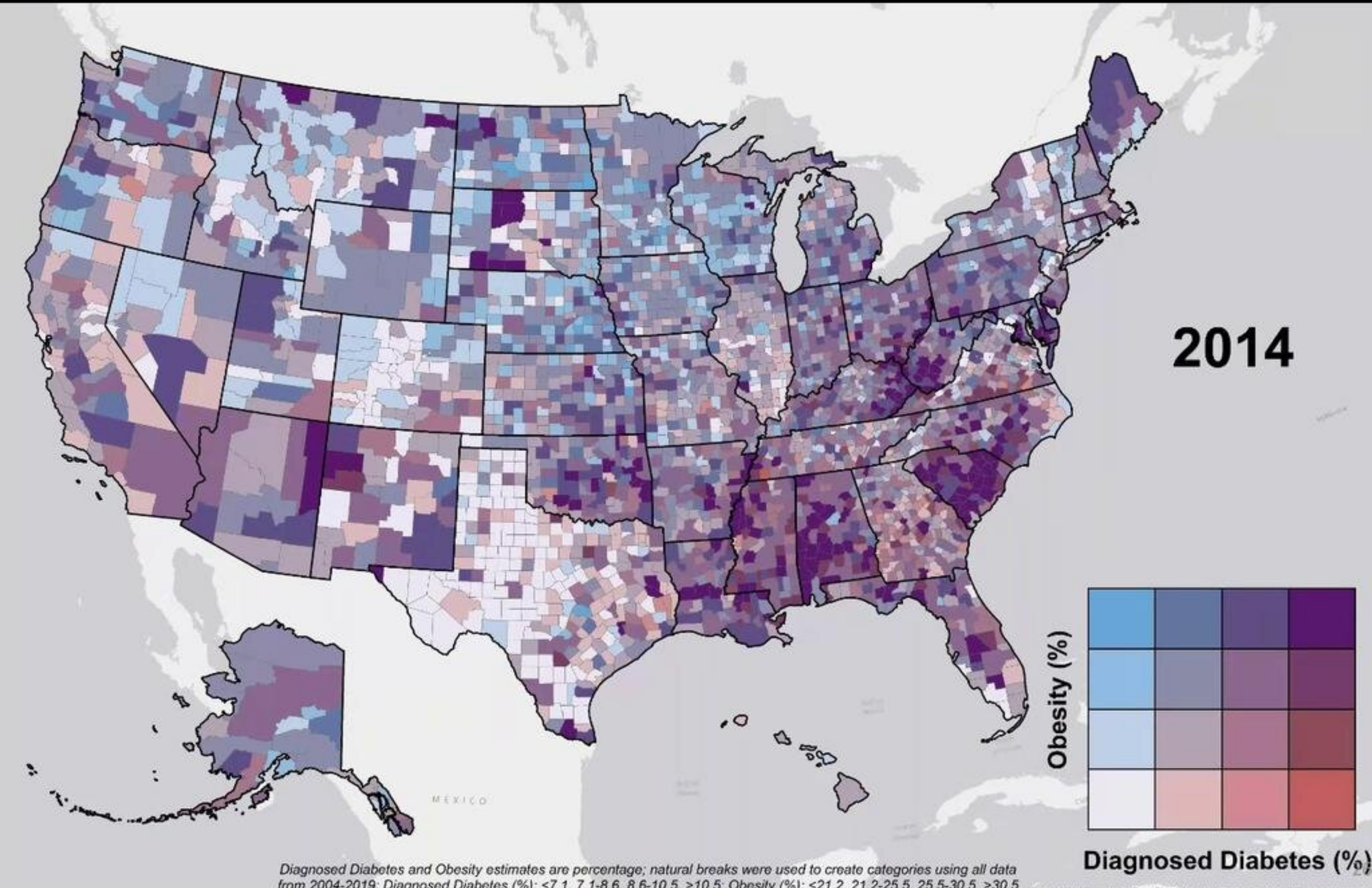




Diagnosed Diabetes and Obesity estimates are percentage; natural breaks were used to create categories using all data from 2004-2019; Diagnosed Diabetes (%): <7.1, 7.1-8.6, 8.6-10.5, >10.5; Obesity (%): <21.2, 21.2-25.5, 25.5-30.5, >30.5



2009
Obesity (%)
Diagnosed Diabetes (%)
MEXICO
Diagnosed Diabetes and Obesity estimates are percentage; natural breaks were used to create categories using all data from 2004-2019; Diagnosed Diabetes (%): <7.1, 7.1-8.6, 8.6-10.5, >10.5; Obesity (%): <21.2, 21.2-25.5, 25.5-30.5, >30.5



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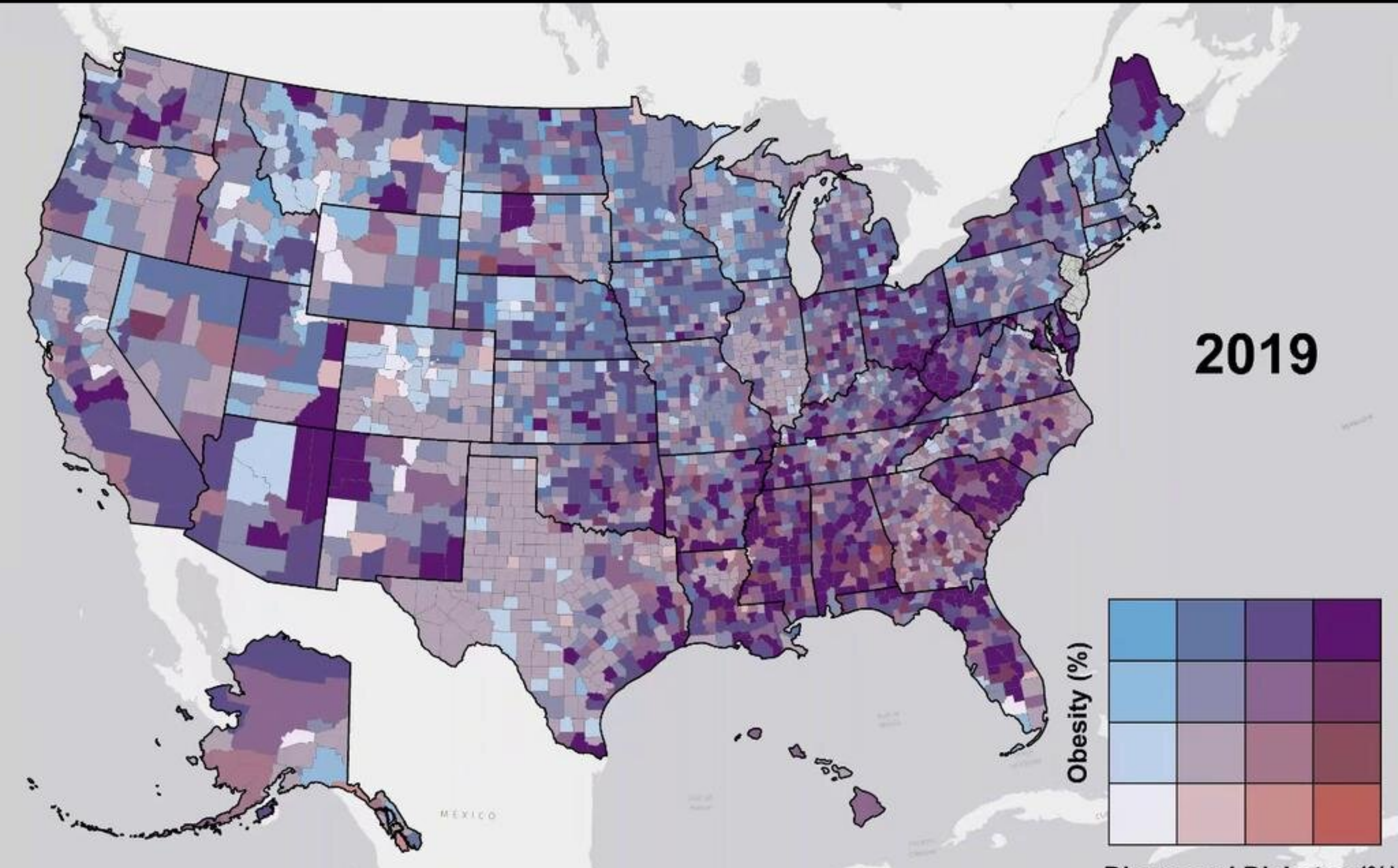

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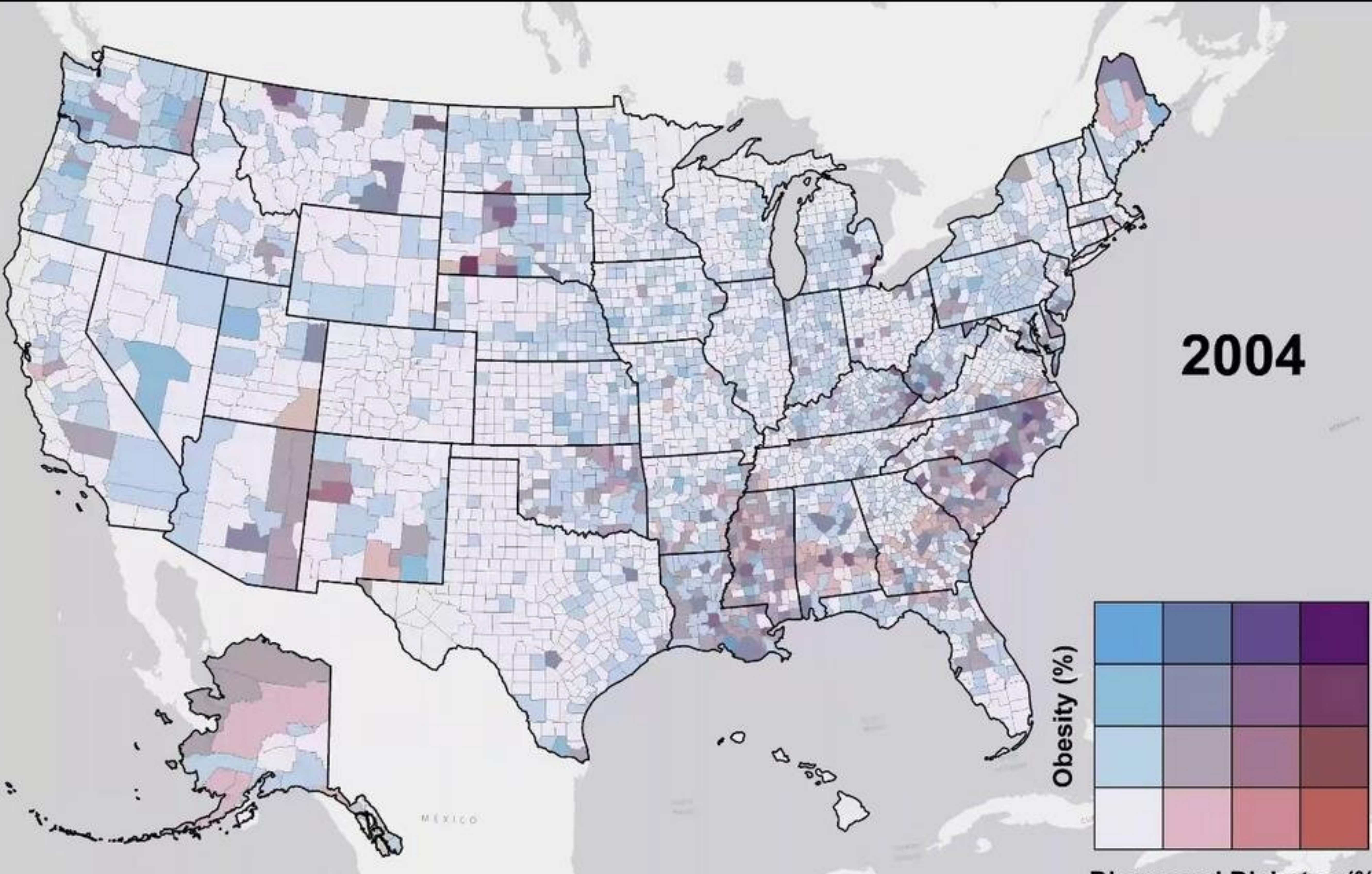

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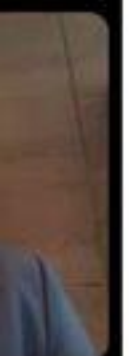
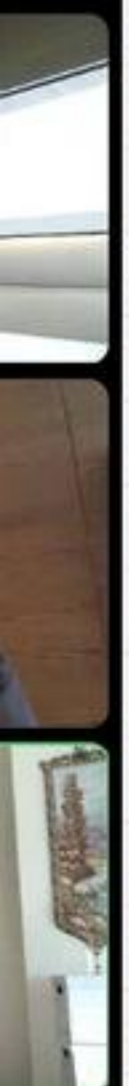


SUMMARY

- Ubiquitous health monitoring is becoming possible, thanks to advances in technology

- Ubiquitous health monitoring has the potential to improve health, safety, and quality of life both individually and collectively

END OF SESSION 2



CONTACT INFORMATION

Thank you!

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  ASarkar@vtti.vt.edu
  asarkar1@vt.edu

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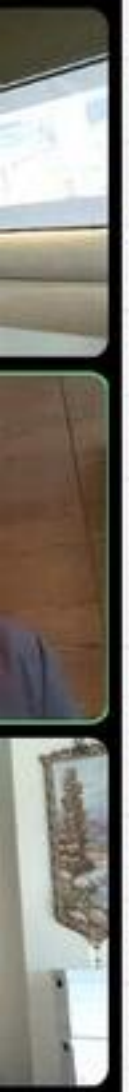

SCOPE OF THIS TUTORIAL

Advancing Transportation through Innovation

TUTORIAL PRESENTATION (PART 2)

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WHY UBIQUITOUS HEALTH MONITORING?

- To promote healthier, happier lives
- To address common health problems (e.g., obesity)
- To assist particular population groups (e.g., infants, elderly, athletes)
- To gain benefits from recent technology

WHAT VITAL SIGNS WILL BE DISCUSSED?

- Heart rate
- Pulse rate
- Respiration rate
- Blood pressure
- . . .

COMMON CONTACT-BASED SENSING METHODS

- Heart rate
- Pulse rate
- Respiration rate
- Blood pressure

[Source: health.clevelandclinic.org]

[Source: healthline.com]

[Source: biopac.com]

[Source: fitbit.com]

NON-CONTACT SENSING METHODS

- Heart rate
- Pulse rate
- Respiration rate
- Blood pressure

(END OF PART 2)



APPLICATIONS

SESSION 4

WHY SHOULD WE MEASURE?

DRIVING EXAMPLE

- Understand psychophysiological condition of a person
  - Cognitive load
  - Drowsiness
  - Effect of Alcohol/ drug / other impairment
  - Customer Satisfaction
  - Effectivity of training
  - Chronic depression

A. Sarkar, A. L. Abbott and Z. Doerzaph, "Assessment of psychophysiological characteristics using heart rate from naturalistic face video data," *IEEE International Joint Conference on Biometrics*, 2014, pp. 1-6, doi: 10.1109/BTAS.2014.6996264.

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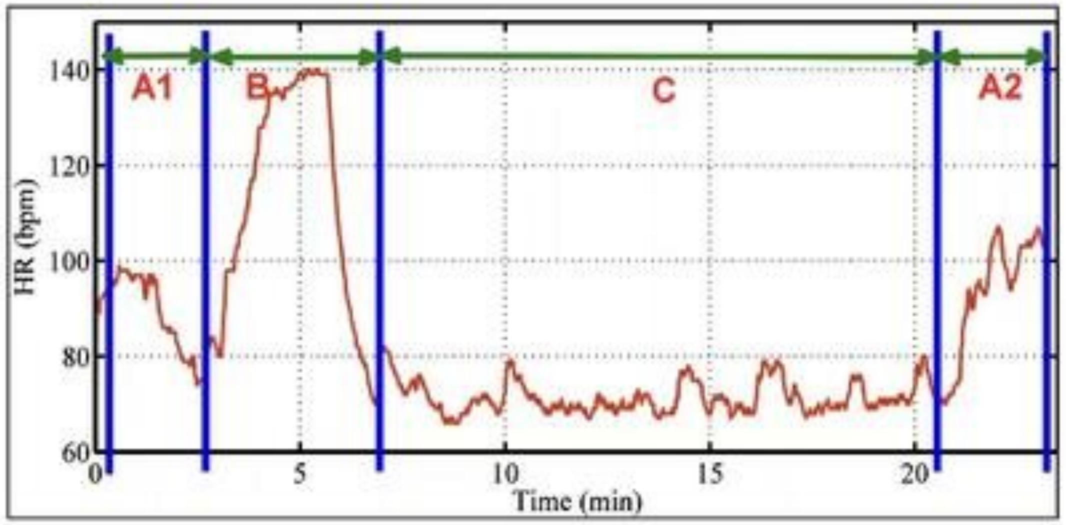
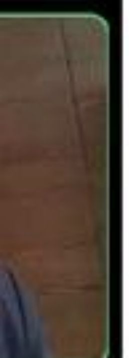


A1 and A2 – City driving – high cognitive load
C – Interstate driving – low cognitive load
B – Panic – High cognitive load

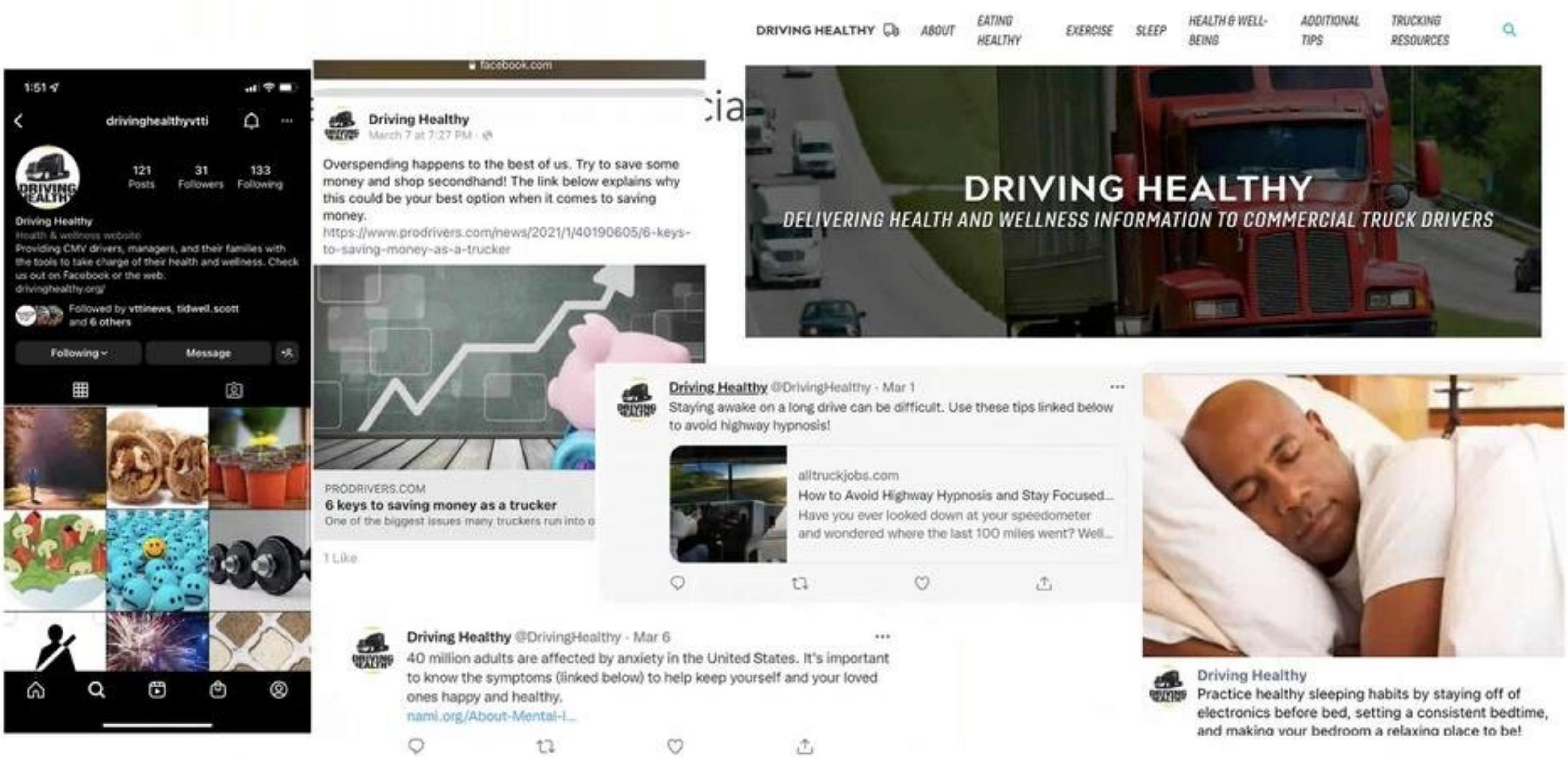
A. Sarkar, A. L. Abbott and Z. Doerzaph, "Assessment of psychophysiological characteristics using heart rate from naturalistic face video data," *IEEE International Joint Conference on Biometrics*, 2014, pp. 1-6, doi: 10.1109/BTAS.2014.6996264.

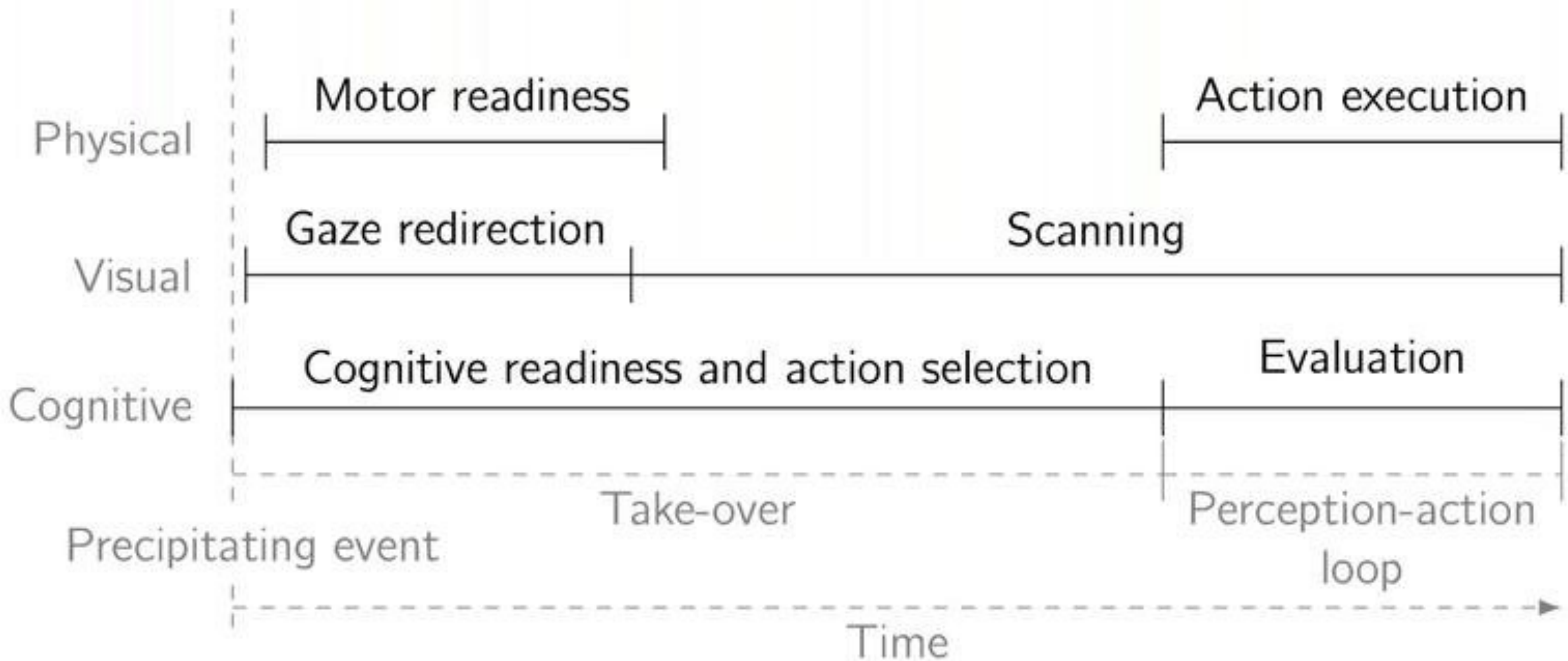

COMMERCIAL DRIVER SAFETY RISK FACTORS STUDY

- Goal: examine driver and situational factors that impact CMV safety
  - Demographic characteristics, work experience, lifestyle and behavioral habits, medical conditions
  - Identify personal, medical, and situational factors that increase crash or violation risk
  - Identify factors associated with presence of obstructive sleep apnea (OSA)
  - Follow CMV drivers' safety records for up to three years
- Demographics
  - 29% overweight; 58% obese
  - 88% not or sometimes on a regular sleep schedule
- Predictive factors for OSA: BMI, hypertension, age, and Berlin Questionnaire
- Drivers being treated for medical conditions were no riskier than drivers without the same medical conditions
  - OSA treatment reduced crash risk ~40%
  - non-treatment increased risk by ~200%

Mabry, J. E., Camden, M., Miller, A., Sarkar, A., Manke, A., Ridgeway, C., ... & Hanowski, R. J. (2022). Unravelling the complexity of irregular shiftwork, fatigue and sleep health for commercial drivers and the associated implications for roadway safety. *International journal of environmental research and public health*, *19*(22), 14780.


1:51
drivinghealthyvtti
121
Posts
31
Followers
133
Following
Driving Healthy
Health & wellness website
Providing CMV drivers, managers, and their families with the tools to take charge of their health and wellness. Check us out on Facebook or the web.
drivinghealthy.org/
Followed by vttinews, tidwell.scott and 6 others
Following
Message
facebook.com
Driving Healthy
March 7 at 7:27 PM
Overspending happens to the best of us. Try to save some money and shop secondhand! The link below explains why this could be your best option when it comes to saving money.
https://www.prodrivers.com/news/2021/1/40190605/6-keys-to-saving-money-as-a-trucker
PRODRIVERS.COM
6 keys to saving money as a trucker
1 Like
DRIVING HEALTHY
ABOUT
EATING HEALTHY
EXERCISE
SLEEP
HEALTH & WELL-BEING
ADDITIONAL TIPS
TRUCKING RESOURCES
DRIVING HEALTHY
DELIVERING HEALTH AND WELLNESS INFORMATION TO COMMERCIAL TRUCK DRIVERS
Driving Healthy @DrivingHealthy · Mar 1
Staying awake on a long drive can be difficult. Use these tips linked below to avoid highway hypnosis!
alltruckjobs.com
How to Avoid Highway Hypnosis and Stay Focused...
Have you ever looked down at your speedometer and wondered where the last 100 miles went? Well...
Driving Healthy @DrivingHealthy · Mar 6
40 million adults are affected by anxiety in the United States. It's important to know the symptoms (linked below) to help keep yourself and your loved ones happy and healthy.
nami.org/About-Mental-I...
Driving Healthy
Practice healthy sleeping habits by staying off of electronics before bed, setting a consistent bedtime, and making your bedroom a relaxing place to be!

DRIVER APPLICATION IN MODERN VEHICLE



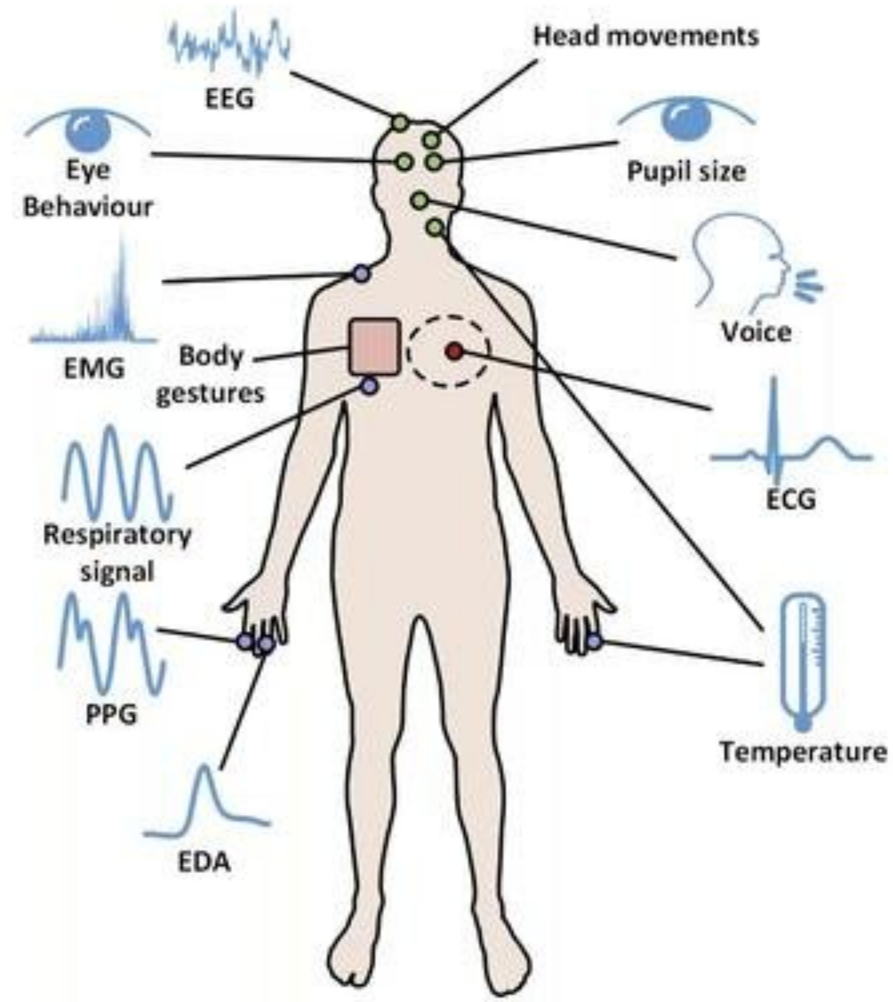
PATIENT MONITORING

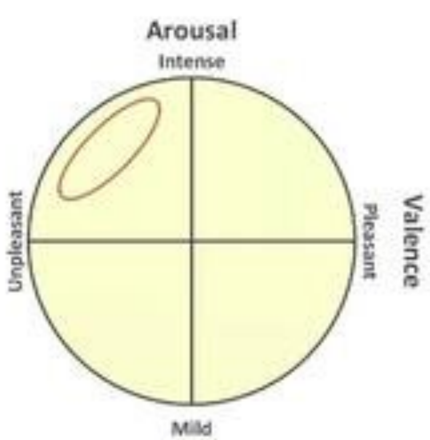
- Continuous monitoring of patients
- Sleep monitoring
- Telehealth
- Health screening (airport)
- Biometrics

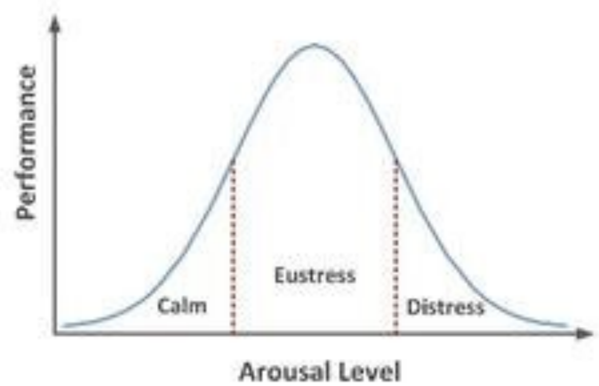
STRESS MEASUREMENT

STRESS MEASUREMENT

- Stress has three major components:
  - Psychological, behavioral, physical
- Biosignal features are involuntary
- Surveys can be biased and manipulated







Giannakakis, G., Grigoriadis, D., Giannakaki, K., Simantiraki, O., Roniotis, A., & Tsiknakis, M. (2019). Review on psychological stress detection using biosignals. *IEEE transactions on affective computing*, *13*(1), 440-460.

AUTONOMIC NERVOUS SYSTEM

- Parasympathetic and sympathetic balance
- Flight or Fight Vs Relax
- Involuntary response
- Reflects stress level

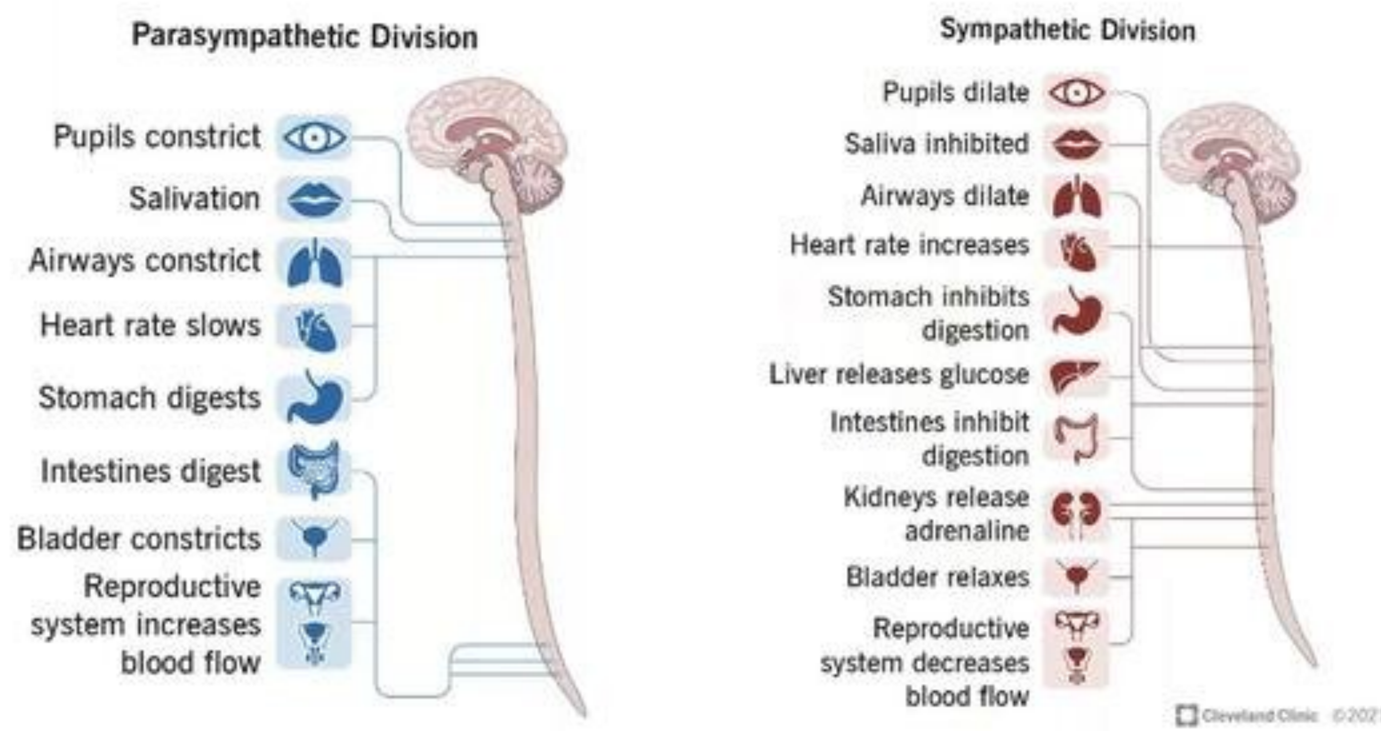


Image: https://my.clevelandclinic.org/health/body/23273-autonomic-nervous-system

THERMAL IMAGING

Temperature Features from Different Body ROI Used in Automatic Stress Detection and Significant Changes During Stress Conditions

Feature	Studies	↑	↓	=
Body	1 [129]	1	0	0
Finger	5 [127], [130], [131], [132], [133]	0	4	1
Whole Facial	5 [130], [131], [134], [135], [136]	4	1	0
Temp variability	1 [133]	0	1	0
Forehead	5 [131], [137], [138], [139]	3	0	2
Periorbital	2 [110], [131]	1	0	1
Nose	3 [131], [132], [140]	0	3	0
Maxillary	2 [135], [139]	0	2	0

↑: significant increase ($p < 0.05$) during stress.
↓: significant decrease ($p < 0.05$) during stress.
=: no difference.

Giannakakis, G., Grigoriadis, D., Giannakaki, K., Simantiraki, O., Roniotis, A., & Tsiknakis, M. (2019). Review on psychological stress detection using biosignals. *IEEE transactions on affective computing*, *13*(1), 440-460.

HEART RATE VARIABILITY

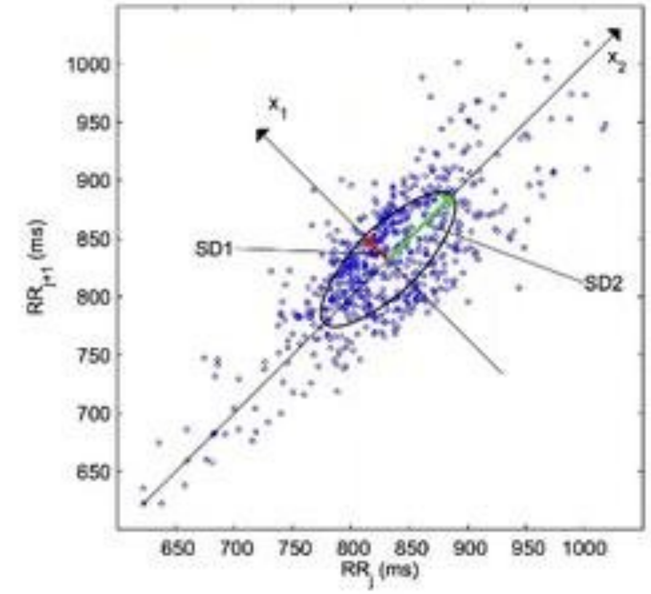
DIFFERENT MEASUREMENTS OF HRV

	Measure	Units	Description	References
Time-Domain	$\overline{RR}$	[ms]	The mean of RR intervals	
	STD RR (SDNN)	[ms]	Standard deviation of RR intervals [Eq. (3.1)]	
	$\overline{HR}$	[1/min]	The mean heart rate	
	STD HR	[1/min]	Standard deviation of intantaneous heart rate values	
	RMSSD	[ms]	Square root of the mean squared differences between successive RR intervals [Eq. (3.3)]	
	NN50		Number of successive RR interval pairs that differ more than 50 ms	
	pNN50	[%]	NN50 divided by the total number of RR intervals [Eq. (3.4)]	
	HRV triangular index		The integral of the RR interval histogram divided by the height of the histogram [44]	
	TINN	[ms]	Baseline width of the RR interval histogram	[44]

Tarvainen, M. P., & Niskanen, J. P. (2012). Kubios HRV. *Finland: Biosignal Analysis and Medical Imaging Group (BSAMIG), Department of Applied Physics, University of Eastern Finland, 39.*

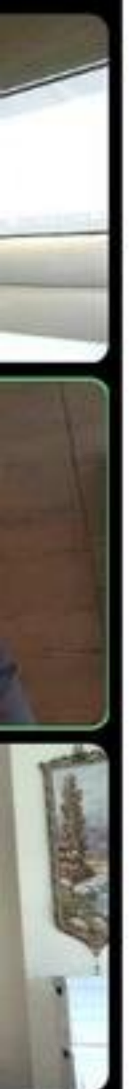
HEART RATE VARIABILITY

DIFFERENT MEASUREMENTS OF HRV



Nonlinear	SD1, SD2	[ms]	The standard deviation of the Poincaré plot perpendicular to (SD1) and along (SD2) the line-of-identity	[6, 7]
	ApEn		Approximate entropy [Eq. (3.11)]	[41, 14]
	SampEn		Sample entropy [Eq. (3.14)]	[41]
	D_2		Correlation dimension [Eq. (3.21)]	[17, 19]
	DFA		Detrended fluctuation analysis:	[37, 38]
	α_1		Short term fluctuation slope	
	α_2		Long term fluctuation slope	
	RPA		Recurrence plot analysis:	[47, 9, 49]
	Lmean	[beats]	Mean line length [Eq. (3.26)]	
	Lmax	[beats]	Maximum line length	
	REC	[%]	Recurrence rate [Eq. (3.24)]	
	DET	[%]	Determinism [Eq. (3.27)]	
	ShanEn		Shannon entropy [Eq. (3.28)]	

Tarvainen, M. P., & Niskanen, J. P. (2012). Kubios HRV. *Finland: Biosignal Analysis and Medical Imaging Group (BSAMIG), Department of Applied Physics, University of Eastern Finland, 39.*



HEART RATE VARIABILITY
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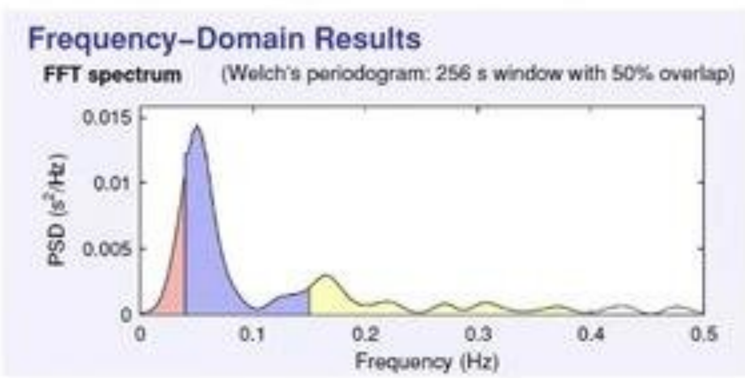
HEART RATE VARIABILITY
DIFFERENT MEASUREMENTS OF HRV



VLF → < 0.04 Hz
LF → > 0.04 Hz and <0.15 Hz
HF → > 0.15 Hz and <0.4 Hz

Frequency-Domain	Peak frequency	[Hz]	VLF, LF, and HF band peak frequencies
	Absolute power	[ms^2]	Absolute powers of VLF, LF, and HF bands
	Relative power	[%]	Relative powers of VLF, LF, and HF bands $\mathrm{VLF}\,[\%] = \mathrm{VLF}\,[\mathrm{ms}^2]/\text{total power}\,[\mathrm{ms}^2] \times 100\%$ $\mathrm{LF}\,[\%] = \mathrm{LF}\,[\mathrm{ms}^2]/\text{total power}\,[\mathrm{ms}^2] \times 100\%$ $\mathrm{HF}\,[\%] = \mathrm{HF}\,[\mathrm{ms}^2]/\text{total power}\,[\mathrm{ms}^2] \times 100\%$
	Normalized power	[n.u.]	Powers of LF and HF bands in normalized units $\mathrm{LF}\,[\mathrm{n.u.}] = \mathrm{LF}\,[\mathrm{ms}^2]/(\text{total power}\,[\mathrm{ms}^2] - \mathrm{VLF}\,[\mathrm{ms}^2])$ $\mathrm{HF}\,[\mathrm{n.u.}] = \mathrm{HF}\,[\mathrm{ms}^2]/(\text{total power}\,[\mathrm{ms}^2] - \mathrm{VLF}\,[\mathrm{ms}^2])$
	LF/HF		Ratio between LF and HF band powers

Tarvainen, M. P., & Niskanen, J. P. (2012). Kubios HRV. *Finland: Biosignal Analysis and Medical Imaging Group (BSAMIG), Department of Applied Physics, University of Eastern Finland, 39.*

Feature	Studies	↑	↓	=
HR	23 [109], [131], [132], [151], [154], [160], [165], [180], [182], [187], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197], [198], [199], [200]	18	0	5
STD HR	1 [198]	0	0	1
RR	8 [180], [198], [200], [201], [202], [203], [204], [205]	0	6	2
SDNN	12 [180], [187], [193], [194], [197], [198], [200], [201], [203], [204], [205], [206]	1	7	4
RMSSD	6 [187], [190], [197], [198], [203], [204]	0	5	1
NN50	2 [187], [200]	0	2	0
pNN50	6 [116], [194], [198], [200], [203], [207]	0	6	0
HRV triangular	2 [198], [200]	0	1	1
Total power	4 [133], [197], [204], [206]	0	4	0
VLF	3 [187], [204]	0	0	3
LF	12 [180], [187], [192], [193], [194], [195], [197], [199], [203], [204], [205], [208]	5	3	4
HF	14 [180], [187], [192], [193], [194], [197], [199], [201], [203], [204], [205], [208], [209], [210]	1	6	7
LF/HF	17 [165], [180], [187], [188], [192], [193], [194], [198], [199], [200], [202], [203], [204], [207], [208], [209], [210]	10	0	7

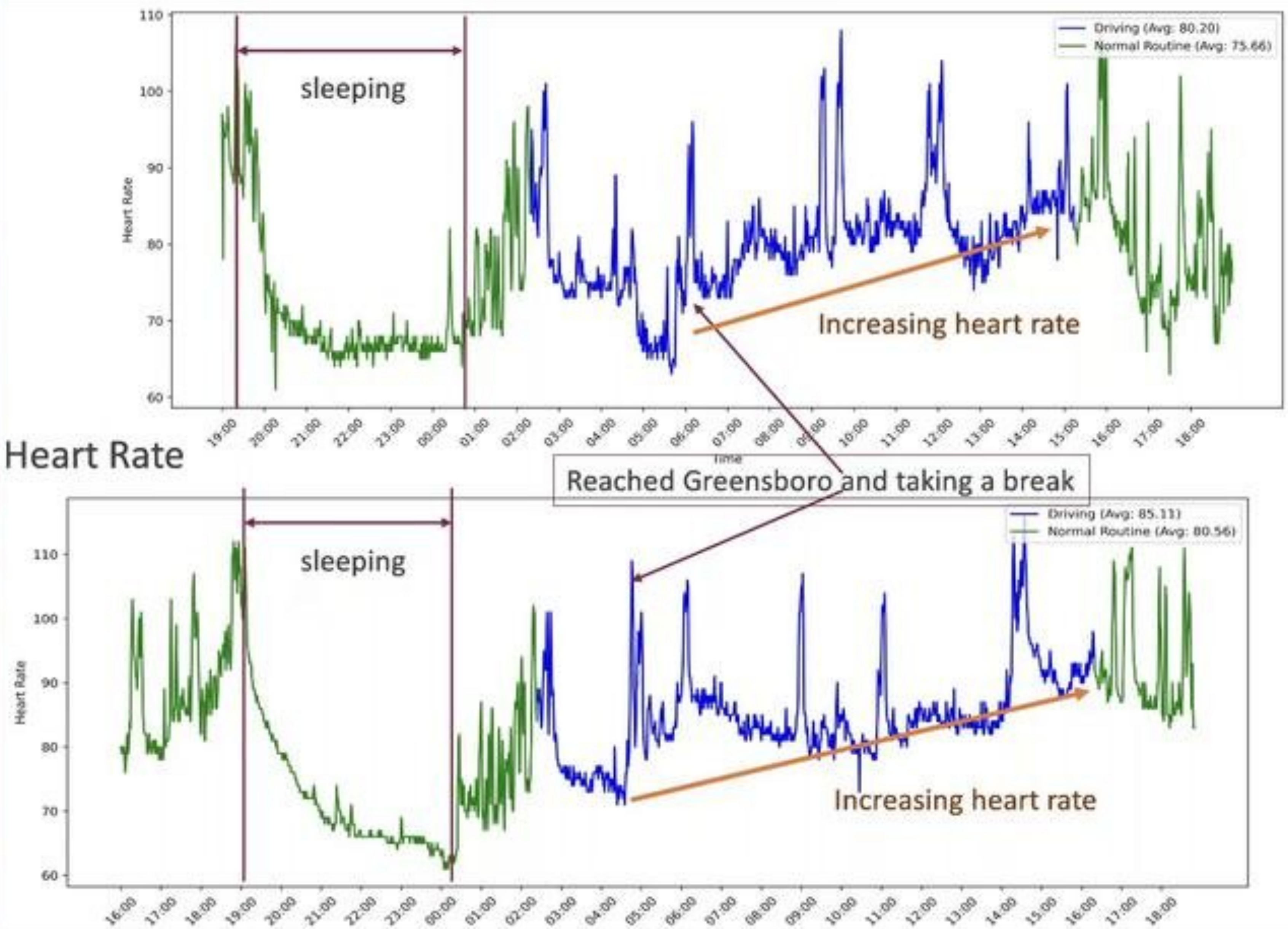
Feature	Studies	↑	↓	=
VLF relative	2 [187], [188]	2	0	0
LF relative	8 [187], [188], [200], [201], [202], [204], [208]	4	1	3
HF relative	7 [187], [200], [201], [202], [204], [208]	0	4	3
SD1	1 [211]	0	0	1
SD2	1 [211]	0	1	0
D2	2 [211]	0	2	0
BR	5 [165], [180], [193], [199], [204]	2	0	3
SBP	15 [129], [132], [151], [154], [160], [188], [189], [190], [191], [195], [201], [206], [212], [213], [214]	15	0	0
DBP	15 [129], [132], [151], [154], [160], [188], [189], [190], [191], [195], [201], [209], [212], [213], [214]	15	0	0
BP HF	1 [206]	1	0	0
ApEn	1 [211]	0	1	0
SampEn	1 [192]	0	0	1

↑: significant increase ($p < 0.05$) during stress.
↓: significant decrease ($p < 0.05$) during stress.
=: no significant difference.

HEART RATE VARIABILITY, BLOOD PRESSURE

Giannakakis, G., Grigoriadis, D., Giannakaki, K., Simantiraki, O., Roniotis, A., & Tsiknakis, M. (2019). Review on psychological stress detection using biosignals. *IEEE transactions on affective computing*, *13*(1), 440-460.

Heart Rate



- Increasing heart rate indicates higher cognitive load
- Before Greensboro, the driver's HR is low. This may indicate low traffic situation in the early morning

BEHAVIORAL CUES FROM CAMERAS

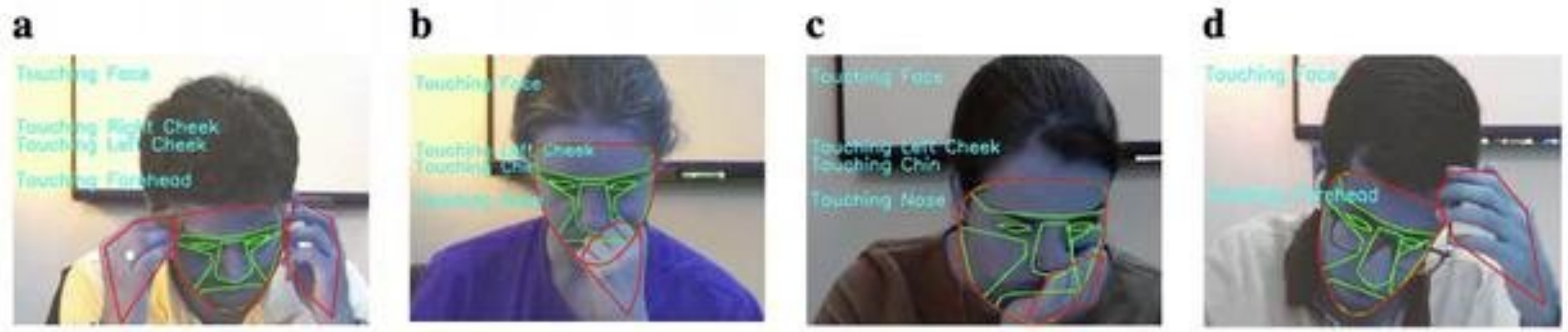


Fig. 2: Examples of sFST from the DKW data set highlighting the diversity of face-hand interactions. In most cases, participants touch their chin, cheeks, and forehead. The annotations in cyan text are provided by the MobileNet CNN and are correct. The snapshots were randomly chosen from the following recordings: [a] Participant T017 in Day 2. [b] Participant T013 in Day 1. [c] Participant T007 in Day 2. [d] Participant T015 in Day 2.

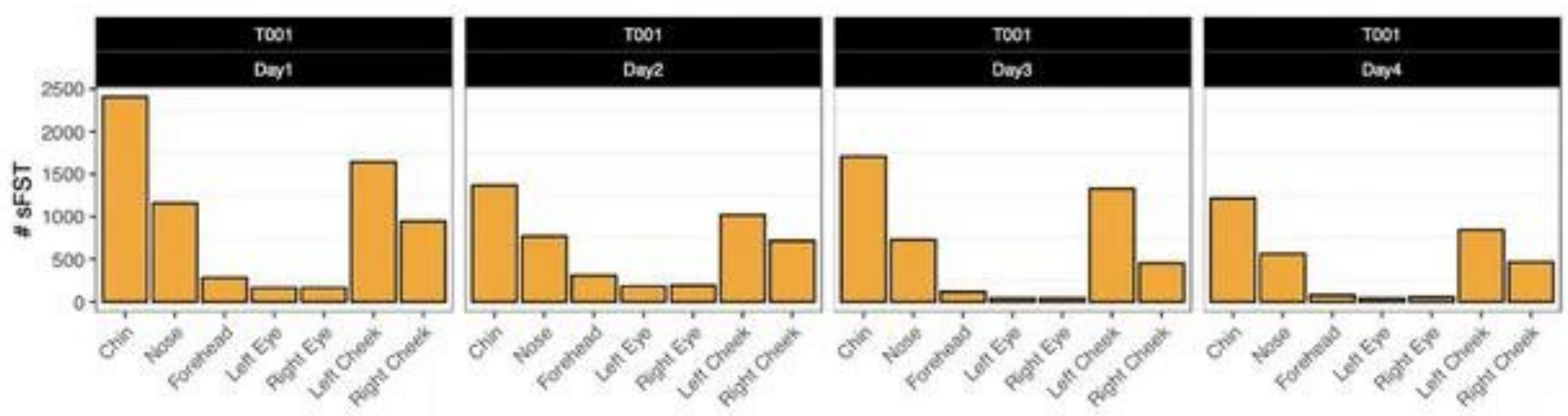


Fig. 3: Distribution of frequencies of sFST for participant T001 during the four days of observation. In all four days, the frequency of touching the left cheek is noticeably bigger than the relative frequency of touching the right cheek. The pattern is representative of all study participants. The said pattern is in agreement with prior reports in the psychological literature, suggesting that sFST are acted predominantly by the non-dominant hand [1]. Consequently, this result serves as a validity check for the goodness of the data and the classification we applied.

CHALLENGES AND CONSIDERATION

- Accessibility
- Privacy and data security
- Subjective biases
- Absolute vs relative measurements
- Complex environment and external stimuli

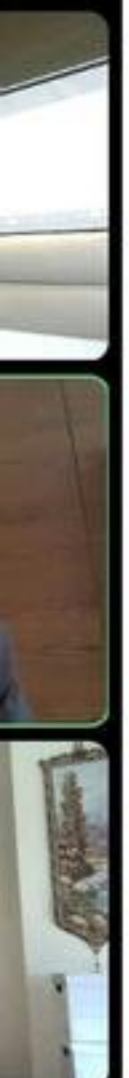
HRV AND RPPG

POSSIBILITIES

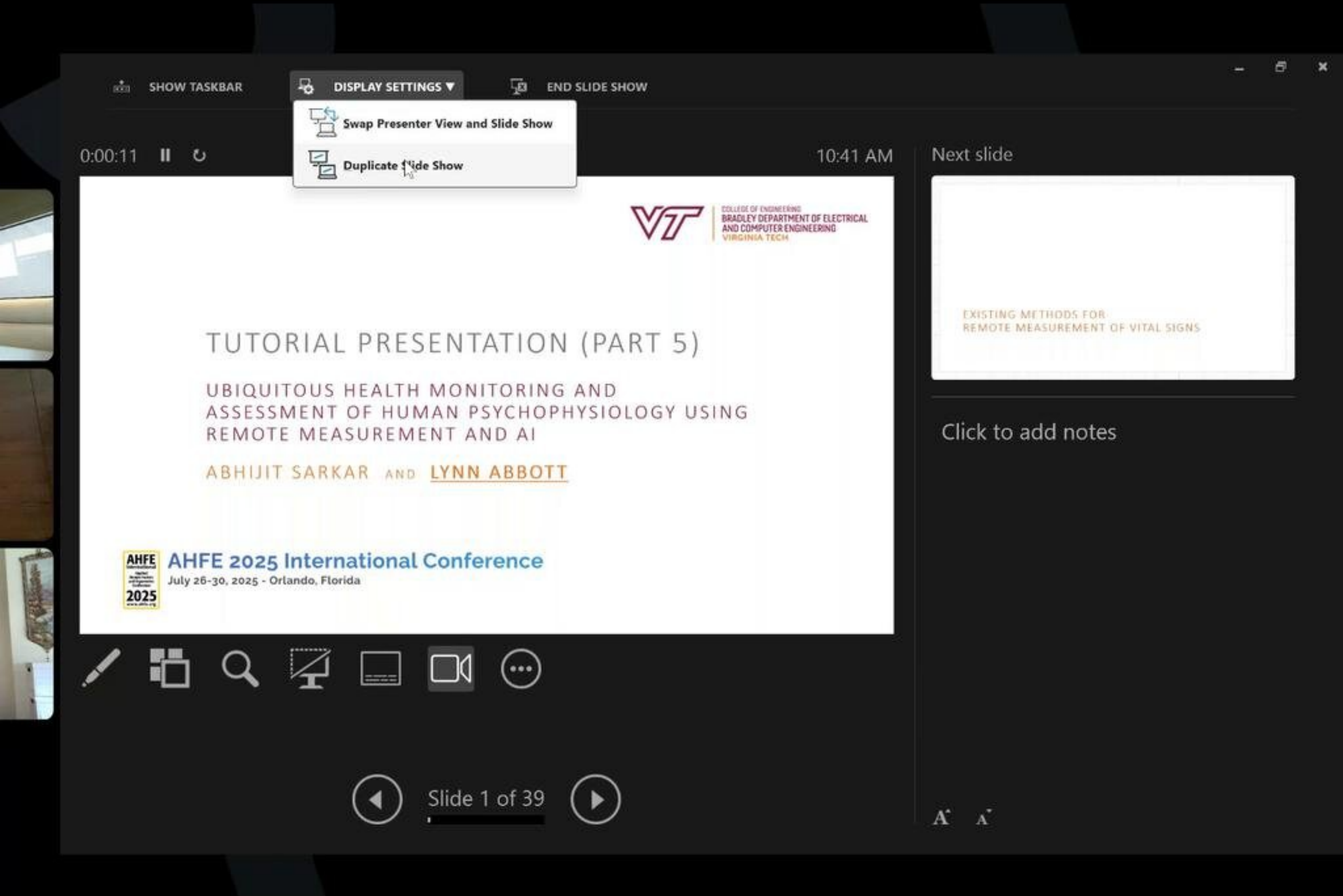
- What if we can use rPPG to measure HRV?
    - We need accurate instantaneous HR information




Asarcikli, L. D., Hayiroglu, M. İ., Osken, A., Keskin, K., Kolak, Z., & Aksu, T. (2022). Heart rate variability and cardiac autonomic functions in post-COVID period. *Journal of Interventional Cardiac Electrophysiology*, *63*(3), 715-721.



END OF SESSION 4


SHOW TASKBAR
DISPLAY SETTINGS ▼
END SLIDE SHOW
Swap Presenter View and Slide Show
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TUTORIAL PRESENTATION (PART 5)
UBIQUITOUS HEALTH MONITORING AND ASSESSMENT OF HUMAN PSYCHOPHYSIOLOGY USING REMOTE MEASUREMENT AND AI
ABHIJIT SARKAR AND LYNN ABBOTT
AHFE 2025
AHFE 2025 International Conference
July 26-30, 2025 - Orlando, Florida
EXISTING METHODS FOR REMOTE MEASUREMENT OF VITAL SIGNS
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Slide 1 of 39

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EXISTING METHODS FOR
REMOTE MEASUREMENT OF VITAL SIGNS

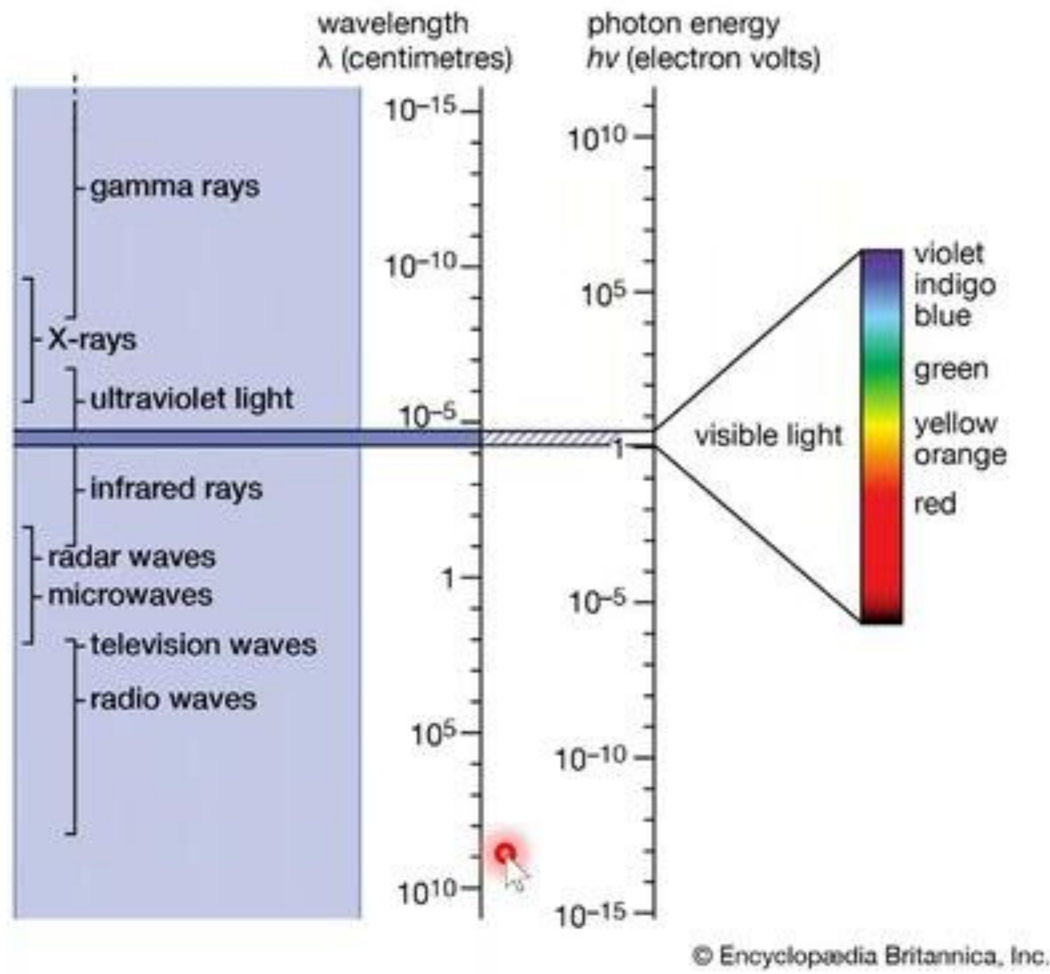
EXISTING METHODS FOR
REMOTE MEASUREMENT OF VITAL SIGNS

WHAT VITAL SIGNS? (REMINDER)

- Heart rate
- Pulse rate
- Respiration rate
- Blood pressure
- . . .

ELECTROMAGNETIC SPECTRUM

Video cameras
Radar
Wi-fi and ultra-wideband



NON-CONTACT SENSING METHODS

- Video camera (visible-light)
- Video camera (infrared)
- Laser Doppler vibrometry (LDV)
- Radar
- Ultra-wideband impulse radio (UWB-IR)
- Wi-Fi

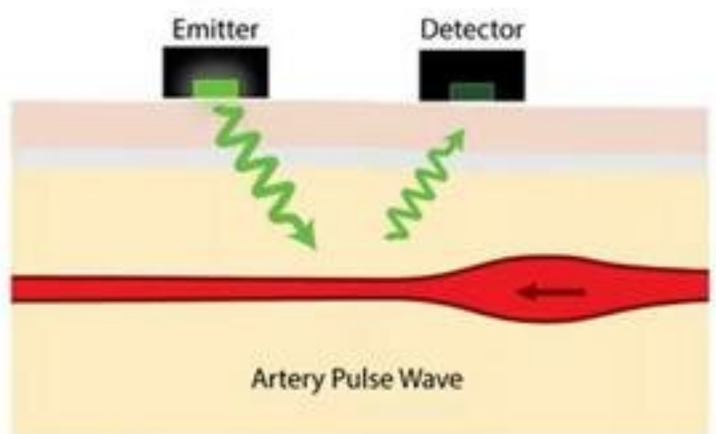
Sense changes in reflectance

Sense motion

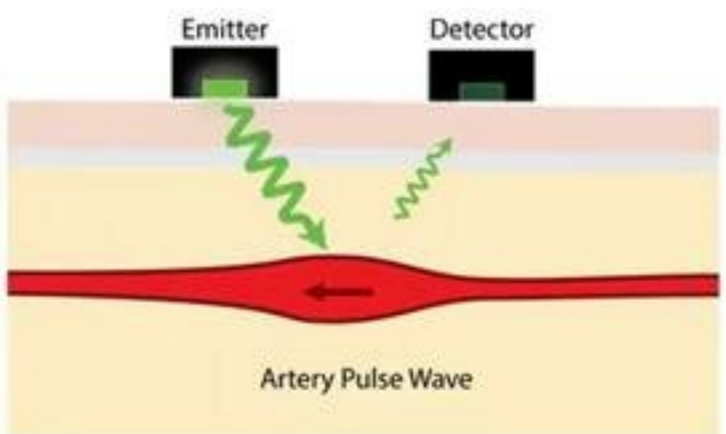
PHOTOPLETHYSMOGRAPHY (PPG)

USE LIGHT TO DETECT
VOLUMETRIC CHANGES IN BLOOD IN PERIPHERAL CIRCULATION

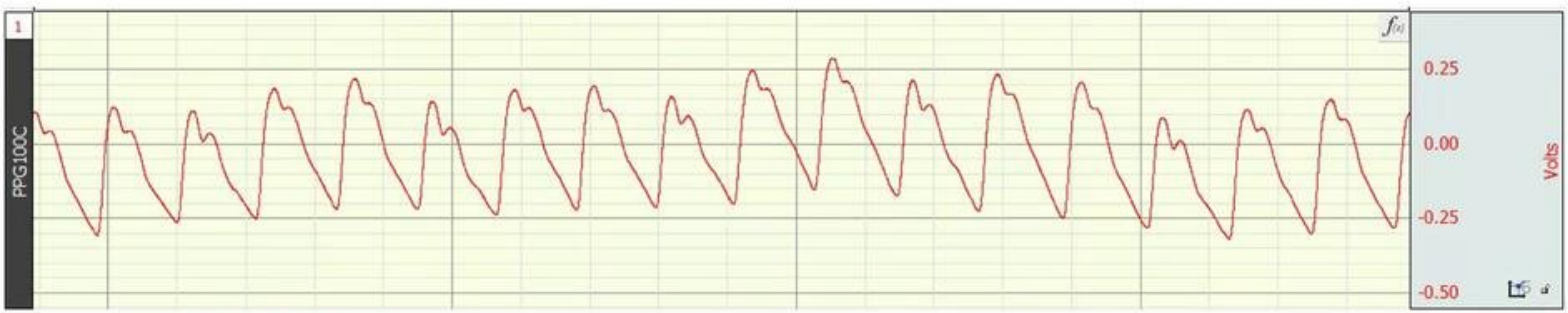
- Contact-based PPG



BVP: Blood Volume Pulse

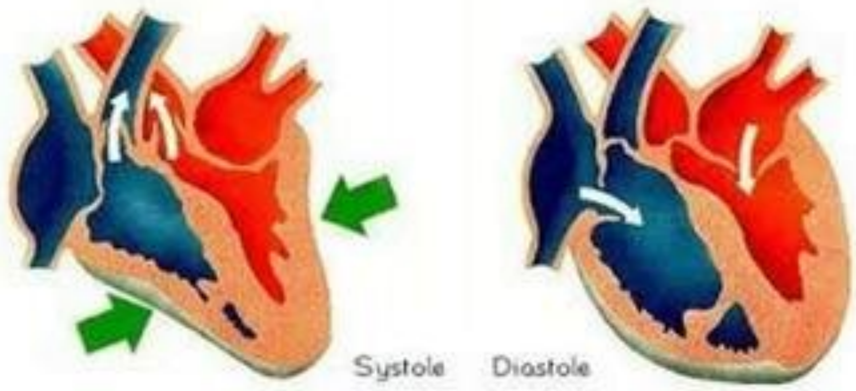


[Source: Collins, TheConversation.com]

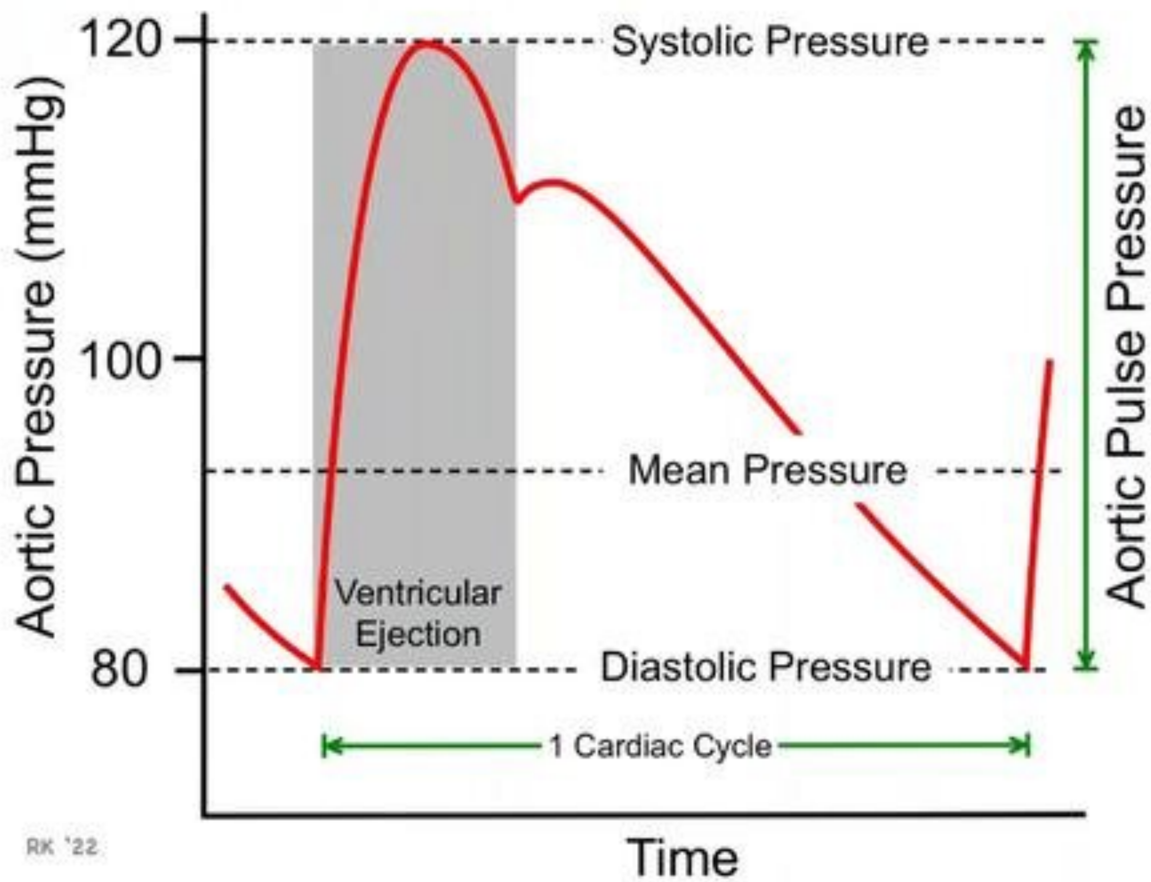


[Source: biopac.com]

DIGRESSION: CARDIAC CYCLE (SIMPLIFIED)

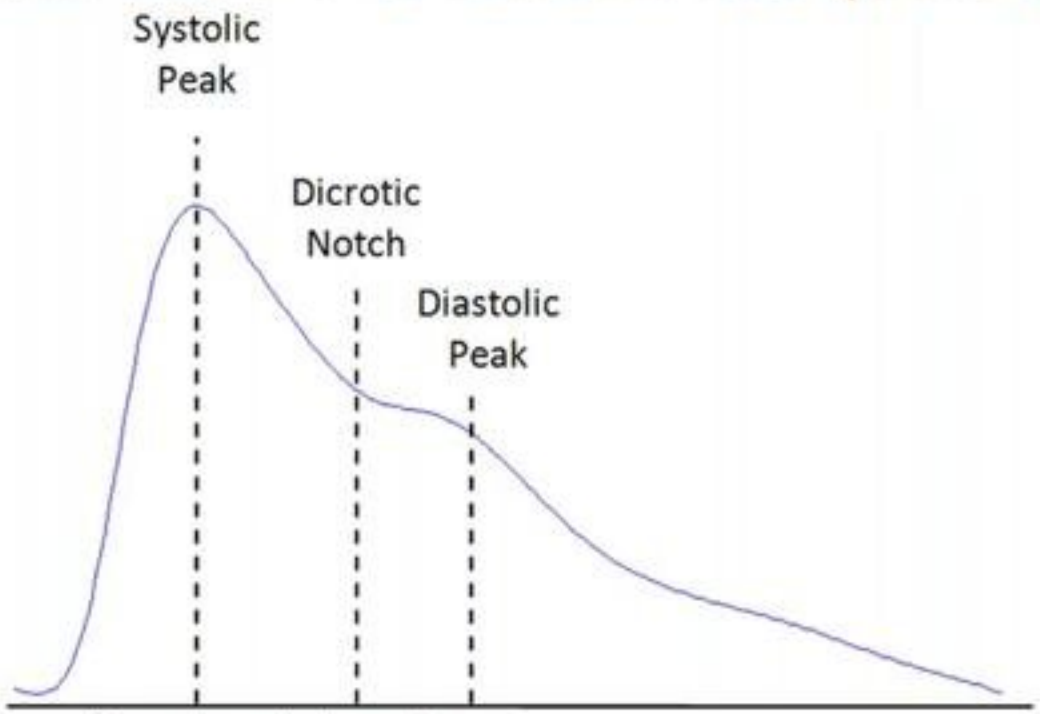


[Source: www.futura-sciences.us]

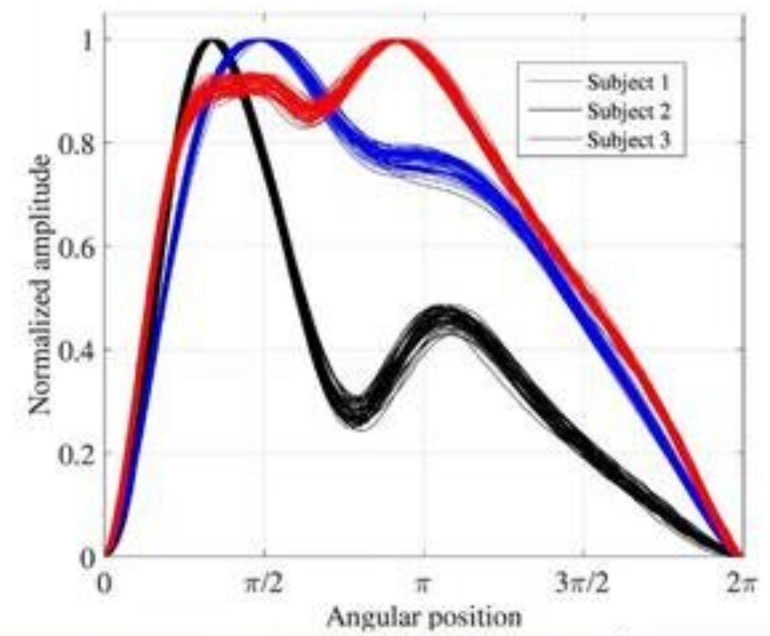


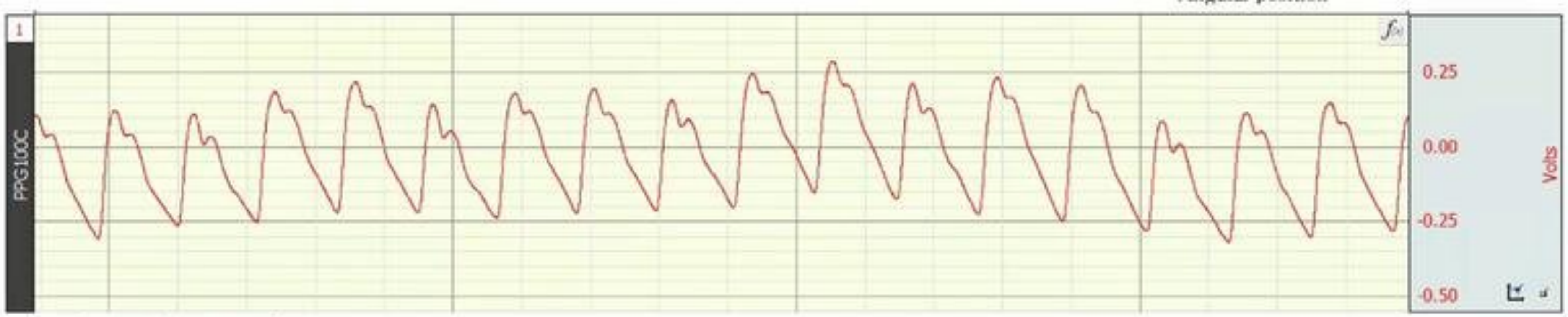
[Source: www.cvphysiology.com]

EXAMPLE PPG SIGNALS (FINGERTIP SENSOR)

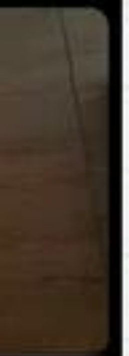


[Source: journals.plos.org]





[Source: biopac.com]


NON-CONTACT SENSING METHODS

- Video camera (visible-light)
- Video camera (infrared)

Sense changes in reflectance

- Laser Doppler vibrometry (LDV)
- Radar
- Ultra-wideband impulse radio (UWB-IR)
- Wi-Fi

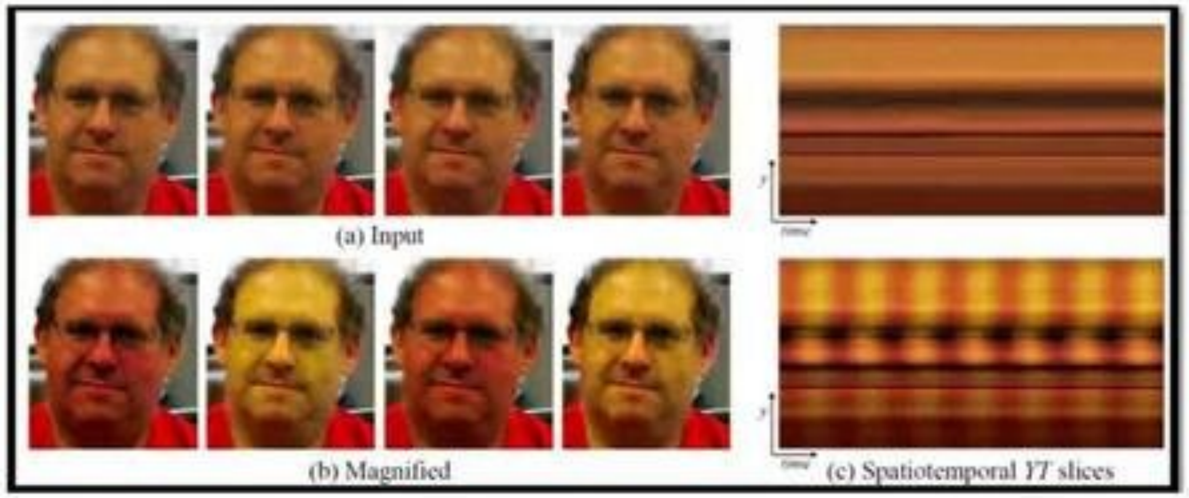
Sense motion

PHOTOPLETHYSMOGRAPHY (PPG)

- Contact-based PPG

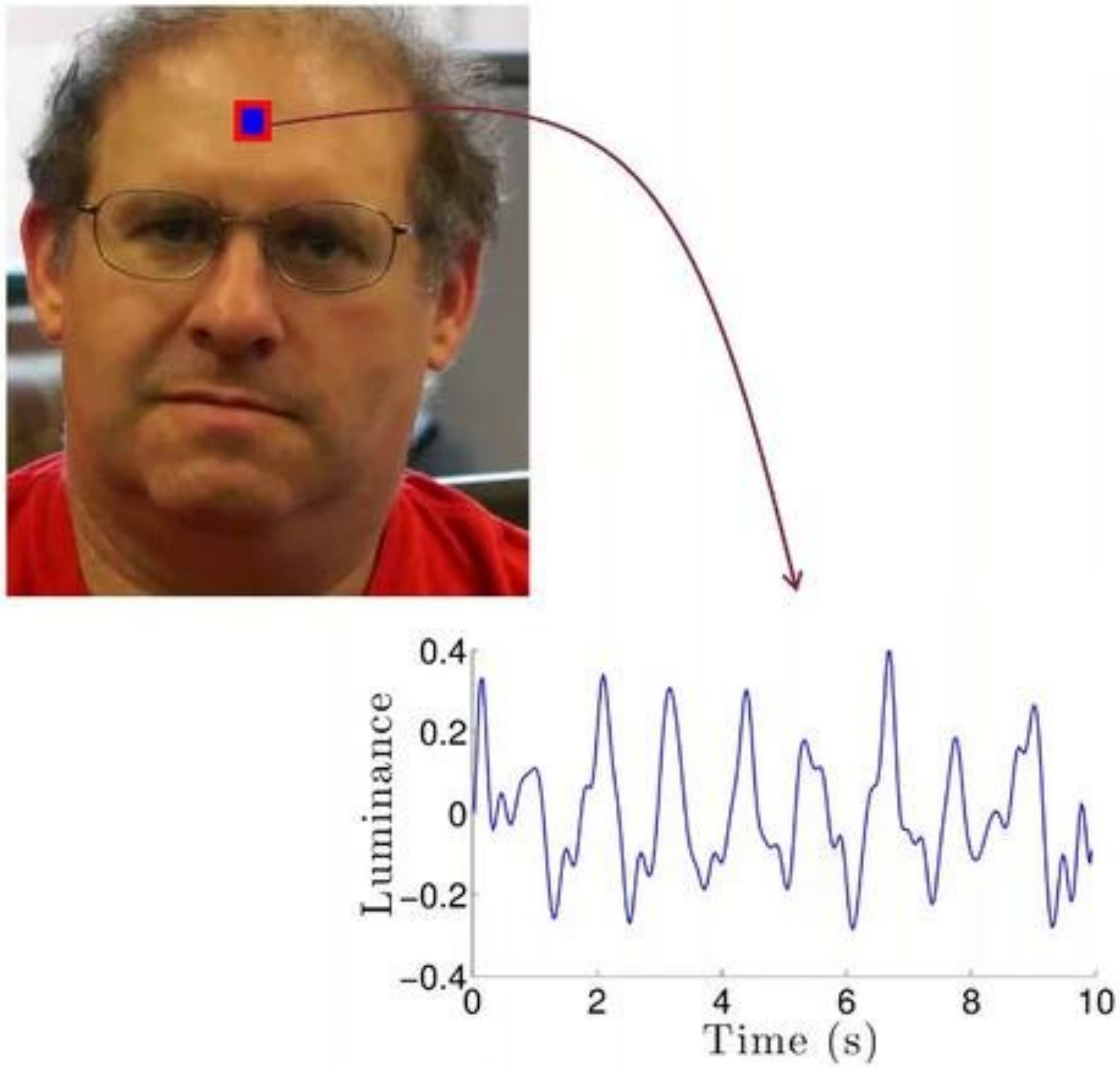
[Source: biopac.com]

- remote PPG (rPPG), also called
- imaging PPG (iPPG)

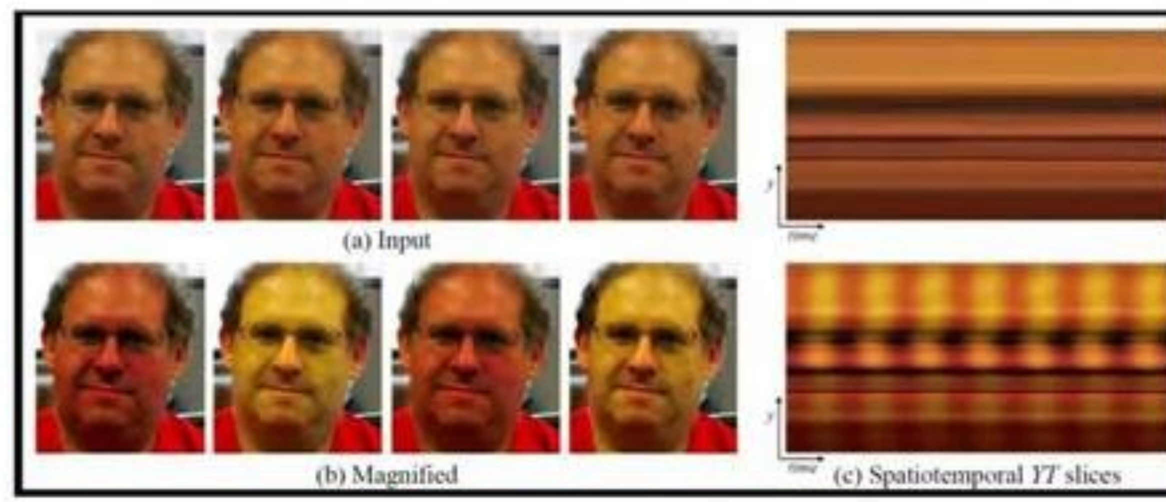


Reference: H.-Y. Wu, M. Rubinstein, E. Shih, J. Guttag, F. Durand, and W. Freeman. "Eulerian video magnification for revealing subtle changes in the world." *ACM Transactions on Graphics,* 31, no. 4 (2012): 1-8.

IMAGING PHOTOPLETHYSMOGRAPHY (IPPG)



- remote PPG (rPPG), also called
- imaging PPG (iPPG)



Reference: H.-Y. Wu, M. Rubinstein, E. Shih, J. Guttag, F. Durand, and W. Freeman. "Eulerian video magnification for revealing subtle changes in the world." *ACM Transactions on Graphics*, 31, no. 4 (2012): 1-8.

IPPG: A MORE RECENT APPROACH

DEEPPHYS

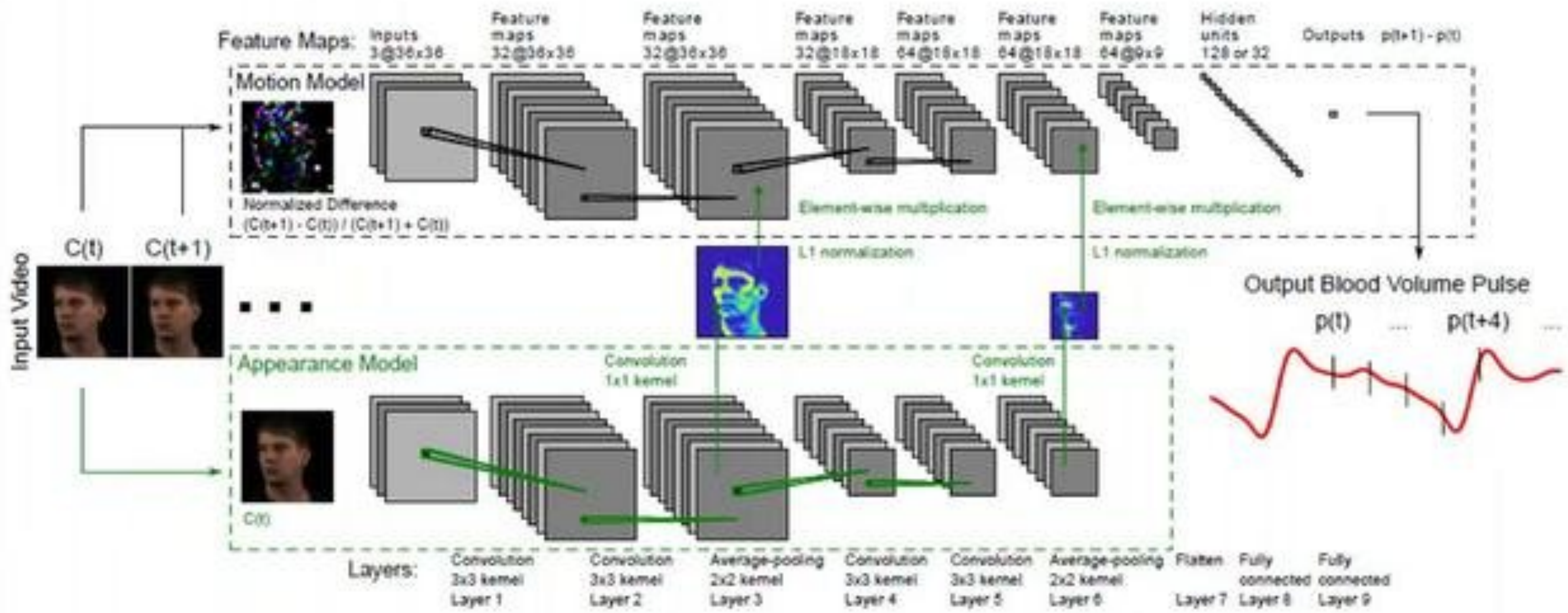
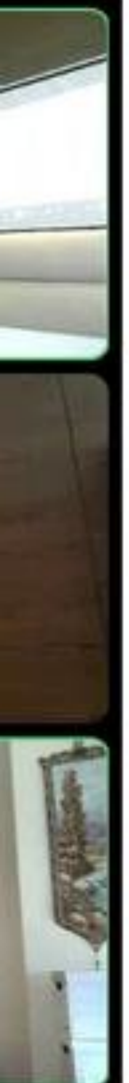


Fig. 2. The architecture of our end-to-end convolutional attention network. The current video frame at time t and the normalized difference between frames at $t+1$ and t are given as inputs to the appearance and motion models respectively. The network learns spatial masks, that are shared between the models, and features important for recovering the BVP and respiration signals.

Reference: W. Chen and D. McDuff. "DeepPhys: Video-based physiological measurement using convolutional attention networks." In *Proceedings of the European Conference on Computer Vision*, pp. 349-365, 2018.



IMAGING PPG: PROS AND CONS

PRO

- Noncontact
- Relatively noninvasive
- Convenient, relatively inexpensive: only a video of the face is needed for extracting a PPG signal
- Long-range sensing may be possible (telephoto lenses)

CON

- To date, iPPG signals are less accurate than contact-based PPG
- Need adequate, consistent illumination
- Movements of the head adversely affect measurement
- Skin must be visible in the video (affected by masks, facial hair, tatoos, etc.)
- Need to assess results for different skin tones

NON-CONTACT SENSING METHODS

- Video camera (visible-light)
- Video camera (infrared)
- Laser Doppler vibrometry (LDV)
- Radar
- Ultra-wideband impulse radio (UWB-IR)
- Wi-Fi

Sense changes in reflectance

Sense motion

LASER DOPPLER VIBROMETRY (LDV)

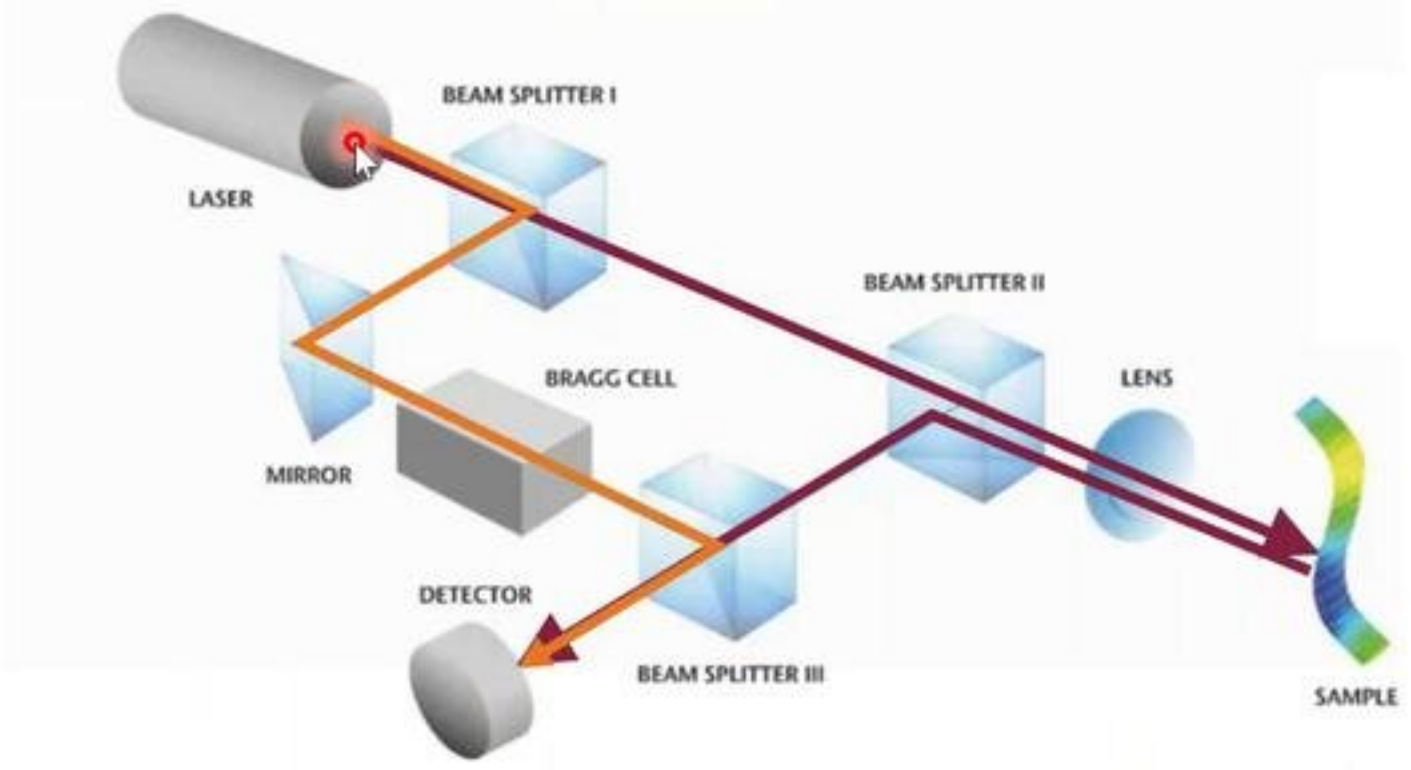
Method:

- Aim a safe, low-power laser at skin overlying a carotid artery
- Blood volume pulses (BVP) cause movement of tissue and skin near these arteries
- Skin movements cause Doppler shifts in reflected laser light, and these shifts can be sensed

[Source: Miami Vascular Specialists]

Reference: A. D. Kaplan, J. A. O'Sullivan, E. J. Sirevaag, P.-H. Lai, and J. W. Rohrbaugh. Hidden state models for noncontact measurements of the carotid pulse using a laser Doppler vibrometer. *IEEE Transactions on Biomedical Engineering*, 59(3):744–753, 2011.

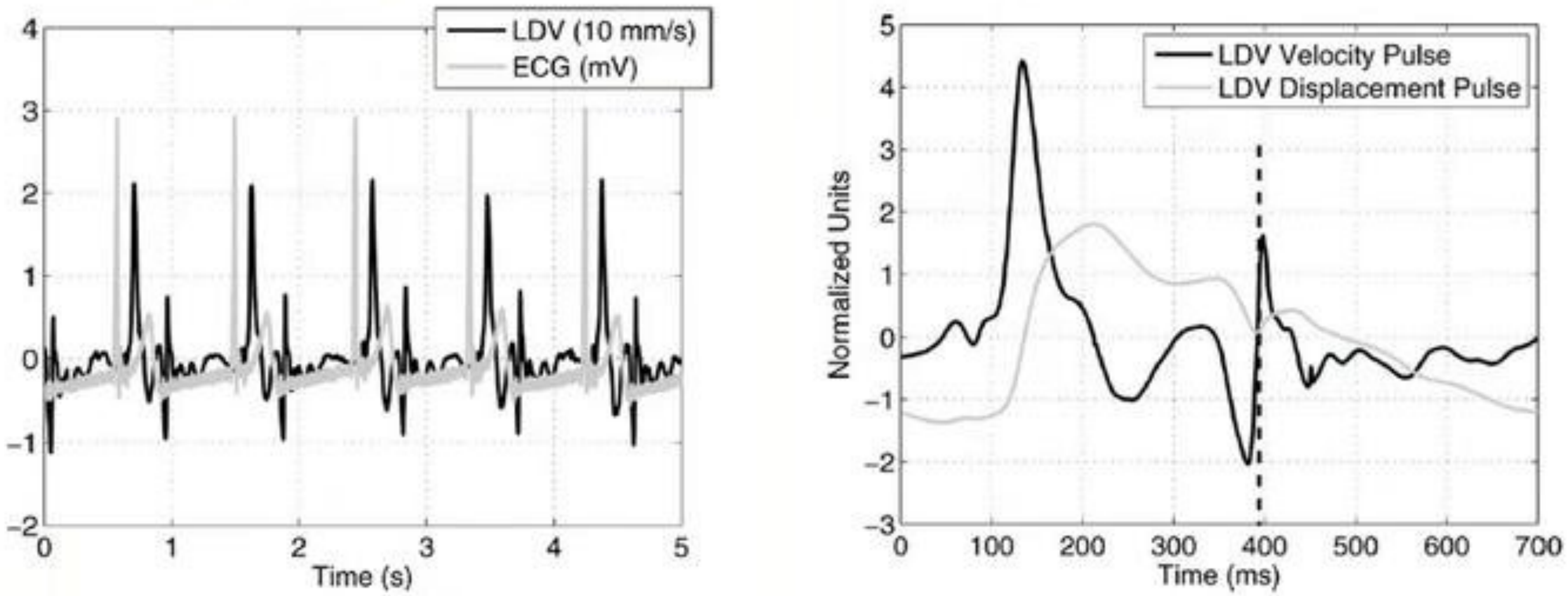
LASER DOPPLER VIBROMETRY (LDV)



Basic measurement principle of vibrometry and setup of a laser Doppler vibrometer

[Source: polytec.com]

LASER DOPPLER VIBROMETRY (LDV)



Reference: A. D. Kaplan, J. A. O'Sullivan, E. J. Sirevaag, P.-H. Lai, and J. W. Rohrbaugh. Hidden state models for noncontact measurements of the carotid pulse using a laser Doppler vibrometer. *IEEE Transactions on Biomedical Engineering*, 59(3):744–753, 2011.

LDV: PROS AND CONS

PRO

- Noncontact
- Relatively noninvasive
- LDV has also been used to infer arterial stiffness and respiration

CON

- Has only been tested with very large arteries (carotid)
- Need careful aim; primarily limited to subjects who are still
- Sensor may be relatively expensive

NON-CONTACT SENSING METHODS

- Video camera (visible-light)
- Video camera (infrared)
- Laser Doppler vibrometry (LDV)
- Radar
- Ultra-wideband impulse radio (UWB-IR)
- Wi-Fi

Sense changes in reflectance

Sense motion

RADAR-BASED SENSING OF THE HEART

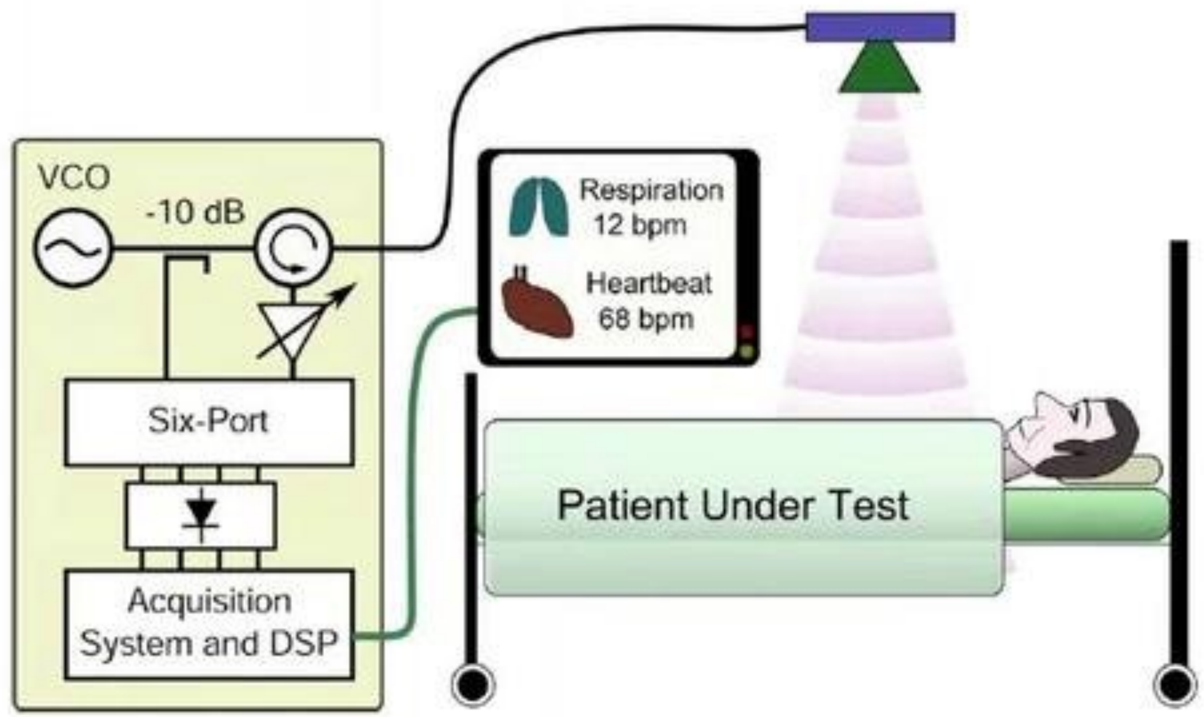


Fig. 1. System concept of the proposed sensor device.

Reference: G. Vinci, S. Lindner, F. Barbon, S. Mann, M. Hofmann, A. Duda, R. Weigel, and A. Koelpin. "Six-port radar sensor for remote respiration rate and heartbeat vital-sign monitoring." *IEEE Transactions on Microwave Theory and Techniques* 61, no. 5 (2013): 2093-2100.

RADAR-BASED SENSING OF THE HEART

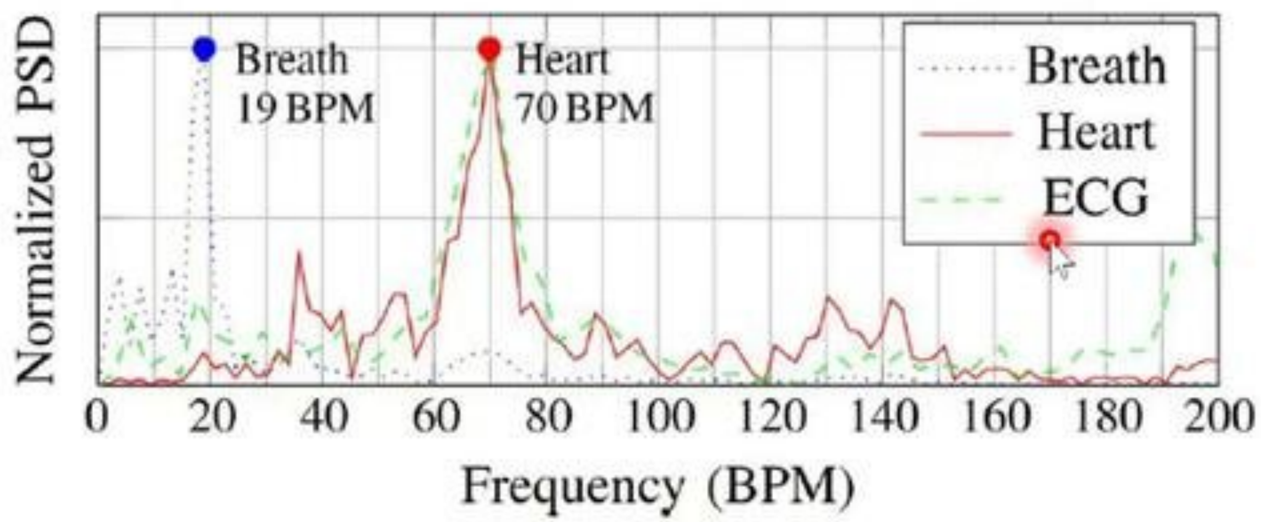


Fig. 11. Normalized PSD of the measured breath and heart-rate signals compared with the PSD of a reference ECG.

Reference: G. Vinci, S. Lindner, F. Barbon, S. Mann, M. Hofmann, A. Duda, R. Weigel, and A. Koelpin. "Six-port radar sensor for remote respiration rate and heartbeat vital-sign monitoring." *IEEE Transactions on Microwave Theory and Techniques* 61, no. 5 (2013): 2093-2100.

RADAR: PROS AND CONS

PRO

- Noncontact
- Relatively noninvasive
- Requires no subject cooperation or knowledge
- Can be used through clothes and potentially through walls
- Long-range use may be feasible
- Feasibility for biometric identification has been demonstrated

CON

- Sensor may be relatively expensive
- Current sensors are not portable
- Safety: need to consider FCC Maximum Permissible Exposure (MPE)

NON-CONTACT SENSING METHODS

- Video camera (visible-light)
- Video camera (infrared)

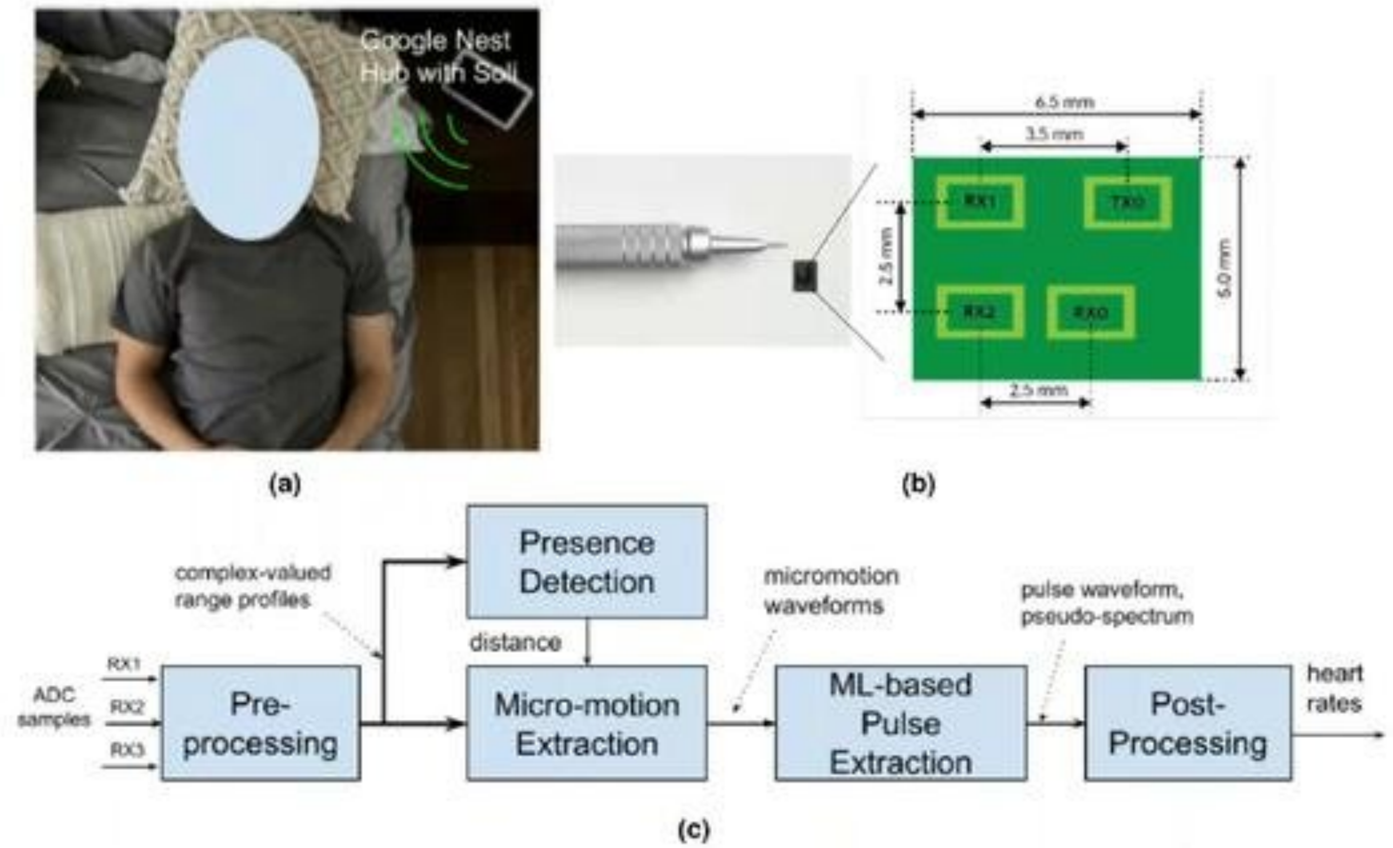
Sense changes in reflectance

- Laser Doppler vibrometry (LDV)
- Radar
- Ultra-wideband impulse radio (UWB-IR)
- Wi-Fi

Sense motion

ULTRA-WIDEBAND (UWB)

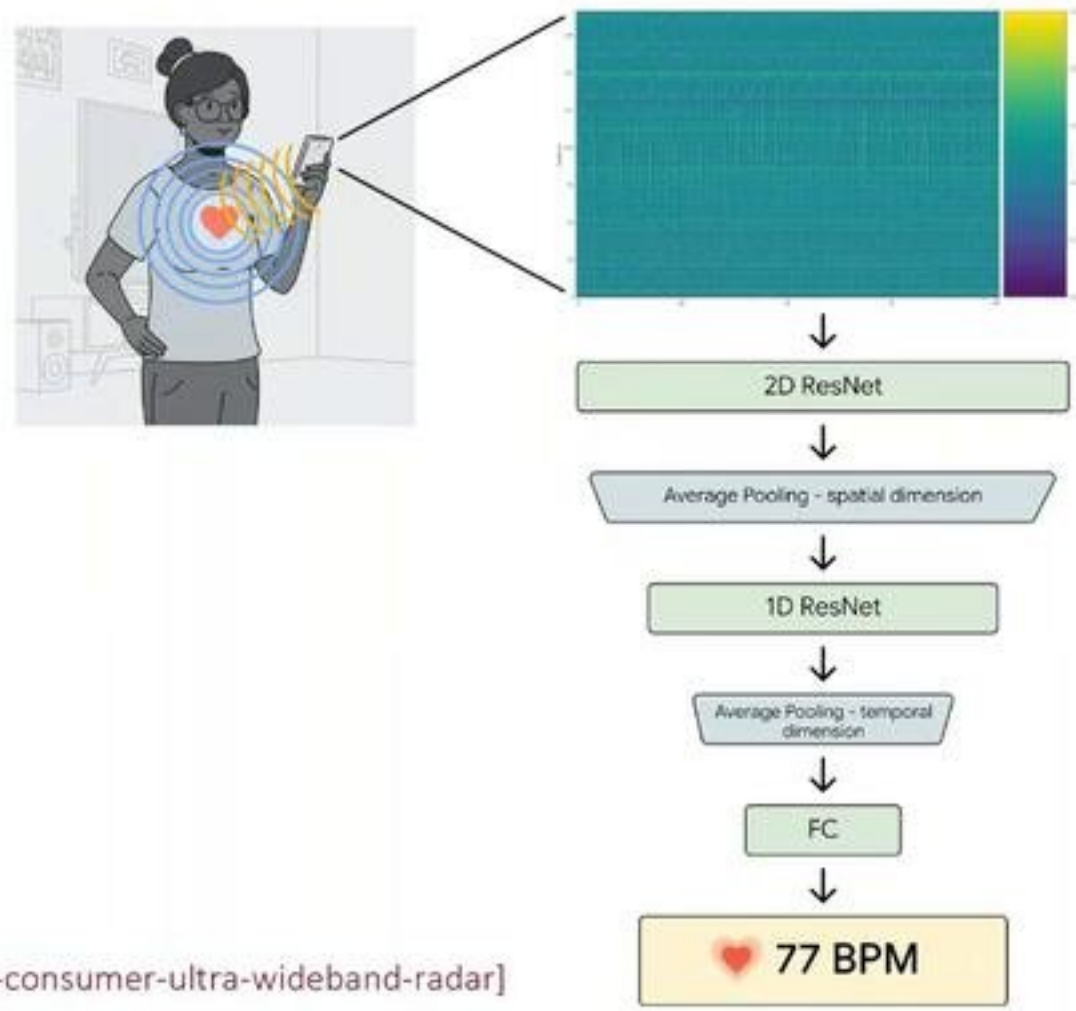
HEART-RATE MONITORING



Reference: L. Xu, J. Lien, H. Li, N. Gillian, R. Nongpiur, J. Li, Q. Zhang, J. Cui, D. Jorgensen, A. Bernstein, L. Bedal, E. Hayashi, J. Yamanaka, A. Lee, J. Wang, D. Shin, I. Poupyrev, T. Thormundsson, A. Pathak, and S. Patel. "Soli-enabled noncontact heart rate detection for sleep and meditation tracking." *Scientific Reports* 13, no. 1, 2023.

ULTRA-WIDEBAND (UWB)

HEART-RATE MONITORING



[Source: https://research.google/blog/measuring-heart-rate-with-consumer-ultra-wideband-radar]

Reference: E. Arasteh, E. S. Veldhoen, X. Long, M. van Poppel, M. van der Linden, T. Alderliesten, J. Nijman, R. de Goederen, and J. Dudink. "Ultra-wideband radar for simultaneous and unobtrusive monitoring of respiratory and heart rates in early childhood: A deep transfer learning approach." *Sensors* 23, no. 18 (2023).

WI-FI & ULTRA-WIDEBAND IMPULSE RADIO (UWB-IR)

RESPIRATION MONITORING

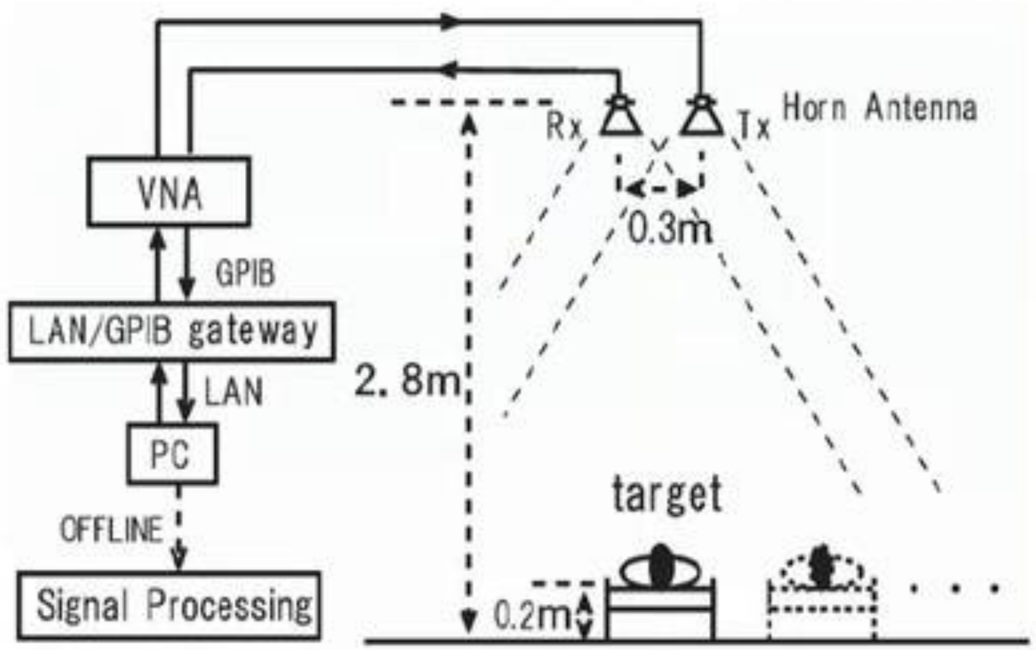


Fig. 2. Measurement environment.

Reference: K. Higashikaturagi, Y. Nakahata, I. Matsunami, and A. Kajiwara. Non-invasive respiration monitoring sensor using UWB-IR. In IEEE Intl. Conf. on Ultra-Wideband, volume 1, pages 101–104, 2008.

WI-FI & ULTRA-WIDEBAND IMPULSE RADIO (UWB-IR)

RESPIRATION MONITORING

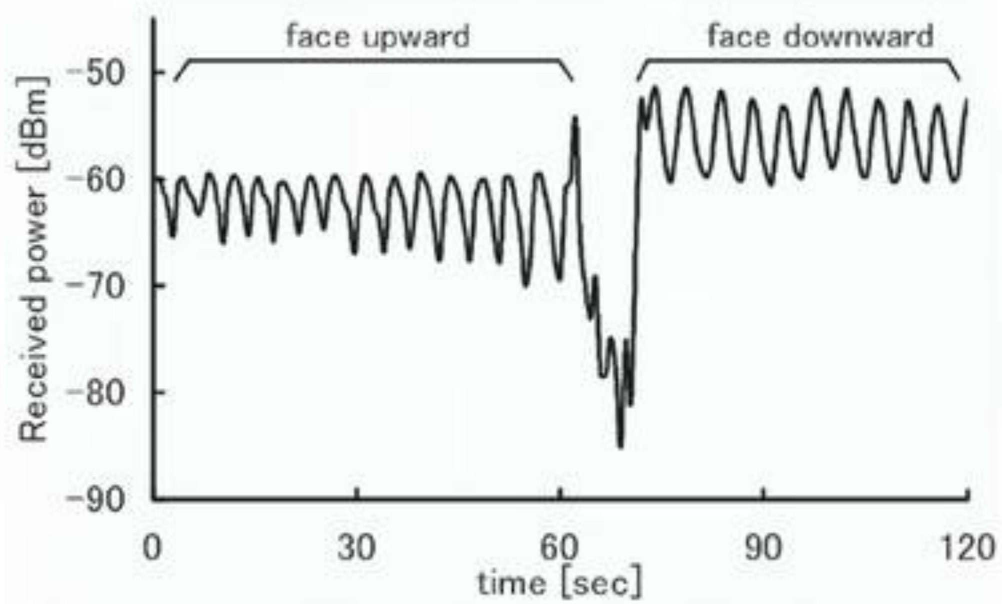


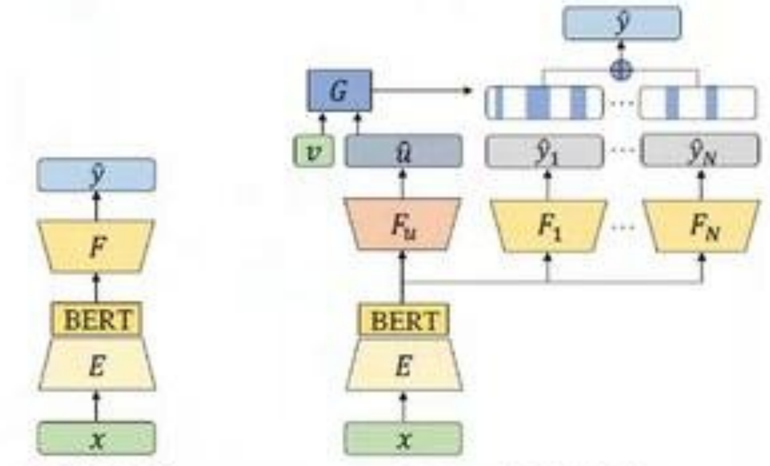
Fig. 6. Respiratory waveforms from face upward to downward.

Reference: K. Higashikaturagi, Y. Nakahata, I. Matsunami, and A. Kajiwara. Non-invasive respiration monitoring sensor using UWB-IR. In *Proc. IEEE Intl. Conf. on Ultra-Wideband*, volume 1, pp. 101–104, 2008.

WI-FI & ULTRA-WIDEBAND (UWB)

OXYGEN MONITORING

Figure 3: The radio device used to collect RF signals.



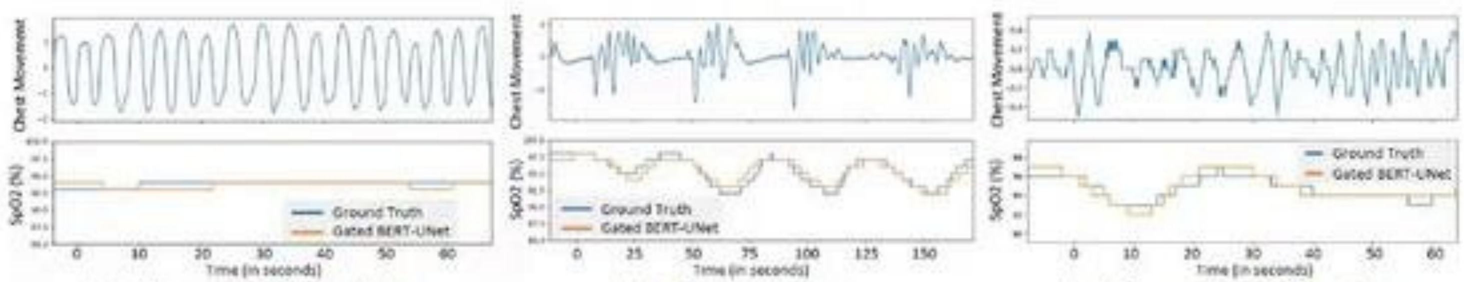
(a) BERT-UNet (b) Gated BERT-UNet

Illustrations of the proposed models: (a) The backbone BERT-UNet model, which contains an encoder E and a predictor F as the UNet structure, and a BERT module at the bottleneck of the UNet. (b) The Gated BERT-UNet, where a gate G, controlled by the accessible variable v and the predicted inaccessible variable $\hat{u}$, is used to select among multiple predictive heads.

Reference: H. He, Y. Yuan, Y.-C. Chen, P. Cao, and D. Katabi, "Contactless Oxygen Monitoring with Radio Waves and Gated Transformer." In *Proc. Machine Learning for Healthcare Conference*, pp. 248-265, PMLR, 2023.

WI-FI & ULTRA-WIDEBAND (UWB)

OXYGEN MONITORING



(a) Normal Breathing (b) Sleep Apnea (c) Irregular Rhythm

Figure 5: Visualization of breathing signals and corresponding predicted oxygen saturation. The top panels are breathing signals. The bottom panels are oxygen saturation with the ground truth in blue and our model's predictions in orange.

Table 2: Performances on the RF dataset.

Model	Corr↑	MAE↓	RMSE↓
CNN	0.45	1.65	1.73
CNN-RNN	0.49	1.85	1.93
BERT-UNet	0.48	1.49	1.58
BERT-UNet + VarAug*	0.49	1.49	1.59
Gated BERT-UNet*	**0.52**	**1.32**	**1.54**

Reference: H. He, Y. Yuan, Y.-C. Chen, P. Cao, and D. Katabi, "Contactless Oxygen Monitoring with Radio Waves and Gated Transformer." In *Proc. Machine Learning for Healthcare Conference*, pp. 248-265, PMLR, 2023.

UWB-IR: PROS AND CONS

PRO

- Noncontact
- Relatively noninvasive
- Requires no subject cooperation or knowledge
- Can be used through clothes and blankets

CON

- Current sensors are not portable
- Safety: need to consider FCC Maximum Permissible Exposure (MPE)

NON-CONTACT SENSING METHODS

- Video camera (visible-light)
- Video camera (infrared)
- Laser Doppler vibrometry (LDV)
- Radar
- Ultra-wideband impulse radio (UWB-IR)
- Wi-Fi

Sense changes in reflectance

Sense motion



SUMMARY

- Contact sensing vs. noncontact (remote) sensing
- Several noncontact methods have been developed for measuring vital signs (heart rate, pulse rate, respiration rate, blood pressure,)
- Most are still in the exploratory stage
- Several applications can benefit from these new techniques

- Invasive sensing vs. noninvasive sensing
  - Some contact-based methods are considered to be noninvasive
  - Some noncontact-based methods might be considered to be invasive (e.g., unwanted video recording of a person's face)

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(END OF PART 5)

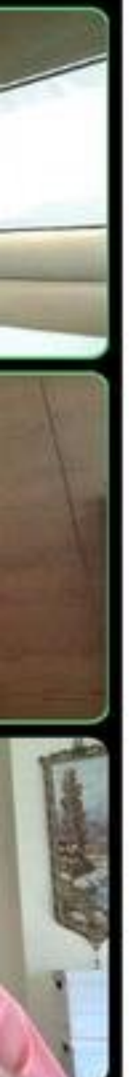
AHFE 2025 International Conference

July 26-30, 2025 - Orlando, Florida

VIRGINIA TECH

VIRGINIA TECH TRANSPORTATION INSTITUTE
VIRGINIA TECH

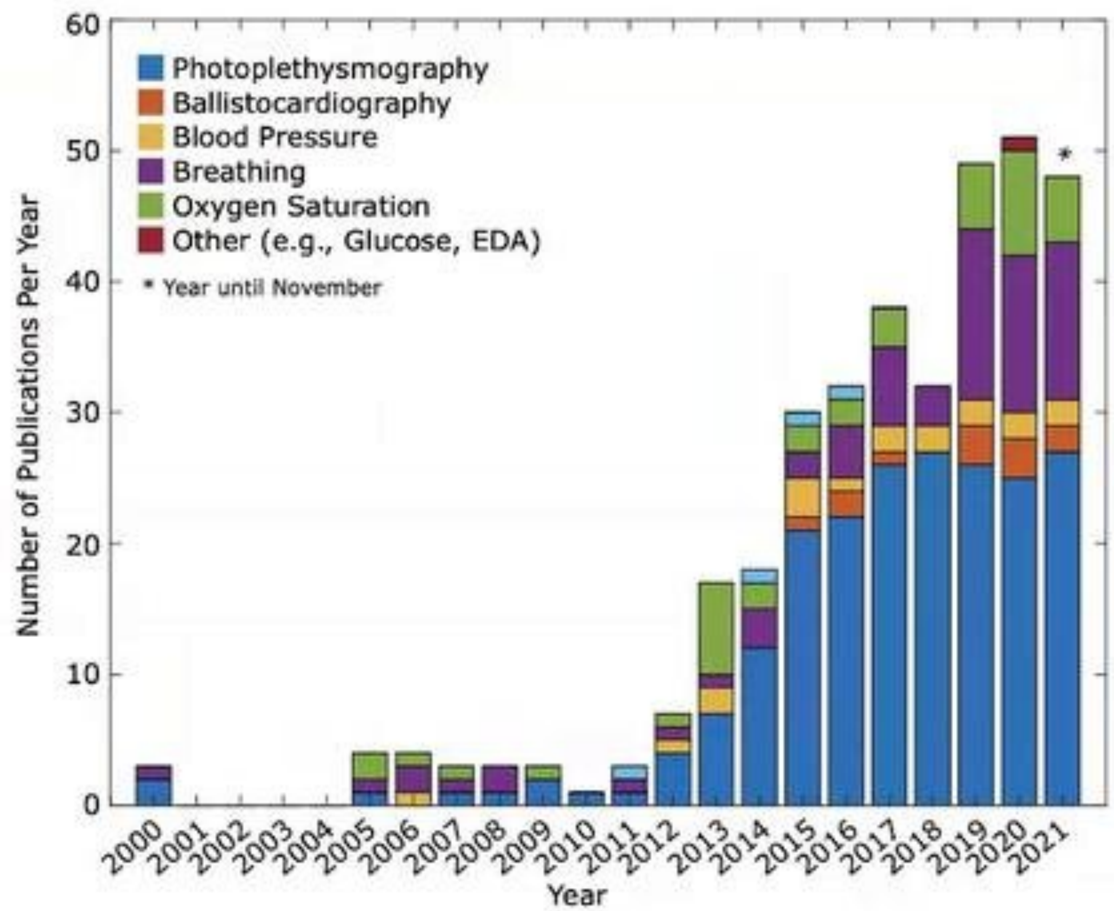
COLLEGE OF ENGINEERING
BRADLEY DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING
VIRGINIA TECH



CAMERA BASED METHODS

SESSION 5

RESEARCH TREND

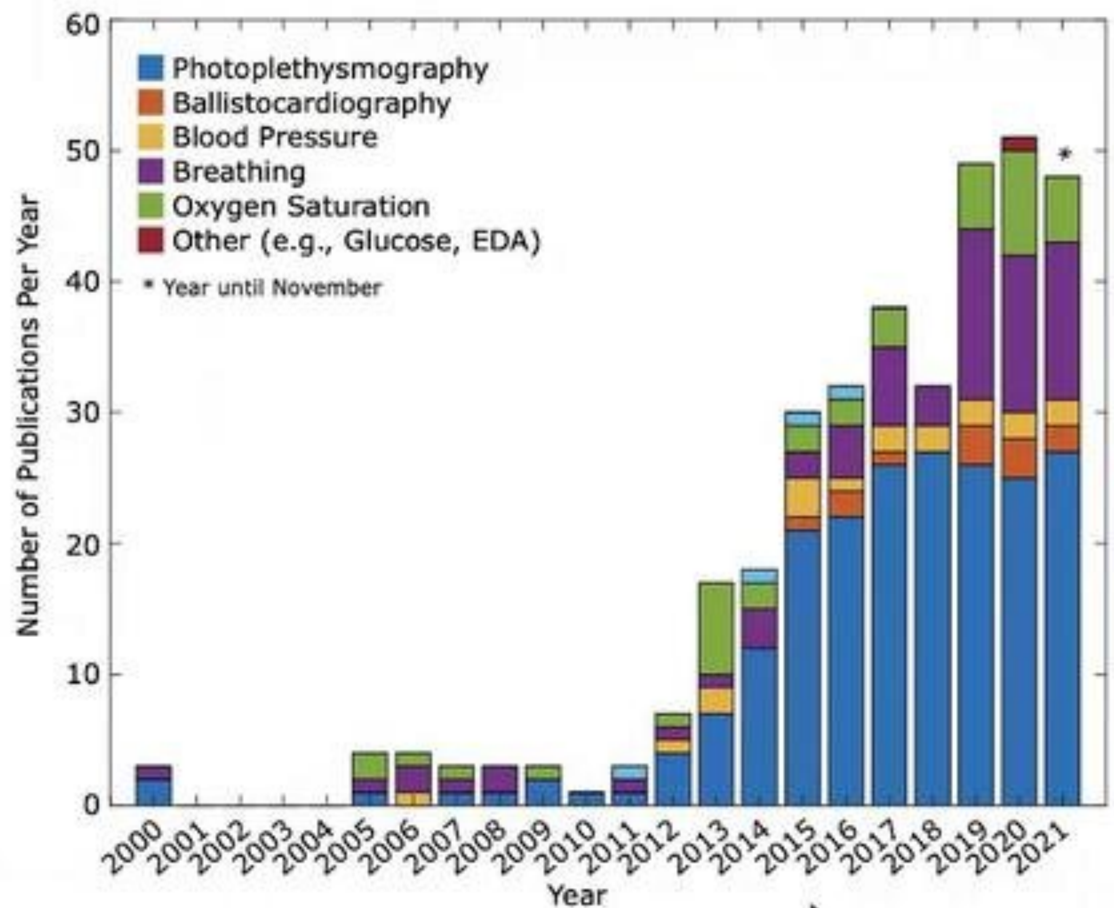


McDuff, D. (2023). Camera measurement of physiological vital signs. *ACM Computing Surveys*, *55*(9), 1-40.

SESSION OVERVIEW

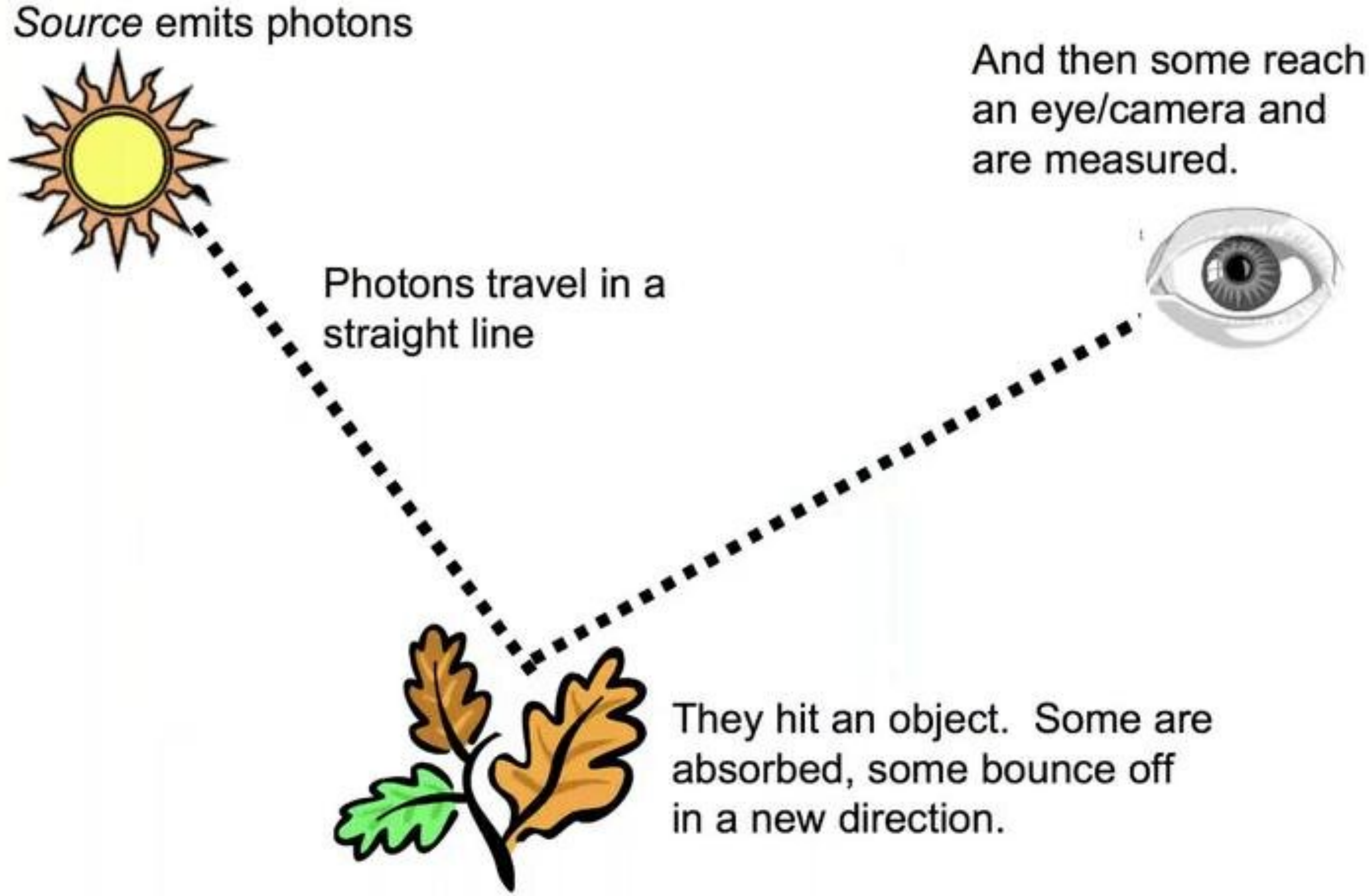
- Current state of research
- First we'll discuss how data from RGB and NIR cameras contains blood volume pulse information from human face.
- Next we'll discuss challenges and methods to address those challenges.
- Next, we'll show how advance computer vision, signal processing and machine learning methods including deep learning are used to extract blood volume pulse, and respiration rate.
- Retrieve different vital signs
- Finally, we'll discuss the open questions

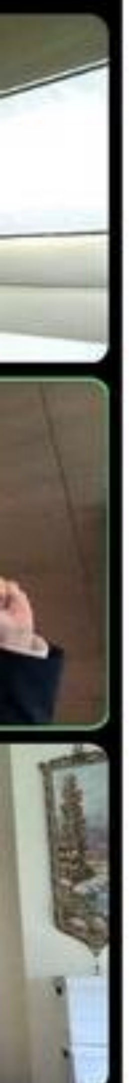
RESEARCH TREND



McDuff, D. (2023). Camera measurement of physiological vital signs. *ACM Computing Surveys*, *55*(9), 1-40.

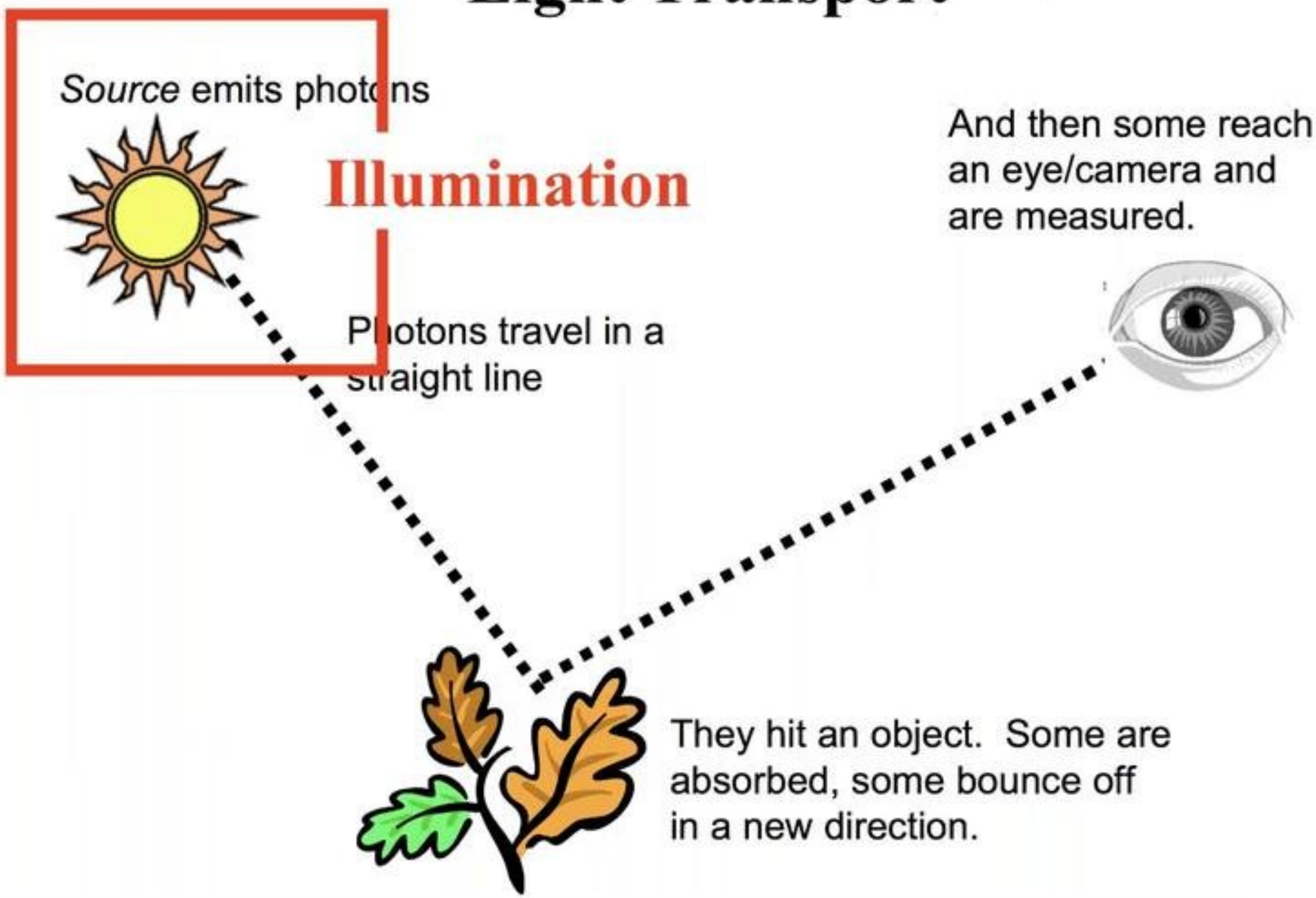
Sketch: Light Transport



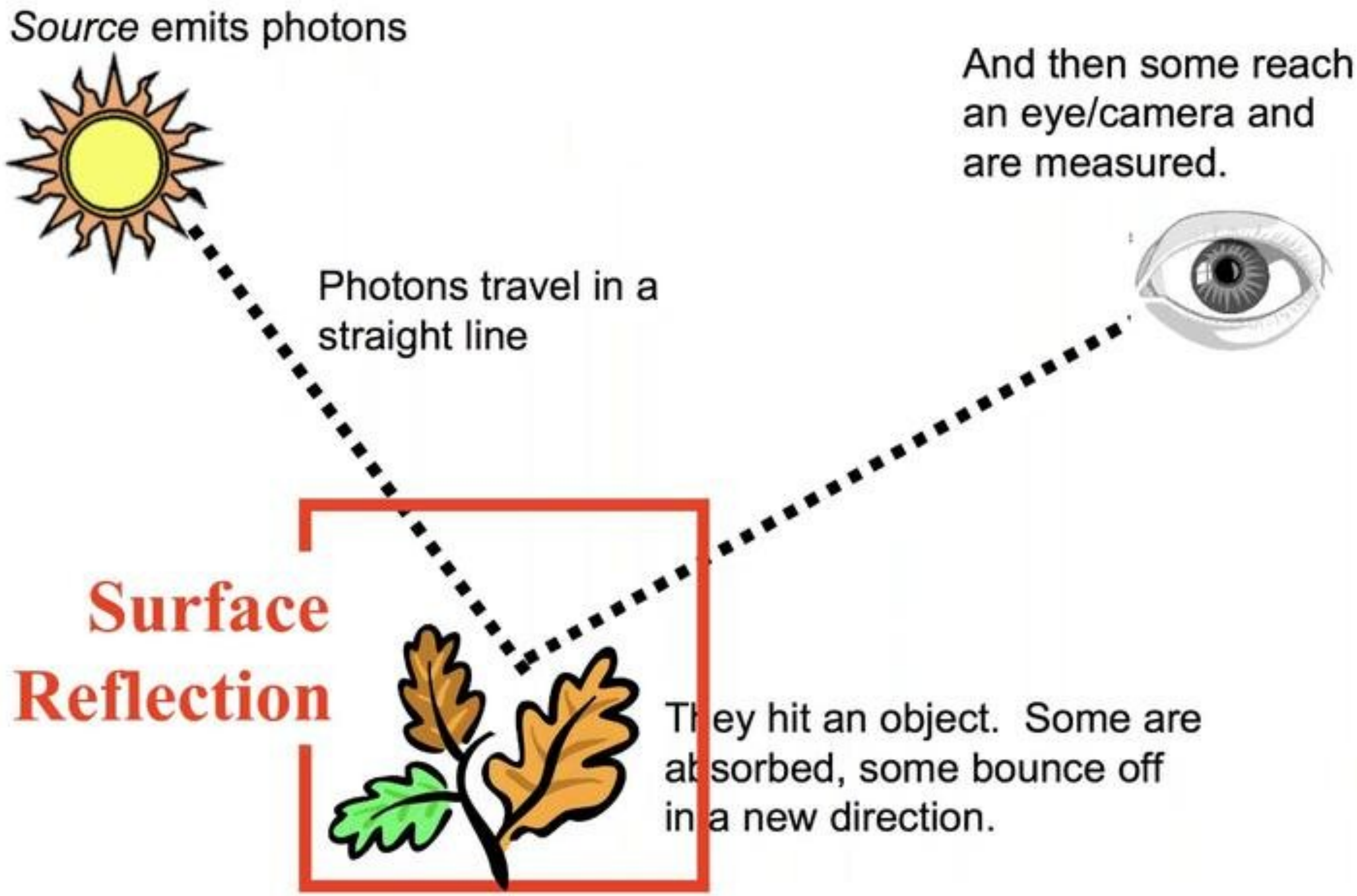


Robert Collins
CSE486, Penn State

Light Transport

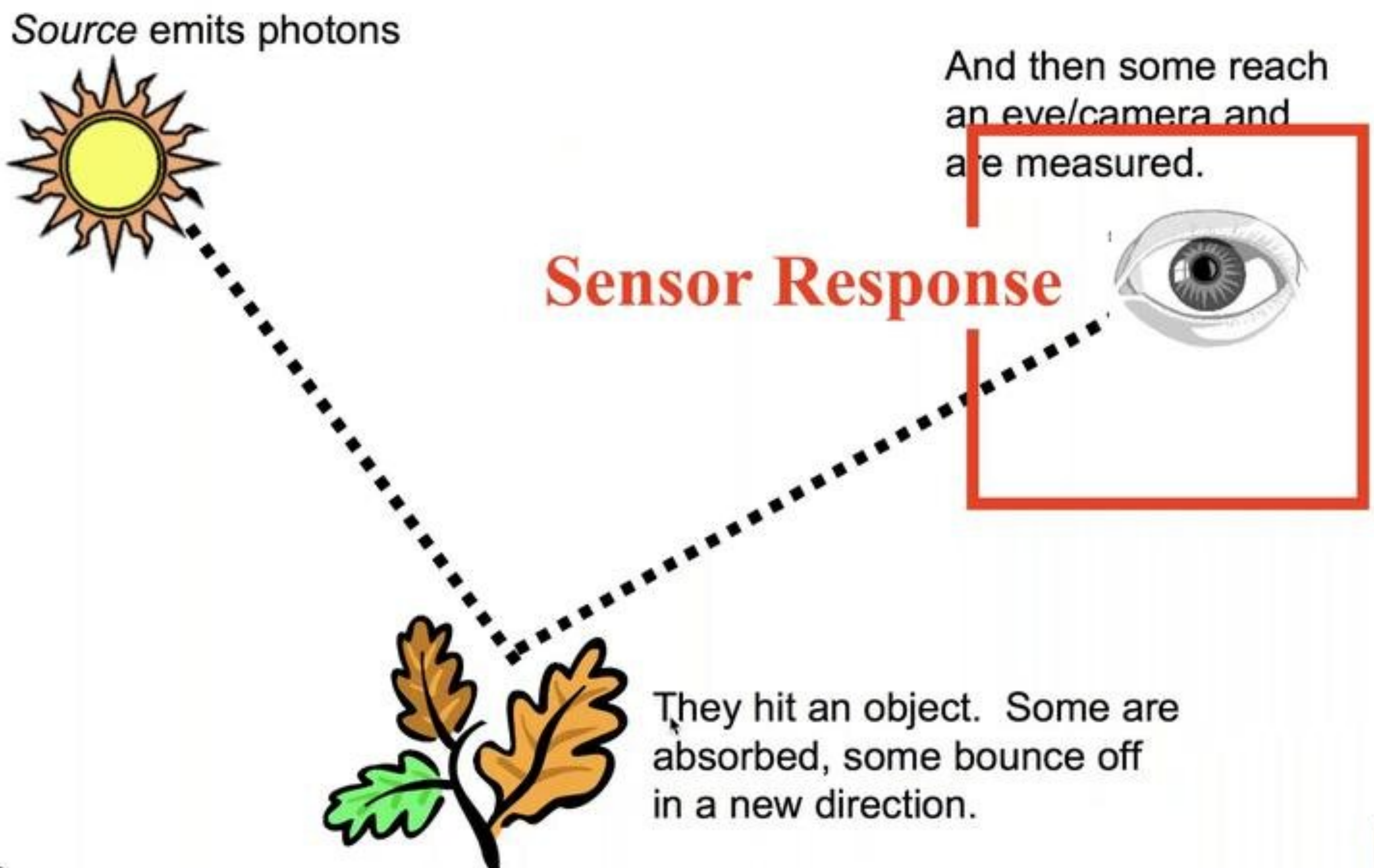


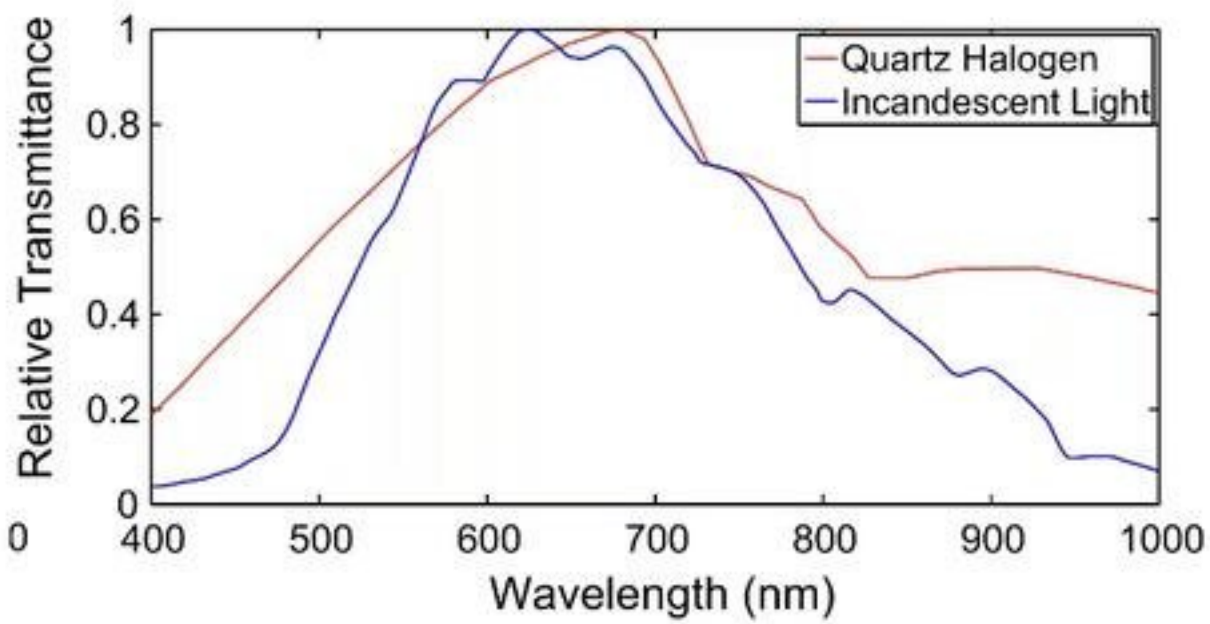
Light Transport

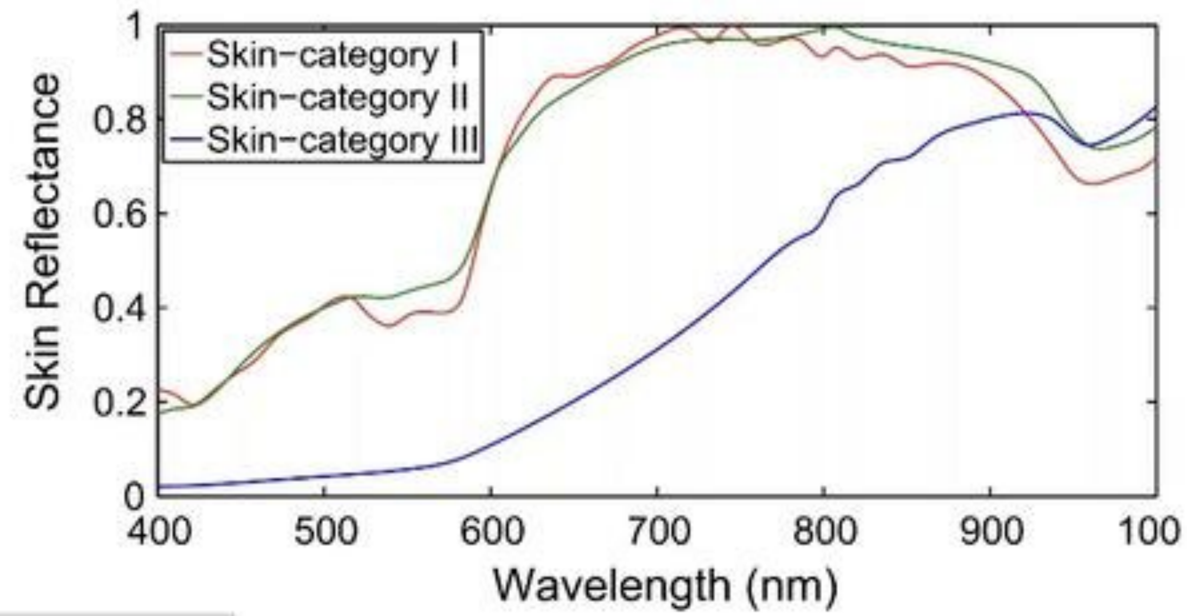


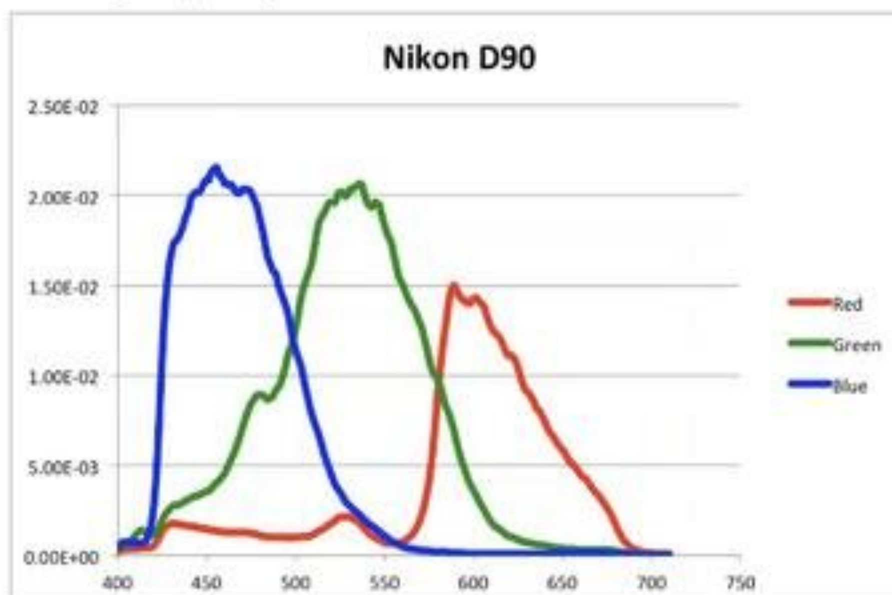
Robert Collins
CSE486, Penn State

Light Transport




Quartz Halogen
Incandescent Light
Relative Transmittance
Wavelength (nm)


Skin−category I
Skin−category II
Skin−category III
Skin Reflectance
Wavelength (nm)


Nikon D90
Red
Green
Blue

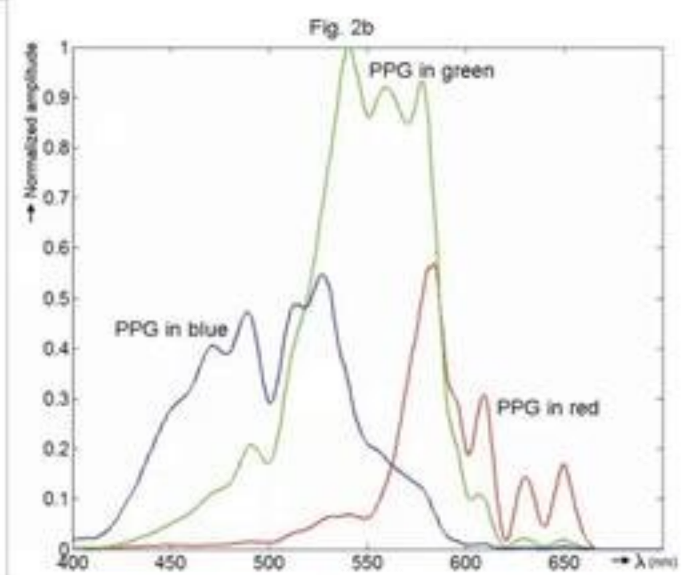
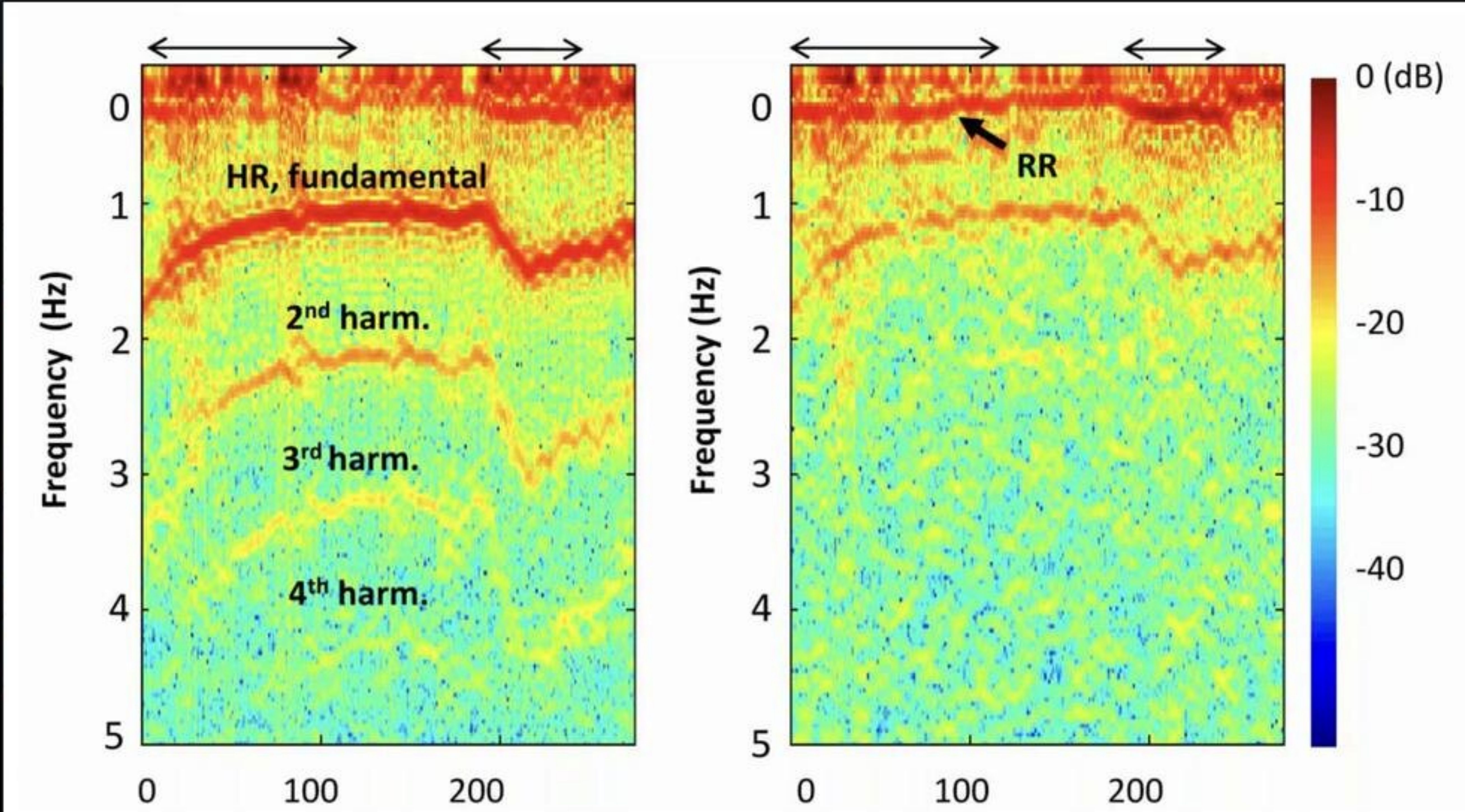


Fig. 2b
PPG in green
PPG in blue
PPG in red
Normalized amplitude



HR, fundamental
2nd harm.
3rd harm.
4th harm.
RR
Frequency (Hz)
0
1
2
3
4
5
0
100
200
0 (dB)
-10
-20
-30
-40

WHAT IS VIDEO MAGNIFICATION

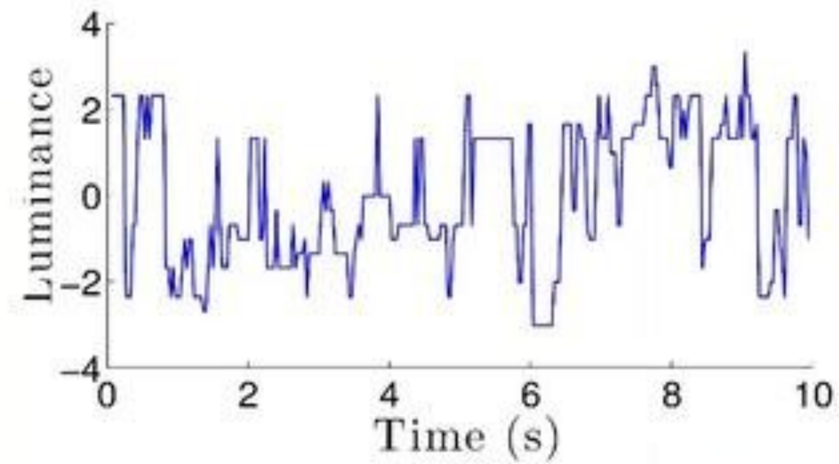
- Blood volume pulses are imperceptible to normal vision

Wu et al. SIGGRAPH 2012

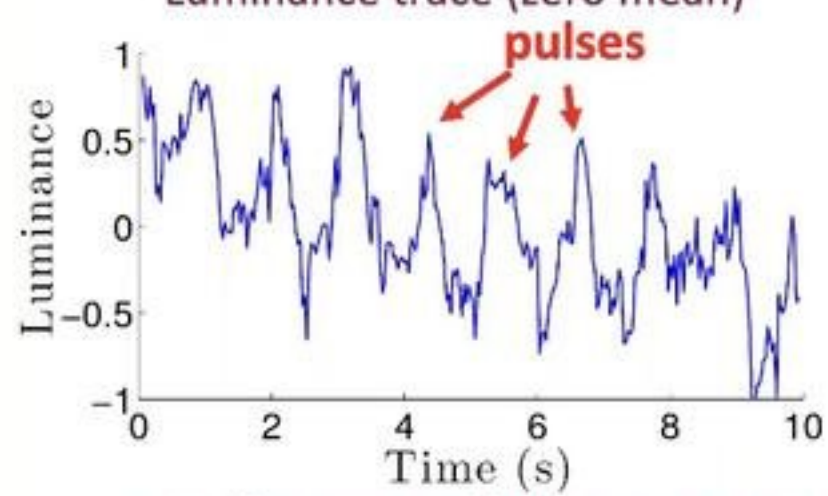
SUBTLE COLOR VARIATIONS

1. Average spatially to overcome sensor and quantization noise

Input frame



Luminance trace (zero mean)

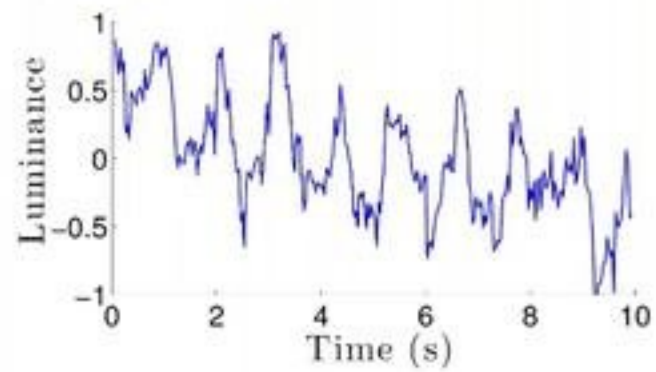


Spatially averaged luminance trace

Wu et al. 2012, SIGGRAPH

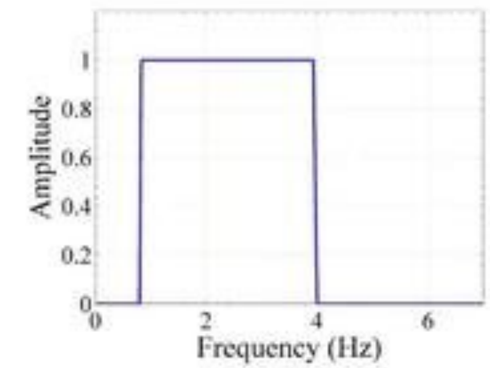
AMPLIFYING SUBTLE COLOR VARIATIONS

2. Filter temporally to extract the signal of interest



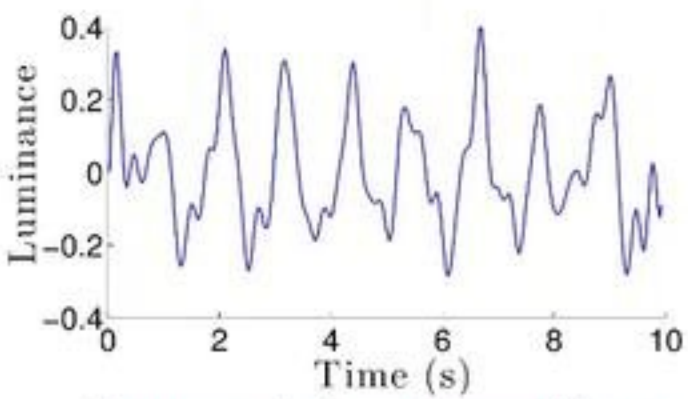
Spatially averaged luminance trace

$\otimes$



Temporal filter

=

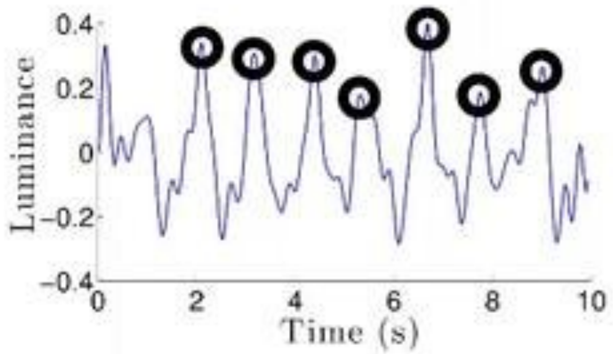


Temporally bandpassed trace

Wu et al. 2012, SIGGRAPH

Heart Rate Extraction

Peak detection

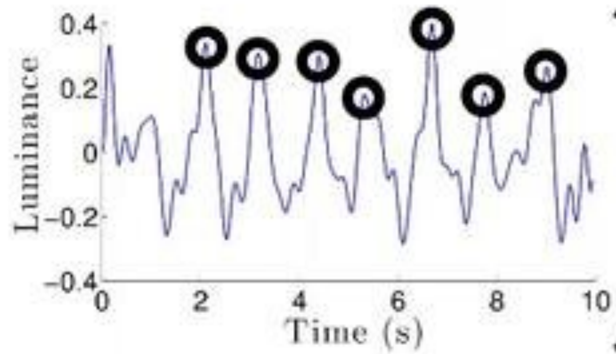


Temporally bandpassed trace (one pixel)

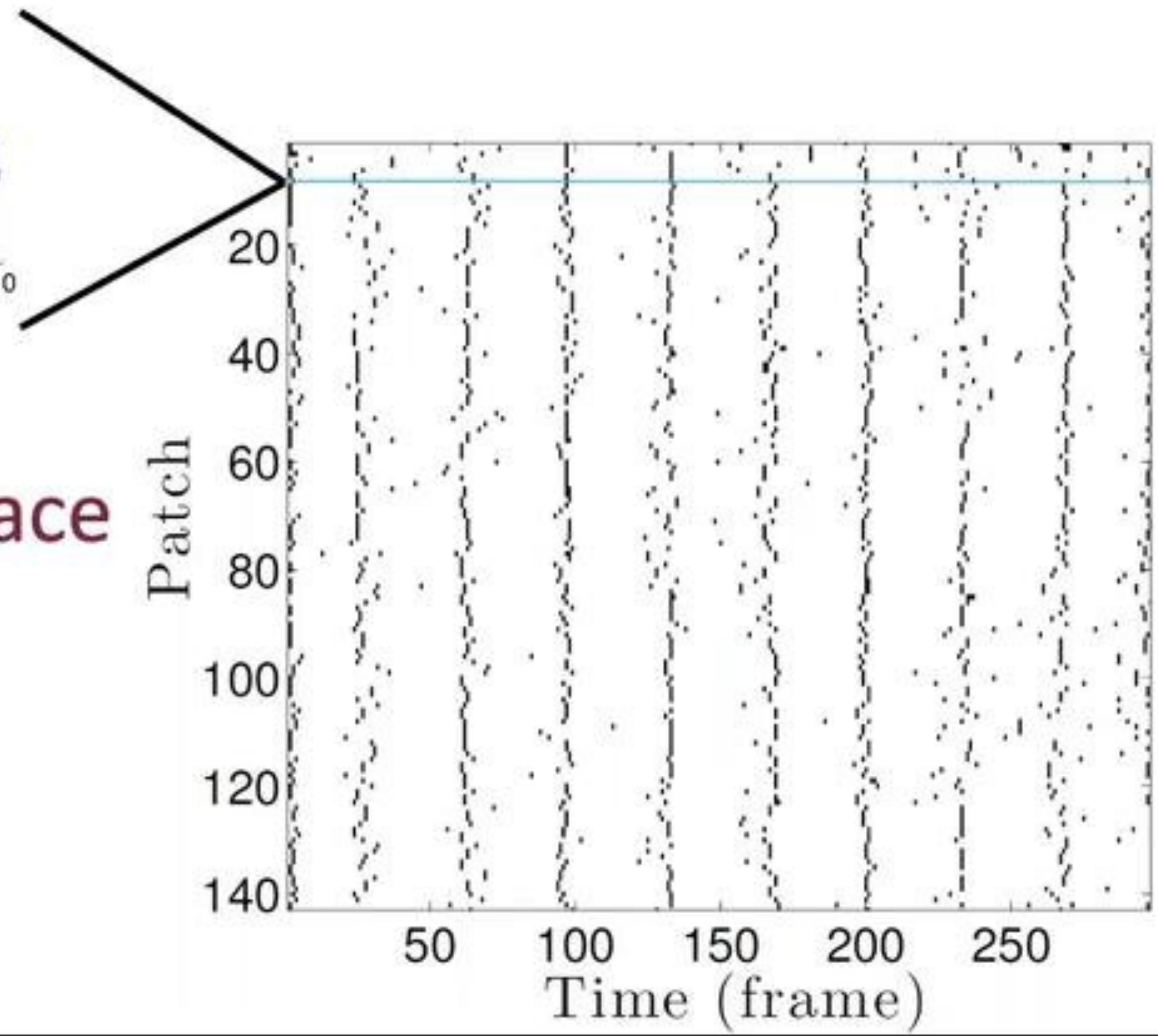
Wu et al. 2012, SIGGRAPH

Heart Rate Extraction

Peak detection

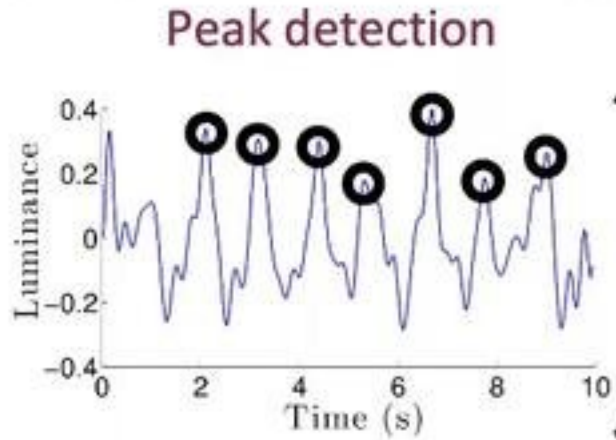


Temporally bandpassed trace (one pixel)

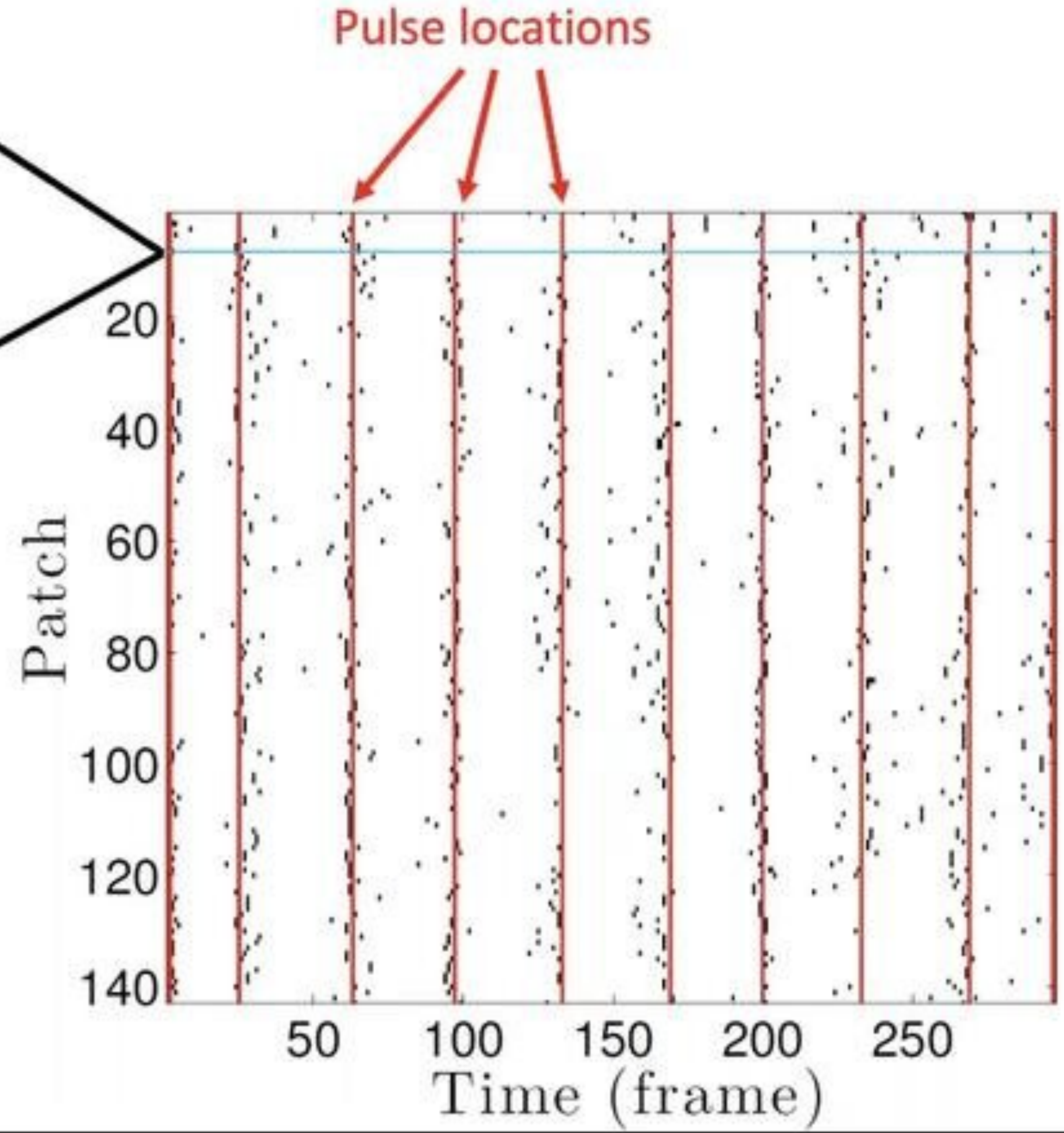


Wu et al. 2012, SIGGRAPH

Heart Rate Extraction



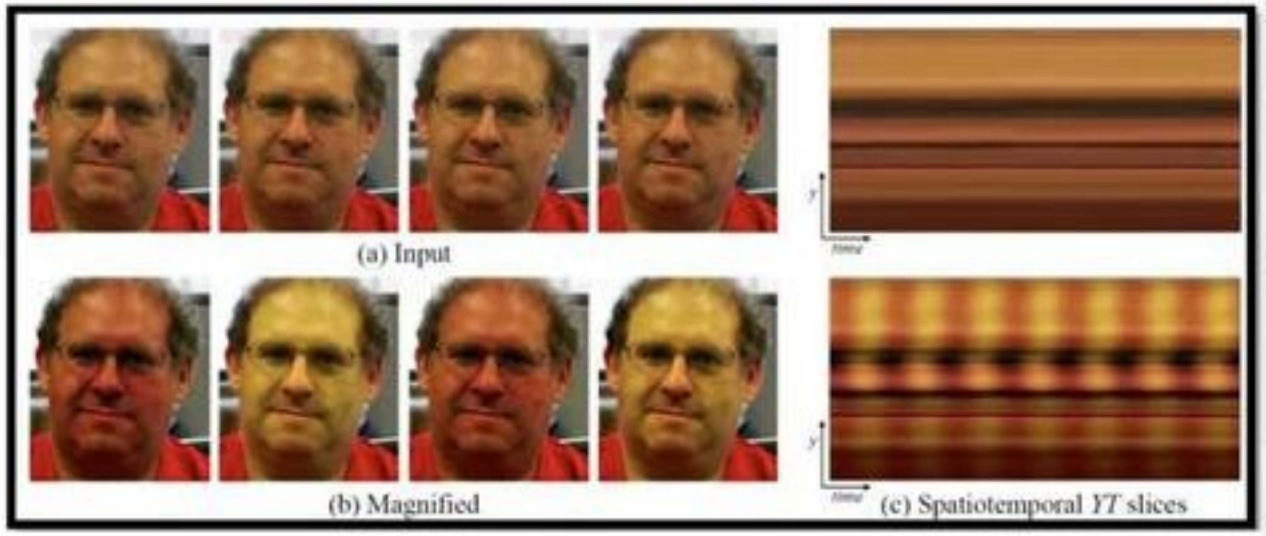
Temporally bandpassed trace (one pixel)



Wu et al. 2012, SIGGRAPH

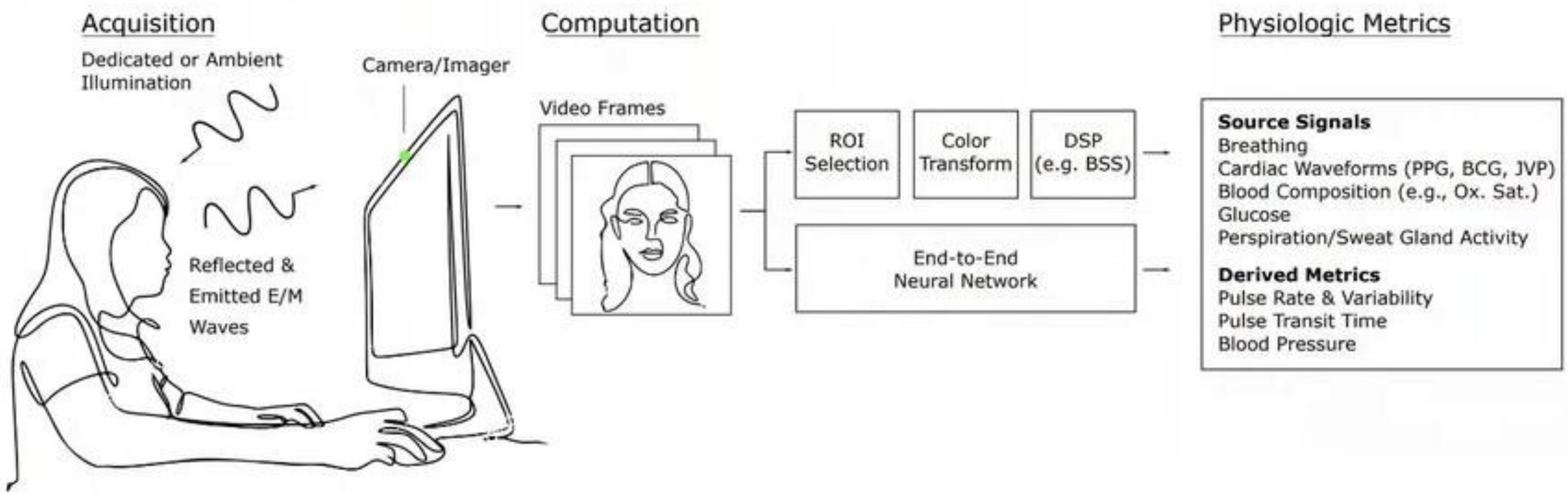
EXTRACT PHYSIOLOGICAL SIGNAL FROM VIDEOS

- Key challenges
  - Which color channels to use? (G vs RGB vs NIR vs IR)
  - How to extract the signal? (VidMag, ICA, CHROM, etc)
  - Effect of motion (Face detection and registration)
  - Face area selection (skin detection and preprocessing)
  - Effect of ambient illumination



Picture from : Hao-Yu Wu, Michael Rubinstein, Eugene Shih, John Guttag, Fŕedo Durand, and William Freeman. Eulerian video magnification for revealing subtle changes in the world. ACM Trans. Graph. (Proceedings SIGGRAPH), 31(4), 2012.

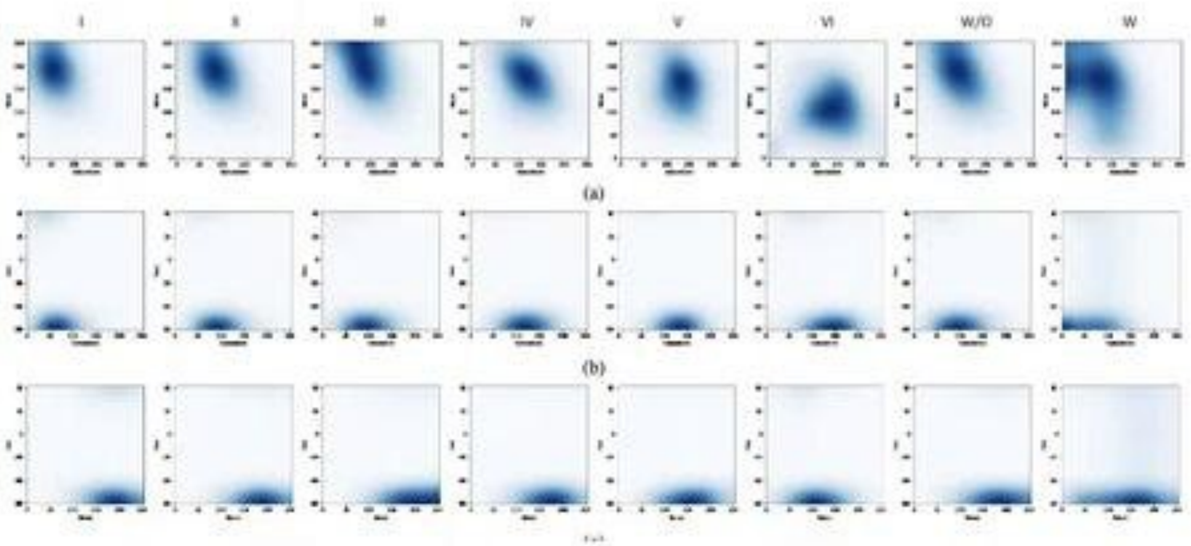
STANDARD PIPELINE



McDuff, D. (2023). Camera measurement of physiological vital signs. *ACM Computing Surveys*, *55*(9), 1-40.

SKIN DETECTION

DEEP LEARNING BASED METHOD



Methods	I	II	III	IV	V	VI	mix	σ
Kolkur *et al.* [24]	67.61	69.96	70.27	70.44	67.61	46.90	72.42	8.14
Dahmani *et al.* [8]	66.10	70.52	71.95	71.01	70.46	56.45	70.45	5.07
Jones *et al.* [21]	64.65	75.89	73.99	74.00	73.28	46.82	77.61	9.99
FCN before aug.	89.03	89.90	90.03	89.56	89.59	83.41	87.37	2.20
FCN after aug.	90.06	90.06	90.34	89.93	90.06	82.98	85.69	2.70
U-Net before aug.	87.16	89.58	90.38	**90.99**	**91.98**	84.72	88.82	2.29
U-Net after aug.	**90.88**	**91.34**	**91.21**	90.55	89.35	**86.05**	**89.60**	**1.84**

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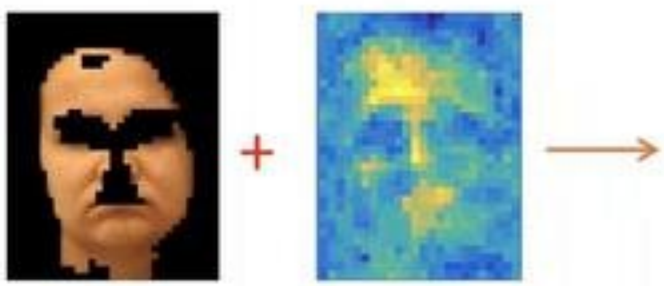
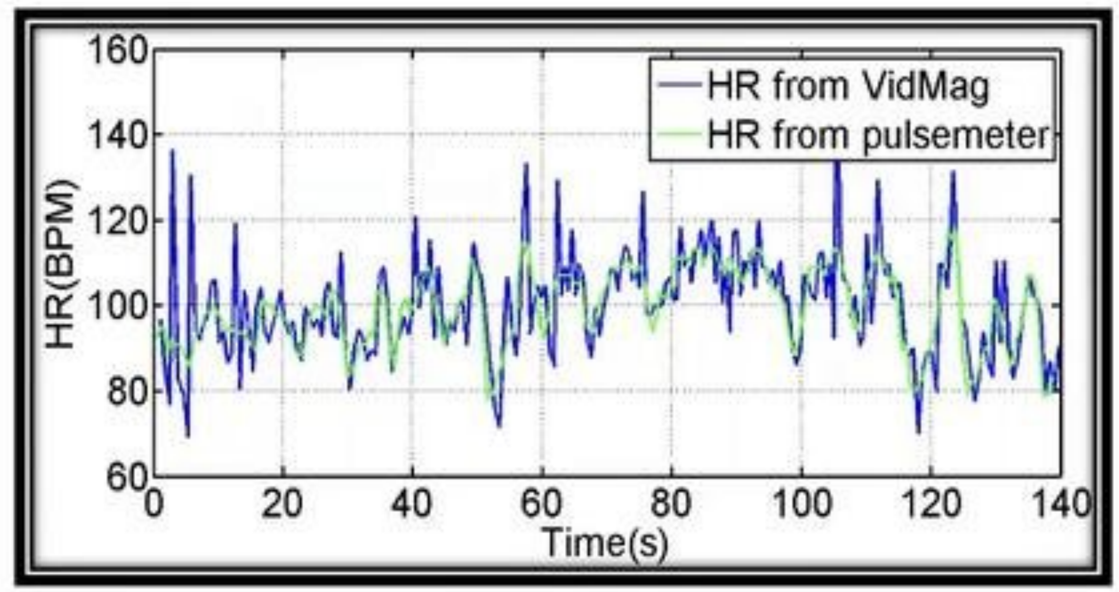
RESEARCH QUESTIONS FOR RPPG

- How accurately can we measure pulse rate?
- Which skin patches are useful?
- What limits the applications and how to assess them?

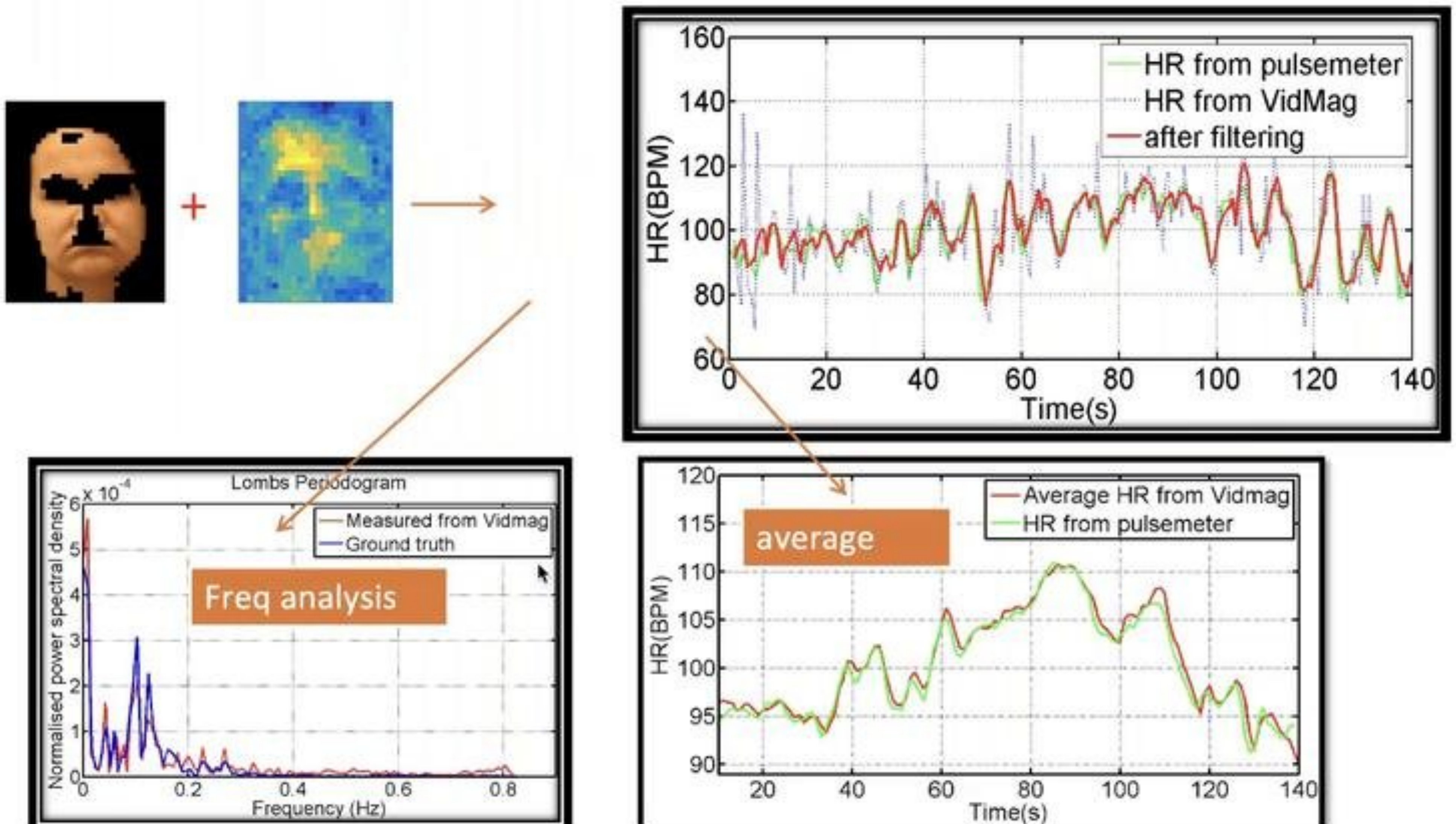
VALIDATION R-R INTERVAL





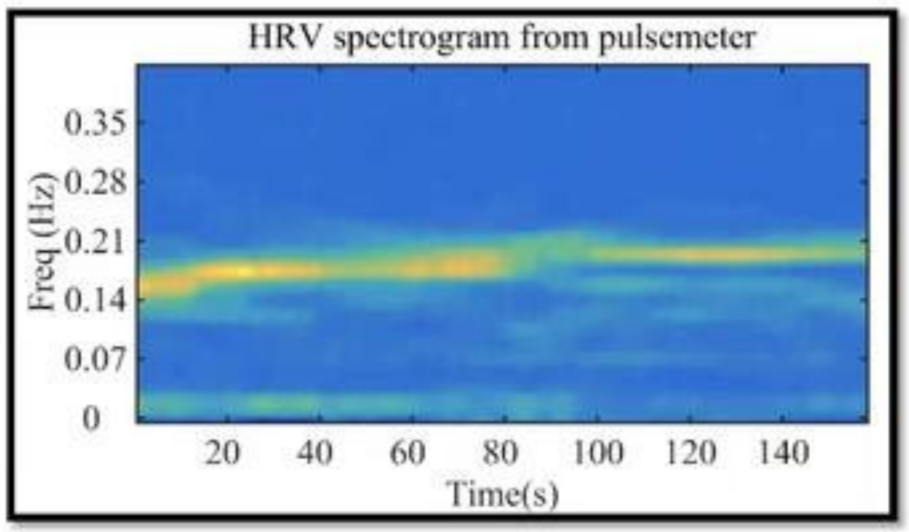
Sarkar, A., Abbott, A. L., Doerzaph, Z., & Sykes, K. (2016, January). Evaluation of video magnification for nonintrusive heart rate measurement. In *2016 IEEE First International Conference on Control, Measurement and Instrumentation (CMI)* (pp. 494-498). IEEE.

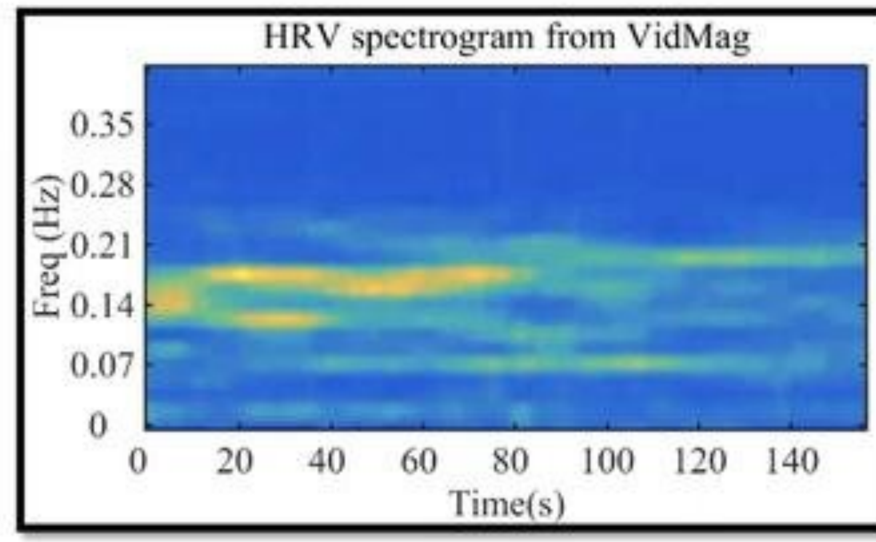
VALIDATION R-R INTERVAL

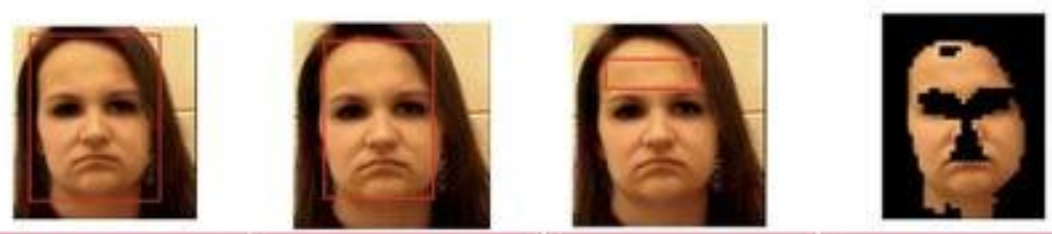


Sarkar, A., Abbott, A. L., Doerzaph, Z., & Sykes, K. (2016, January). Evaluation of video magnification for nonintrusive heart rate measurement. In *2016 IEEE First International Conference on Control, Measurement and Instrumentation (CMI)* (pp. 494-498). IEEE.

VALIDATION OF HRV

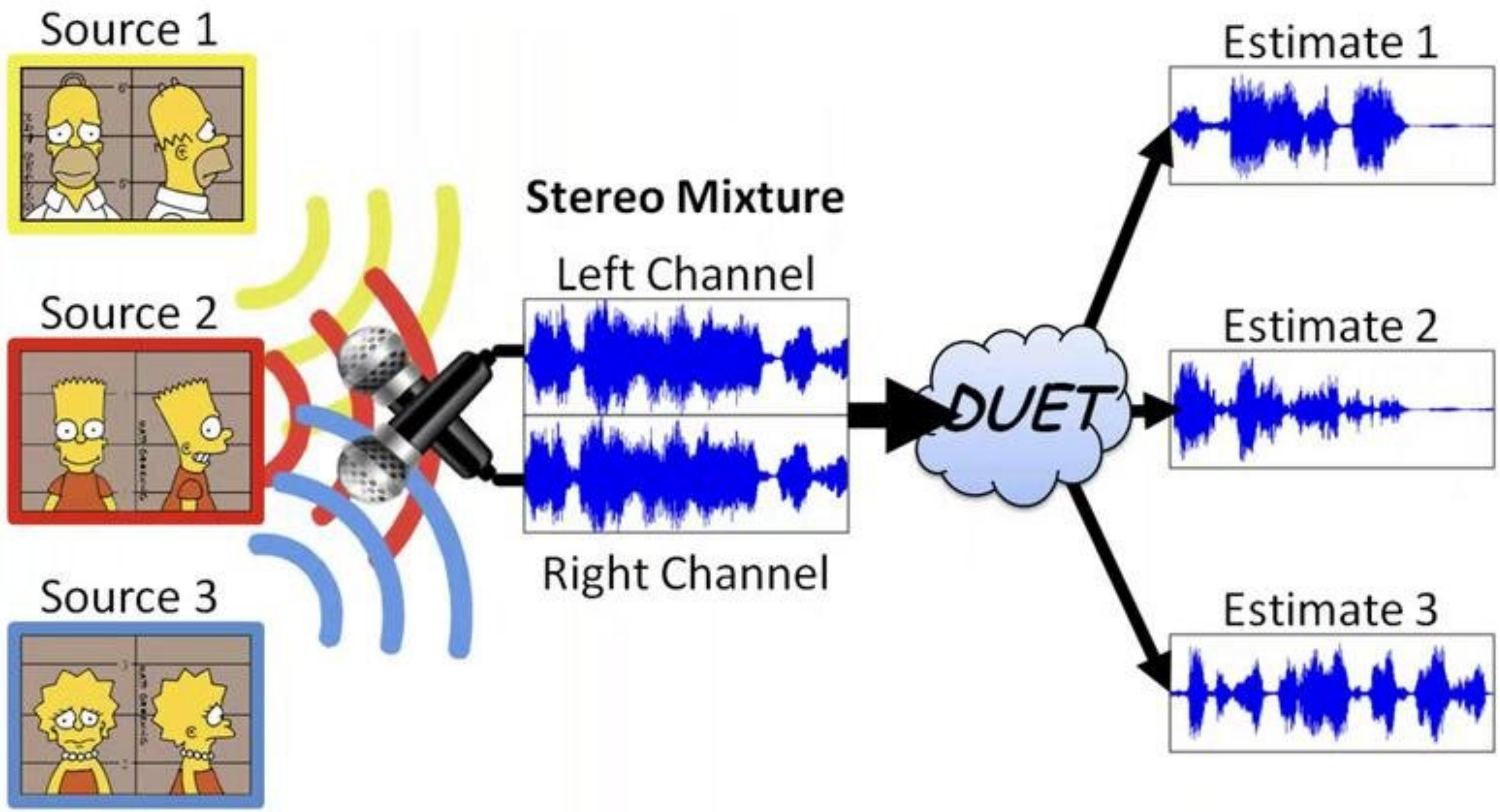


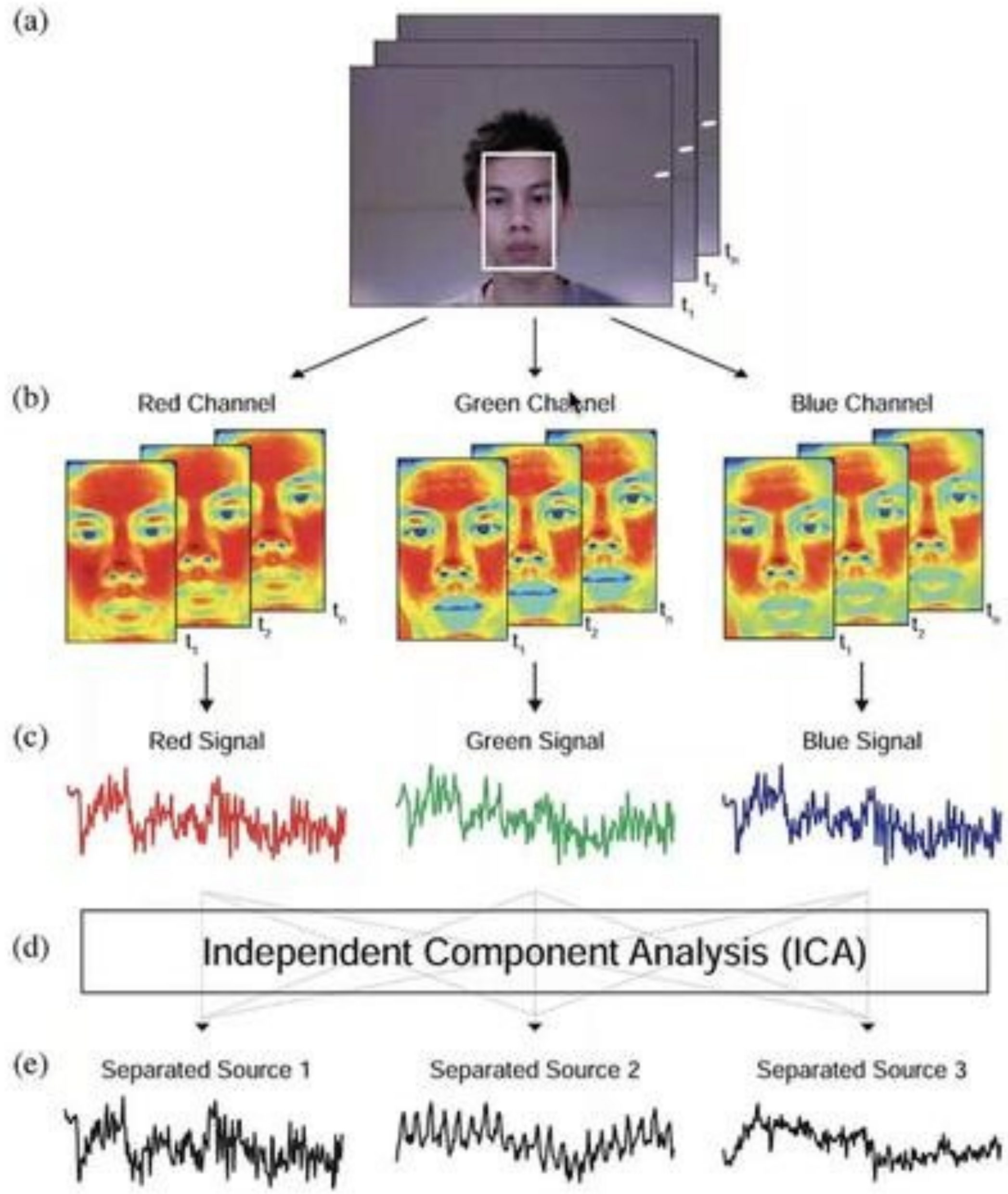


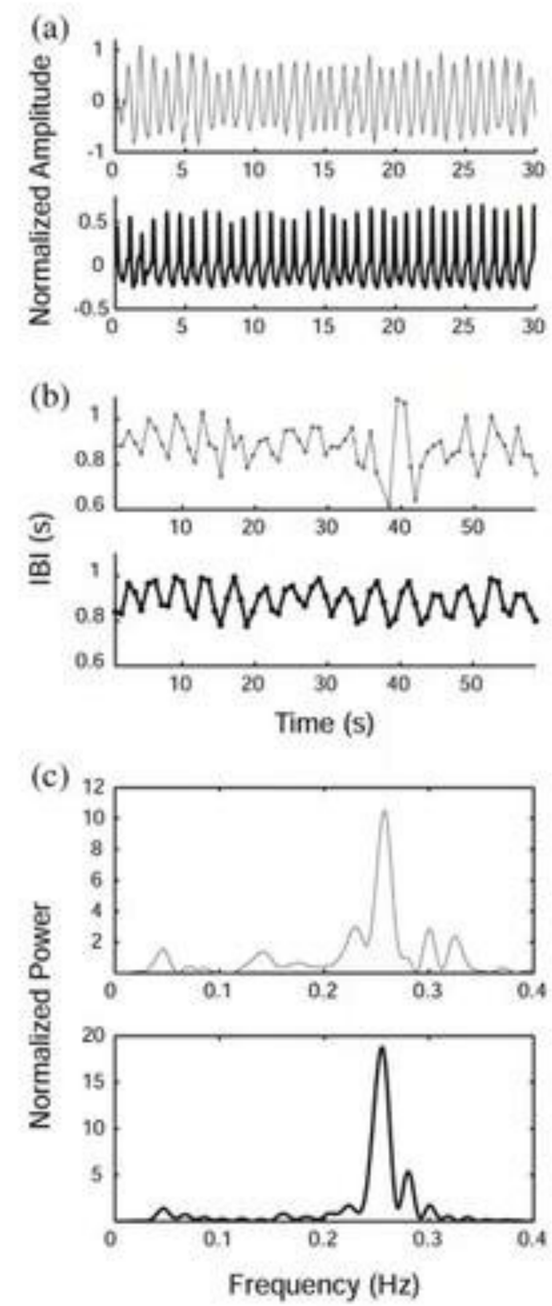


HR_{inst} $error$	**20 BPM**	**8.4 BPM**	**9.1 BPM**	**5.9 BPM**
HR_{avg} $error$	8.2 BPM	1.8 BPM	1.7 BPM	1.35 BPM

Sarkar, A., Abbott, A. L., Doerzaph, Z., & Sykes, K. (2016, January). Evaluation of video magnification for nonintrusive heart rate measurement. In *2016 IEEE First International Conference on Control, Measurement and Instrumentation (CMI)* (pp. 494-498). IEEE.

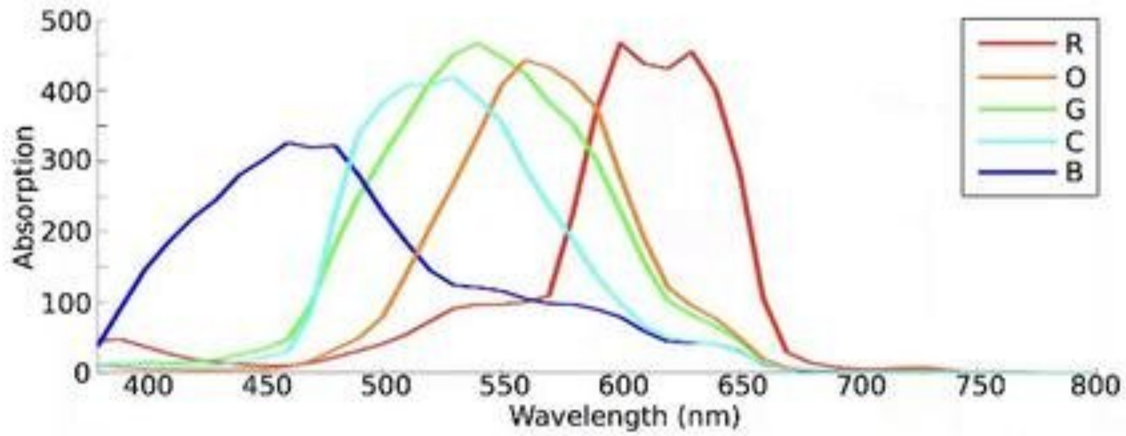

Source 1
Source 2
Source 3
Stereo Mixture
Left Channel
Right Channel
DUET
Estimate 1
Estimate 2
Estimate 3

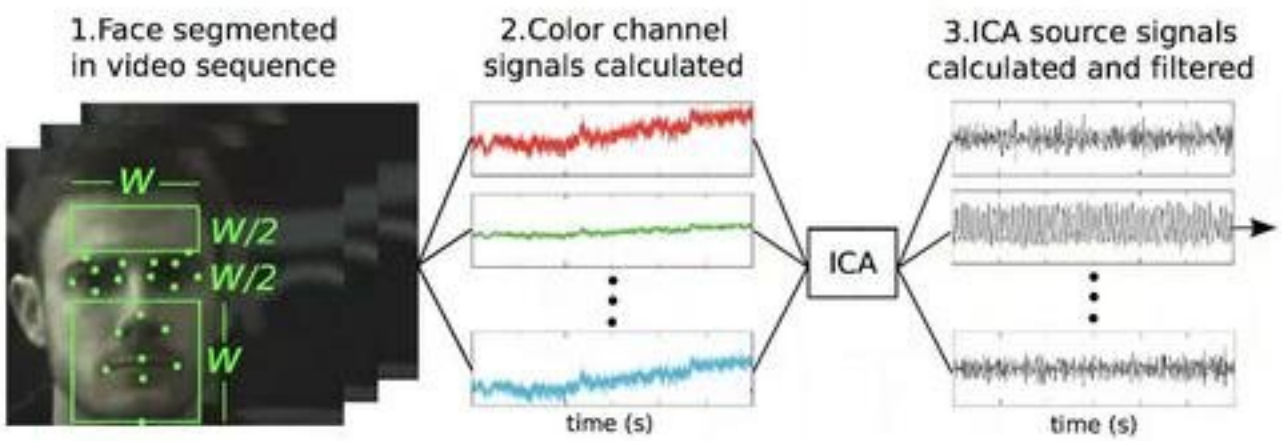


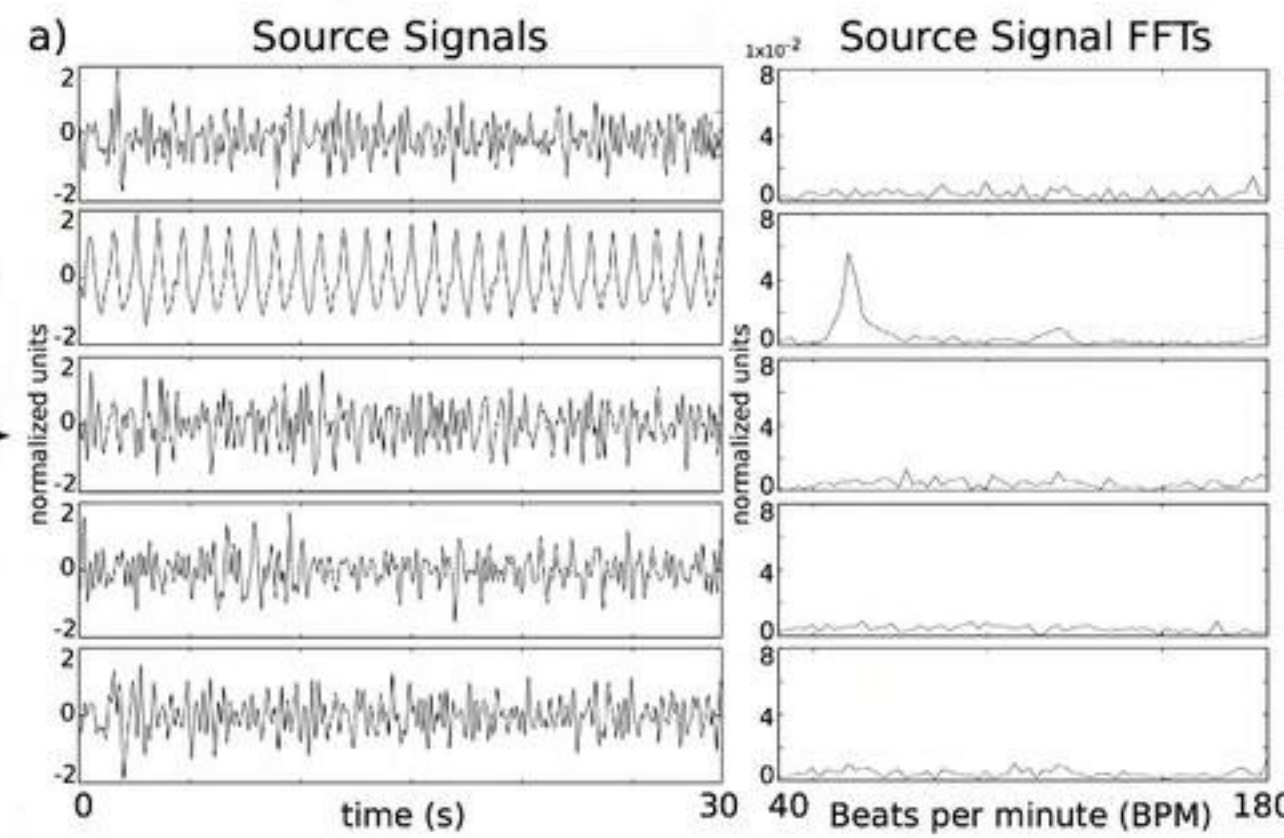


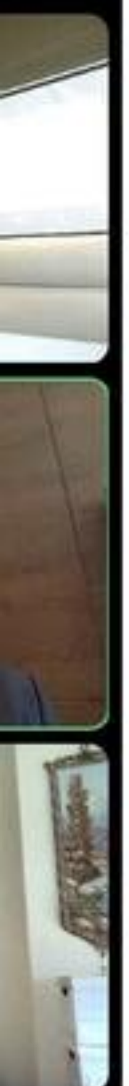
Poh, M. Z., McDuff, D. J., & Picard, R. W. (2010). Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. *Optics express*, 18(10), 10762-10774.

Five Channel Camera









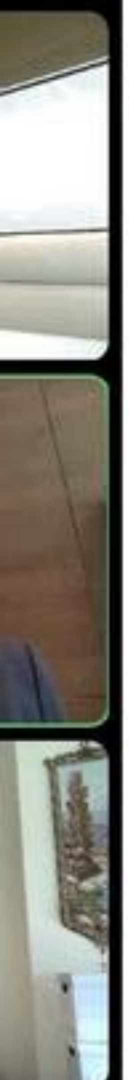
McDuff, D., Gontarek, S., & Picard, R. W. (2014). Improvements in remote cardiopulmonary measurement using a five band digital camera. *IEEE Transactions on Biomedical Engineering*, *61*(10), 2593-2601.



	HR	BR	LF	HF	LF/HF
R	0.99	0.95	0.60	0.60	0.57
G	0.99	0.91	0.63	0.63	0.63
B	0.99	0.93	0.68	0.68	0.70
C	0.85	0.44	0.64	0.64	0.64
O	0.83	-0.02	0.43	0.43	0.34
RG	0.97	0.66	0.72	0.72	0.74
RB	0.95	0.89	0.47	0.47	0.47
RC	0.99	0.67	0.69	0.69	0.73
RO	1.00	0.93	0.88	0.88	0.89
GB	0.89	0.75	0.44	0.44	0.44
GC	0.99	0.83	0.82	0.82	0.82
GO	1.00	0.98	0.88	0.88	0.88
BC	0.99	0.68	0.61	0.61	0.65
BO	1.00	0.92	0.87	0.87	0.87
CO	0.99	0.67	0.40	0.40	0.48
RGB	0.85	0.67	0.45	0.45	0.46
RGC	0.99	0.75	0.67	0.67	0.71
RGO	1.00	0.92	0.83	0.83	0.86
RBC	0.99	0.69	0.71	0.71	0.68
RBO	1.00	0.92	0.83	0.83	0.83
RCO	1.00	0.90	0.91	0.91	0.89
GBC	0.99	0.77	0.80	0.80	0.78
GBO	1.00	0.93	0.84	0.84	0.83
GCO	1.00	0.93	0.93	0.93	0.93
BCO	0.99	0.84	0.69	0.69	0.77
RGBC	0.99	0.89	0.72	0.72	0.68
RGBO	1.00	0.81	0.79	0.79	0.81
RGCO	1.00	0.90	0.87	0.87	0.86
RBCO	1.00	0.90	0.81	0.81	0.77
GBCO	1.00	0.72	0.83	0.83	0.80
RGBCO	1.00	0.74	0.81	0.81	0.79

Lowest $\bar{r}$
O
RGB
CO
GB
C
RB
BC
R
RC
RBC
G
RGC
RG
BCO
B
RGBC
GBC
RGBCO
GBCO
RGBO
GC
RBCO
RBO
GBO
RGO
RGCO
BO
RO
RCO
GO
GCO
Highest $\bar{r}$

McDuff, D., Gontarek, S., & Picard, R. W. (2014). Improvements in remote cardiopulmonary measurement using a five band digital camera. *IEEE Transactions on Biomedical Engineering*, *61*(10), 2593-2601.



Recorded green channel

PPG component
from green channel

$$\boldsymbol{g}_{\text{face}} = \boldsymbol{s} + \boldsymbol{y}$$

Component from Ambient Light

Recorded green channel

PPG component
from green channel

Background

Component from Ambient Light

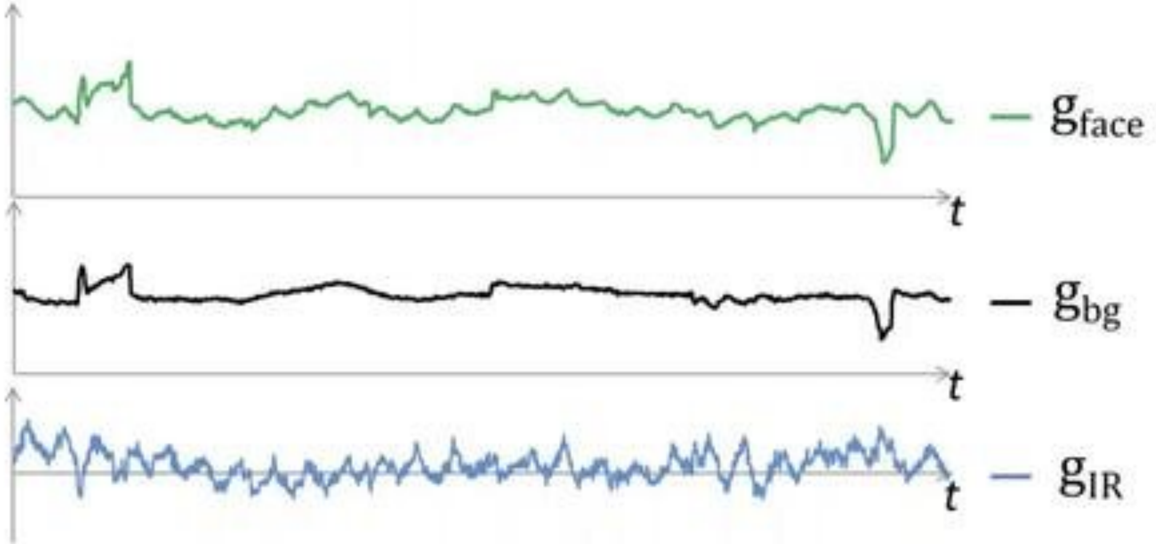
$$g_{\text{face}} = s + y$$

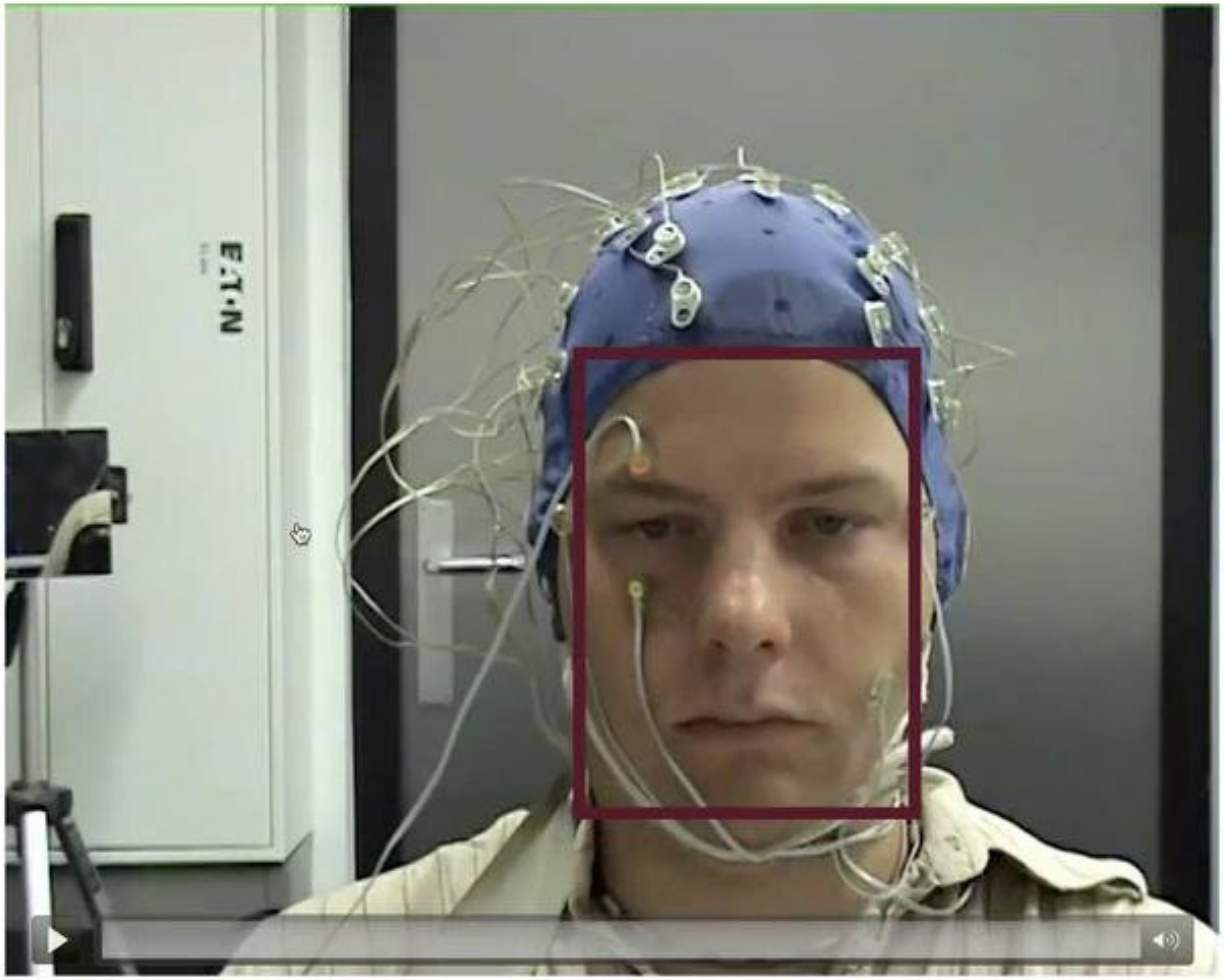
$$y \approx h g_{\text{bg}}$$

Illumination Rectified

$$g_{\text{IR}} = g_{\text{face}} - h g_{\text{bg}}$$

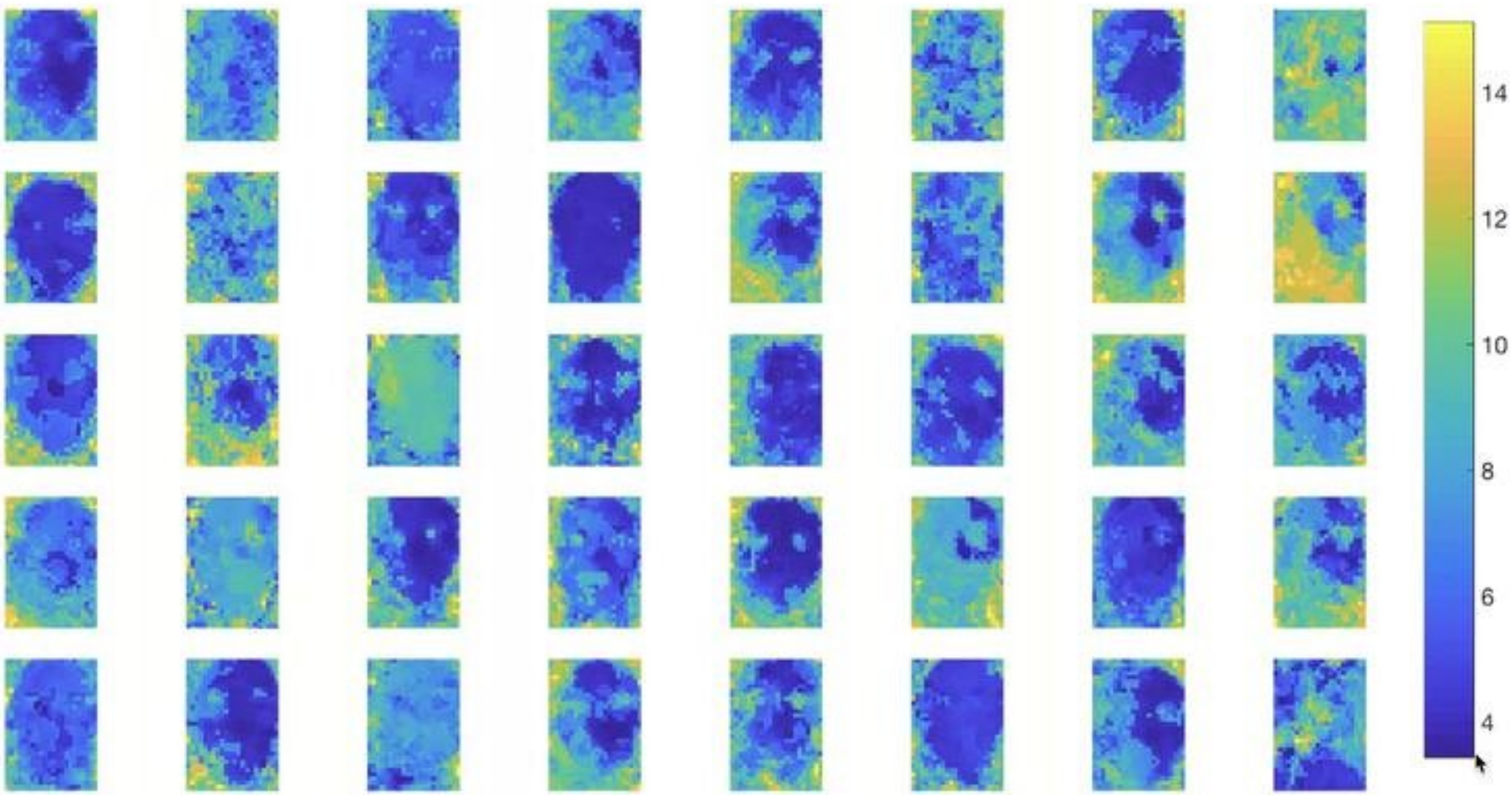
$$g_{\text{IR}} = s + (y - h g_{\text{bg}})$$





Sarkar, A. (2017). *Cardiac signals: remote measurement and applications* (Doctoral dissertation, Virginia Tech).

INFORMATION FROM EACH PATCH

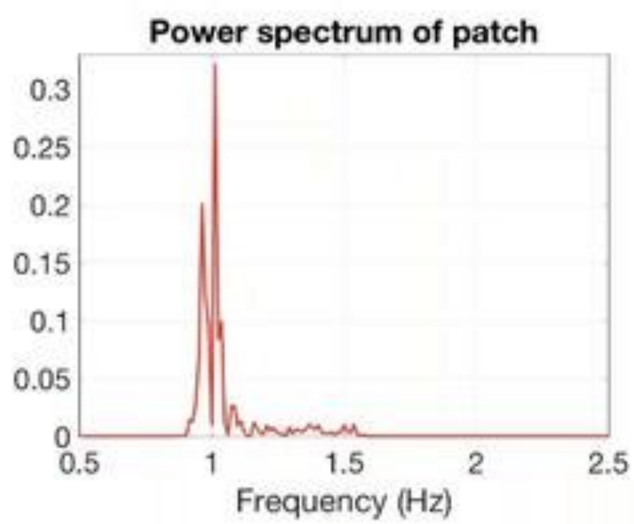


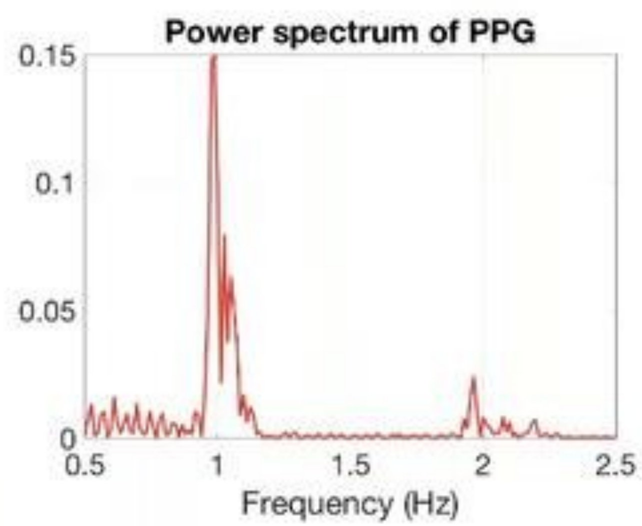
Sarkar, A. (2017). *Cardiac signals: remote measurement and applications* (Doctoral dissertation, Virginia Tech).

GOOD PATCH – BAD PATCH

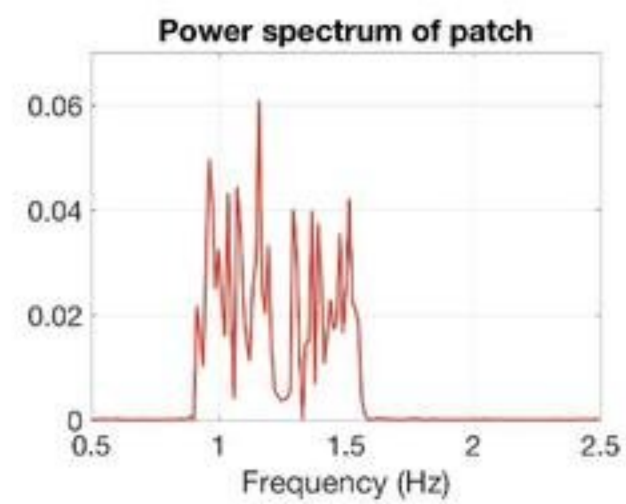
- Heart rate is natural so tend to show normal distribution.
- We use this characteristics to compute entropy of the power spectrum.

Good patch



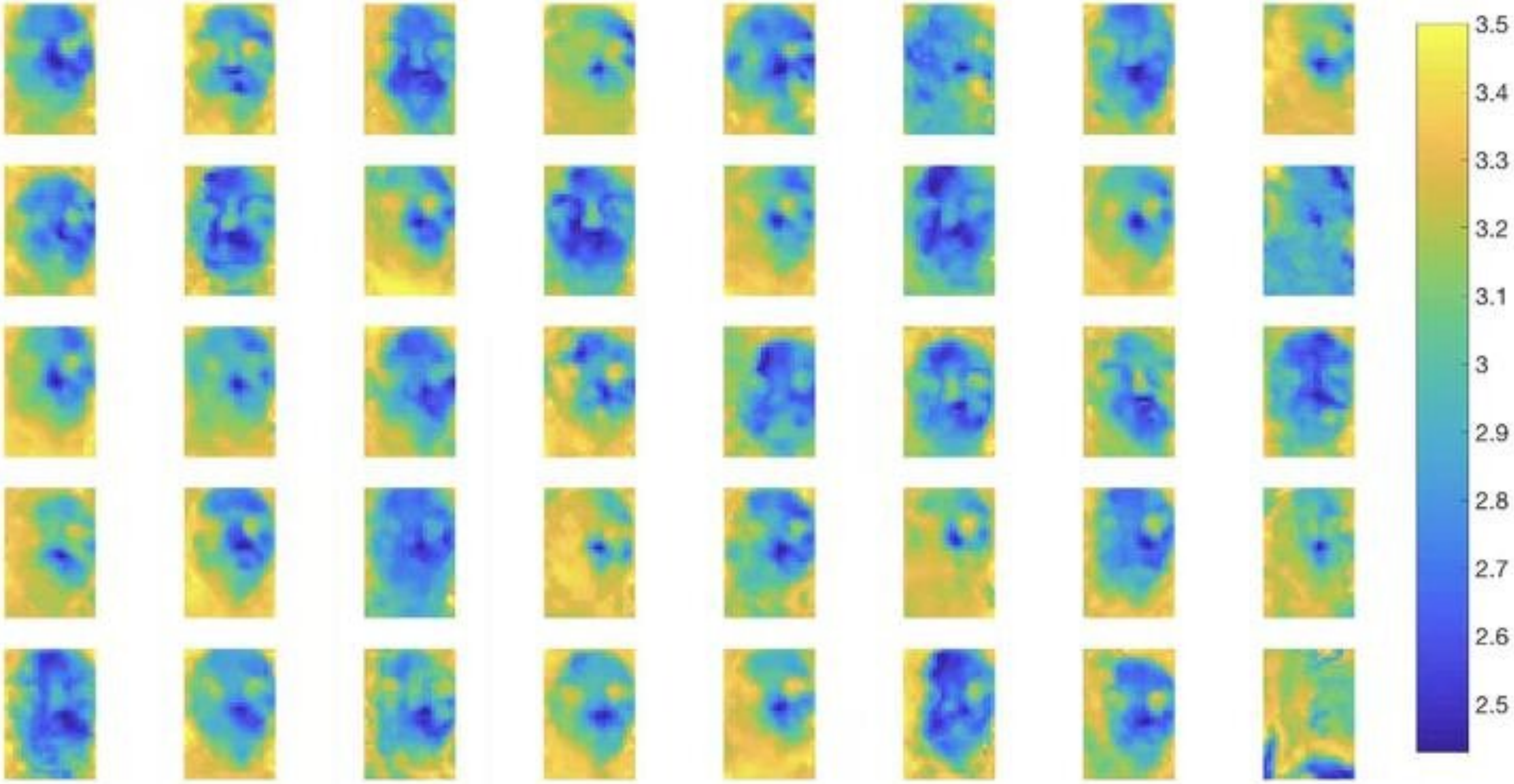


Bad patch



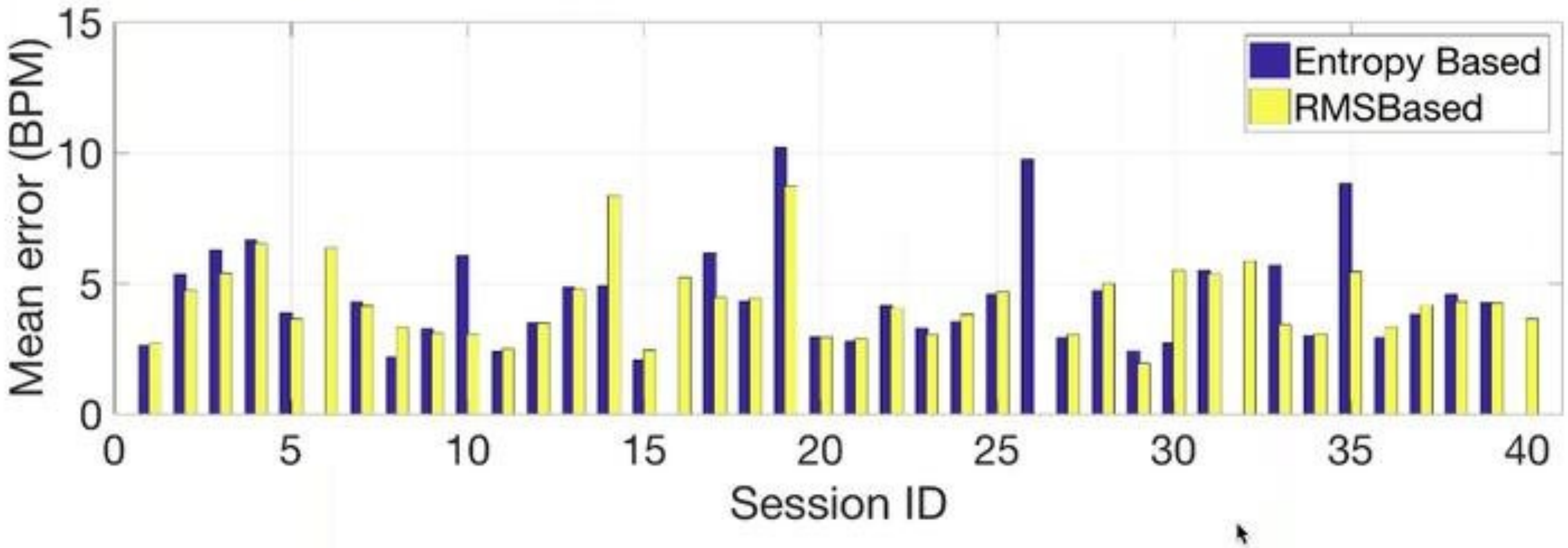
Sarkar, A. (2017). *Cardiac signals: remote measurement and applications* (Doctoral dissertation, Virginia Tech).

UNSUPERVISED RELATIVE PATCH WEIGHT



Sarkar, A. (2017). *Cardiac signals: remote measurement and applications* (Doctoral dissertation, Virginia Tech).

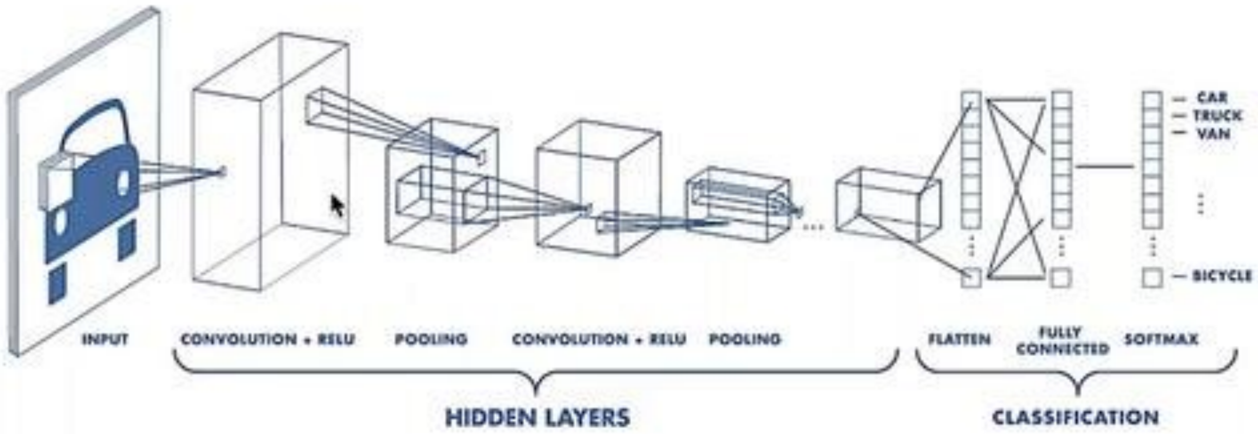
AVERAGE HEART RATE (5 BEATS)



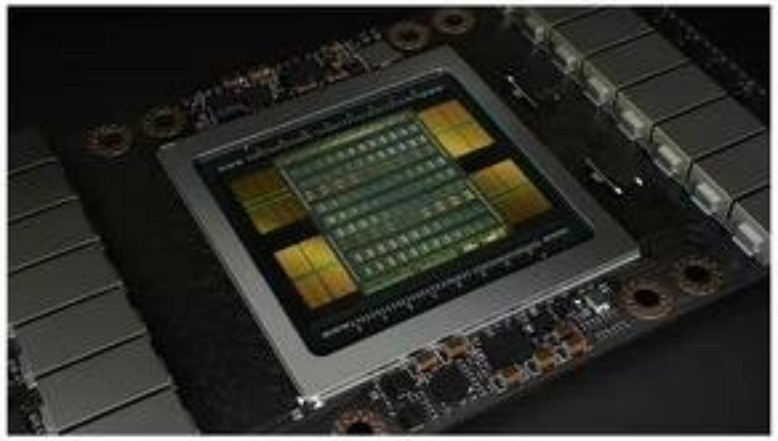
Sarkar, A. (2017). *Cardiac signals: remote measurement and applications* (Doctoral dissertation, Virginia Tech).

INTRODUCTION TO DNN

DEEP LEARNING?

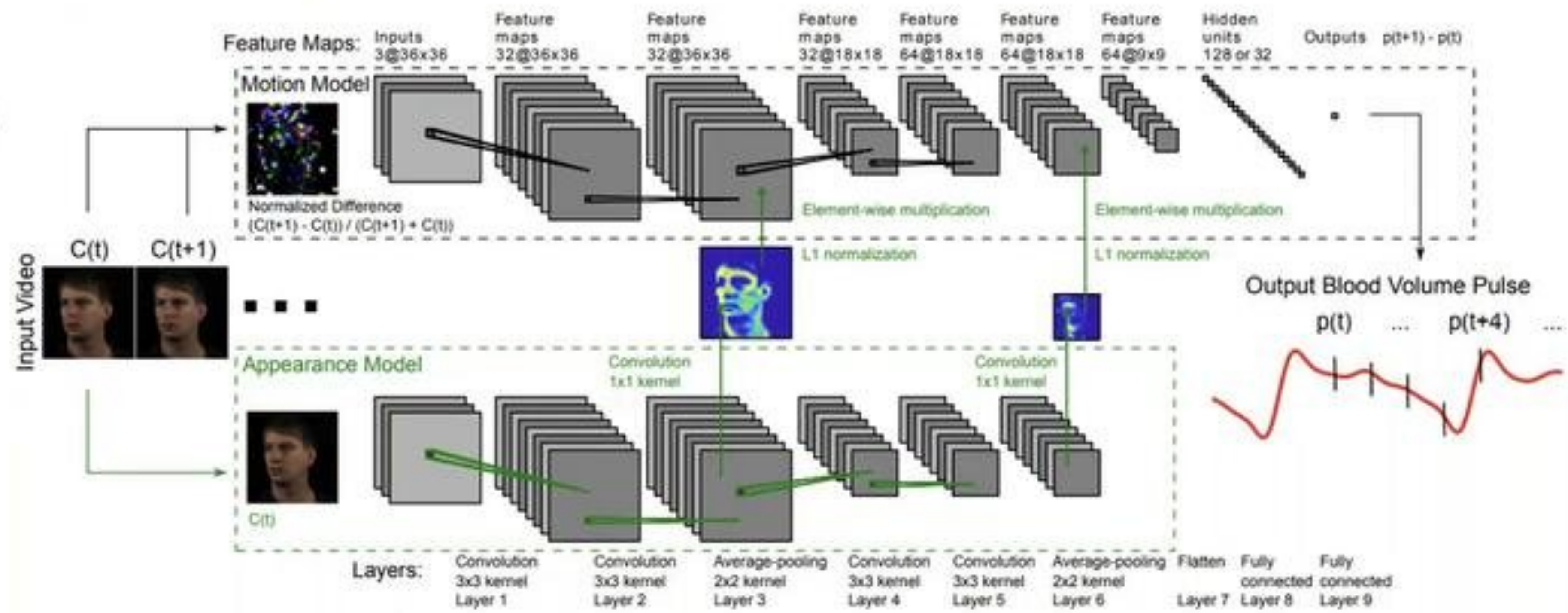


- What is a neural network?
- What is deep neural network?
- What is convolutional neural network and how it is used for object detection?
- Difference with traditional machine learning
  - Big data driven
  - Millions of parameters
  - High performance in speed and accuracy
  - Less interpretability



DEEPPHYS

- Attention
- Temporal patterns
- Signal recovery



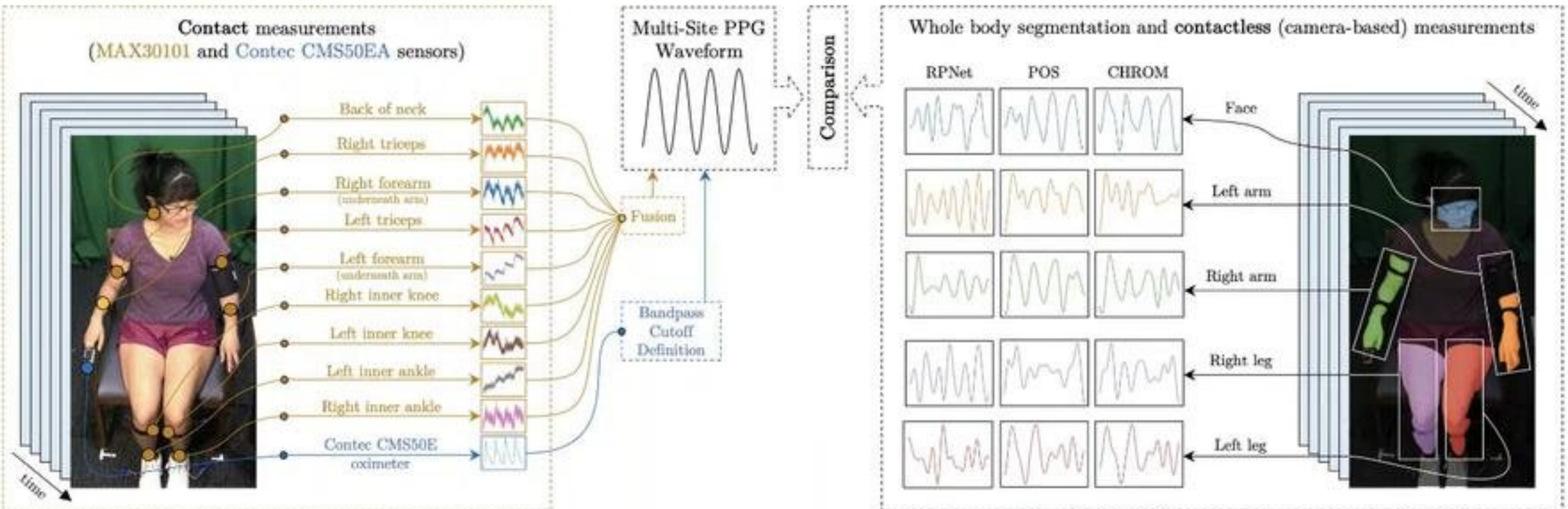
Chen, W., & McDuff, D. (2018). Deepphys: Video-based physiological measurement using convolutional attention networks. In *Proceedings of the european conference on computer vision (ECCV)* (pp. 349-365).

DATASET	RGB VIDEO II		MANHOB-HCI	
	Heart Rate		Heart Rate	
Methods	MAE /BPM	SNR /dB	MAE /BPM	SNR /dB
Estepp et al. [10]	14.7	-13.2	-	-
McDuff et al. [19]	0.25	-4.48	10.5	-10.4
Balakrishnan et al. [3]	11.3	-9.17	17.7	-12.9
De Haan et al. [13]	0.30	-2.30	5.09	-9.12
Wang et al. [39]	0.26	1.50	-	-
Tulyakov et al. [34]	2.27	-0.20	4.96	-8.93
OURS: Transfer Learning				
CAN	0.14	0.03	4.57	-8.98

DATASET	IR Video			
	Heart Rate		Breath. Rate	
Methods	MAE /BPM	SNR /dB	MAE /BPM	SNR /dB
Chen et al. [6]	0.65	3.15	0.27	5.71
OURS: Part. Ind.				
Motion-only CNN	1.44	9.55	0.49	8.95
Stacked CNN	0.87	10.9	0.14	10.4
CAN	0.55	13.2	0.14	10.8

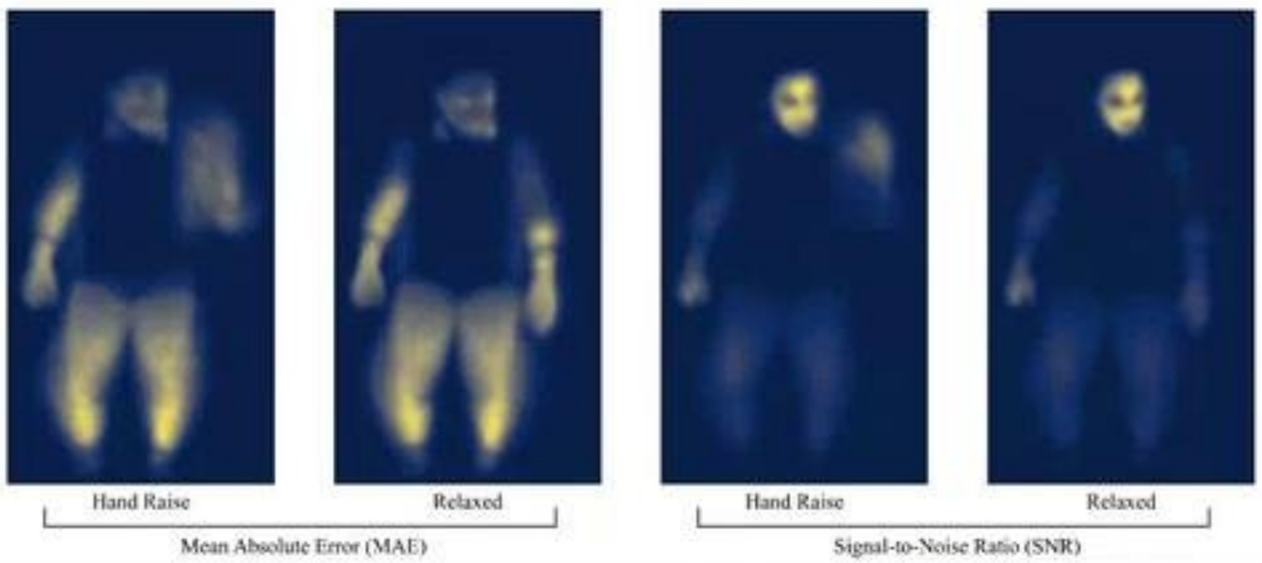
Chen, W., & McDuff, D. (2018). Deepphys: Video-based physiological measurement using convolutional attention networks. In *Proceedings of the european conference on computer vision (ECCV)* (pp. 349-365).

PPG FROM MULTIPLE SITES



Niu, L., Speth, J., Vance, N., Sporrer, B., Czajka, A., & Flynn, P. (2023). Full-Body Cardiovascular Sensing with Remote Photoplethysmography. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 5993-6003).

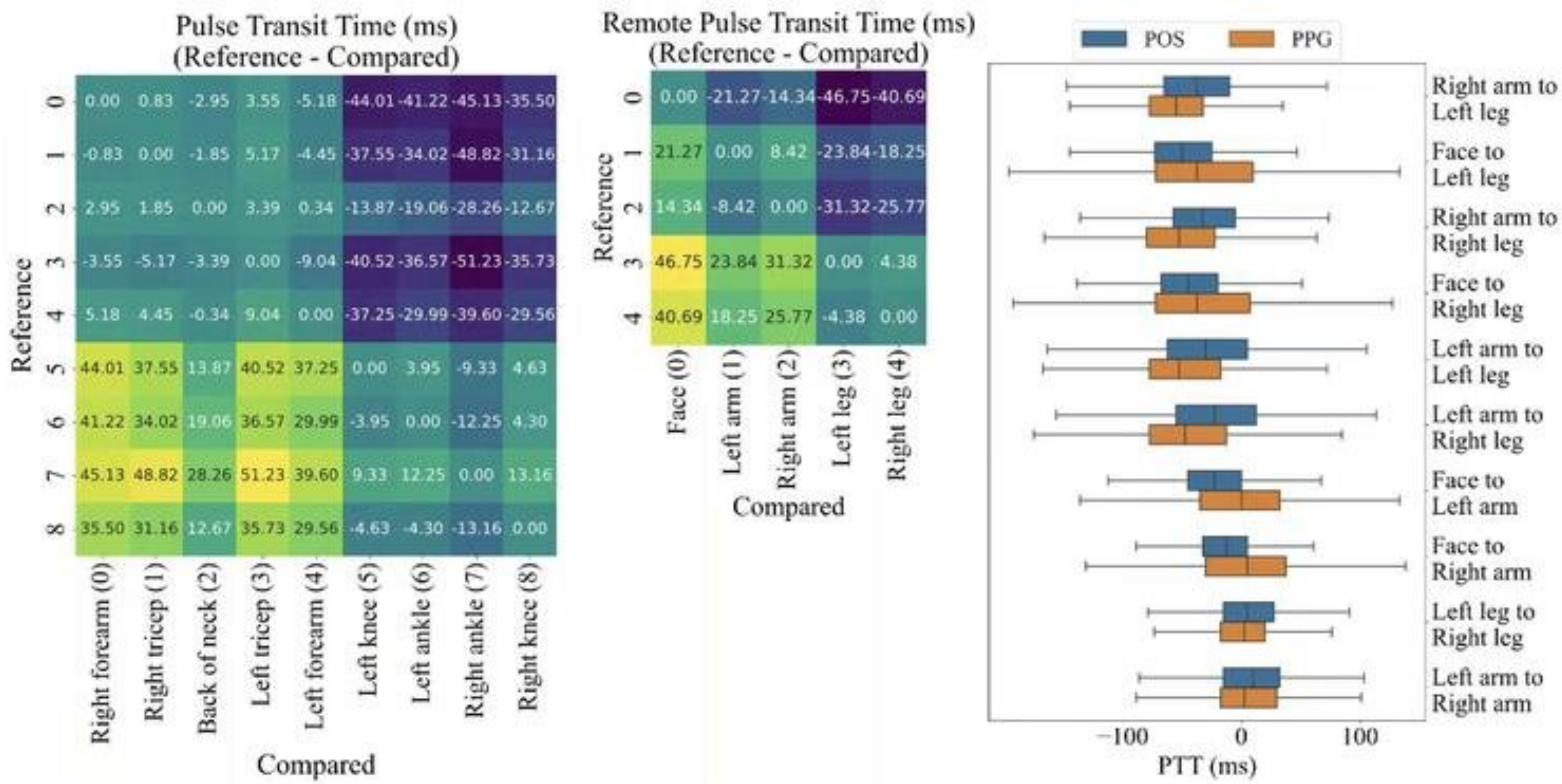
PPG FROM MULTIPLE SITES



Methods	Both relaxed and hand raise										Relaxed		Hand raise			
	Face		Right leg		Left leg		Right arm		Left arm		Left arm		Left arm		Palm	
	MAE (bpm)	r	MAE (bpm)	r	MAE (bpm)	r	MAE (bpm)	r	MAE (bpm)	r	MAE (bpm)	r	MAE (bpm)	r	MAE (bpm)	r
CHROM [9]	2.38	0.85	10.92	0.42	11.07	0.41	9.13	0.50	9.81	0.41	11.57	0.35	4.26	0.71	5.01	0.67
POS [44]	**1.38**	**0.93**	**6.96**	**0.54**	**7.11**	**0.54**	**3.60**	**0.78**	**6.04**	**0.64**	**6.88**	**0.61**	**3.40**	**0.75**	**3.88**	**0.76**
RPNet [36]	2.27	0.87	29.50	0.14	30.42	0.11	23.94	0.15	23.15	0.16	27.01	0.11	11.06	0.38	6.70	0.52

Niu, L., Speth, J., Vance, N., Sporrer, B., Czajka, A., & Flynn, P. (2023). Full-Body Cardiovascular Sensing with Remote Photoplethysmography. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 5993-6003).

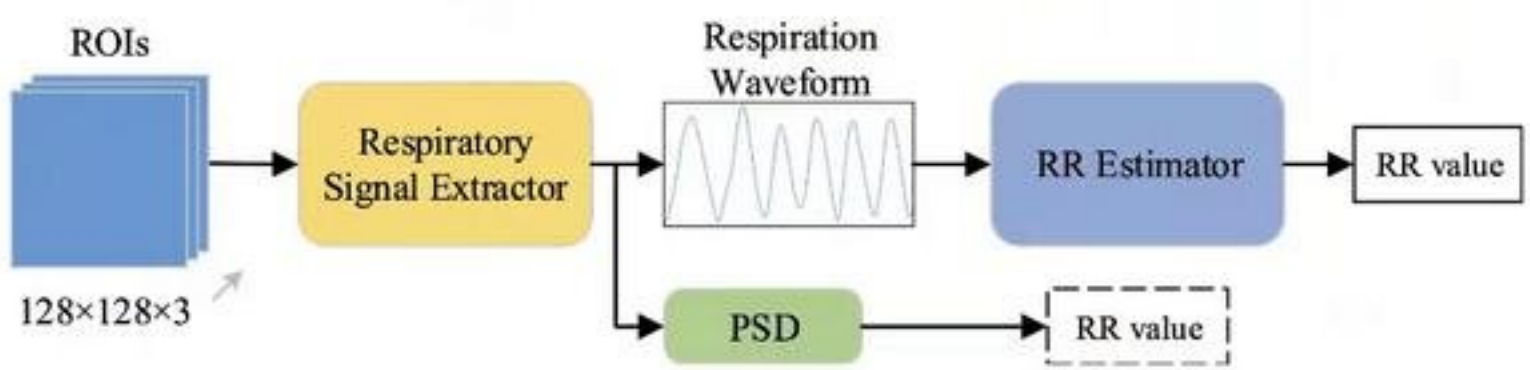
PPG FROM MULTIPLE SITES



Niu, L., Speth, J., Vance, N., Sporrer, B., Czajka, A., & Flynn, P. (2023). Full-Body Cardiovascular Sensing with Remote Photoplethysmography. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 5993-6003).

BREATHING RATE

- Patient monitoring
  - Fear of infection
  - Need specialists

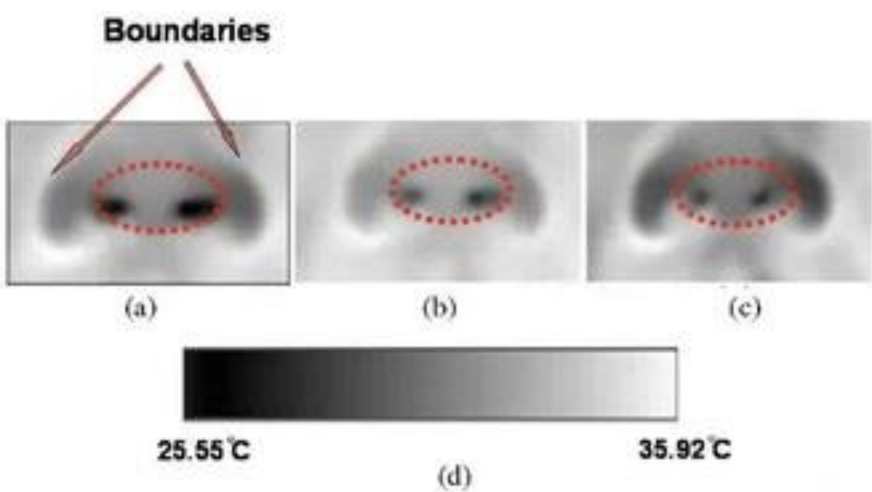


Liu, Z., Huang, B., Lin, C. L., Wu, C. L., Zhao, C., Chao, W. C., ... & Wang, Z. (2023). Contactless Respiratory Rate Monitoring for ICU Patients Based on Unsupervised Learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 6004-6013).

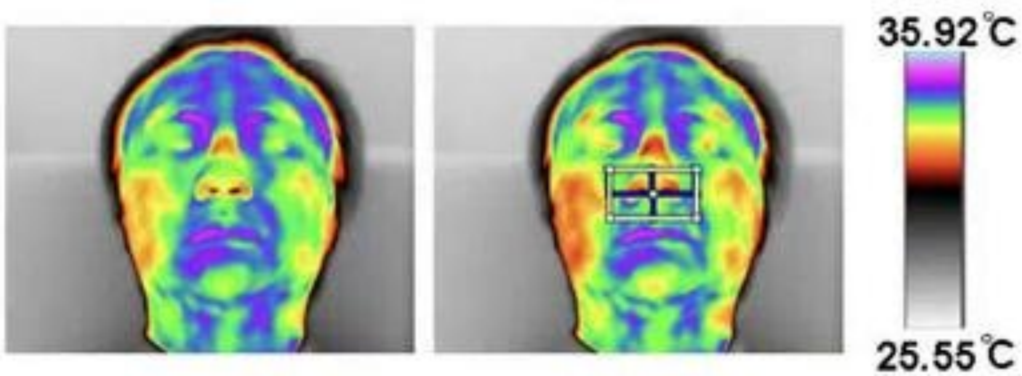
THERMAL IMAGING

BREATHING RATE

- Stress stimuli effects perinasal perspiration
- Stress induced perspiration vs physical activity-based perspiration
  - Transient vs long term
  - Thermoregulatory vs bioevolutionary



Temporal variance of nostril region in thermal imagery during breathing. (a) Inspiration phase. (b) Transition phase. (c) Expiration phase. (d) Thermal color map



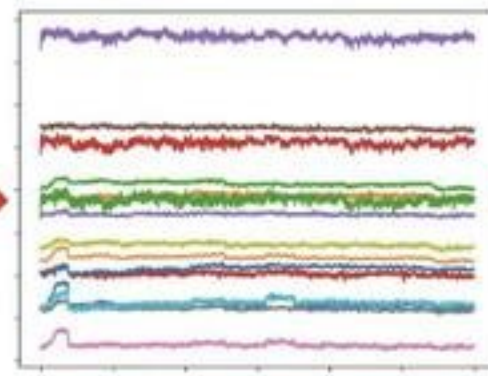
Fei, J., & Pavlidis, I. (2009). Thermistor at a distance: unobtrusive measurement of breathing. *IEEE transactions on biomedical engineering*, *57*(4), 988-998.
Shastri, D., Papadakis, M., Tsiamyrtzis, P., Bass, B., & Pavlidis, I. (2012). Perinasal imaging of physiological stress and its affective potential. IEEE Transactions on Affective Computing, 3(3), 366-378.

MODEL ARCHITECTURE

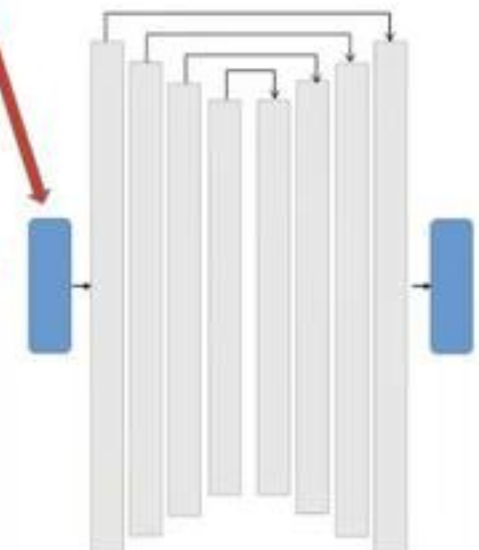
Ground truth PPG

Input video

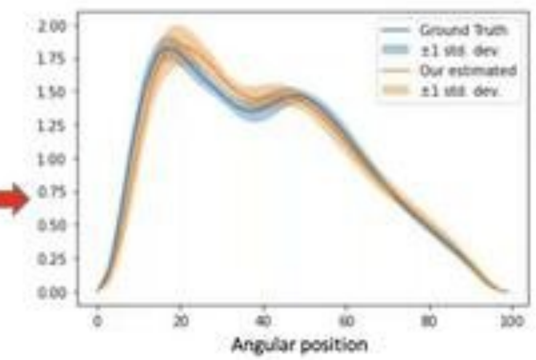
ROI extraction



ROI Color Data array



DEMUCS model



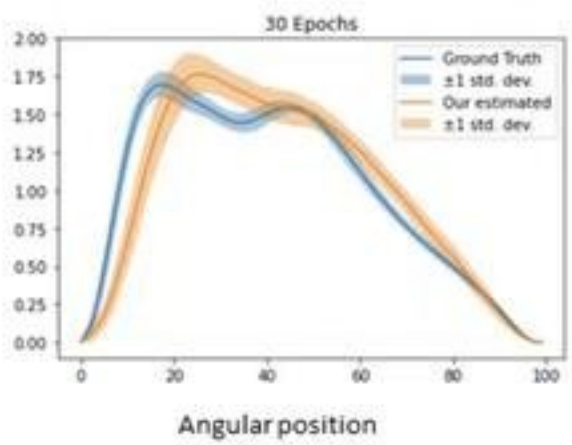
Recovered pulse shape

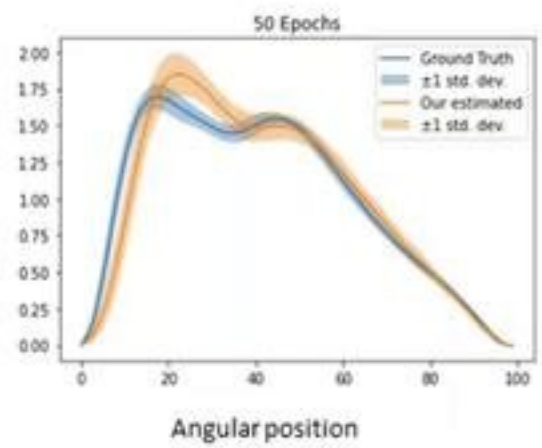
DEMUCS is an encoder-decoder model that are used for audio source separation.

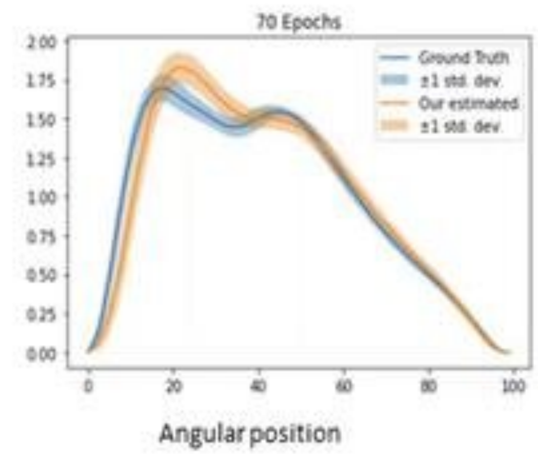
$$L(y, \hat{y}) = (1-\lambda)\|y - \hat{y}\| + \lambda(\|Re(Y) - Re(\hat{Y})\| + \|Im(Y) - Im(\hat{Y})\|)$$

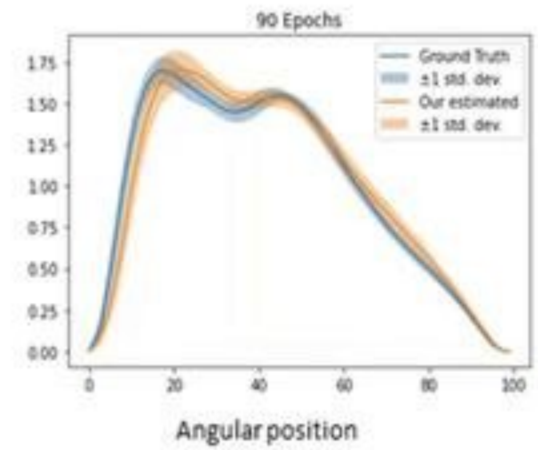
Li, F., Thapa, S., Bhat, S., Sarkar, A., & Abbott, A. L. (2023). A Temporal Encoder-Decoder Approach to Extracting Blood Volume Pulse Signal Morphology From Face Videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 5965-5974).

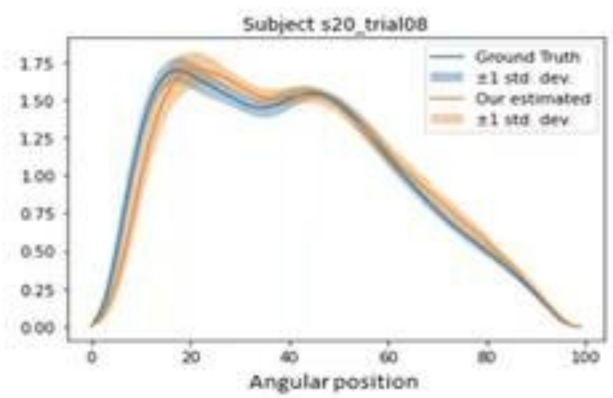
SHAPE RECOVERY

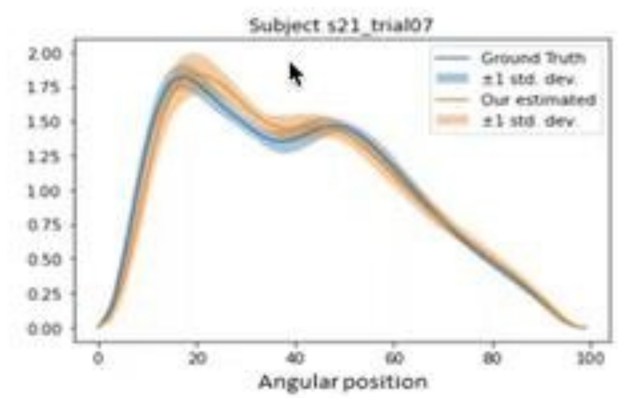


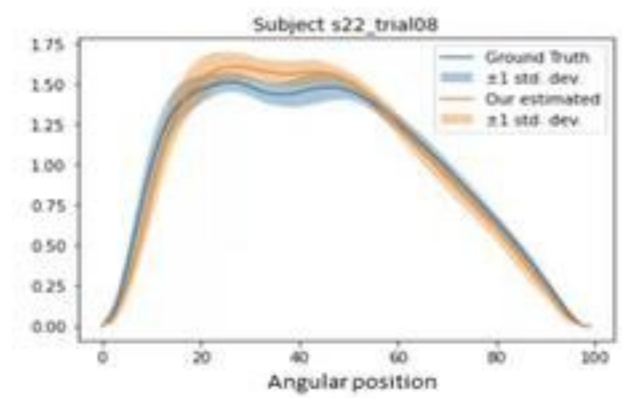










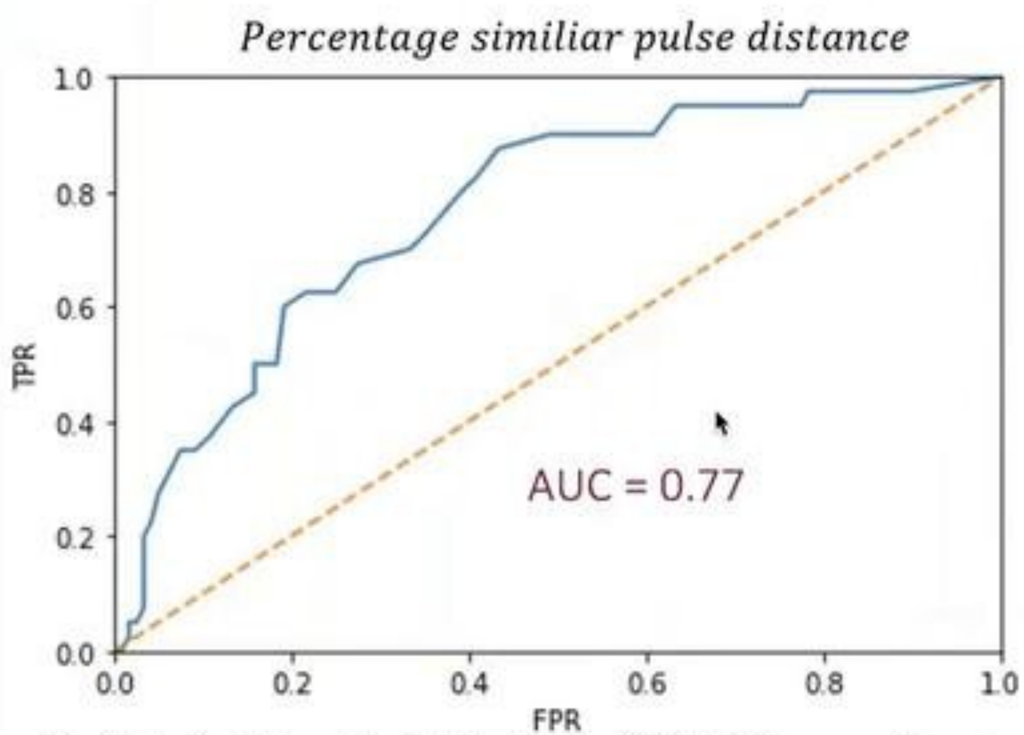


Li, F., Thapa, S., Bhat, S., Sarkar, A., & Abbott, A. L. (2023). A Temporal Encoder-Decoder Approach to Extracting Blood Volume Pulse Signal Morphology From Face Videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 5965-5974).

RESULTS: AUTHENTICATION

- Distance based metrics

$$d(x_{gi}, Y_{Id}) = \frac{1}{K-2} \sum_{j=1}^{K-1} \frac{|x_{gij} - Y_{Idj}[mean]|}{Y_{Idj}[var]}$$



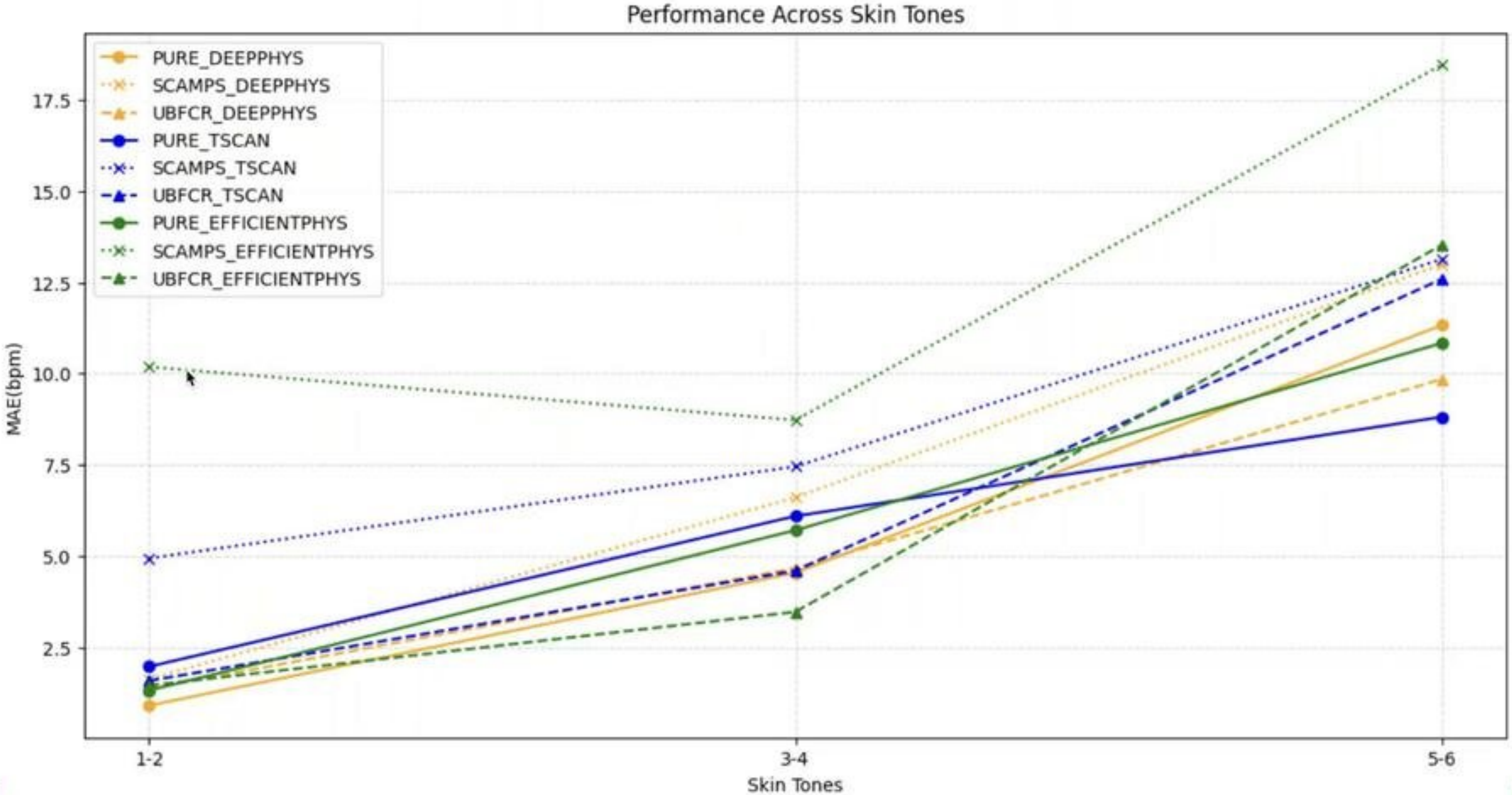
Method	MAE_{bpm} ↓	$RMSE_{bpm}$ ↓	SNR (dB)↑
GREEN [30]	11.22	13.89	-8.07
CHROM [4]	9.70	12.45	-6.04
POS [31]	12.92	16.14	-9.46
HR-CNN [27]	15.91	18.75	-10.38
MTTS-CAN [17]	11.52	14.22	-7.65
Ours (2-ROI)	14.51	17.48	-9.99
Ours (5-ROI)	**9.41**	**11.26**	**-5.36**

Table 1. Heart rate recovery results using the DEAP dataset. The bottom rows indicate a significant performance improvement for our system when using 5 ROIs as input, compared with initial attempts using only 2 ROIs. (MAE = Mean Absolute Error, MSE = Mean Square Error, SNR = Signal-To-Noise Ratio)

Li, F., Thapa, S., Bhat, S., Sarkar, A., & Abbott, A. L. (2023). A Temporal Encoder-Decoder Approach to Extracting Blood Volume Pulse Signal Morphology From Face Videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 5965-5974).

BIAS

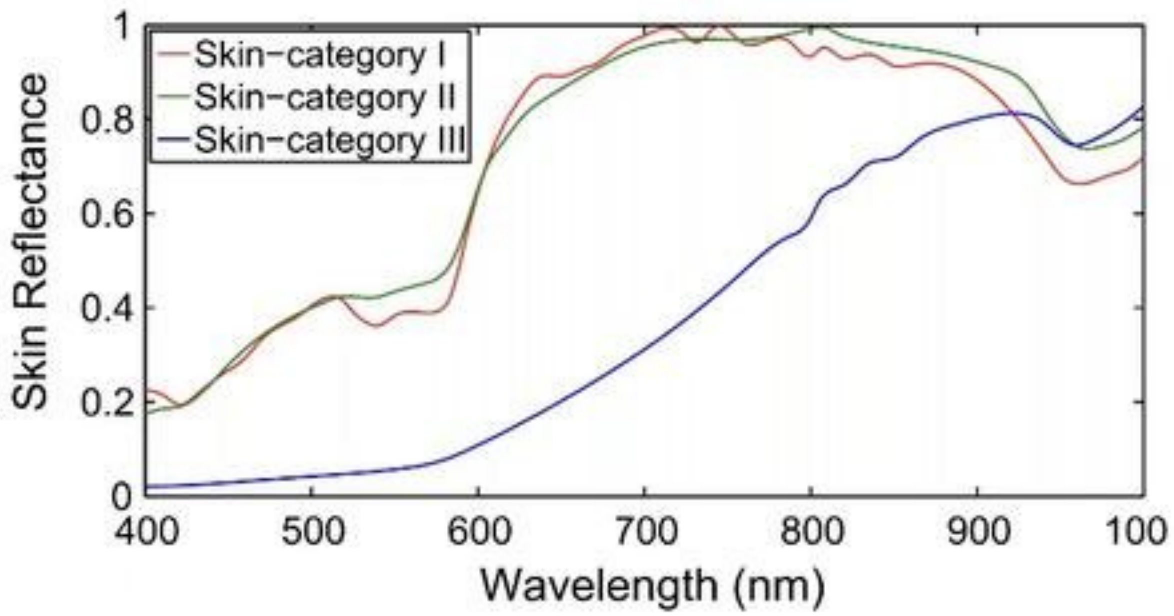
Three Models: DEEPPHYS, TSCAN and EFFICIENTPHYS

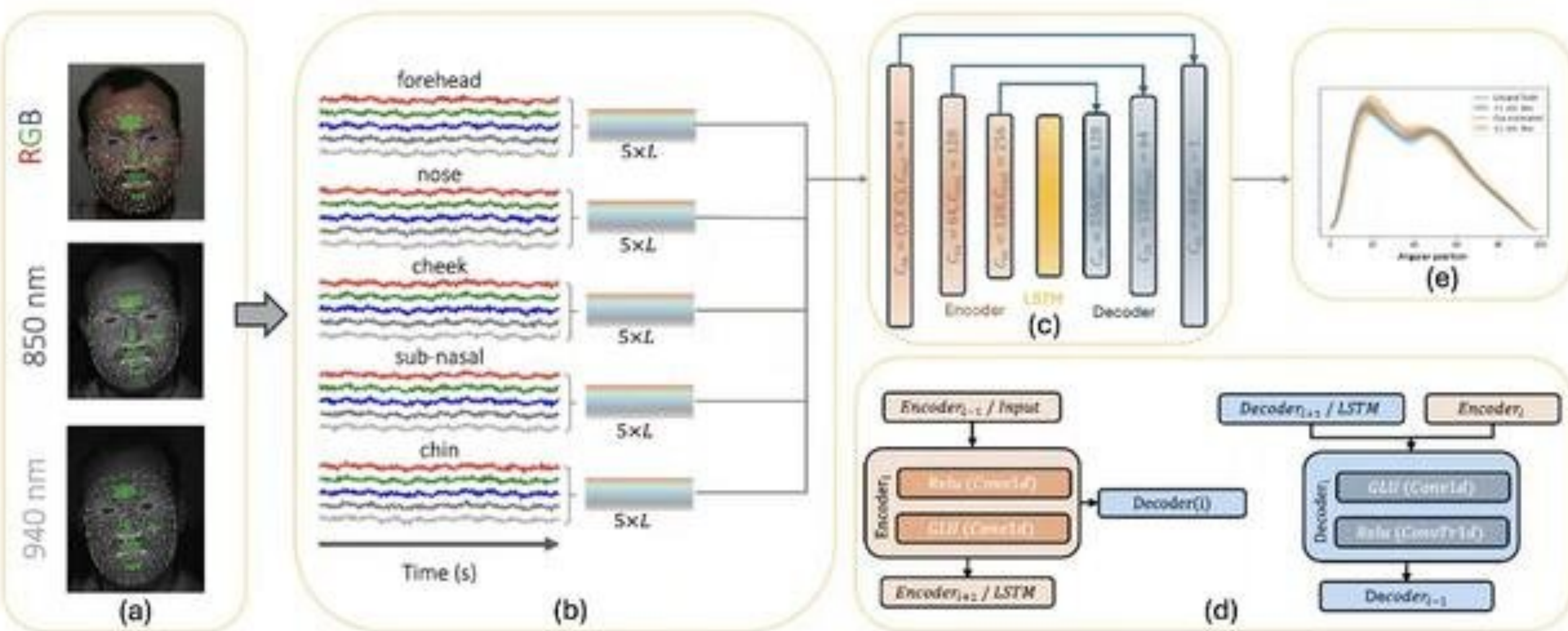


USE OF NIR

CAN IT ELIMINATE BIAS?

- We used our VT-Tricam dataset
- Trained through the DEMUCS + LSTM model





Tyler et al., 2025, ICIP

NIR IMPROVES

- Results on VT-Tricam dataset

Metrics	**RGB**	**RGBIR**	**RG850**	**RG940**	**RIR**	**GIR**	**BIR**
Instant HR MAE (bpm) ↓	10.24	**7.06**	7.48	9.06	9.99	9.82	9.90
Instant HR RMSE (bpm) ↓	20.43	**10.93**	12.09	17.80	21.03	17.10	15.27
Clip HR MAE (bpm) ↓	6.45	**4.18**	4.27	5.12	6.23	6.26	6.42
Clip HR RMSE (bpm) ↓	12.21	**6.46**	7.18	8.62	10.52	9.78	9.56
SNR (dB) ↑	2.10	**5.18**	4.61	4.21	3.34	2.59	0.96

USE OF NIR

IT IMPOROVES

Metrics	with-LSTM Models							no-LSTM Models	
	RG850	RG940	RIR	GIR	BIR	RGB	RGBIR	RGB	RGBIR
Skin Tone 2 (lighter)									
Time Corr. ↑	0.871	**0.879**	0.873	0.873	0.871	0.872	0.872	0.869	**0.879**
Frequency Corr. ↑	0.954	0.949	0.952	0.945	0.947	0.952	**0.956**	0.945	0.949
Power Corr. ↑	0.746	**0.759**	**0.759**	0.727	0.707	0.744	0.743	0.701	0.725
IHR MAE (bpm) ↓	**5.849**	6.560	7.468	8.530	7.410	7.370	6.070	8.530	8.340
SNR (dB) ↑	**7.266**	5.439	5.575	4.362	3.908	4.854	**7.300**	2.885	3.949
Skin Tone 3									
Time Corr. ↑	0.859	0.866	0.867	0.865	0.856	**0.871**	0.851	0.857	0.867
Frequency Corr. ↑	0.953	0.955	0.955	0.948	0.936	0.953	**0.956**	0.948	0.951
Power Corr. ↑	0.700	**0.776**	0.761	0.704	0.648	0.725	0.698	0.685	0.726
IHR MAE (bpm) ↓	**8.297**	11.145	12.303	9.565	11.881	12.595	7.023	11.838	10.285
SNR (dB) ↑	5.200	**5.876**	4.459	2.753	-0.532	2.951	5.769	0.519	2.884
Skin Tone 4 (darker)									
Time Corr. ↑	0.895	0.903	**0.907**	0.900	0.905	0.901	0.893	0.900	0.898
Frequency Corr. ↑	0.960	**0.965**	0.958	0.963	0.960	0.960	0.961	0.958	0.957
Power Corr. ↑	0.513	0.558	0.518	**0.575**	0.541	0.526	0.509	0.479	0.446
IHR MAE (bpm) ↓	**9.425**	10.965	11.686	12.671	11.894	12.498	8.960	12.418	14.053
SNR (dB) ↑	-1.586	-0.756	-2.830	-1.196	-2.719	-4.676	**0.060**	-6.522	-7.419

BEHAVIORAL CUES FROM CAMERAS

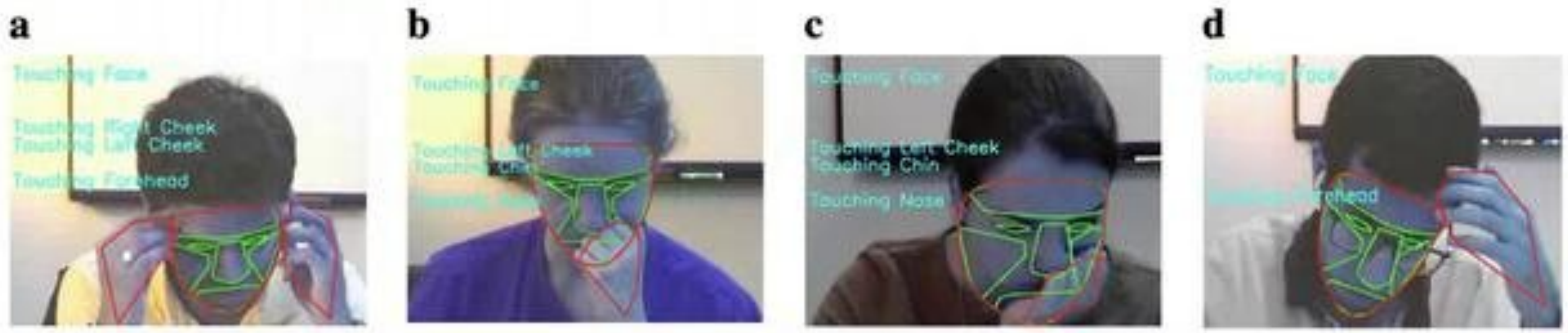


Fig. 2: Examples of sFST from the DKW data set highlighting the diversity of face-hand interactions. In most cases, participants touch their chin, cheeks, and forehead. The annotations in cyan text are provided by the MobileNet CNN and are correct. The snapshots were randomly chosen from the following recordings: [a] Participant T017 in Day 2. [b] Participant T013 in Day 1. [c] Participant T007 in Day 2. [d] Participant T015 in Day 2.

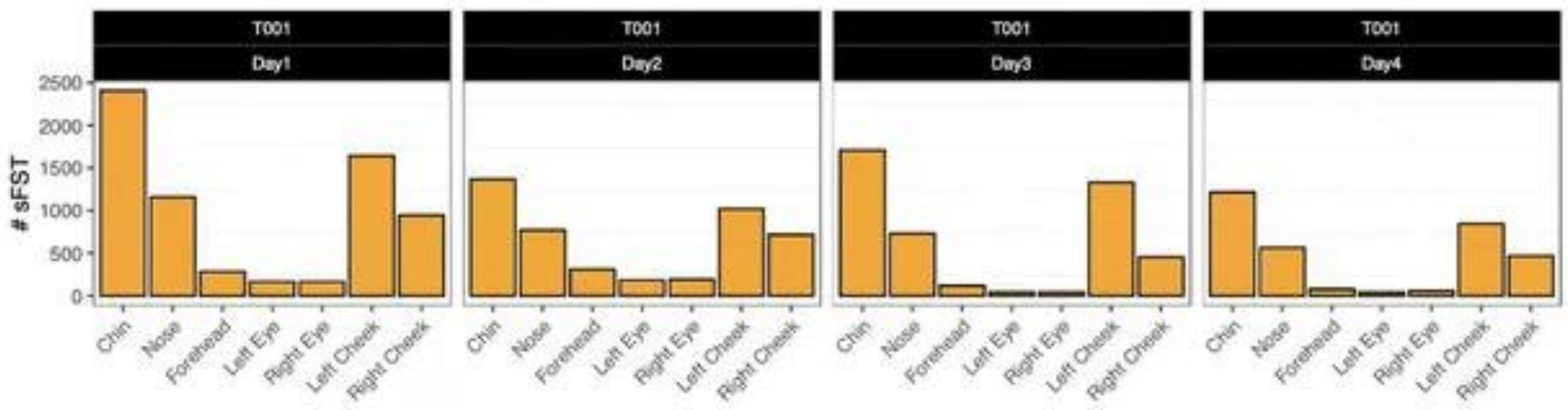


Fig. 3: Distribution of frequencies of sFST for participant T001 during the four days of observation. In all four days, the frequency of touching the left cheek is noticeably bigger than the relative frequency of touching the right cheek. The pattern is representative of all study participants. The said pattern is in agreement with prior reports in the psychological literature, suggesting that sFST are acted predominantly by the non-dominant hand [1]. Consequently, this result serves as a validity check for the goodness of the data and the classification we applied.

END OF SESSION 5

NEW DATASET

- Video collected
  - two NIR Cameras (940nm and 850nm), and one RGB Camera
  - Video Resolution: 2064 X 2464
  - 60 Hz
- Two different lighting conditions
- PPG Collected with Biopac Sensor
- 20 Subjects
- 7 Tasks in two sessions
  - Reading, watching videos
- Videos are collected raw as well with total dataset size to be around 20 TB.
- We will avail compressed versions as well (lesser dataset size).

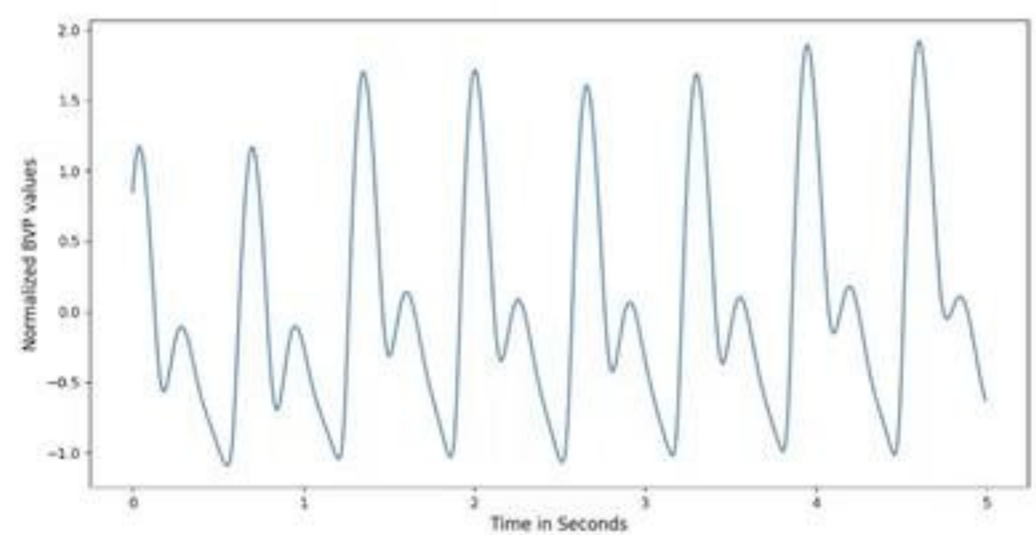
Lighting Type 1 with RGB Camera

850 nm Camera

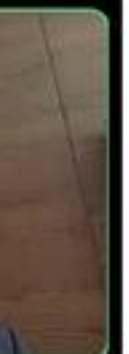
950 nm Camera

Candidate Revealing Neck Region

Lighting Type 2 with RGB Camera



BVP Sample taken using BioPac Sensor


CODEBASE

- NVIDIA HeartRateNet

A non-invasive heart rate estimation network, which aims to estimate heart rates from RGB facial videos.

- iphys-toolbox

Toolbox for PPG analysis.

- PPGI-Toolbox

Toolbox containing implementations of different models for image based Photoplethysmography.

- rppg.base package

Baseline Algorithms for Remote Photoplethysmography (rPPG)

- https://sites.google.com/view/vt-tricam-ppg
  - Work of our team
- https://physiodatatoolbox.leidenuniv.nl/docs/user-guide/physioanalyzer-modules/hrv-module.html
  - Physiodata toolbox for HRV analysis and analysis of PPG signals
- https://github.com/ubicomplab/rPPG-Toolbox
  - New rPPG toolbox

CONTACT INFORMATION

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