ACII 2019 Tutorial

Thermal Imaging-based Physiological and Affective Computing

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Key reference

Physiological and Affective Computing through Thermal Imaging: A Survey

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NADIA BIANCHI-BERTHOUZE, Division of Psychology and Language Sciences, University College London (UCL), United Kingdom

ABSTRACT

Thermal imaging-based physiological and affective computing is an emerging research area enabling technologies to monitor our bodily functions and understand psychological and affective needs in a contactless manner. However, up to recently, research has been mainly carried out in very controlled lab settings. As small size and even low-cost versions of thermal video cameras have started to appear on the market, mobile thermal imaging is opening its door to ubiquitous and real-world applications. Here we review the literature on the use of thermal imaging to track changes in physiological cues relevant to affective computing and the technological requirements set so far. In doing so, we aim to establish computational and methodological pipelines from thermal images of the human skin to affective states and outline the research opportunities and challenges to be tackled to make ubiquitous real-life thermal imaging-based affect monitoring a possibility.

KEYWORDS

Thermal imaging, physiological computing, affective computing, human temperature, thermography

Cho and Berthouze (2019)
arXiv:1908.10307

Tutorial Slides available

youngjuncho.com/tipa

What do we learn today?

Part II & Part III
(15:30 – 17:30)

Computational Pipeline & Practical guide with TIPA opensource toolkit

Challenges and research opportunities

UCL Computer Science

UCL

ACII 2019 Tutorial

Part II: Computational Pipeline & Practical guide with TIPA opensource toolkit

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UCLIC

Global Disability Innovation Hub

What do we learn during Part II?

We will dive into

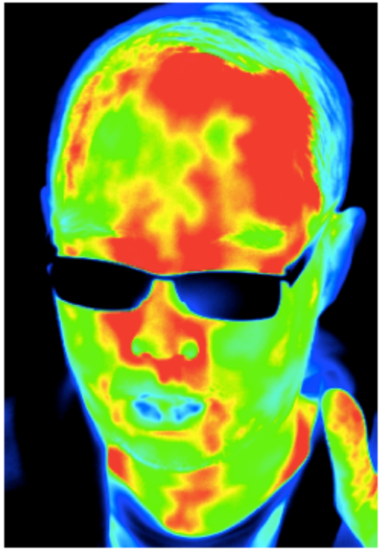
1) The computational pipeline for thermal imaging-based physiological computing

We will provide

2) A practical guide to thermal imaging-based physiological computing

Computational pipeline
for
thermal imaging-based physiological computing

Physiological Thermal Signatures



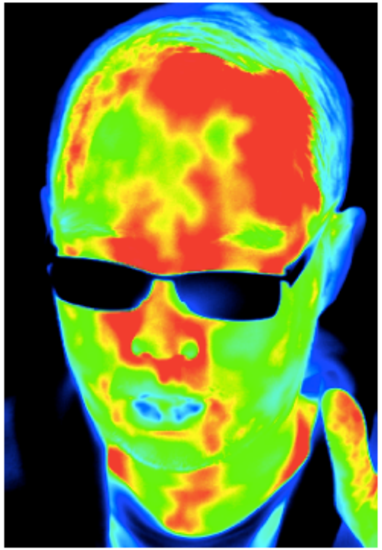
1 Cardiovascular signature

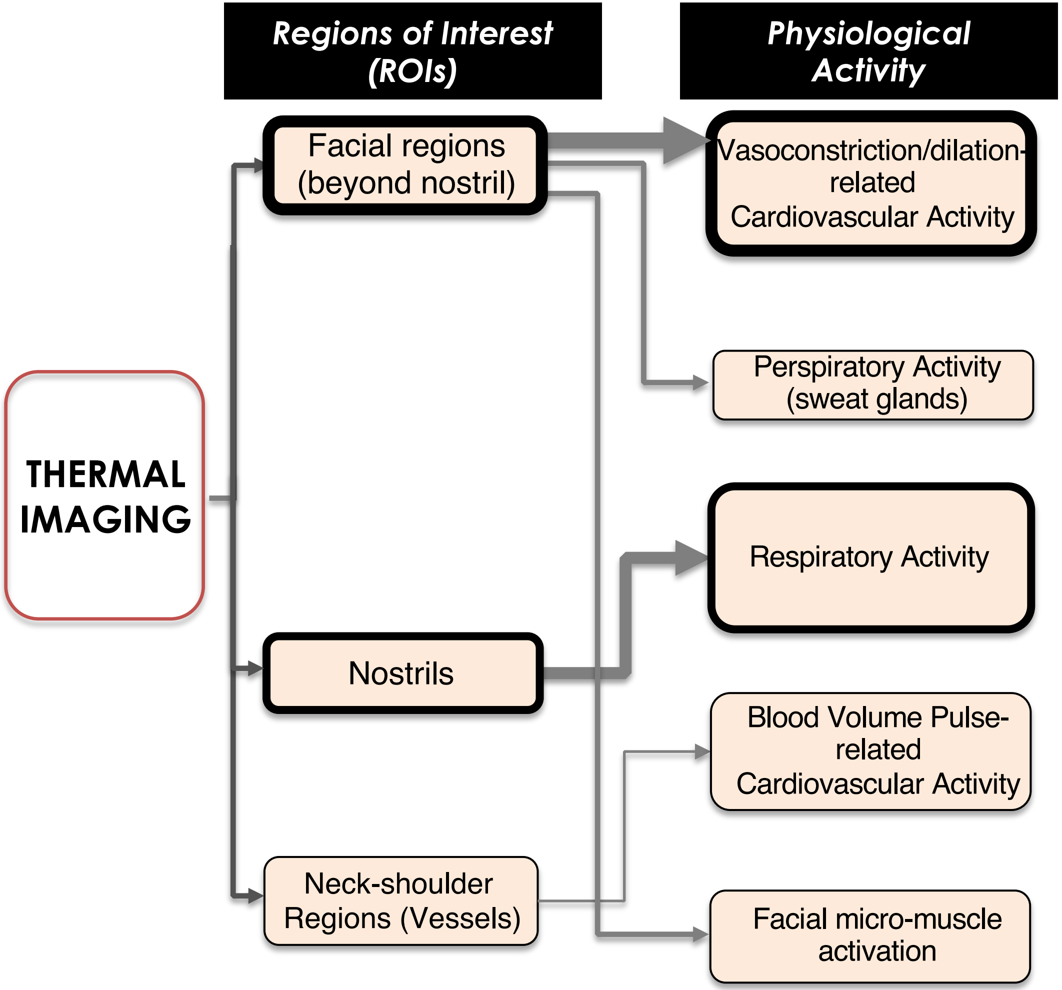
2 Respiratory signature

3 Perspiratory signature

4 Muscular signature

Cho et al. (2019)




Regions of Interest (ROIs)
Physiological Activity
THERMAL IMAGING
Facial regions (beyond nostril)
Nostrils
Neck-shoulder Regions (Vessels)
Vasoconstriction/dilation-related Cardiovascular Activity
Perspiratory Activity (sweat glands)
Respiratory Activity
Blood Volume Pulse-related Cardiovascular Activity
Facial micro-muscle activation

Cho (2019)

Computational Pipeline

Case 1 Without Automatic ROI (Motion) Tracking

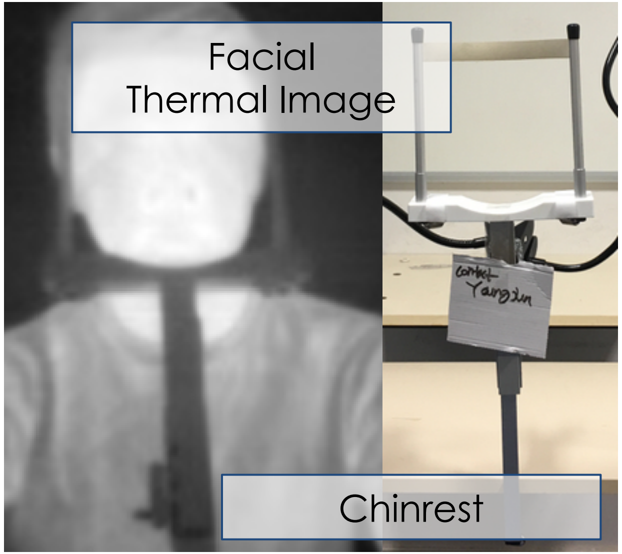
Case 2 With Automatic ROI (Motion) Tracking

Cho et al. (2019)

Computational Pipeline

Case 1 Using a head fixation mount

Jarlier et al. (2011)



A variety of studies

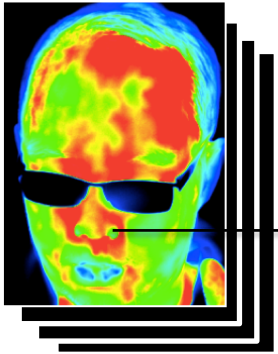
Or

asking
not to move

Computational Pipeline

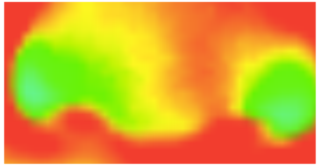
Case 1 Without Automatic ROI (Motion) Tracking

Temperature Matrices



ROI Selection

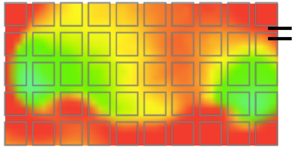
e.g. Nostrils



Spatial Interpretation

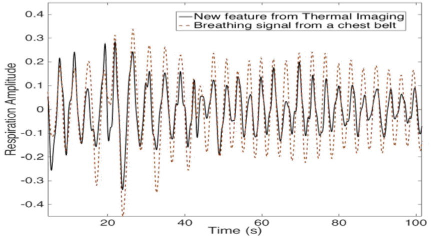
e.g.

Averaging temperature elements on the ROI



=35.7°C

Physiological Signals from all images

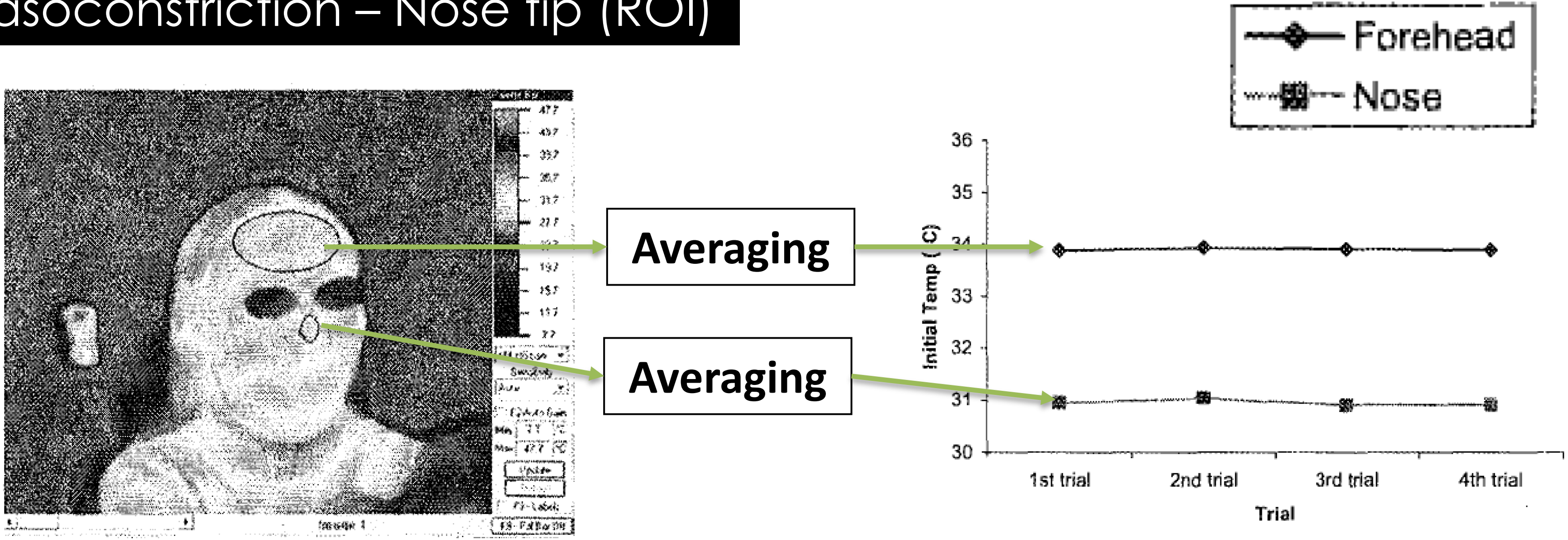


Cho et al. (2019)

How does it work?

Case 1

Vasoconstriction – Nose tip (ROI)

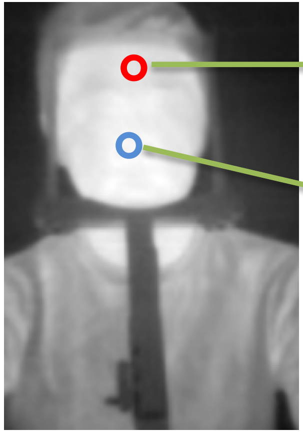


Or and Duffy (2007)

How does it work?

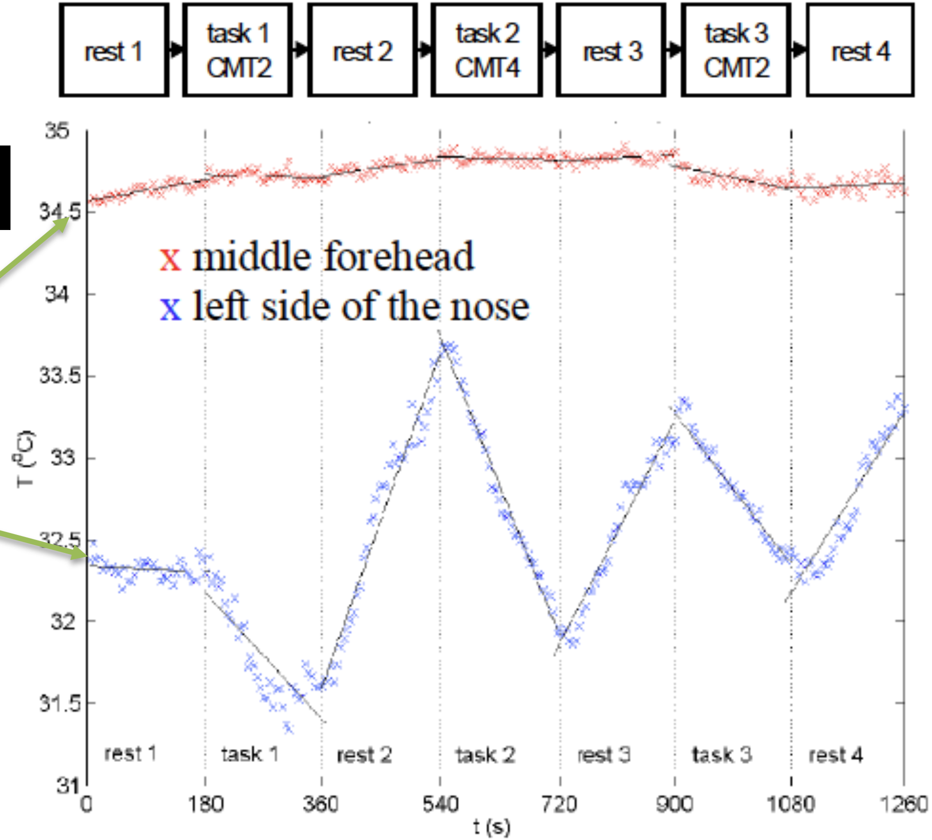
Case 1

Vasoconstriction – Nose tip (ROI)



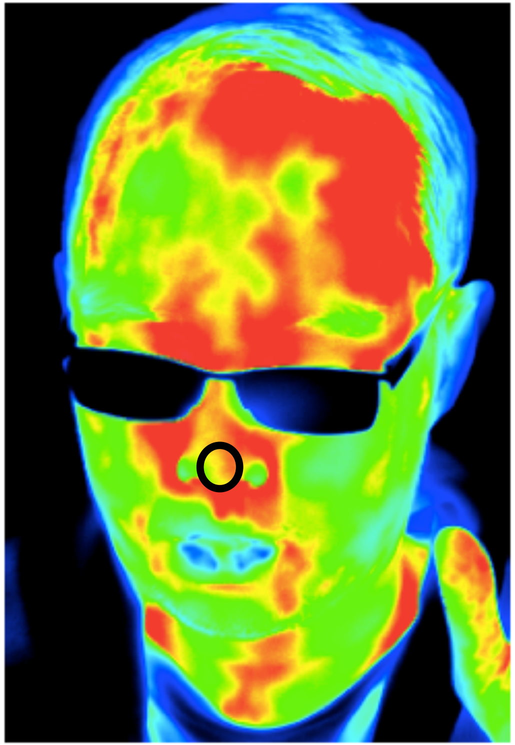
Averaging

Averaging



Veltman et al. (2005)

Remind you



Mental Stress, Mental workload

O Nose tip

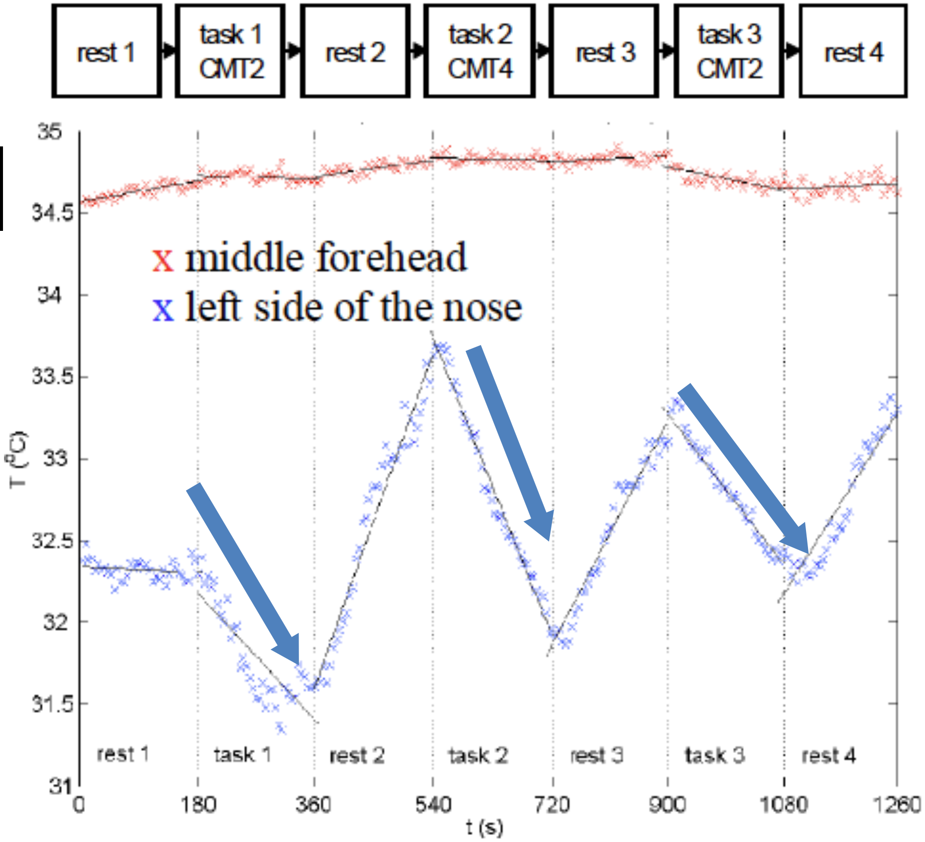
Veltman et al. (2005),
Or and Duffy (2007),
Engert et al. (2014),
Cho et al. (2019) ...

How does it work?

Case 1

Vasoconstriction – Nose tip (ROI)

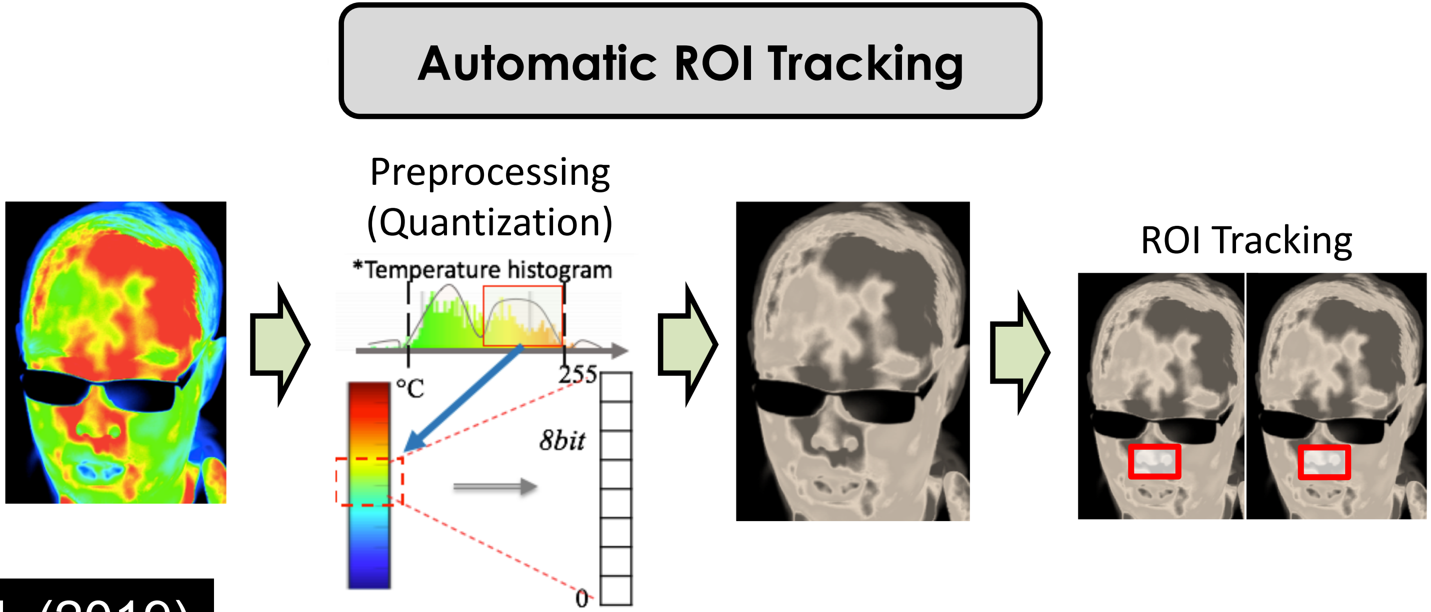
In response to **Mental Stressors**



Veltman et al. (2005)

Computational Pipeline

Case 2 Without a head fixation mount

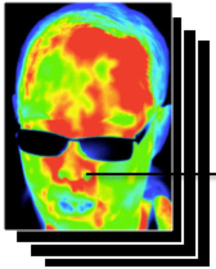


Cho et al. (2019)

Computational Pipeline

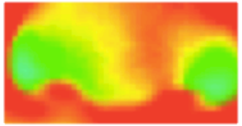
Case 2 With Automatic ROI (Motion) Tracking

Temperature Matrices



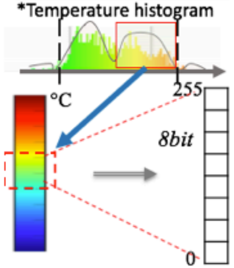
ROI Selection

e.g. Nostrils

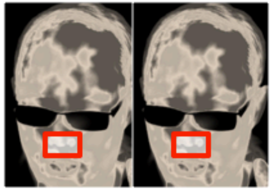


Automatic ROI Tracking

Preprocessing (Quantization)

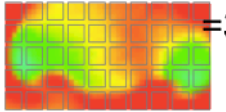


ROI Tracking



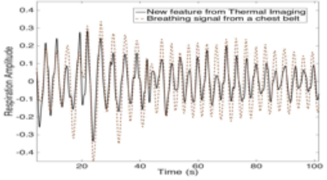
Spatial Interpretation

e.g.
Averaging
temperature
elements
on a tracked ROI



=35.7°C

Physiological Signals from all images



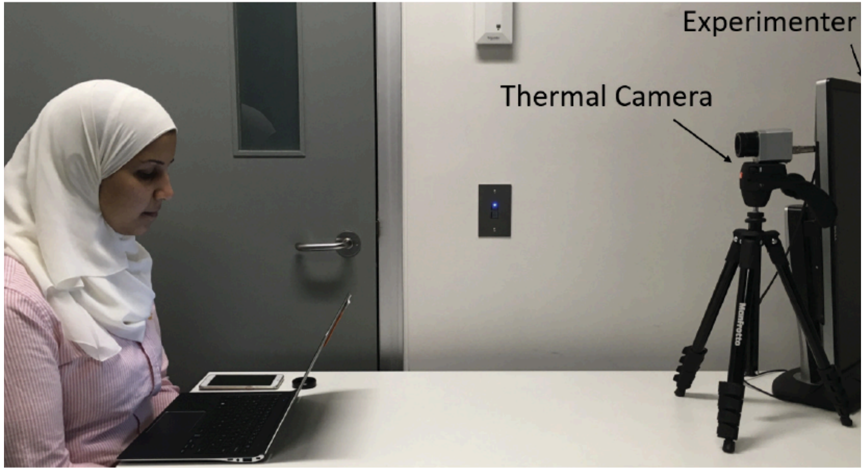
Cho et al. (2019)

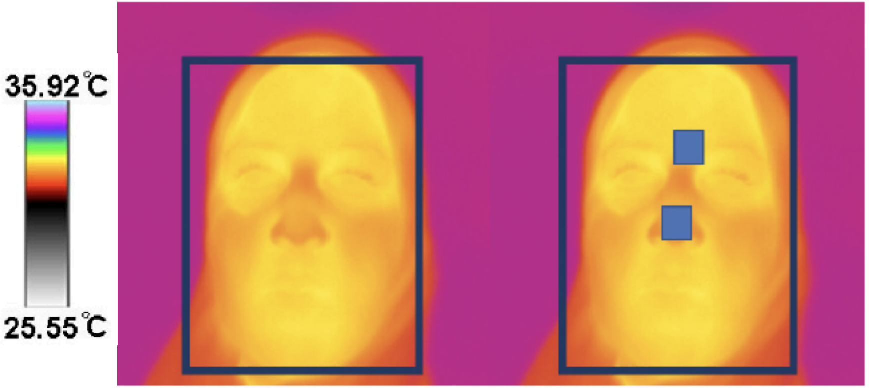
How does it work?

Case 2

Vasoconstriction – Nose tip (ROI)

"The participants were asked to look to the front facing the thermal camera"





Face tracking

ROI selection

Abdelrahman et al. (2017)

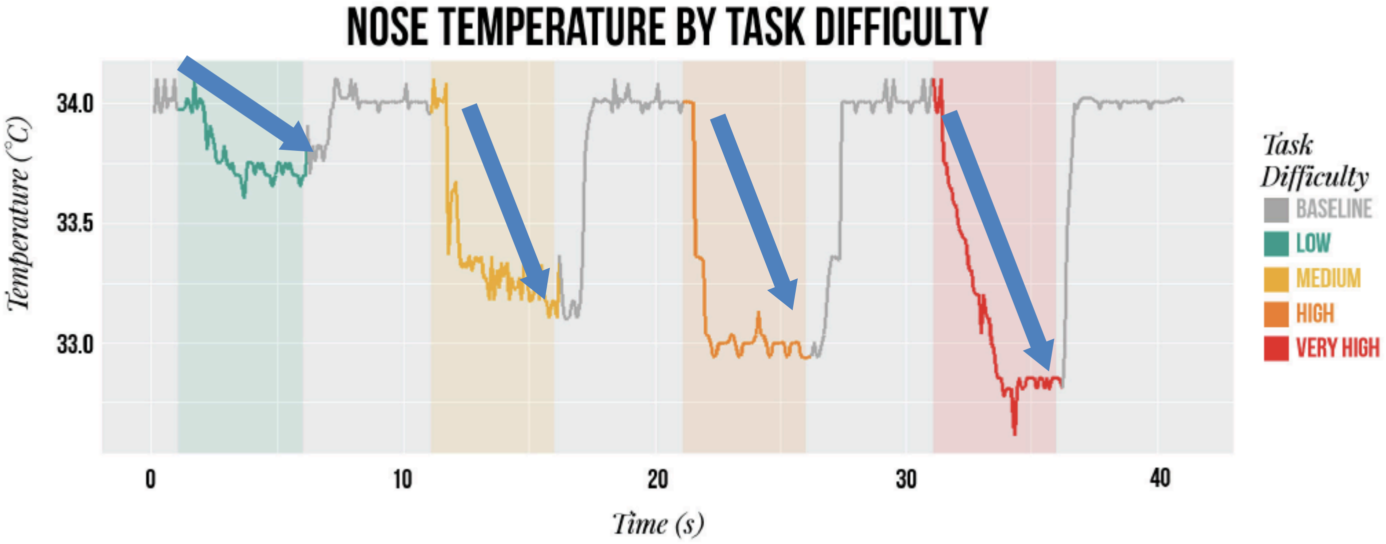
How does it work?

Case 2

Vasoconstriction – Nose tip (ROI)

Cognitive Load (Stroop test)

YELLOW BLUE ORANGE
BLACK RED GREEN
PURPLE YELLOW RED

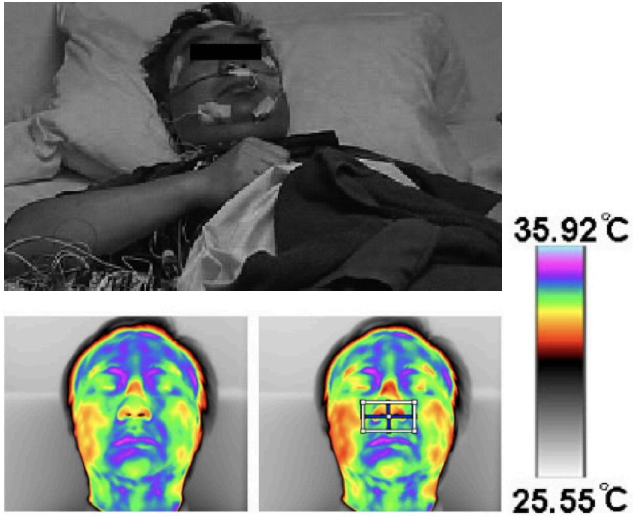


Abdelrahman et al. (2017)

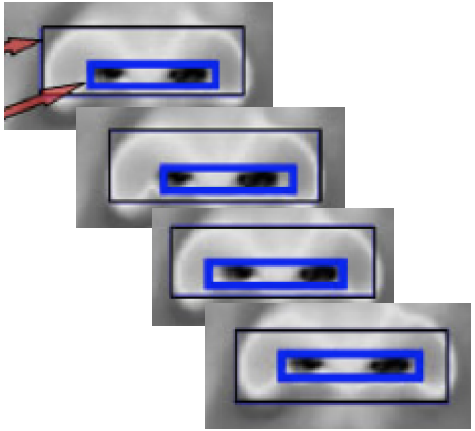
How does it work?

Case 2

Breathing – Nostril (ROI)



Automatic ROI Tracking
(coalitional tracking algorithm)

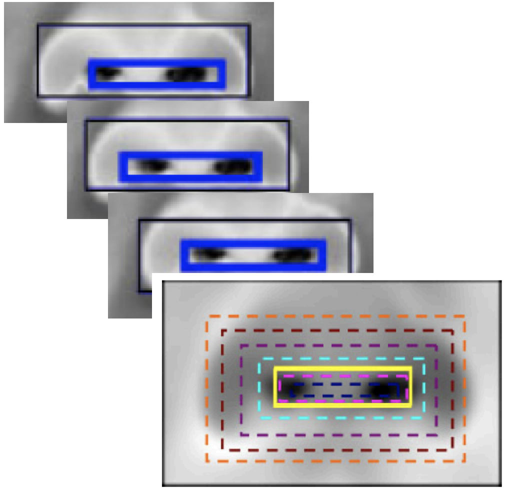


Fei and Pavlidis (2010)

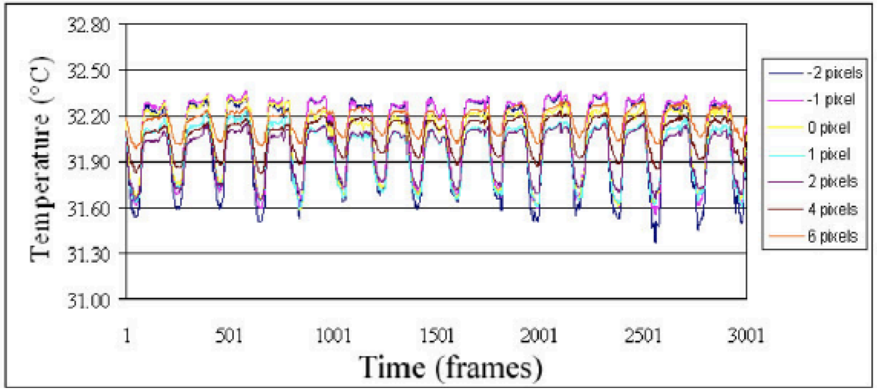
How does it work?

Case 2

Breathing – Nostril (ROI)



Averaging temperatures on the nostril ROI

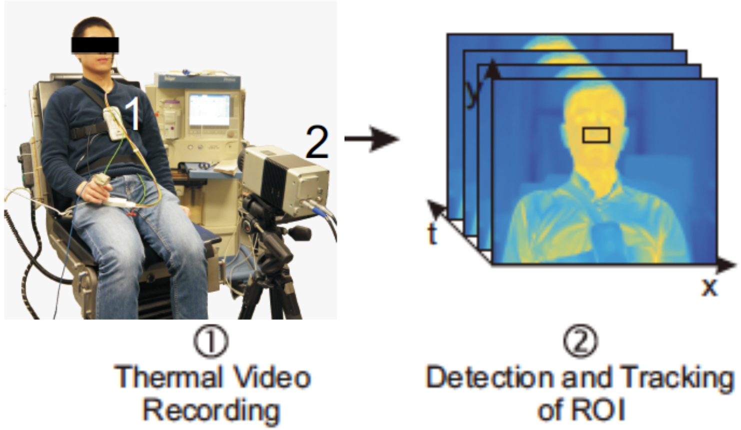


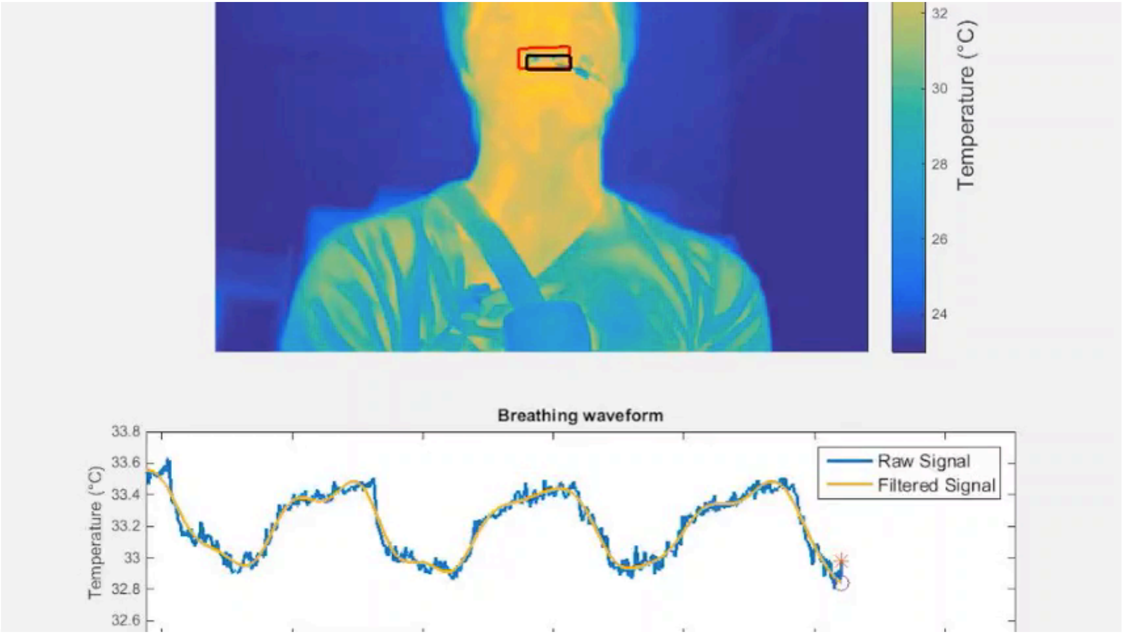
Fei and Pavlidis (2010)

How does it work?

Case 2

Breathing – Nostril (ROI)



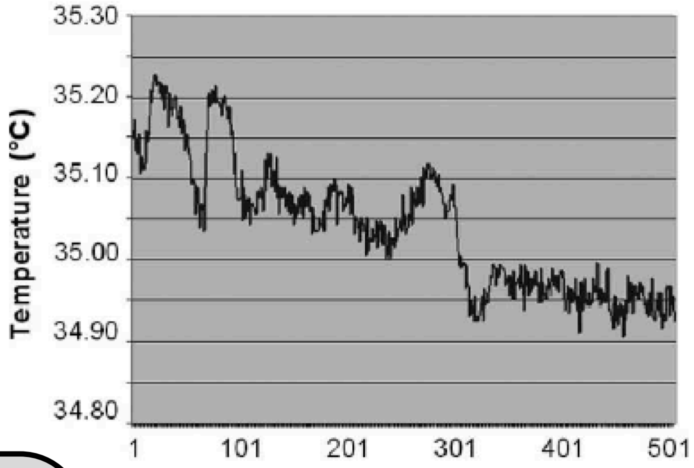


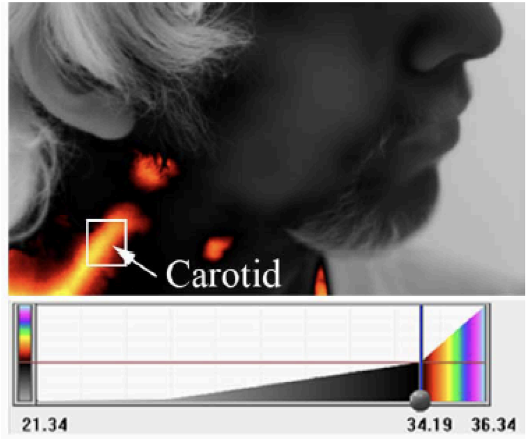
Pereira et al. (2015)

How does it work?

Case 2

Cardiac pulse – Neck blood vessel





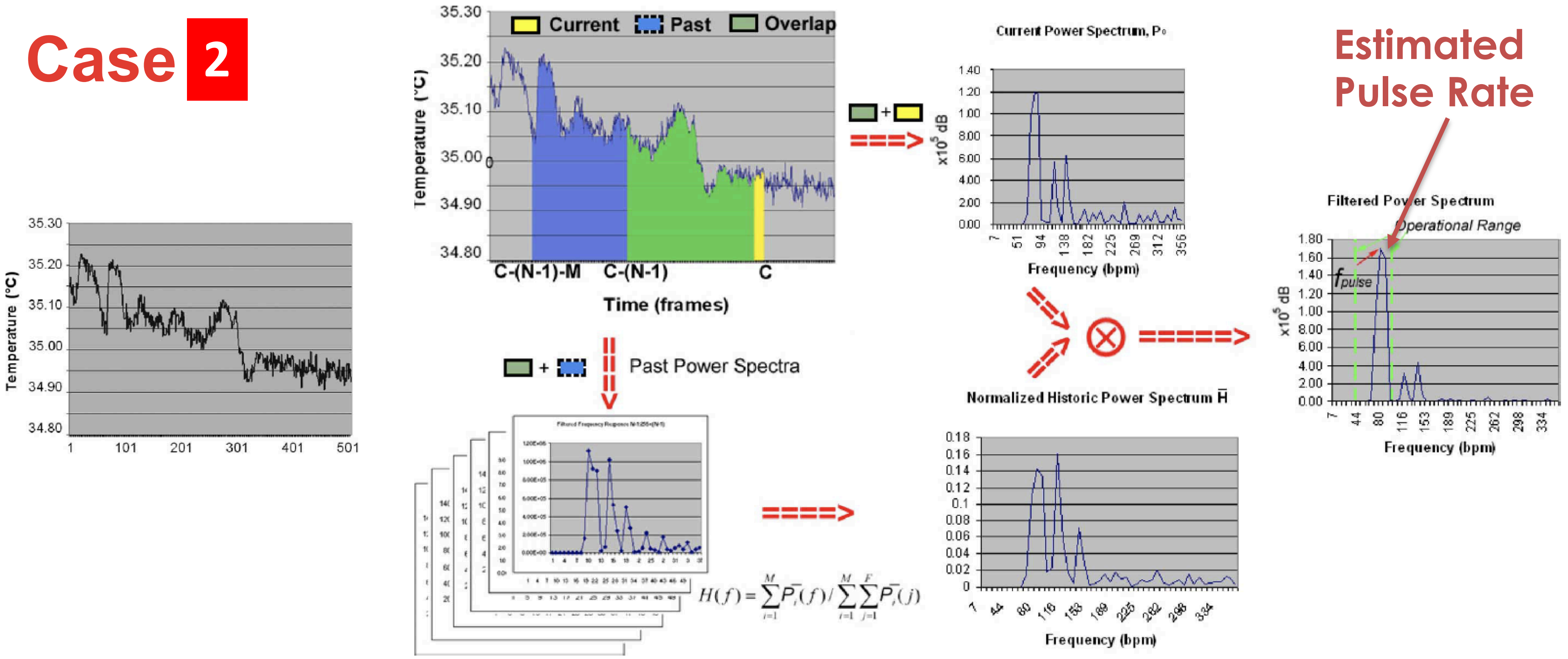
Automatic ROI Tracking (conditional density propagation tracker)

Averaging temperatures on the blood vessel

Garbey et al. (2007)

How does it work?

Case 2



$$H(f) = \sum_{i=1}^{M} \bar{P_i}(f) / \sum_{i=1}^{M} \sum_{j=1}^{F} \bar{P_i}(j)$$

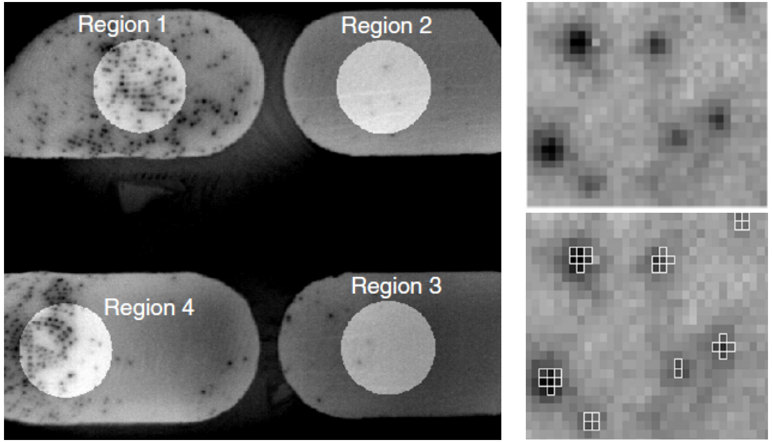
Garbey et al. (2007)

How does it work?

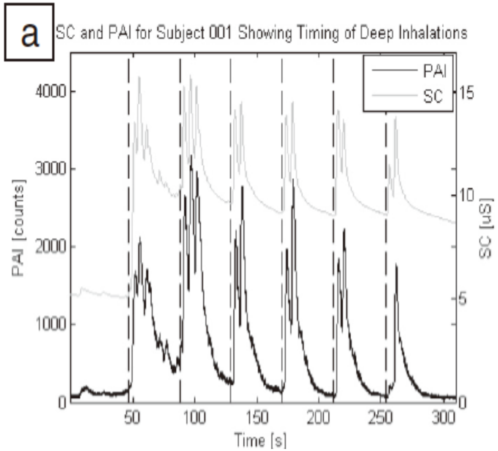
Case 2

Perspiration – finger tip (ROI)

Active pores



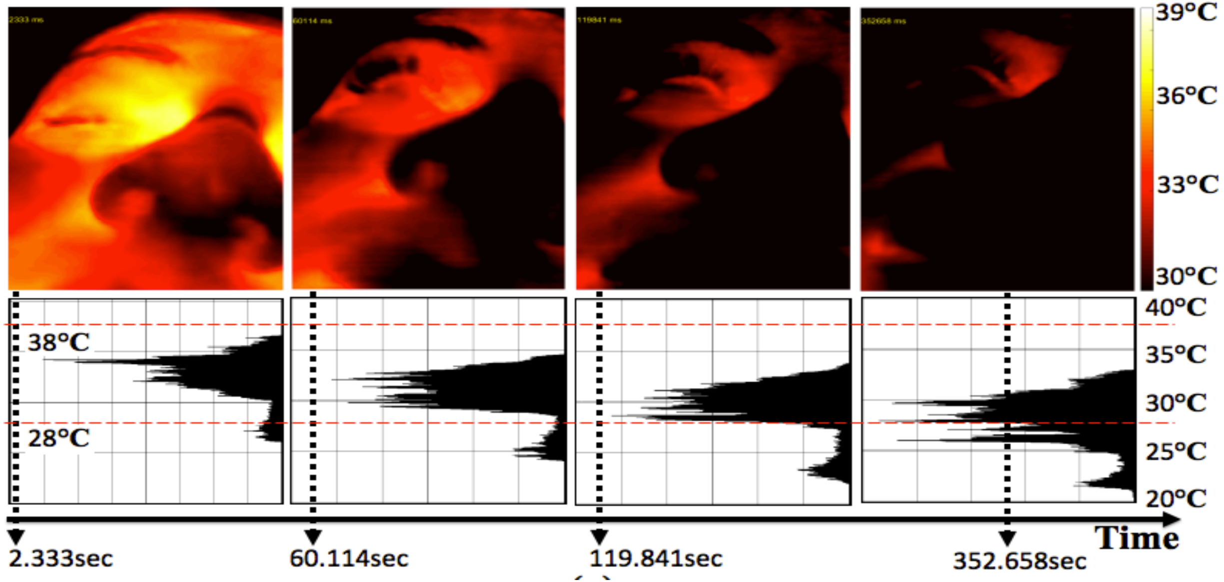
Counting
# of Active Pores



Krzywicki et al. (2014)

Beyond controlled lab settings?

Main Challenge: Environmental Temperature Changes

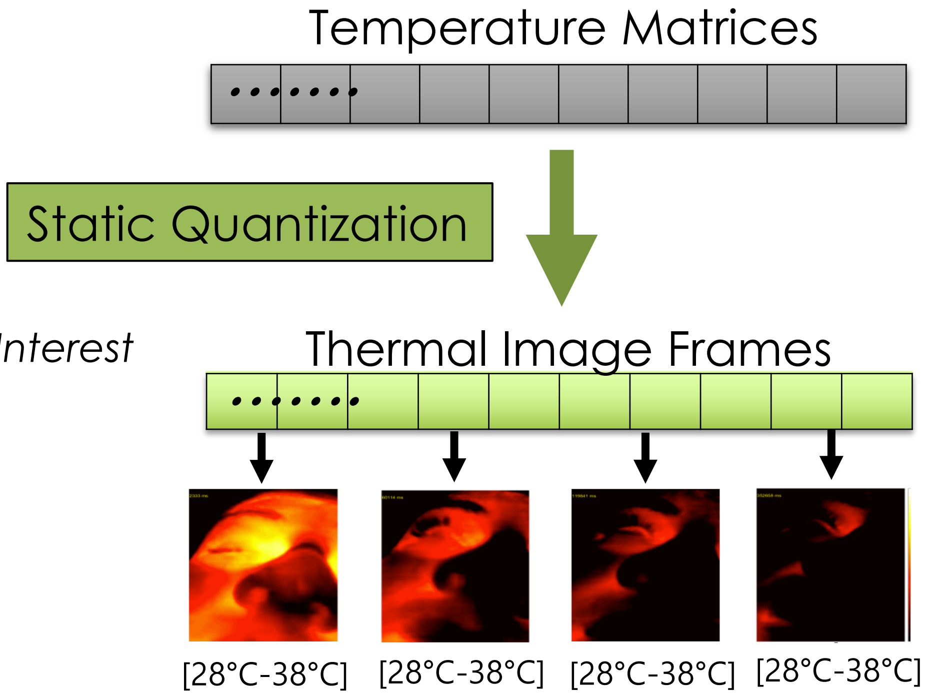


Cho et al. 2017 (*Biomedical Optics Express 8(10)*)

Given environmental temperature changes

Quantization is important

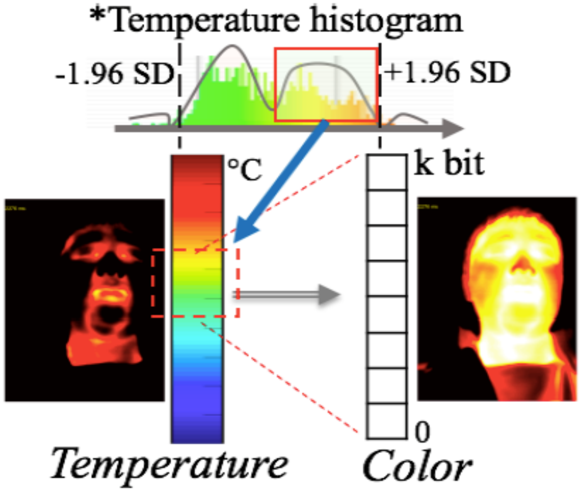
Fixed
Temperature Range of Interest
e.g. [28°C-38°C]

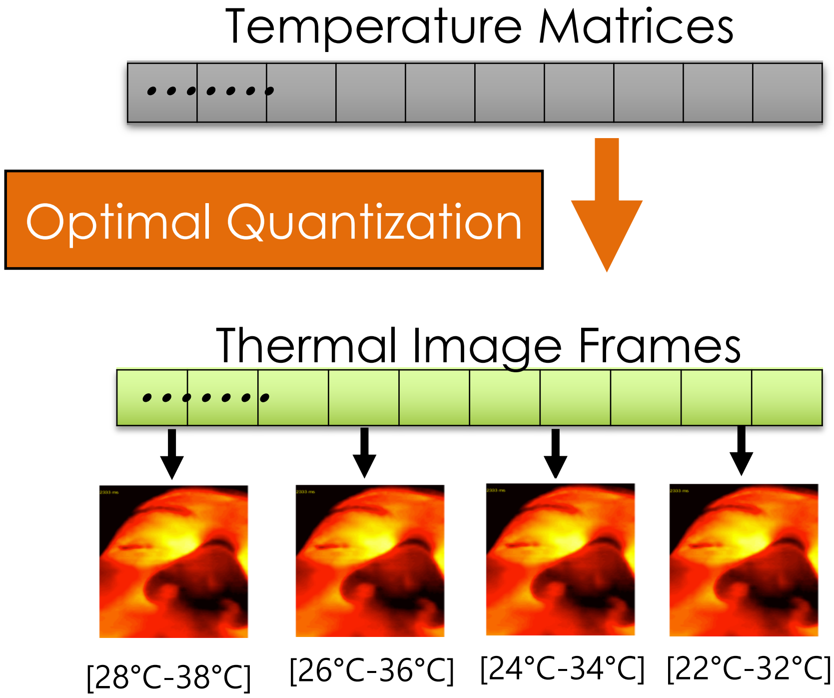


Cho et al. 2017 (*Biomedical Optics Express 8(10)*)

Given environmental temperature changes

Optimal Quantization to address this challenge





Cho et al. 2017 (*Biomedical Optics Express 8(10)*) Featured by the Journal

Given environmental temperature changes

Optimal Quantization to address this challenge

thermal range $[T'_{\min}, T'_{\max}]$:

$$T'_{\min} = \bar{c} - 1.96\frac{\sigma_c}{\sqrt{n \cdot m}}, \quad T'_{\max} = \bar{c} + 1.96\frac{\sigma_c}{\sqrt{n \cdot m}} \tag{1}$$

$$T_{opt}(0) = T'_{\min} \tag{2}$$

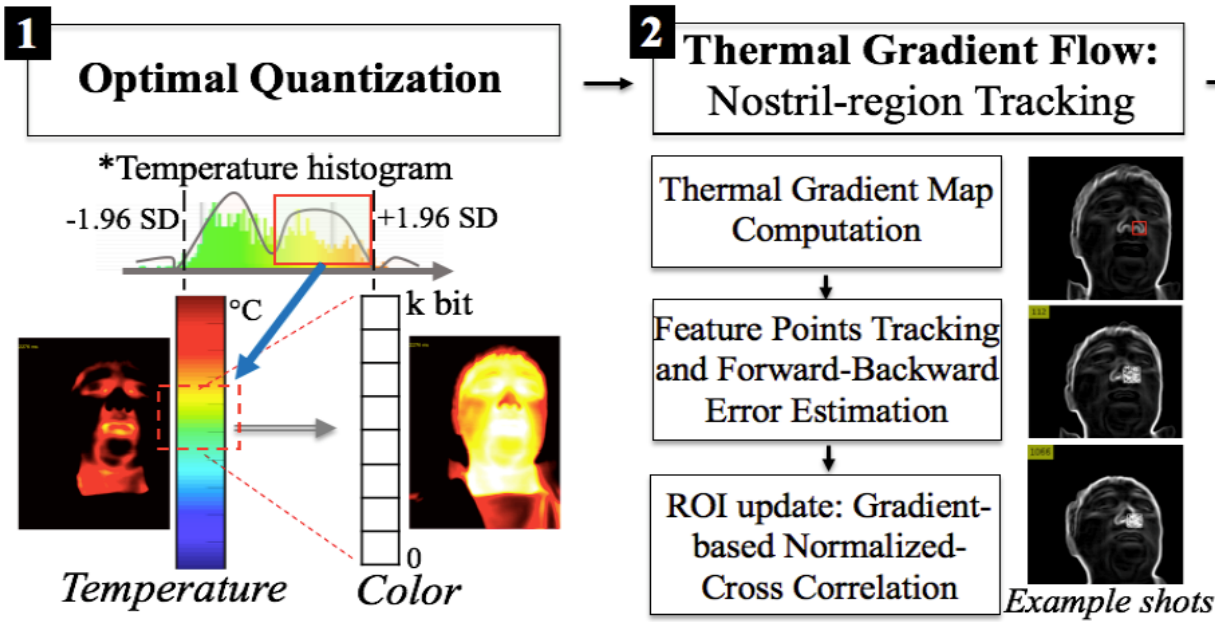
$$T_{opt}(t+1) = \frac{\mu_1(t) + \mu_2(t)}{2} \tag{3}$$

where $\mu_1(t)$ and $\mu_2(t)$ are the mean values when $c(x) \le T_{opt}(t)$, $c(x) > T_{opt}(t)$

The process is iterated until $T_{opt}(p) - T_{opt}(p-1) \approx 0$ is satisfied

Cho et al. 2017 (*Biomedical Optics Express 8(10)*) Featured by the Journal

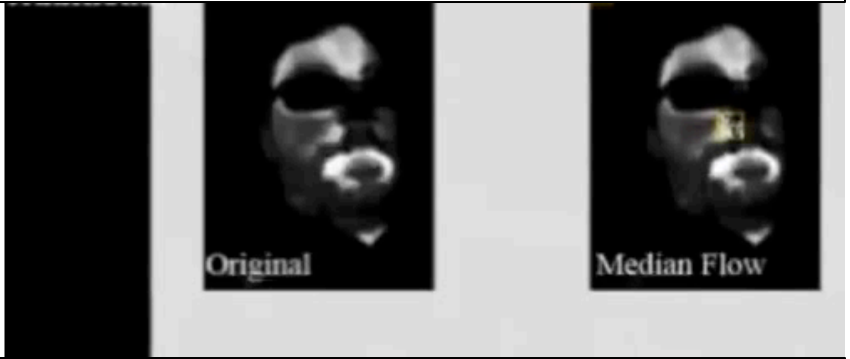
Optimal Quantization-enabled advanced ROI tracking



Cho et al. 2017 (*Biomedical Optics Express 8(10)*) Featured by the Journal

Optimal Quantization-enabled advanced ROI tracking

Pereira et al. (2015)'s method (previous state-of-the-art)



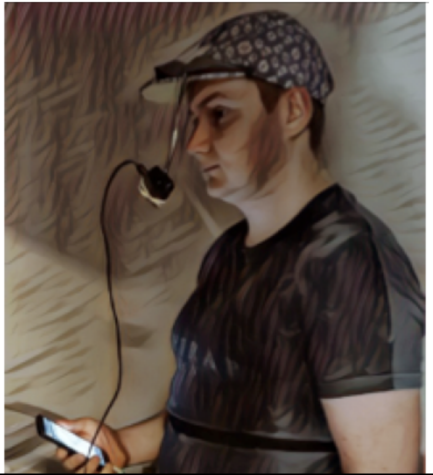
Cho et al. (2017)'s method (Optimal Quantization-enabled)

Cho et al. 2017 (*Biomedical Optics Express 8(10)*) Featured by the Journal

How does it work?

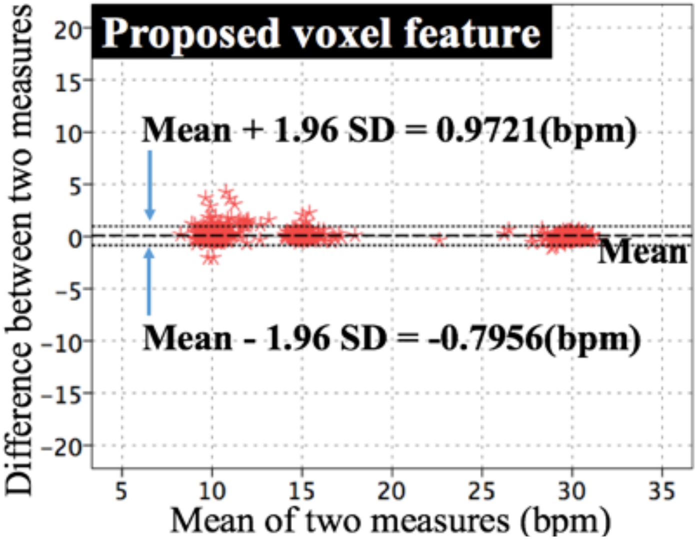
Case 2

Breathing – Nostril (ROI)



Mobile Thermal Imaging

Strong Correlation:
r= 0.9987 with

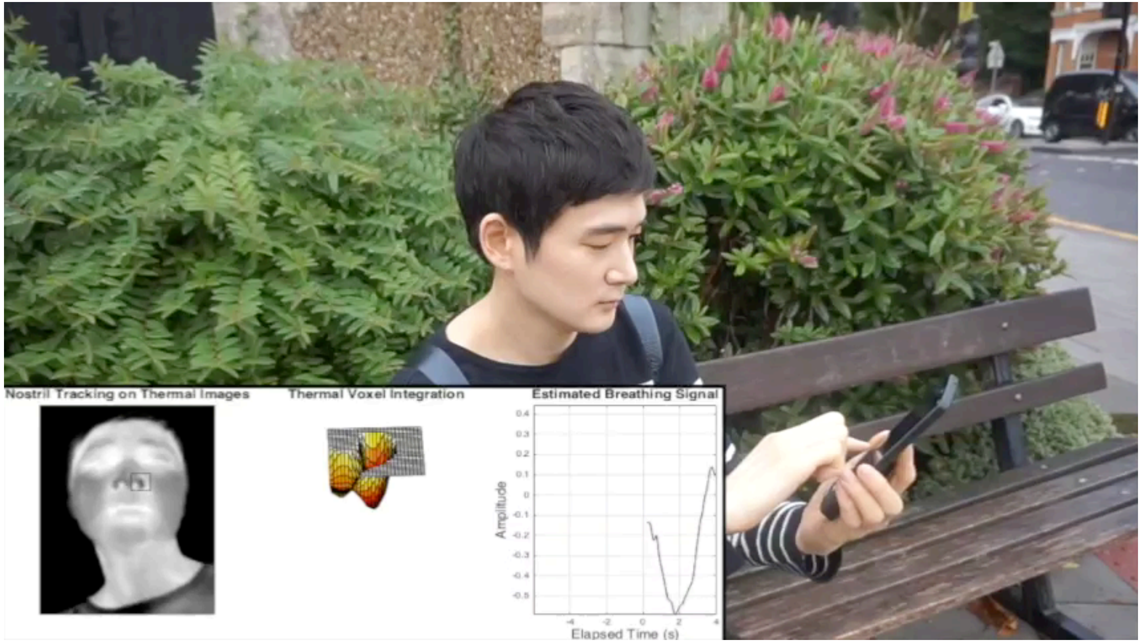


Cho et al. (2017)

How does it work?

Case 2

Breathing – Nostril (ROI)



Cho et al. 2017 (*Biomedical Optics Express 8(10)*) Featured by the Journal

Practical Guide to thermal imaging-based physiological computing

Practical guide with TIPA opensource toolkit

- http://youngjuncho.com/TIPA

youngjuncho.com/tipa

youngjuncho.com/tipa/

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TIPA Opensource project

Thermal Imaging-bas… Affective computing

TIPA Opensource projec…

Created: August 2019 (very initial stage)

Author(s): Dr. Youngjun Cho (Assistant Professor, Department of Computer Science, University College London, UCL)

This project is to support the ACII 2019's tutorial on Thermal Imaging-based Physiological and Affective computing

Full source code: https://github.com/deepneuroscience/TIPA
Example dataset: Link
Temporary TIPA opensource project website: http://youngjun.cho/TIPA

Key Reference

[1] Youngjun Cho and Nadia Bianchi-Berthouze. 2019. Physiological and Affective Computing through Thermal Imaging: A Survey. arXiv:1908.10307 [cs], http://arxiv.org/abs/1908.10307

Further Technical References

Created: August 2019 (very initial stage)

deepneuroscience Update README.md

- TIPA_library
- data
- figures
- README.md
- TIPA_basic_run.ipynb

Brief guideline

1. Download Anaconda (latest version) - Python 3.7 (recommended)

   https://www.anaconda.com/distribution/

2. Install basic libraries on the Conda console.

   conda install -c conda-forge opencv

   conda install scikit-learn

   pip install --upgrade numpy

   pip install --upgrade matplotlib

   conda install -c anaconda scipy

   - For your information

     print(python_version())

     3.7.3

     print(np.version.version)

     1.16.4

     print(cv2.**version**)

     3.4.2

     scipy (1.3.1)

3. Run "TIPA_basic_run.ipynb" on the Jupyter notebook

   You can find a basic instruction on the notebook.

1. Import TIPA libraries

In [9]:
```
import sys
from platform import python_version
# sys.path.insert(0,'./TIPA_library/')

from TIPA_library.main.data_preparation import *
from TIPA_library.main.thermal_image_processing import *
from TIPA_library.utils import timshow as tim
from TIPA_library.utils import rvs
```

2. Loading a raw sequence of thermal 2d matrices

The TIPA project mainly uses the TIPA frame protocol below by default.

For FLIR ONE (SDK) users, you can simply implement the code from the link below. https://github.com/deepneuroscience/DeepThermalImaging/tree/master/example%20code%20for%20FLIR%20One%20sdk

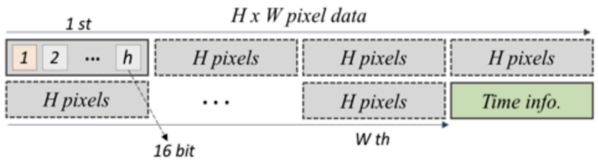

Figure 1. TIPA (Thermal Imaging-based Physiological and Affective computing) Project Dataframe protocol

Example Dataset

We provide example data.

Download this dataset - Link
Unzip, move them to a directory (./data)
./data/example_data.dat
./data/example_data_in_front_of_building.dat

In [10]:
```
# The matrix size has to be known in advance. e.g.320 x 240
# data = data_preparation_TIPA_protocol('./data/example_data.dat',320,240)
data = data_preparation_TIPA_protocol('./data/example_data_in_front_of_building.dat',320,240)
# print(data.time_stamp)
```

ACII 2019 Tutorial

Part III:
Challenges and research opportunities

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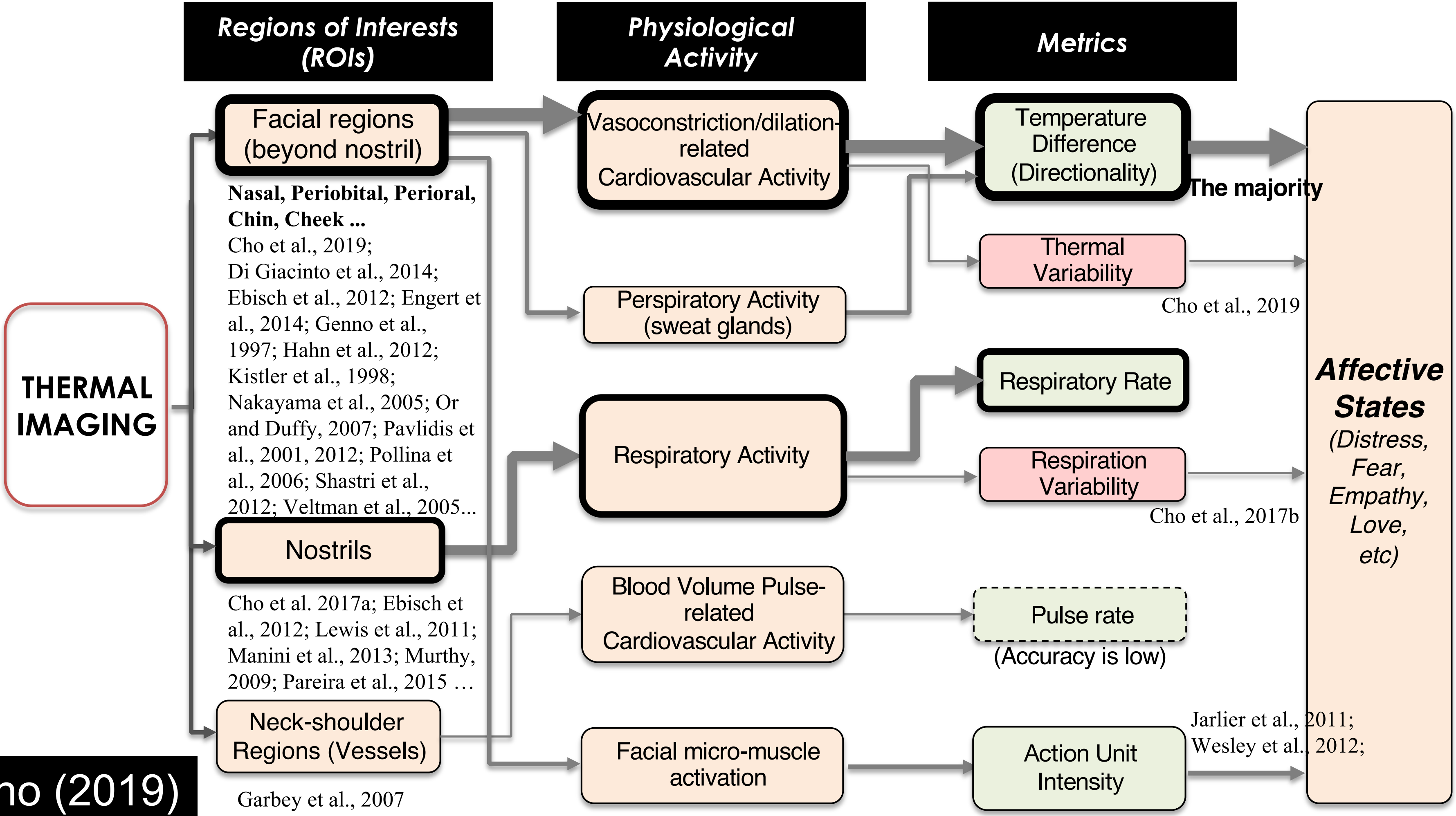
Global Disability Innovation Hub

What do we learn during Part III?

We will discuss the challenges and limitations emerged from the literature to explore research opportunities and directions

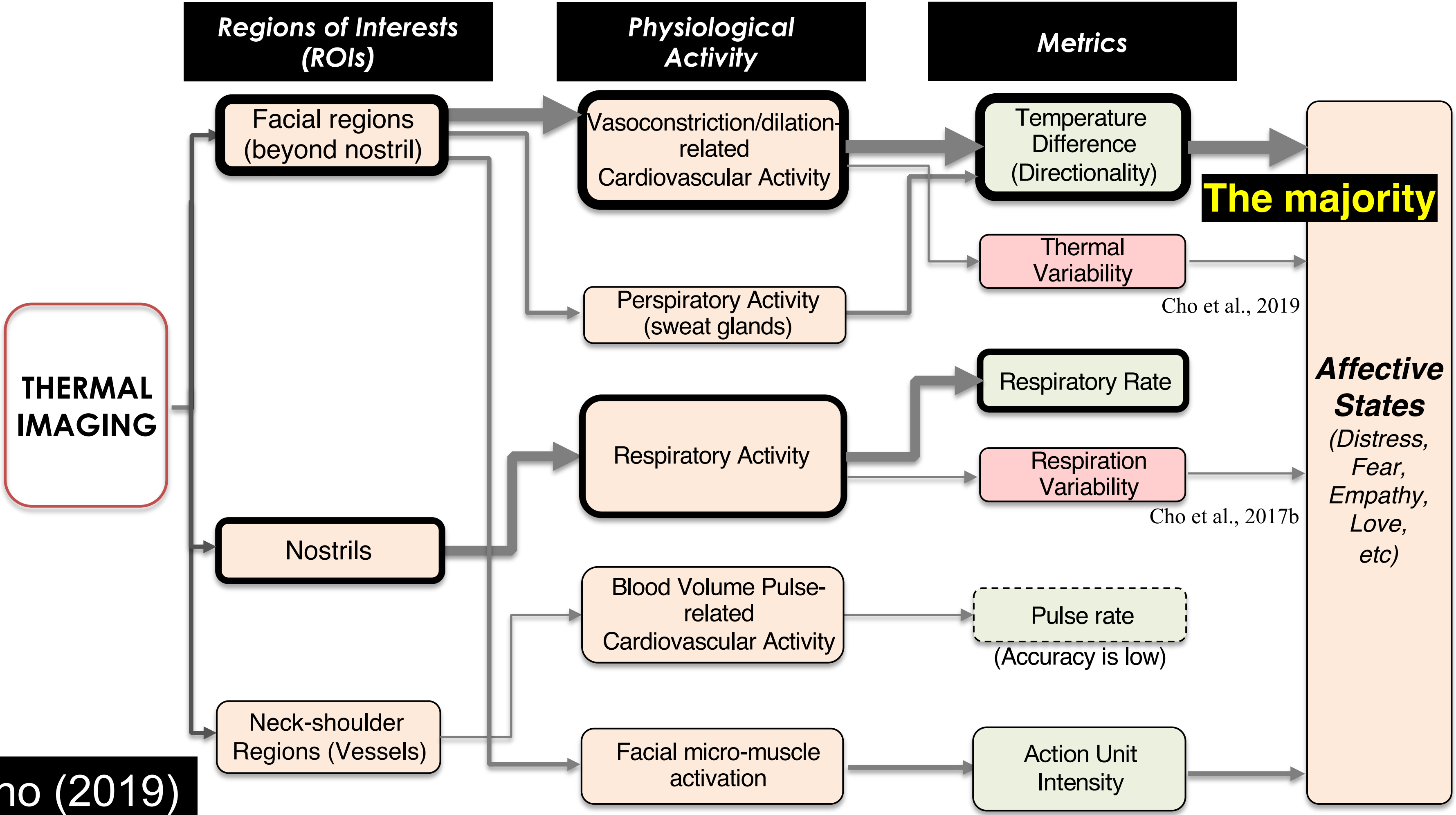
I. Beyond thermal directional changes
II. Limitations of evaluation methods used in the literature
III. Towards real-world situations: Mobile Thermal Imaging

I. Beyond Thermal Directional Changes?



Regions of Interests (ROIs)
Physiological Activity
Metrics
THERMAL IMAGING
Facial regions (beyond nostril)
Nasal, Periobital, Perioral, Chin, Cheek ...
Cho et al., 2019; Di Giacinto et al., 2014; Ebisch et al., 2012; Engert et al., 2014; Genno et al., 1997; Hahn et al., 2012; Kistler et al., 1998; Nakayama et al., 2005; Or and Duffy, 2007; Pavlidis et al., 2001, 2012; Pollina et al., 2006; Shastri et al., 2012; Veltman et al., 2005...
Nostrils
Cho et al. 2017a; Ebisch et al., 2012; Lewis et al., 2011; Manini et al., 2013; Murthy, 2009; Pareira et al., 2015 …
Neck-shoulder Regions (Vessels)
Garbey et al., 2007
Vasoconstriction/dilation-related Cardiovascular Activity
Perspiratory Activity (sweat glands)
Respiratory Activity
Blood Volume Pulse-related Cardiovascular Activity
Facial micro-muscle activation
Temperature Difference (Directionality)
The majority
Thermal Variability
Cho et al., 2019
Respiratory Rate
Respiration Variability
Cho et al., 2017b
Pulse rate
(Accuracy is low)
Action Unit Intensity
Jarlier et al., 2011; Wesley et al., 2012;
Affective States (Distress, Fear, Empathy, Love, etc)

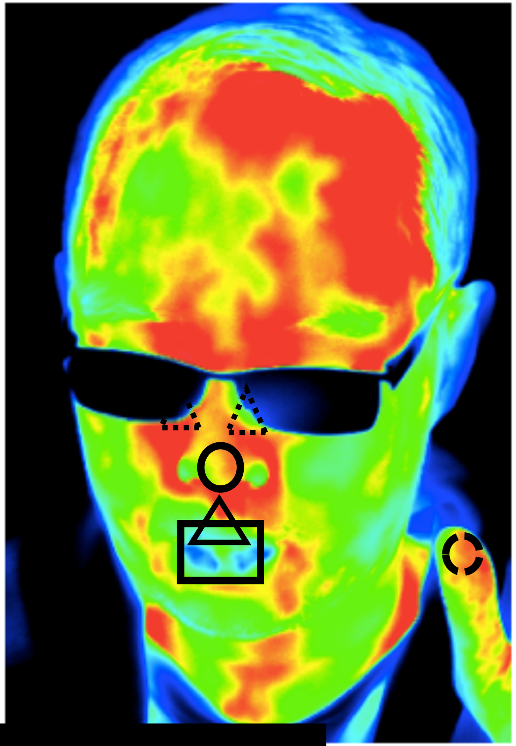
Cho (2019)


Regions of Interests (ROIs)
Physiological Activity
Metrics
THERMAL IMAGING
Facial regions (beyond nostril)
Nostrils
Neck-shoulder Regions (Vessels)
Vasoconstriction/dilation-related Cardiovascular Activity
Perspiratory Activity (sweat glands)
Respiratory Activity
Blood Volume Pulse-related Cardiovascular Activity
Facial micro-muscle activation
Temperature Difference (Directionality)
The majority
Thermal Variability
Cho et al., 2019
Respiratory Rate
Respiration Variability
Cho et al., 2017b
Pulse rate
(Accuracy is low)
Action Unit Intensity
Affective States
(Distress, Fear, Empathy, Love, etc)

Cho (2019)

Limitations of Thermal Directional Changes

Temperature Directional Change along with Affective States



Cho et al. (2019)

Mental Stress, Mental workload

Nose tip ↓ Genno et al. (1997), Or and Duffy (2007), Veltman et al. (2005), Engert et al. (2014), Cho et al. (2019)

Fear

Finger tip ↓ Kistler et al. (1998)

Startled

Upper lip ↓ Periorbital ↑ Shastri et al. (2012) Pavlidis et al. (2001)

Sexual Arousal

Mouth Nose tip Periorbital ↑ Hahn et al. (2012)

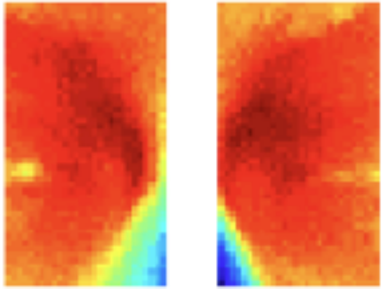
Love

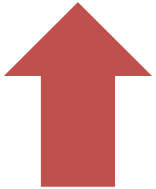
Whole face ↑ Salazar-López et al. (2015)

Incongruent findings

When being startled (Auditory Startle stimulus)

Periorbital temperature





warming

Stable

Pavlidis et al. (2001)

Gane et al. (2011)

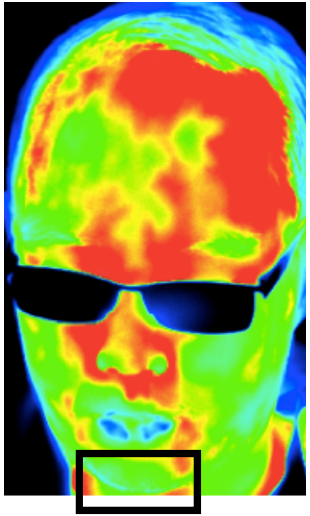
Incongruent findings

When mentally stressed

Chin temperature

Not changed

Veltman et al. (2005)



decrease

Engert et al. (2014)

Single metric (temperature direction) can be susceptible to many factors

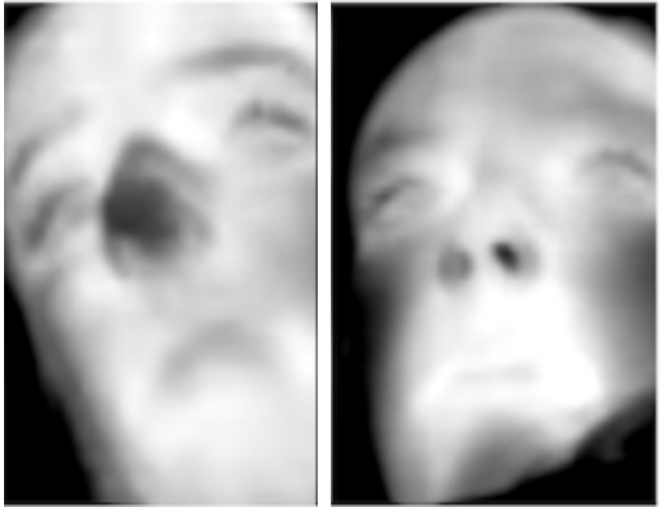
1. Ambient temperature
2. Complex physiological mechanism
3. Interaction effects between affective states

Cho et al. (2019)

Single metric (temperature direction) can be susceptible to many factors

1. Ambient Temperature

   e.g. Large variation in temperature
   between the waiting space and the experiment room

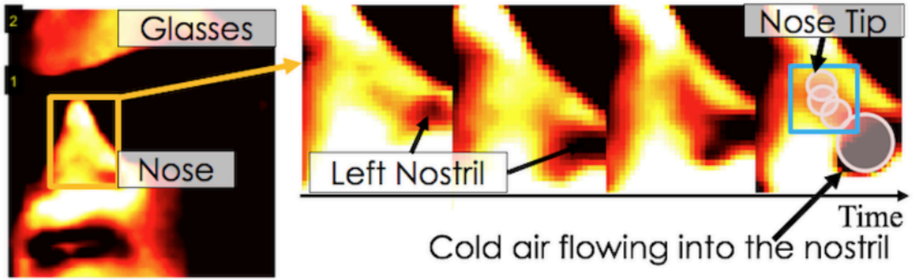


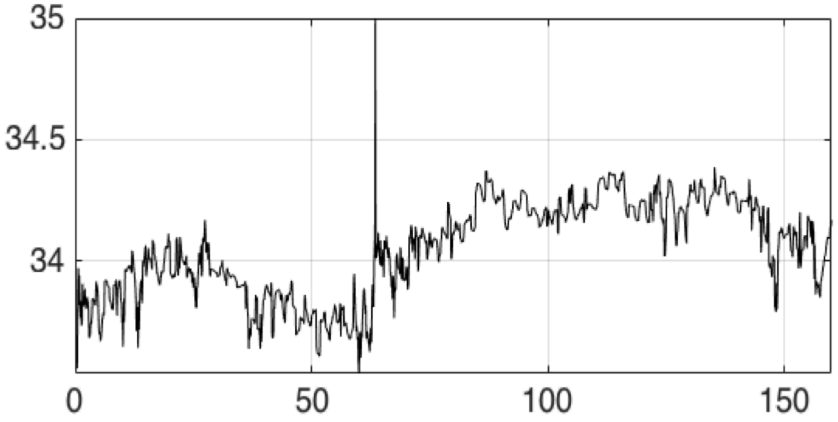
Cho et al. (2019) Instant Stress

Single metric (temperature direction) can be susceptible to many factors

2. Complex physiological mechanisms

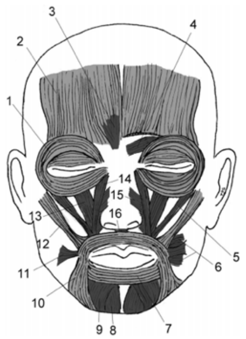
Respiration affecting nose temperature





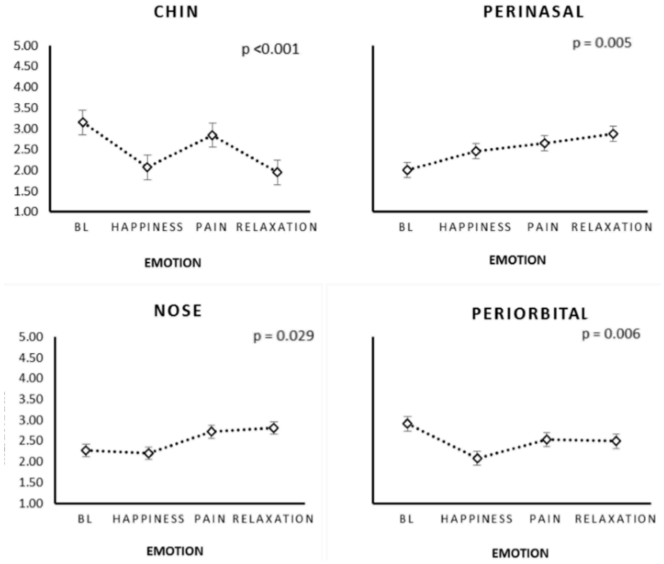
Cho et al. (2019) Instant Stress

Single metric (temperature direction) can be susceptible to many factors



2. Complex physiological mechanisms

Voluntary muscular action affecting facial temperature

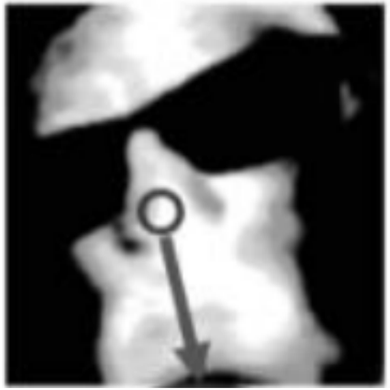


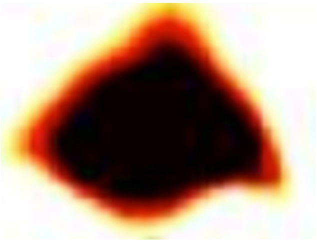
Medina et al. (2018)

Single metric (temperature direction) can be susceptible to many factors

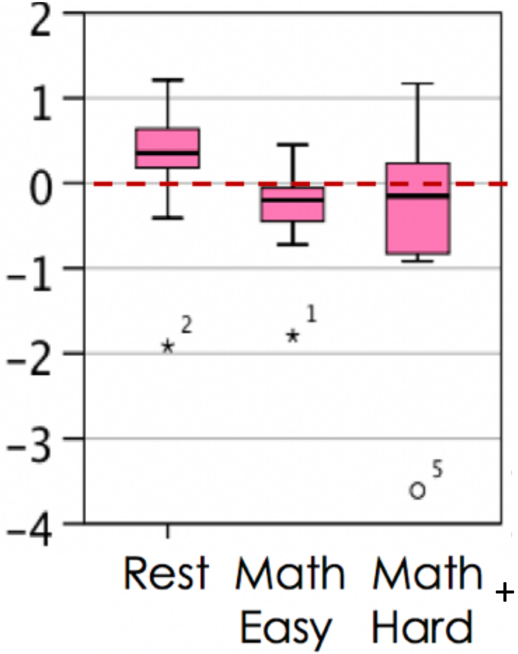
3. Interaction effects between affective states**?**

Mental workload vs. embarrassment ?





Nose Temperature Directional change



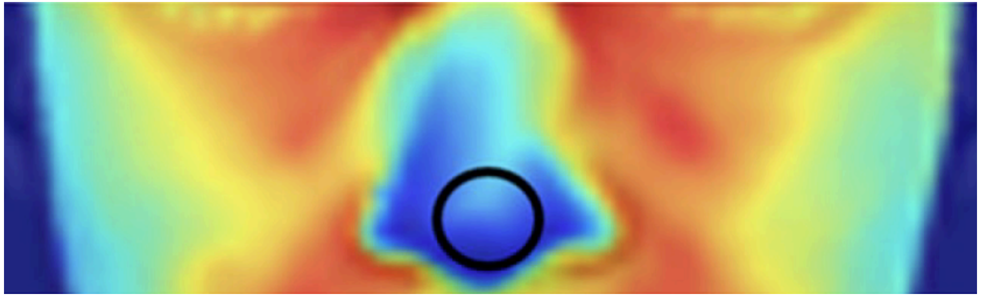
Social
+ Evaluative
Threats

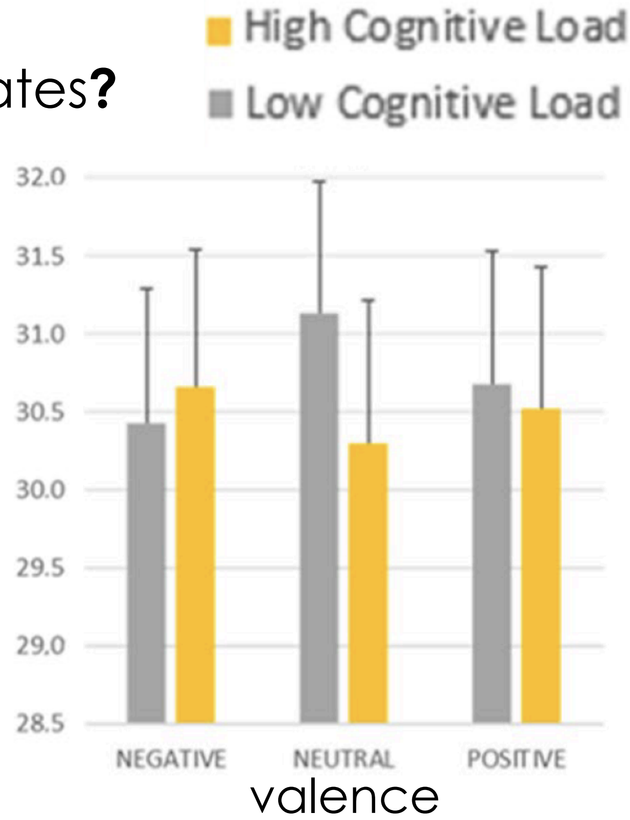
Cho et al. (2019) Nose Heat

Single metric (temperature direction) can be susceptible to many factors

3. Interaction effects between affective states?

Mental workload vs. valence ?





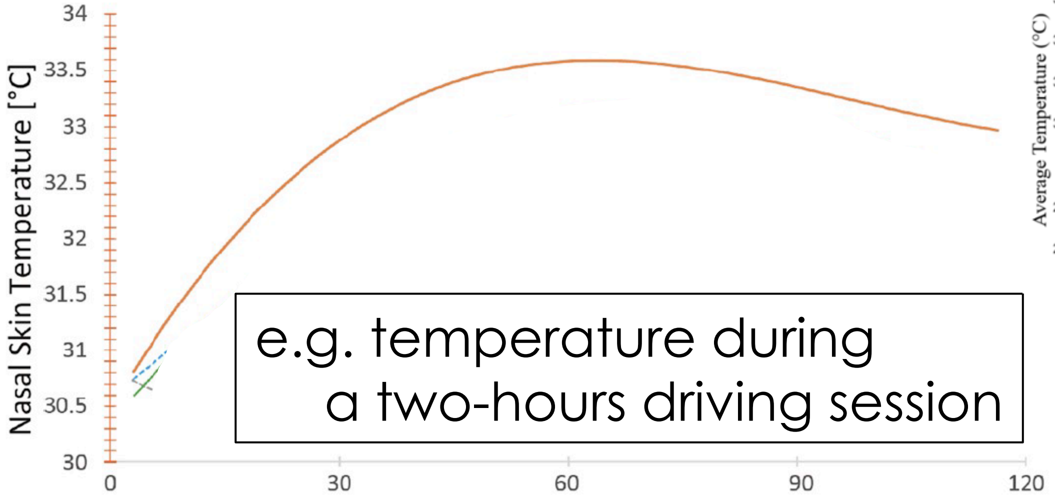
Panasiti et al. (2019)

Single metric (temperature direction) can be susceptible to many factors

Need to diversify thermal metrics

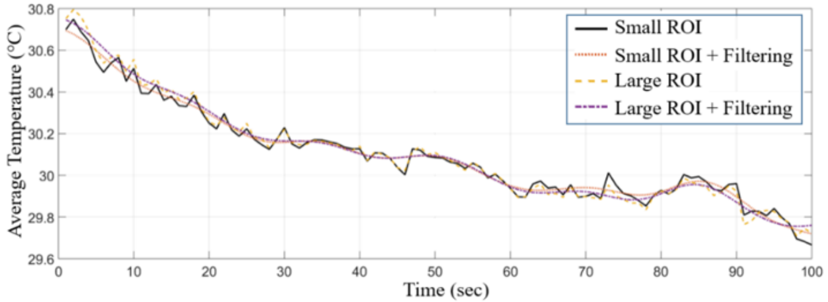
Towards a richer set of thermal metrics

Thermal Variability**?**



e.g. temperature during
a two-hours driving session

Diaz-Piedra et al. (2019)



e.g. temperature during
a100s- resting session

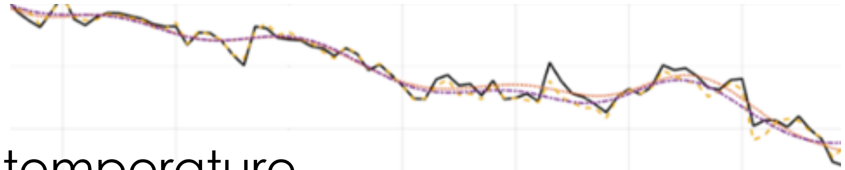
Cho et al. (2019) Nose Heat

Towards a richer set of thermal metrics

A very recently proposed set of metrics

TD	**T**emperature **D**ifference between data from the start and the end
	Suppose a thermal variable signal $x(k)$, $k\in[0, n\text{-}1]$, $x(n-1)-x(0)$
STV	**S**lope of **T**hermal **V**ariable signal
	$\beta_1 = \frac{y-\beta_0-\varepsilon}{x}$ *(from linear polynomial fitting)*
SDSTV	**S**tandard **D**eviation of **S**uccessive differences of **T**hermal **V**ariable signal
	Suppose $\hat{x}(k)=x(k+1)-x(k)$, $\sqrt{\frac{\sum(\hat{x}-\bar{\hat{x}})^2}{n-1}}$
SDTV	**S**tandard **D**eviation of **T**hermal **V**ariable signal
	$\sqrt{\frac{\sum(x-\bar{x})^2}{n-1}}$

Existing metric

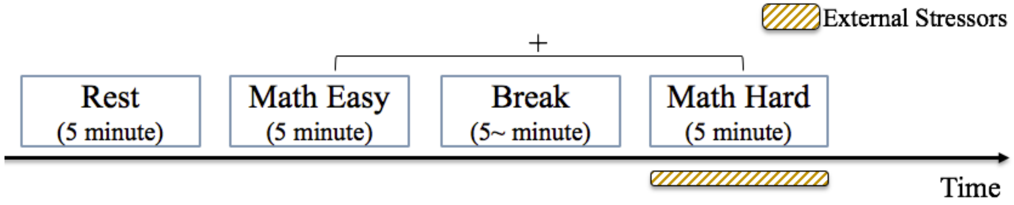


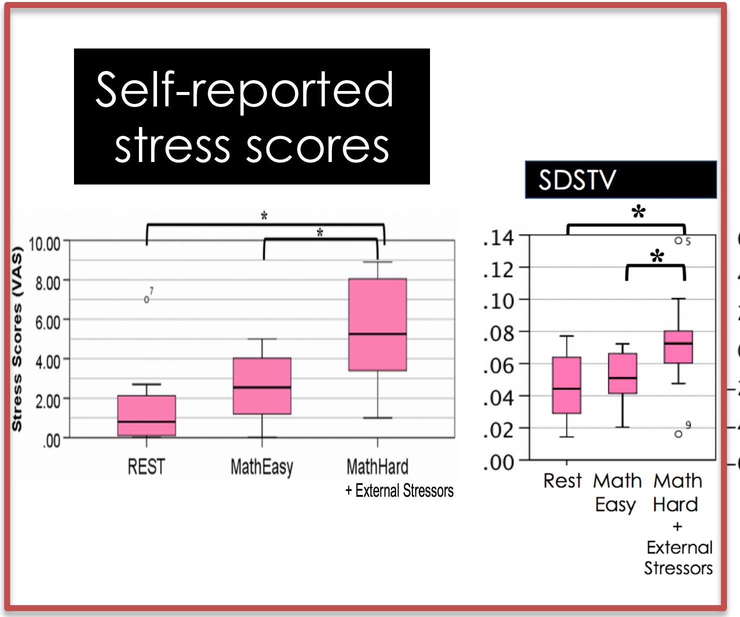
temperature

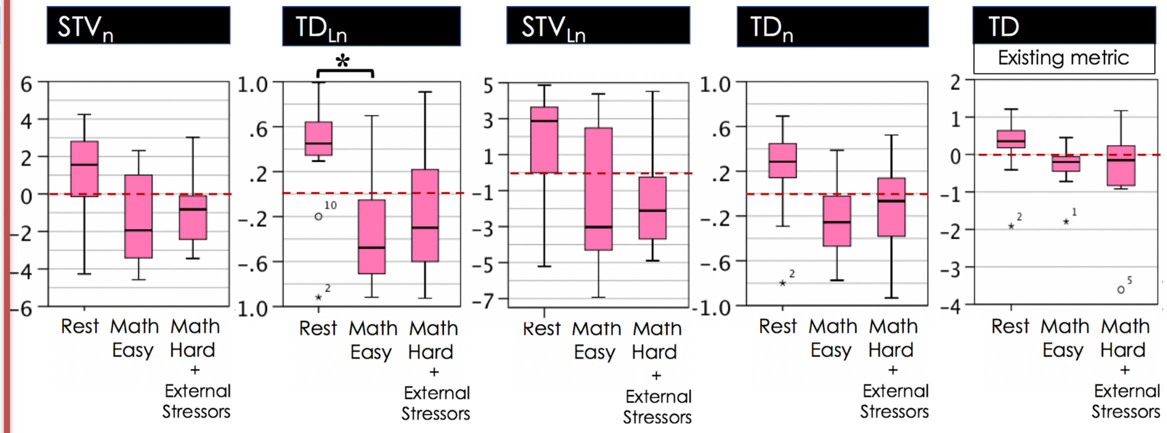
Cho et al. (2019) Nose Heat

Towards a richer set of thermal metrics

Sedentary Mental stress task



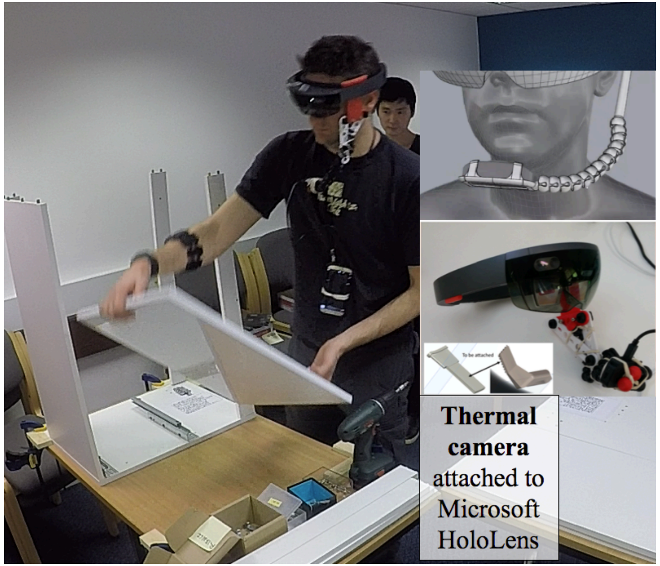


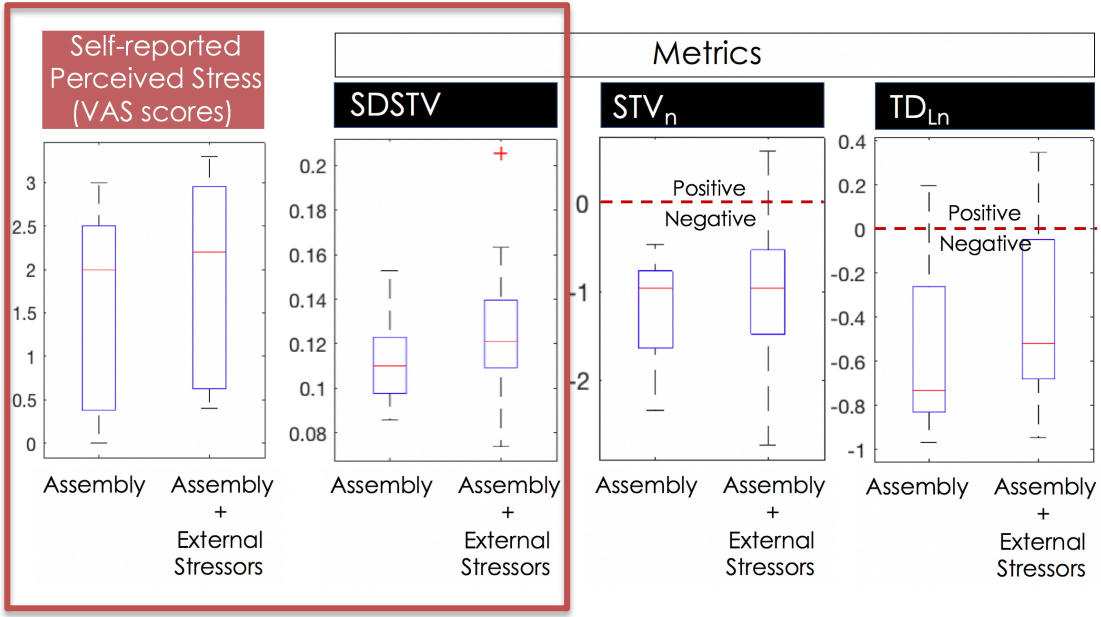


Cho et al. (2019) Nose Heat

Towards a richer set of thermal metrics

Real-world task in a furniture factory





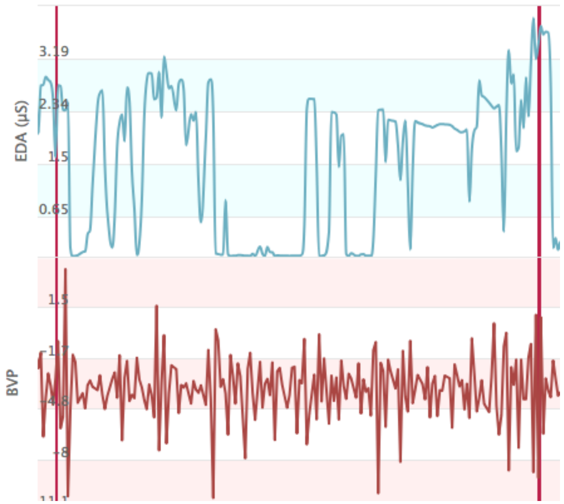
Cho et al. (2019) Nose Heat

Further efforts are needed to diversify metrics

Given the limited metrics,
only a few studies have used
thermal imaging for **automatic affect recognition**

Affect Recognition: Typical approach

e.g. Multimodal (GSR + BVP)

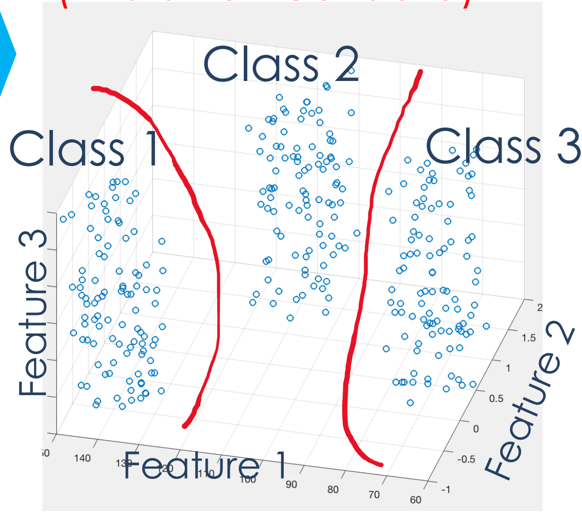


Signal processing & Feature Extraction

e.g.
Feature 1: mean HR
Feature 2: mean IBI
Feature 3: mean SCR Amplitude
…

Classification (e.g. KNN, SVM)

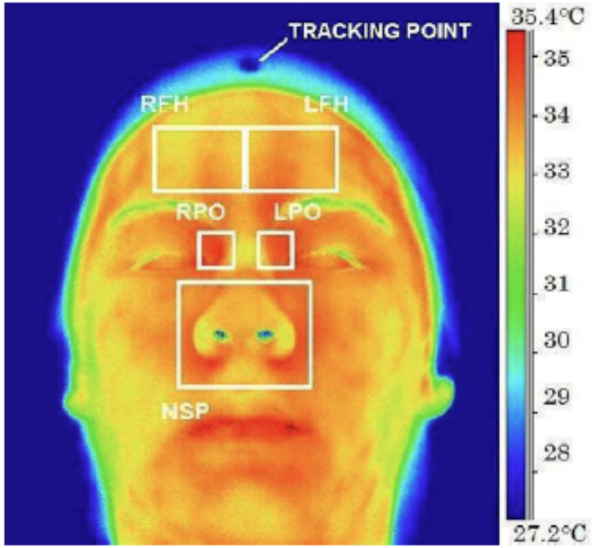
(This is not real data)



Nhan's (2010) automatic affect recognition

Binary classification: Baseline – high arousal, Baseline – low arousal, …

Task:
International Affective Picture System (IAPS)



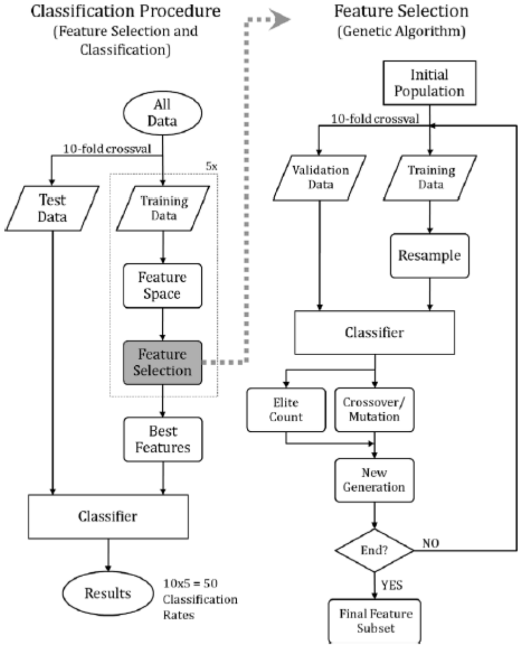
Traditional features in computer vision applied to the five ROIs

→ 402 features

Nhan and Chau (2010)

Nhan's (2010) automatic affect recognition

Binary classification: Baseline – high arousal, Baseline – low arousal, …



GA SETTINGS FOR CLASSIFICATION TASKS OUTLINED IN SECTION III-D

GA Parameters	Parameter Settings
Population number	100
Feature vector lengths	2 to 12
Number of features	402
Fitness function/ Classifier	Fisher LDA with 10-fold cross-valid.
Fitness value	adjusted error
Elite count	1
Parent selection	roulette-wheel
Crossover function	scattered
Crossover rate	0.7
Mutation function	uniform
Mutation rate	0.2
Max generations	50
External cross-valid.	10-fold cross-valid.

Nhan and Chau (2010)

Nhan’s (2010) automatic affect recognition

Binary classification: Baseline – high arousal, Baseline – low arousal, …

CLASSIFICATION ACCURACIES FOR AROUSAL CLASSIFICATION TASKS

Feature subset dimensionality	Classification accuracy (mean±std)		
	BASE−HA	BASE−LA	HA−LA
12	80.6±6.6	74.5±17.0	58.8±9.3
11	81.1±7.2	74.1±15.9	58.2±11.2
10	80.3±6.8	72.7±15.7	54.6±10.3
9	80.1±7.2	73.5±14.8	56.8±11.5
8	79.2±7.9	71.2±13.9	54.5±9.5
7	79.2±6.8	69.4±14.8	54.3±10.6
6	78.0±7.1	67.8±17.1	56.9±9.6
5	75.2±8.5	67.1±16.8	58.0±9.4
4	73.4±7.3	65.8±17.2	54.5±10.3
3	72.7±7.6	65.5±17.0	56.2±12.0
2	70.9±8.7	65.3±18.1	56.9±11.7
Best Performance	**81.1±7.2**	**74.5±17.0**	**58.8±9.3**
Subset Dimension	11	12	12

CLASSIFICATION ACCURACIES FOR VALENCE CLASSIFICATION TASKS

Feature subset dimensionality	Classification accuracy (mean±std)		
	BASE−HV	BASE−LV	HV−LV
12	81.4±7.7	73.7±12.6	58.6±9.9
11	79.9±8.6	70.3±12.8	60.1±11.5
10	81.3±9.3	70.1±11.1	58.0±11.3
9	79.5±9.7	70.7±11.5	57.4±9.8
8	78.1±9.9	71.3±10.4	60.3±13.3
7	79.1±10.0	72.1±10.9	58.5±10.8
6	78.9±10.1	71.4±12.5	58.9±11.3
5	77.7±9.6	70.6±11.4	58.9±12.4
4	73.9±8.0	68.9±10.7	61.5±11.7
3	71.2±6.8	68.9±12.1	58.7±9.2
2	69.3±11.5	64.3±11.7	59.5±10.1
Best Performance	**81.4±7.7**	**73.7±12.6**	**61.5±11.7**
Subset Dimension	12	12	4

A couple of studies followed Nhan and Chau's work

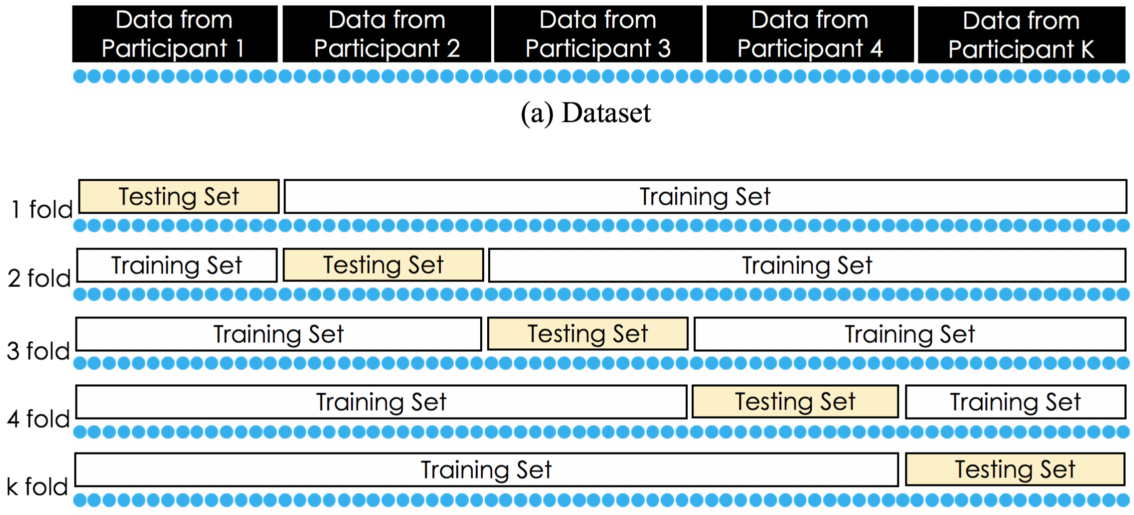
Authors		Key difference
Latif et al. (2015)	**SVM**	binary detection of sadness and happiness K-fold cross-validation result: 63.5% (accuracy)
Khan et al. (2016)	**LDA**	binary detection of sadness and happiness separately K-fold cross-validation results: 73.7%, 68.4%
Goulart et al. (2019)	**LDA**	binary detection of 5 emotions (disgust, fear, happiness, sadness, surprise), 3-fold cross-validation: ranging 74.7 - 89.88%

Other works reporting **90%** in detecting affective states:
a proper **cross validation** was not used (e.g. Hong et al. 2016 – stress detection)

Detection performance needs to be improved given that..

K-fold cross validation tends to produce artificially high accuracies in handling sequential data

To test the ability to generalize,
Leave-one-subject-out (LOSO) cross-validation is recommended



(b) k-fold Leave-One-Subject-Out (LOSO) Cross Validation

Hernandez et al. (2011)
Ellis et al. (2014)
Cho et al. (2019)

Detection performance needs to be improved given..

The limitation of hand-engineered features

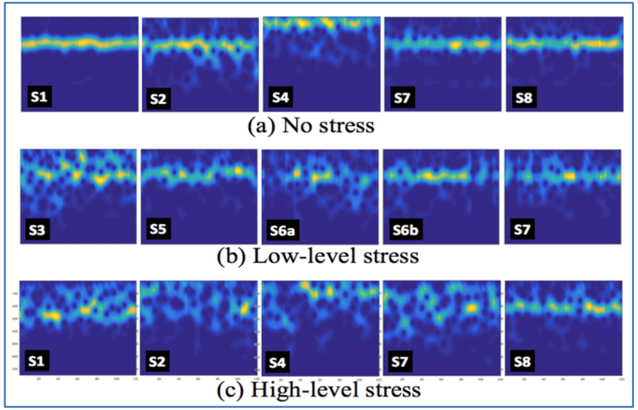
LeCun et al. (2015)

End-to-end learning approach with a new representation method

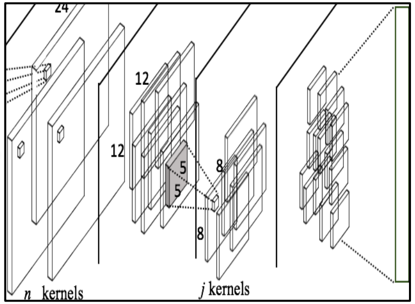
Automatic stress detection using respiratory thermal signatures

Respiration Variability Spectrogram

(2D Representation of breathing signals)



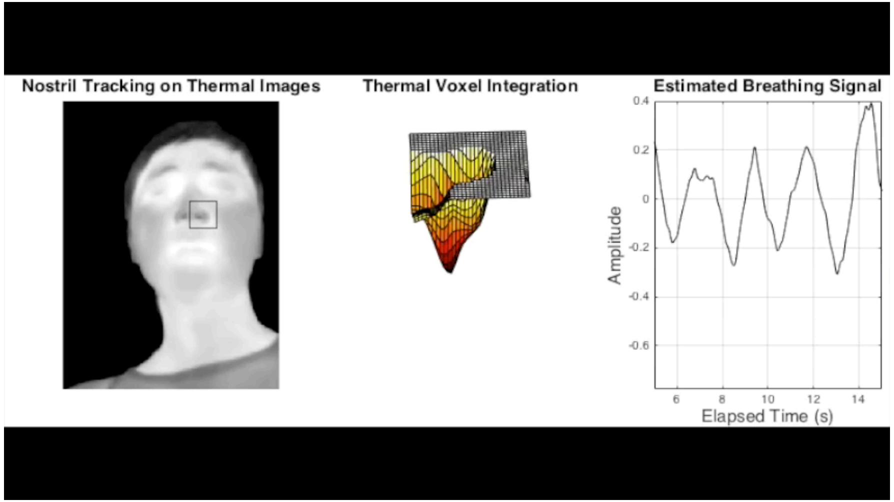
Artificial Neural Network

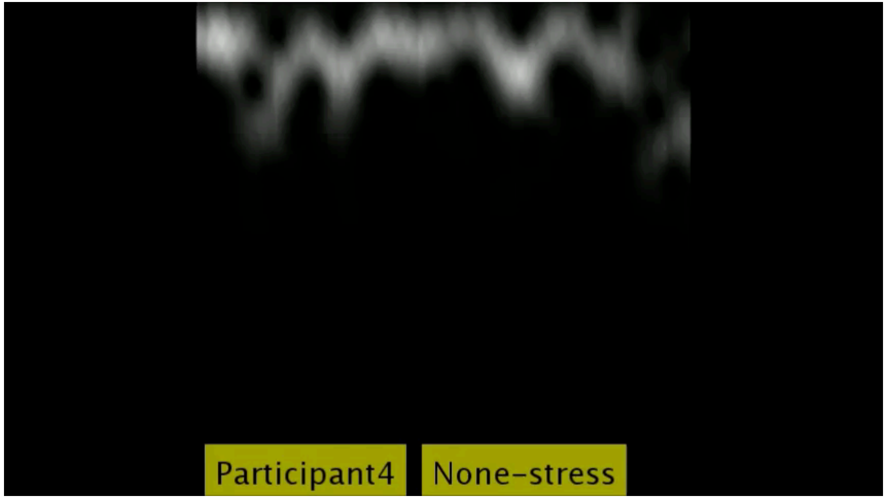


Cho et al. (ACII 2017) DeepBreath

End-to-end learning approach with a new representation method

Automatic stress detection using respiratory thermal signatures

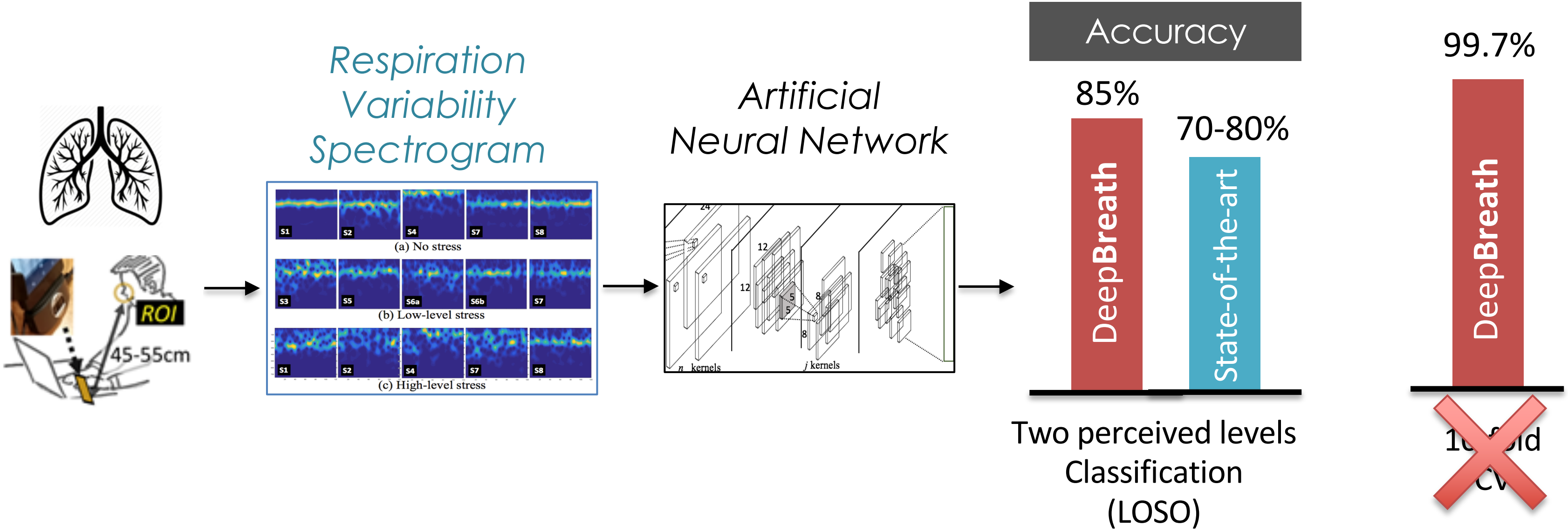




Cho et al. (ACII 2017) DeepBreath

End-to-end learning approach with a new representation method

Automatic stress detection using respiratory thermal signatures



Cho et al. (ACII 2017) DeepBreath

Further attentions need to be paid to
Advanced machine learning and
Physiological representation

II. Limitations of evaluation methods used in the literature (to test the quality of physiological signals)

Table 2. A summary table of the literature on thermal imaging-based physiological computing.

Authors	Physiological Signature	Participants / activities	Automatic ROI Tracking	Physiological Metrics	Evaluation & Results	
					Reference signals	Evaluation metrics
Garbey et al. (2007)	Cardiovascular signature (cardiac pulse)	34 healthy participants / resting in an armchair	Conditional density propagation tracker [60]	Average pulse rate (bpm) per participant	Piezo electric pulse transducer	Non-standard CAND =88.52% (not reliable)**
Hamedani et al. (2016)		22 healthy participants / resting	TLD Tracker [64]	Average pulse rate (bpm) per participant	PPG sensor	Non-standard CAND =92.47% (not reliable)**
Pavlidis et al. (2012)	Perspiration	17 surgeons / laparoscopic drill test	Tissue tracker [121]	GSR timeseries signal	Finger EDA sensor	Correlation r=0.968 (finger) r=0.943 (perinasal)
Krzywicki et al. (2014)		20 healthy participants / respiration exercise	Not reported	Pore activation index (PAI) (equivalent to skin conductance response)	Finger EDA sensor	Correlation r=0.71

Cho et al. (2019)

Standard evaluation metrics in computational physiology

Bland-Altman plot

to analyze the agreement between two different measurements

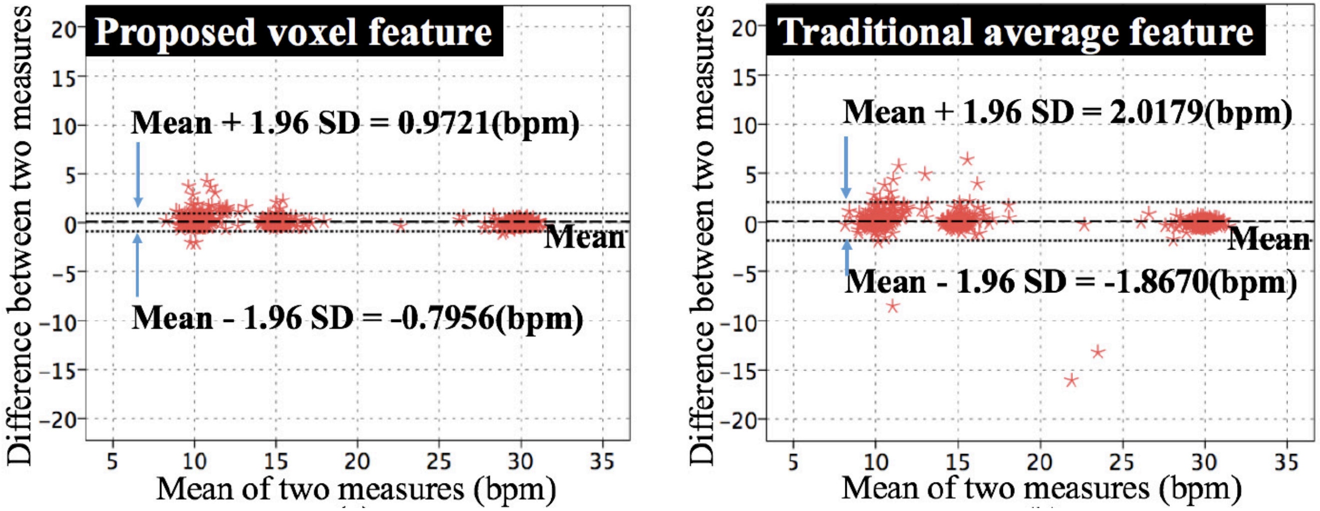


Image adapted from Cho et al. (2017)

Standard evaluation metrics in computational physiology

Scatter plot and correlation

to test statistical association between two different measurements

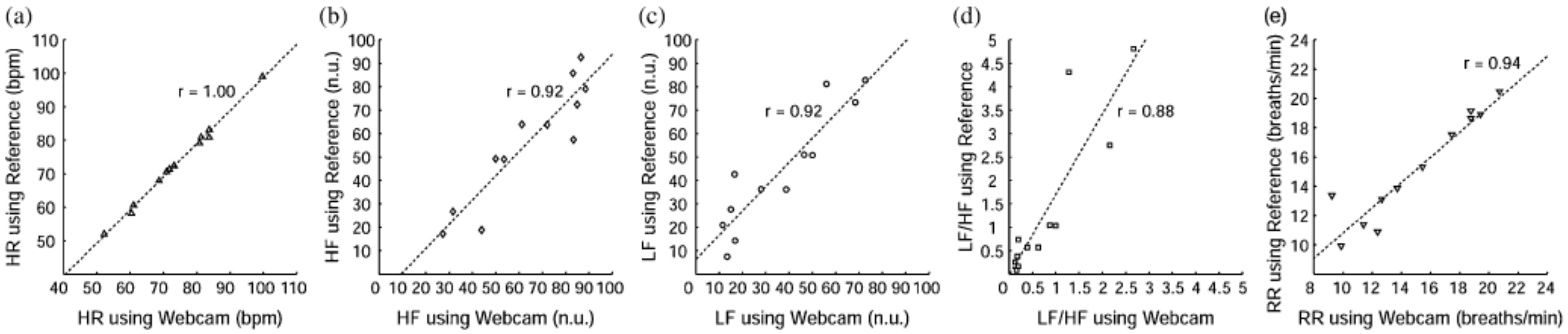
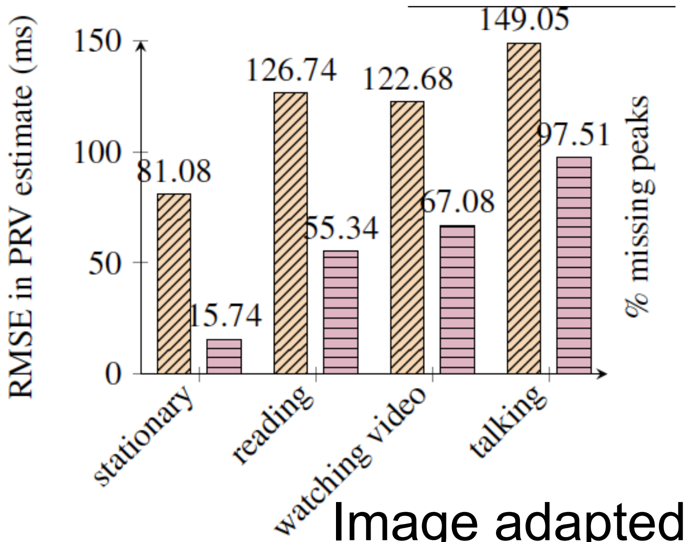


Image adapted from Poh et al. (2010)

Standard evaluation metrics in computational physiology

RMSE (Root Mean Square Error)

to measure how spread out residuals are
(residual: a measure of how far from the regression line data points are)



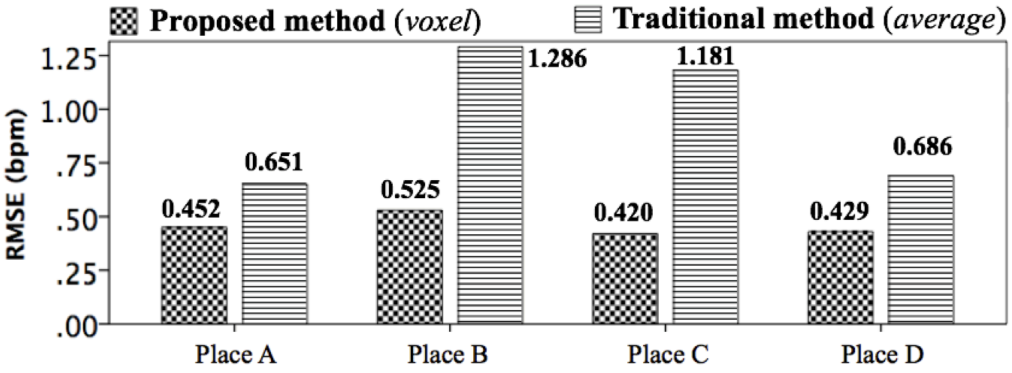


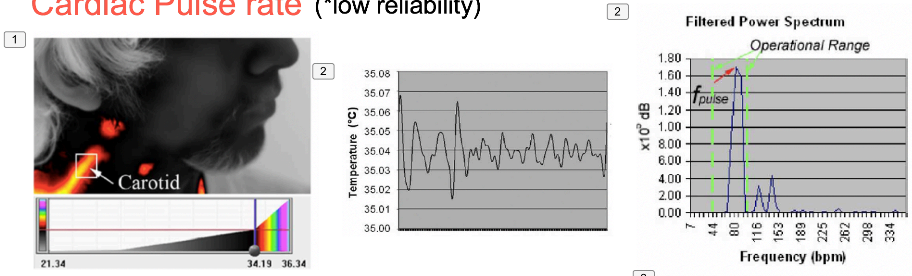
Image adapted from Kumar et al. (2015) and Cho et al. (2017)

Some studies in this field missing standard evaluation

Physiological Thermal Signatures

1 Cardiovascular signature

Cardiac Pulse rate (*low reliability)



Garbey et al. (2007)

(during the introduction)

Authors	Physiological Signature	Physiological Metrics	Evaluation & Results: Reference signals	Evaluation & Results: Evaluation metrics
Garbey et al. (2007)	Cardiovascular signature (cardiac pulse)	Average pulse rate (bpm) per participant	Piezo electric pulse transducer	Non-standard CAND =88.52% (not reliable)**
Hamedani et al. (2016)		Average pulse rate (bpm) per participant	PPG sensor	Non-standard CAND =92.47% (not reliable)**

Custom evaluation metric

$$\mathrm{CAND} = 1 - \frac{|\mathrm{GT} - \mathrm{TI}|}{\mathrm{GT}}$$

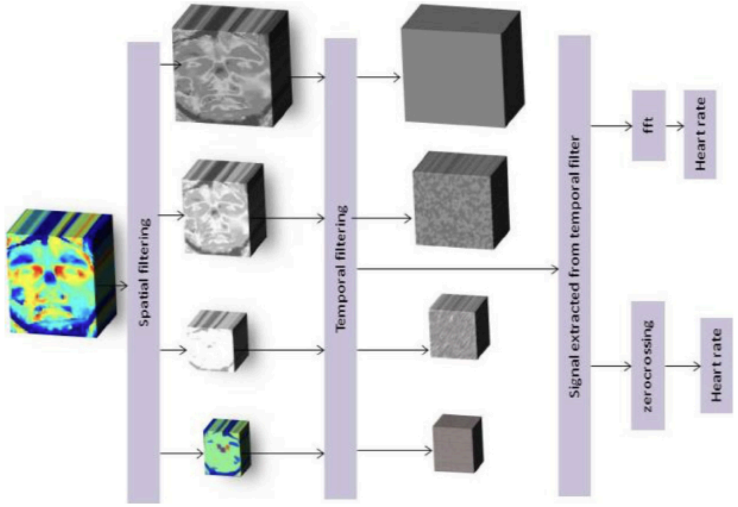
Nonstandard evaluation metrics tend to report extremely high values

Subject Code	Gender	Tissue	Thermal Imprint	GT Pulse (bmp)	TI Pulse (bmp)	$CAND$ %
Subject 01	Male	Carotid	Clear	75.9	63.8	84.02
Subject 03	Male	Carotid	Clear	68.8	63.7	92.62
Subject 04	Male	Carotid	Not Clear	63.3	60.5	95.60
Subject 06	Male	Temporal	Not Clear	59.9	67.3	87.65
Subject 07	Male	Carotid	Clear	68.0	61.4	90.32
Subject 08	Male	Temporal	Clear	72.5	63.6	84.21
Subject 09	Male	Carotid	Clear	72.6	67.9	93.53
Subject 10	Male	Carotid	Clear	82.3	66.9	81.25
Subject 11	Male	Carotid	Clear	83.3	76.8	92.17
Subject 12	Male	Carotid	Not Clear	63.8	62.8	98.43
Subject 13	Male	Carotid	Clear	64.7	64.4	99.58
Subject 15	Male	Carotid	Clear	76.9	62.3	80.99
Subject 16	Male	Carotid	Not Clear	57.2	63.2	89.54
Subject 17	Female	Carotid	Clear	67.4	63.6	94.32
Subject 19	Female	Carotid	Clear	70.5	62.3	88.34
Subject 20	Female	Carotid	Not Clear	81.1	57.4	70.72
Subject 21	Male	Carotid	Clear	75.2	72.2	96.00
Subject 22	Female	Supra-Orbital	Clear	77.1	74.3	96.32
Subject 23	Male	Carotid	Not Clear	76.1	67.8	89.09
Subject 24	Male	Carotid	Not Clear	55.6	78.1	59.63
Subject 25	Male	Carotid	Not Clear	61.6	74.1	79.77
Subject 26	Female	Carotid	Not Clear	62.9	61.1	97.19
Subject 27	Female	Temporal	Not Clear	62.4	62.9	99.17
Subject 28	Female	Carotid	Clear	74.0	73.1	98.81
Subject 29	Male	Temporal	Clear	74.6	65.4	87.65
Subject 31	Female	Carotid	Clear	70.7	58.1	82.22
Subject 33	Male	Carotid	Not Clear	86.1	65.4	75.91
Subject 34	Male	Carotid	Not Clear	79.3	61.1	77.06
Subject 35	Male	Carotid	Not Clear	59.9	64.1	92.95
Subject 36	Female	Carotid	Clear	68.3	72.9	93.28
Subject 37	Male	Carotid	Clear	67.5	60.9	90.15
Subject 38	Male	Temporal	Clear	75.1	63.3	84.24
Subject 39	Female	Carotid	Clear	72.3	71.8	99.31
Subject 40	Male	Supra-Orbital	Clear	70.6	61.9	87.71

Reported accuracy
CAND = **88.52%**

Garbey et al. (2007)

Nonstandard evaluation metrics tend to report extremely high values



Subject#	GT	Face	
		STF-FFT	STF-zerocross
1	80.75	67.69	74.02
2	73.20	82.64	72.09
3	70.56	61.02	70.99
4	82.11	54.80	65.88
5	57.11	73.70	65.45
6	79.72	54.67	70.78
7	72.52	65.64	69.98
8	92.64	67.12	73.09
9	68.97	58.96	69.01
10	78.66	63.03	74 .03
11	83.99	54.92	72.90
12	73.46	58.82	69.93
13	66.00	65.46	67.93
14	69.84	61.30	77.11
15	75.30	61.09	72.98
16	86.94	74.26	78.02
17	81.28	64.16	71.02
18	65.28	58.49	66.94
19	71.54	55.75	74.07
20	83.47	74.94	77.03
21	63.10	58.47	66.85
22	77.55	71.72	74.58
Average CAND		82.86%	92.46%

Reported accuracy
CAND = **92.46%**

Hamedani et al. (2016)

This sounds very reliable!

We have computed their correlation coefficients

Subject#	GT	Face	
		STF-FFT	STF-zerocross
1	80.75	67.69	74.02
2	73.20	82.64	72.09
3	70.56	61.02	70.99
4	82.11	54.80	65.88
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Average CAND		82.86%	92.46%

GT	Face	
	STF(FFT)	STF(zerocross)
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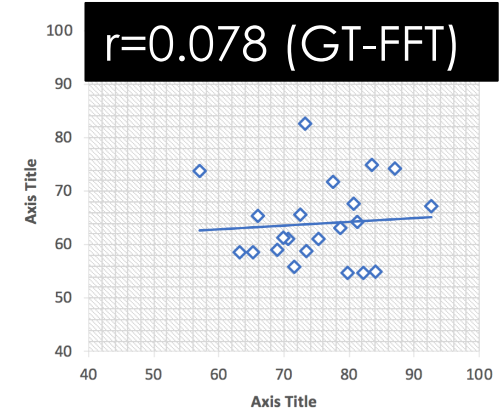
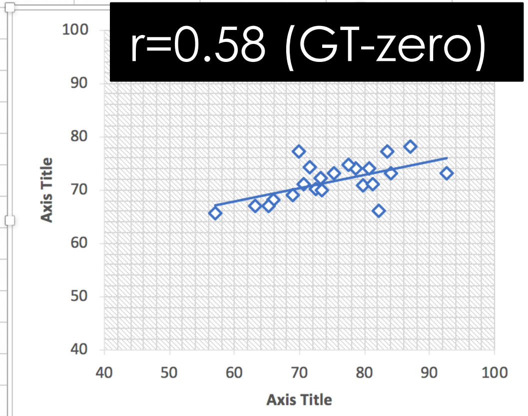
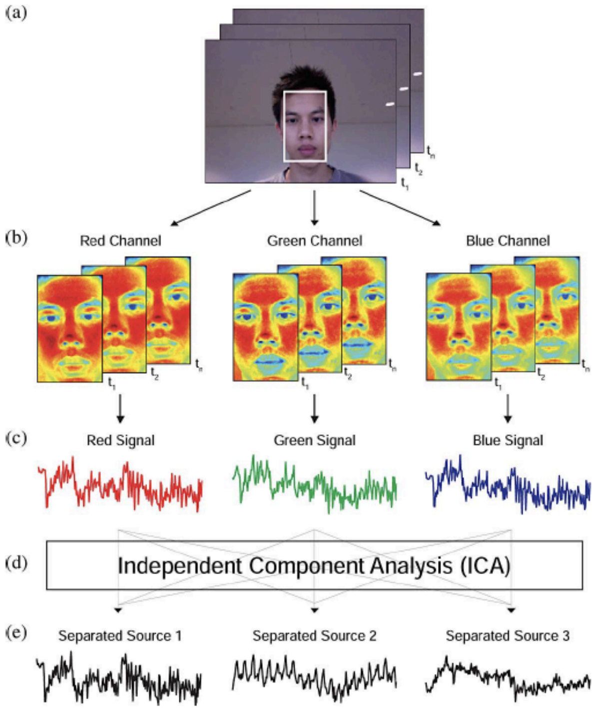
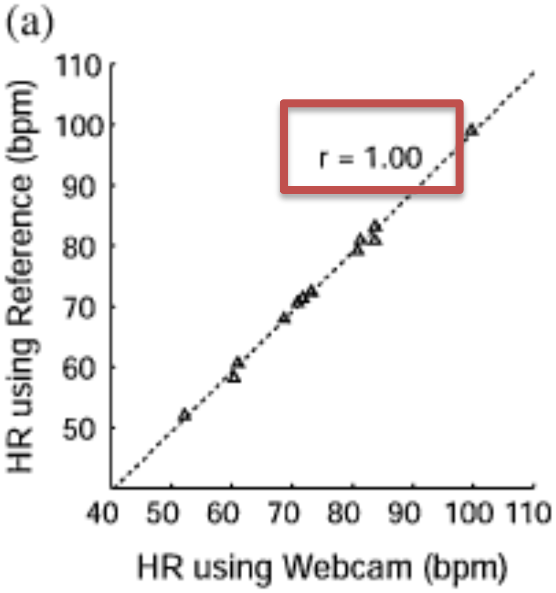
92.64	67.12	73.09
68.97	58.96	69.01
78.66	63.03	74
83.99	54.92	72.9
73.46	58.82	69.93
66	65.46	67.93
69.84	61.3	77.11
75.3	61.09	72.98
86.94	74.26	78.02
81.28	64.16	71.02
65.28	58.49	66.94
71.54	55.75	74.07
83.47	74.94	77.03
63.1	58.47	66.85
77.55	71.72	74.58
average CAND	**82.86%**	**92.46%**
correlation GT-STF(FFT)		0.07787025
correlation GT-STF(FFT)		0.58083563





For your reference, remote PPG (Photoplethysmography)

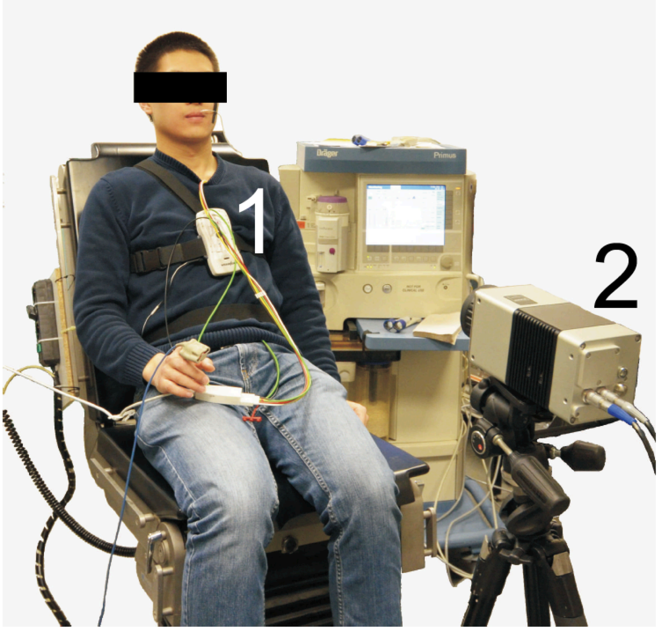




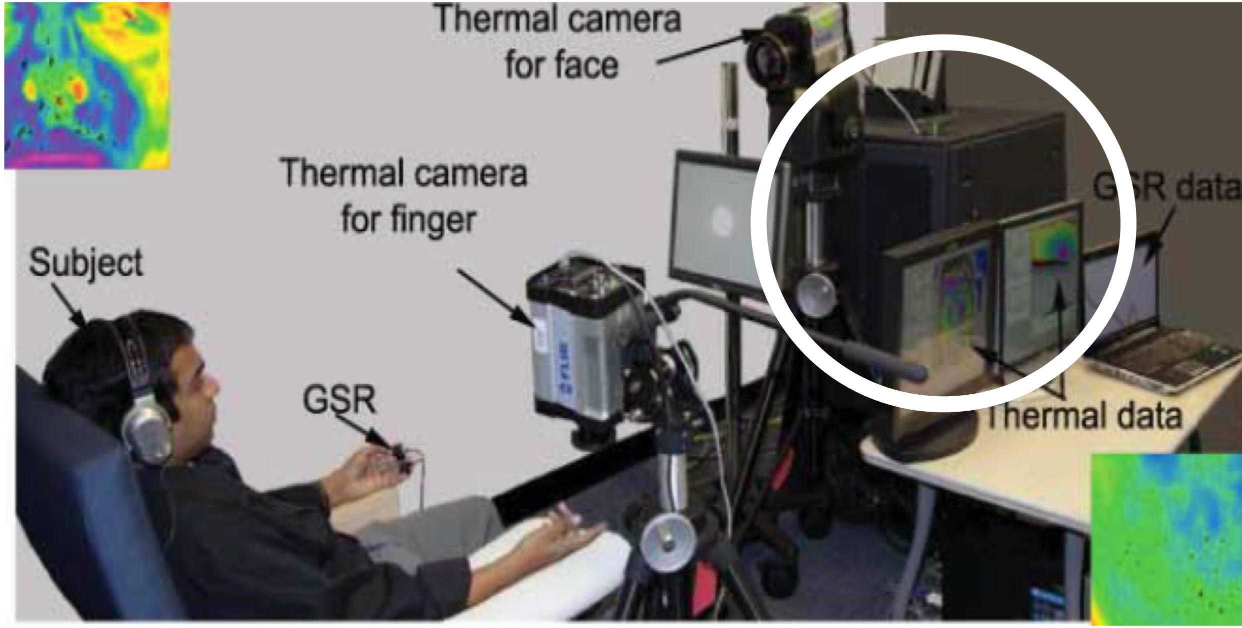
Poh et al. (2011)

III. Towards the real world with Mobile Thermal Imaging

Expensive and Heavyweight Thermal Imaging Systems



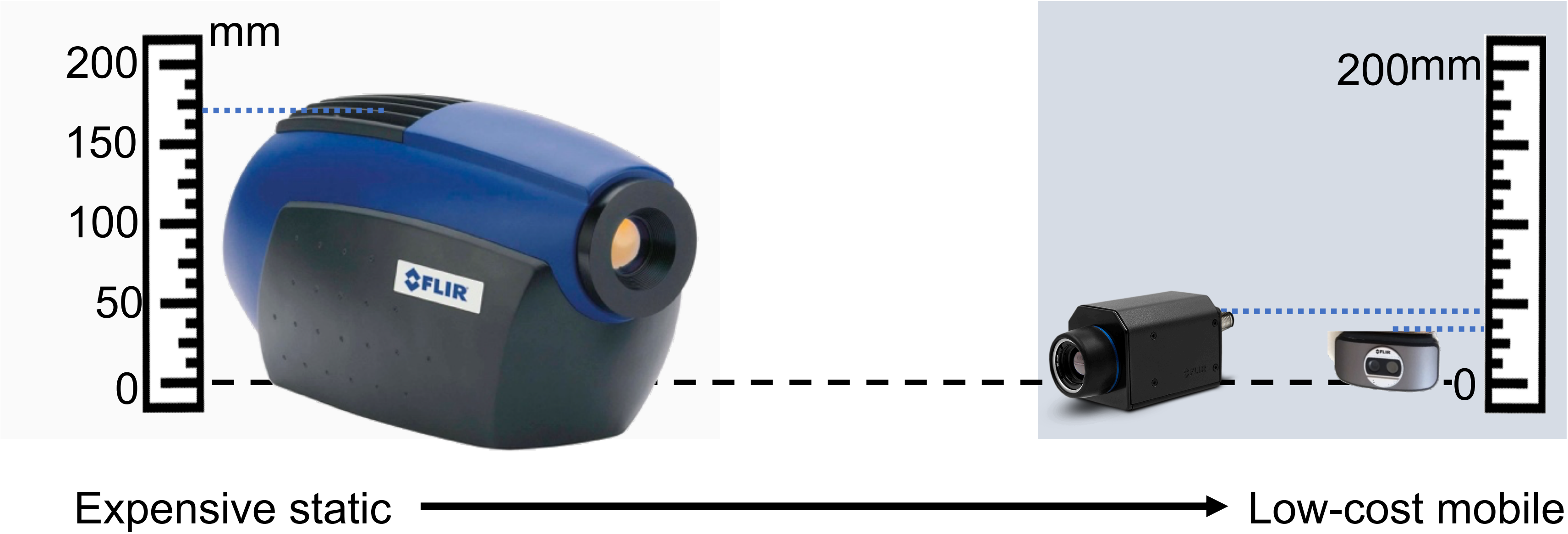
Pereira et al. (2015)



Pavlidis et al. (2012)

Advanced technology has emerged:

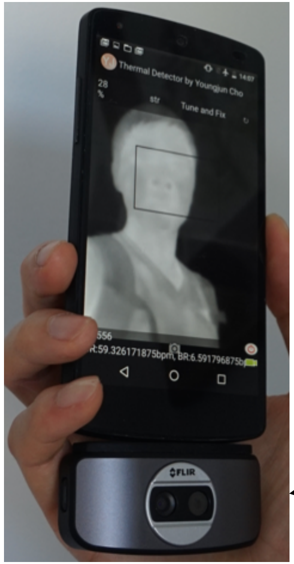
Mobile, Low-cost Thermal Imaging device

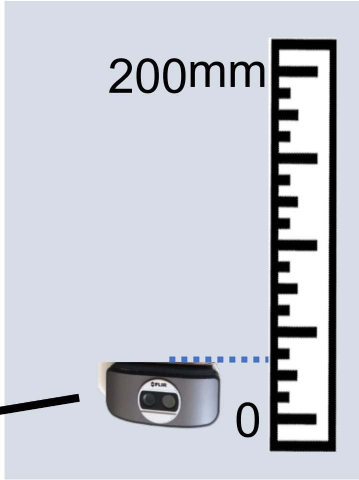


Cho et al. (2019)

Advanced technology has emerged:

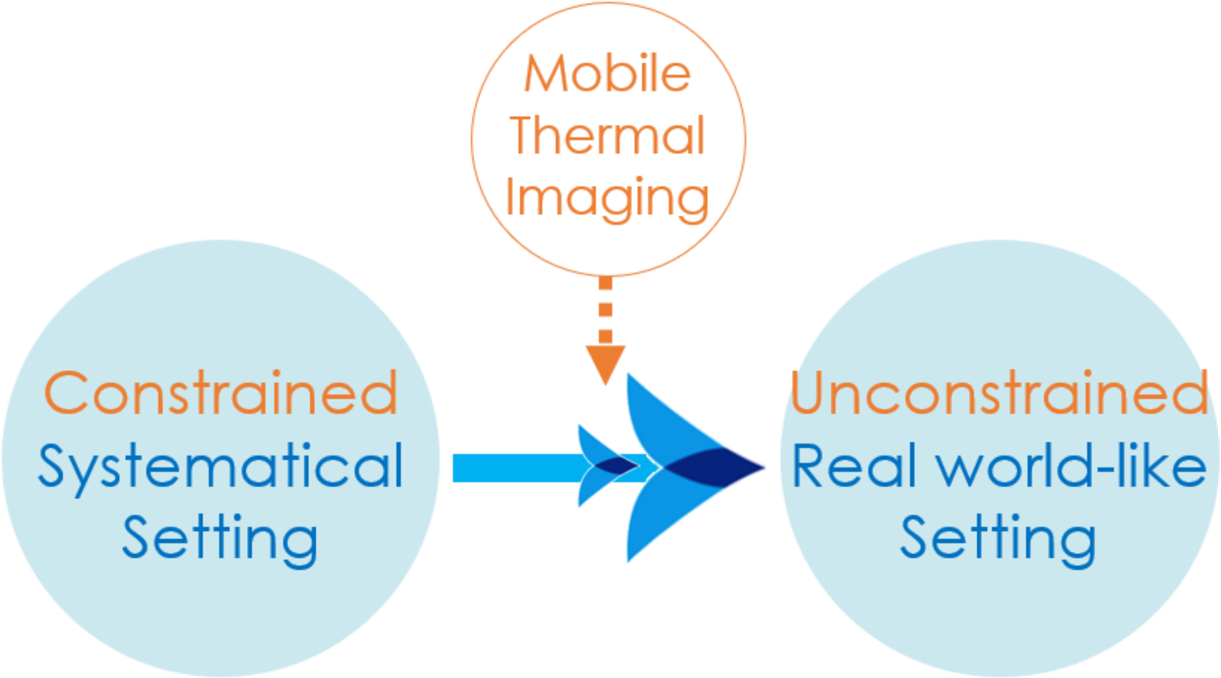
Mobile, Low-cost Thermal Imaging device





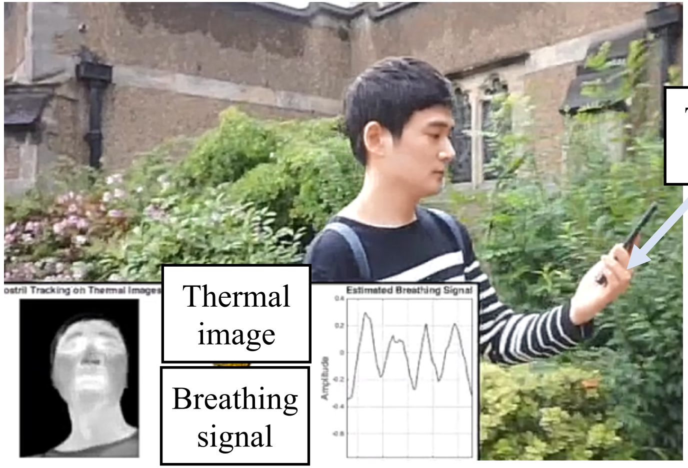
Integrated into a smartphone

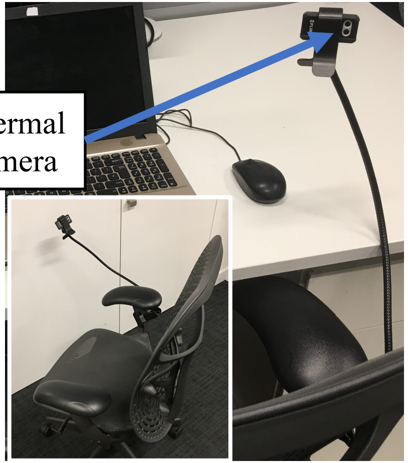
Low-cost mobile

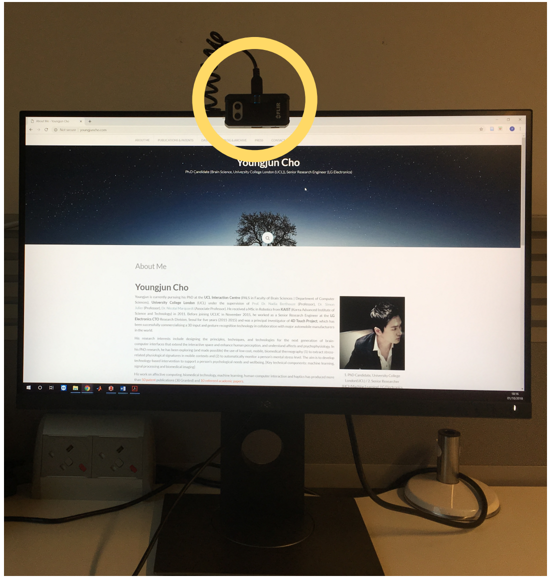

Mobile
Thermal
Imaging
Constrained
Systematical
Setting
Unconstrained
Real world-like
Setting

Cho (2019)

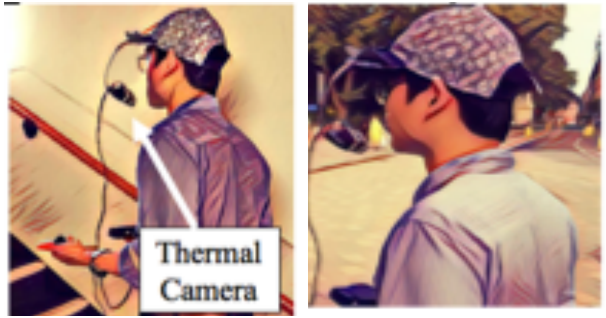
Use cases of Mobile thermal imaging



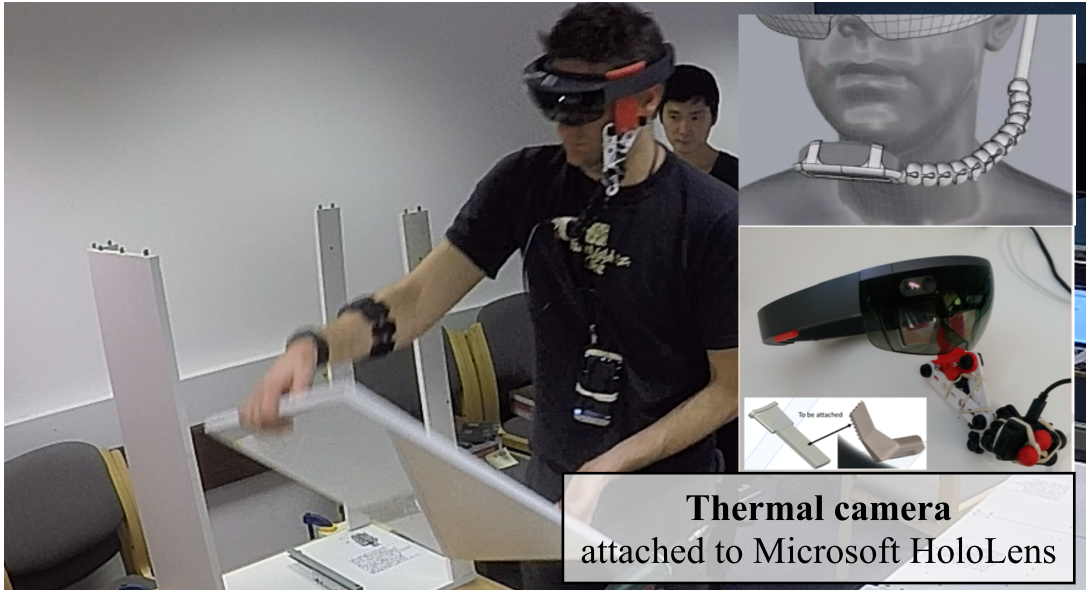




Use cases of Mobile thermal imaging



Cho et al. (2017)



Cho et al. (2019) Nose Heat

Use cases of Mobile thermal imaging

Nearly everywhere
without
privacy concerns

Towards real-world situations, we must

1. Improve **ROI tracking** performance
   (given ambient temperature and motion artefacts)

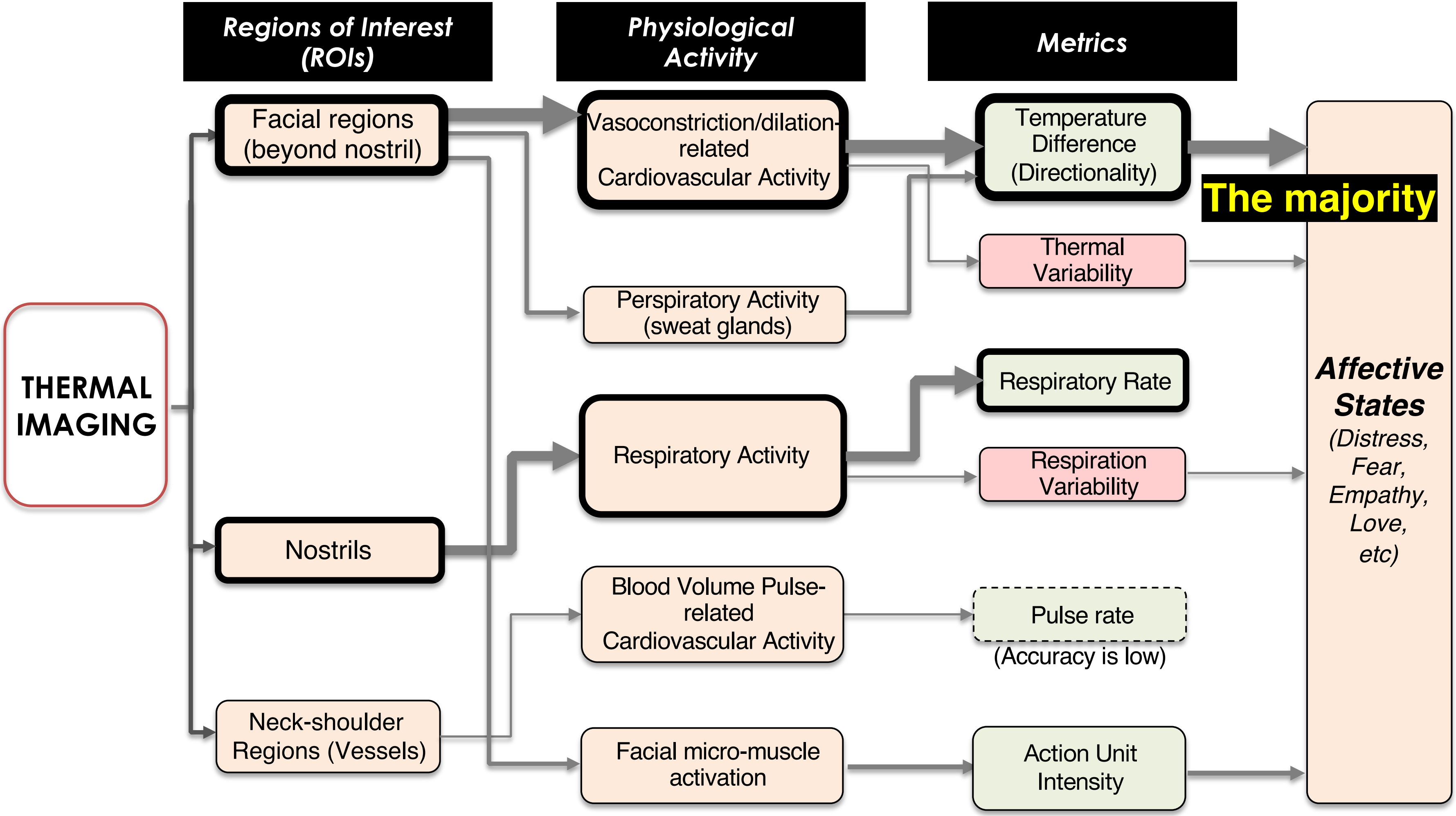
2. Improve the quality of **physiological thermal signatures**

3. Improve / build thermal metrics

4. Enrich datasets and opensource toolkits

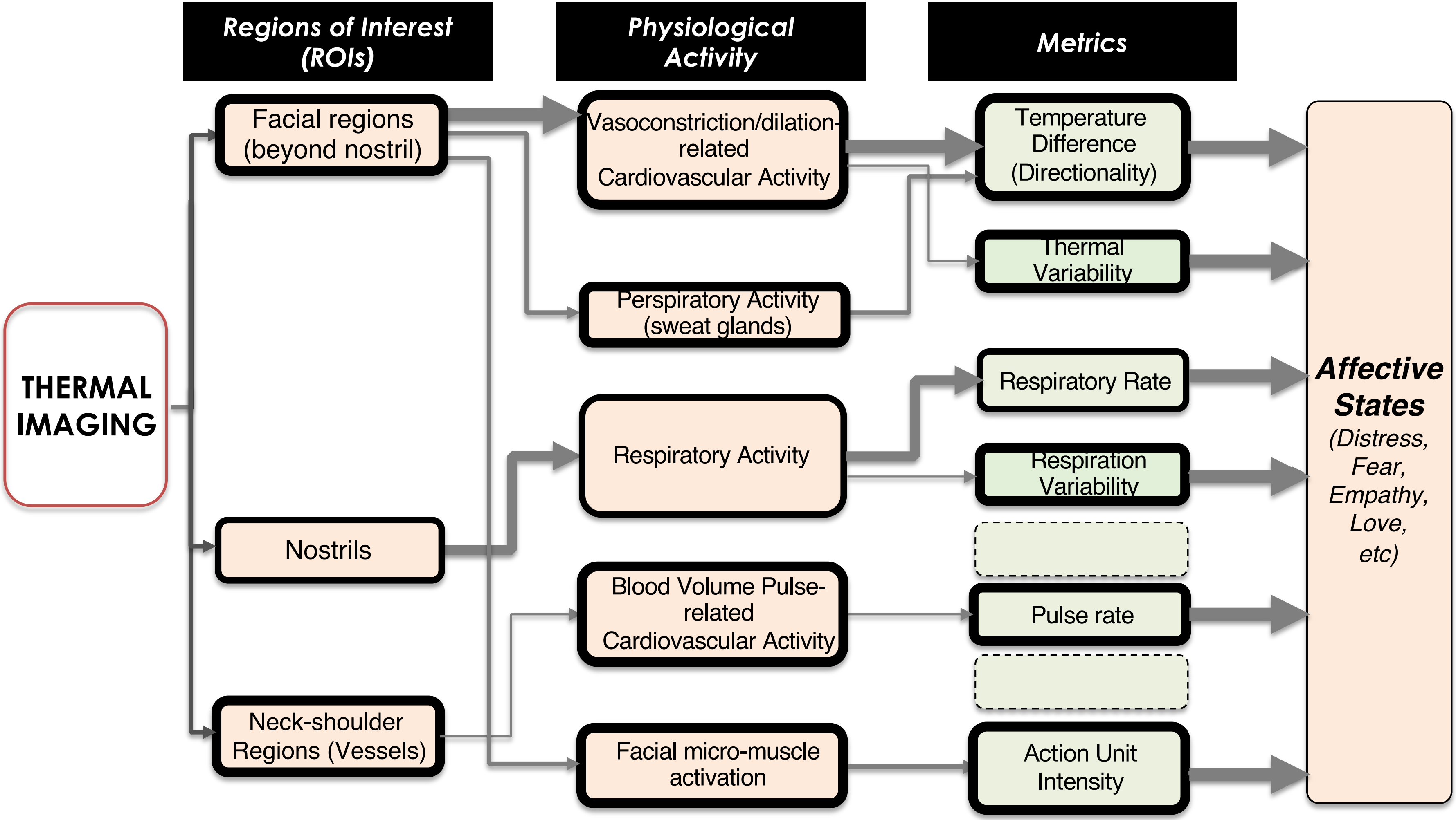
Cho et al. (2019)

From



Regions of Interest (ROIs)
Physiological Activity
Metrics
THERMAL IMAGING
Facial regions (beyond nostril)
Nostrils
Neck-shoulder Regions (Vessels)
Vasoconstriction/dilation-related Cardiovascular Activity
Perspiratory Activity (sweat glands)
Respiratory Activity
Blood Volume Pulse-related Cardiovascular Activity
Facial micro-muscle activation
Temperature Difference (Directionality)
Thermal Variability
Respiratory Rate
Respiration Variability
Pulse rate
(Accuracy is low)
Action Unit Intensity
The majority
Affective States
(Distress, Fear, Empathy, Love, etc)

Towards



Regions of Interest (ROIs)
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Respiratory Rate
Respiration Variability
Pulse rate
Action Unit Intensity
Affective States
(Distress, Fear, Empathy, Love, etc)


Thank You!

Thank you !

PhD studentship available at UCL Computer Science in 2020

Call: talented students are invited to propose a PhD research project in areas related to **machine learning, physiological and affective computing**, with the aim to create novel assistive technology and boost disability innovation.

* You can also apply for the project described below.

Project Title
Mobile thermography-based cardiovascular and cortical imaging for detecting anxiety in hospitalised children

Applications for 2020-21 are now being accepted

http://youngjuncho.com/news/phdstudentship/