Computer Vision for Physiological Measurements: Methods and Applications

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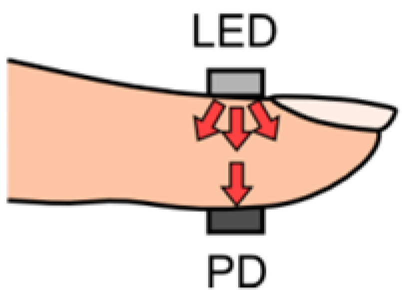
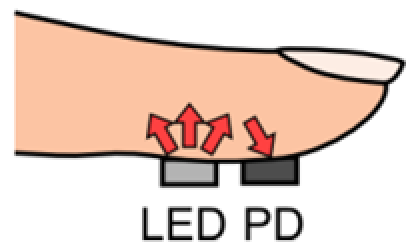
Background on photoplethysmography

Photoplethysmography (PPG)

- A low-cost non-invasive optical technique
- Detects blood volume changes in tissues beneath the skin which are due to the pulsatile nature of the circulatory system

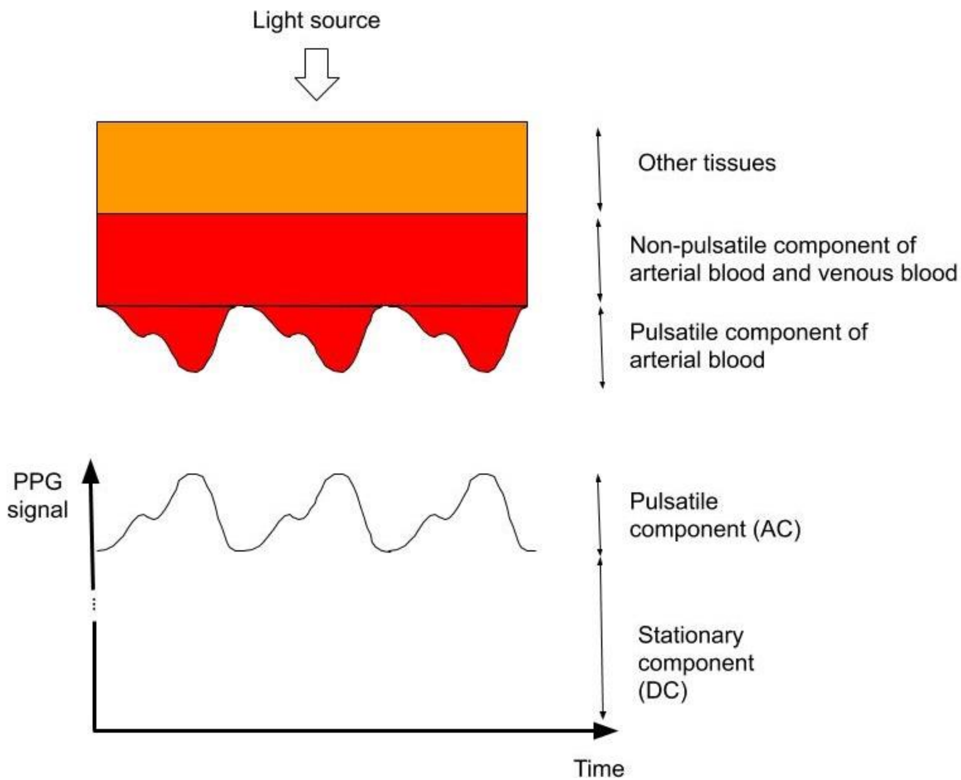


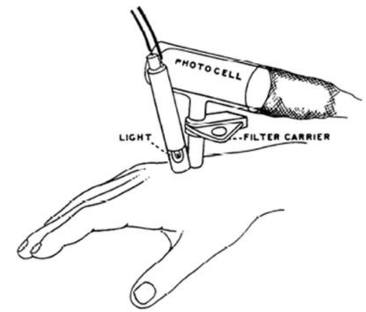
PPG in transmission mode



PPG in reflection mode

Background on photoplethysmography





1st prototype by Alrick B. Hertzman in 1937

PPG is widely used (clinic or research)

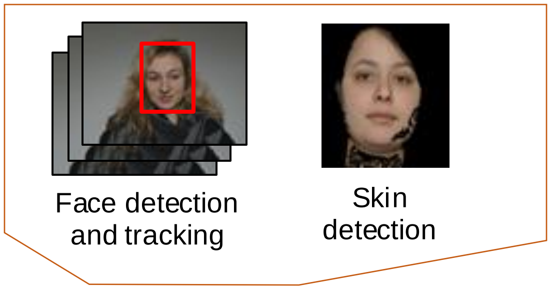
- for the monitoring of various physiological parameters (e.g. SPO2, HR, BP, BR, …)
- for vascular assessment (e.g. arterial diseases)
- for autonomic function assessment (i.e. pulse rate variability - PRV)
- smartwatches

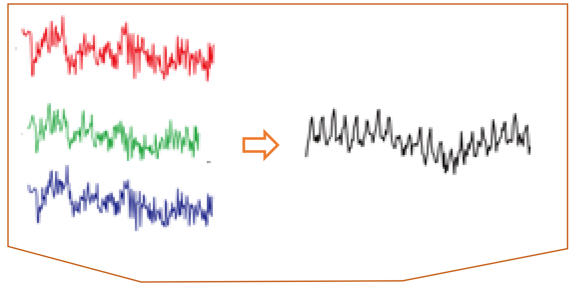
Background on photoplethysmography

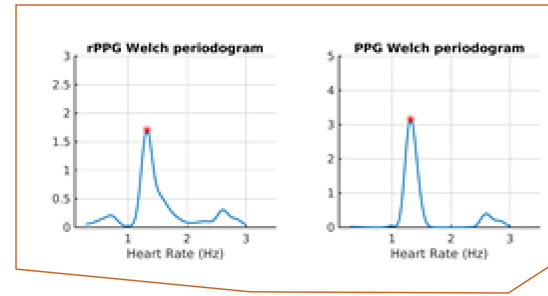
We measure temporal variations of the diffused light due to the pulsatile nature of the circulatory system with simple cameras.

Remote photoplethysmography

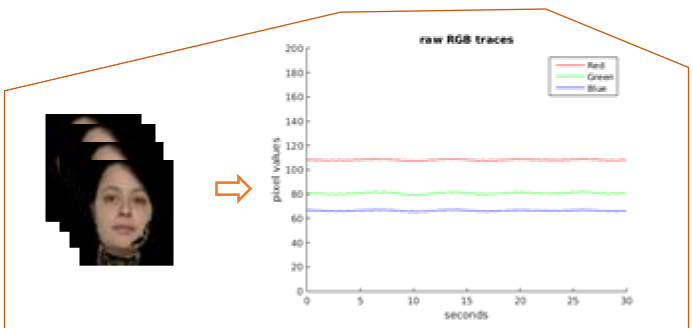
Pipeline

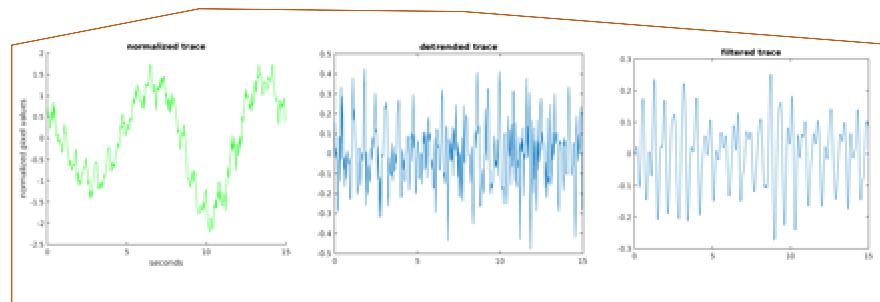






Spatial ROI selection and tracking → Spatial averaging → Color channel selection - combination → Denoising → Physiological parameters estimation





Remote photoplethysmography

Spatial ROI selection and tracking → Spatial averaging → Color channel selection - combination → Denoising → Physiological parameters estimation

This pipeline-based framework emphasizes the importance of the ROI segmentation

Regular spatial averaging considers that all pixels have the same amount of information

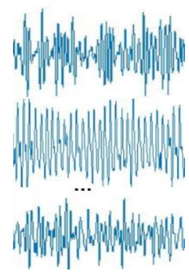
- We have proposed a data-driven based ROI segmentation that implicitly favors regions where the rPPG signal is predominant

Remote photoplethysmography

Spatial ROI selection and tracking → Spatial averaging → Color channel selection - combination → Denoising → Physiological parameters estimation

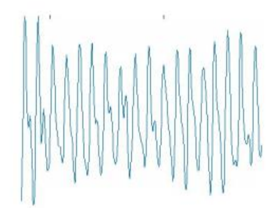
Video frames

Temporal superpixel segmentation



Pulse trace extraction

Signal quality estimation



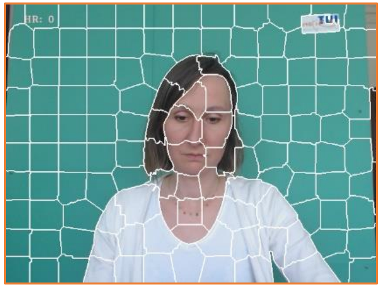
Weighted average

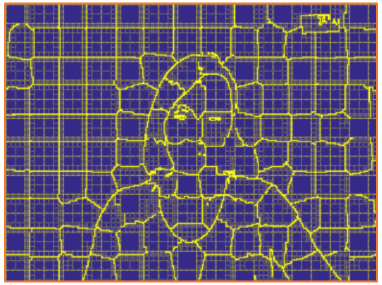
S. Bobbia et al., Unsupervised skin tissue segmentation for remote photoplethysmography, PRL, 2017

Remote photoplethysmography

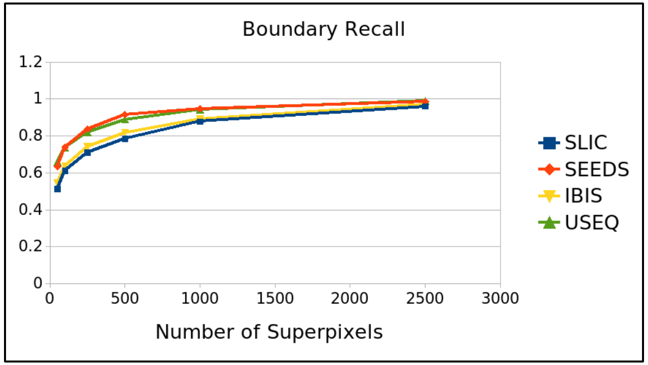
Data-driven ROI segmentation

Ultra-fast superpixel segmentation method

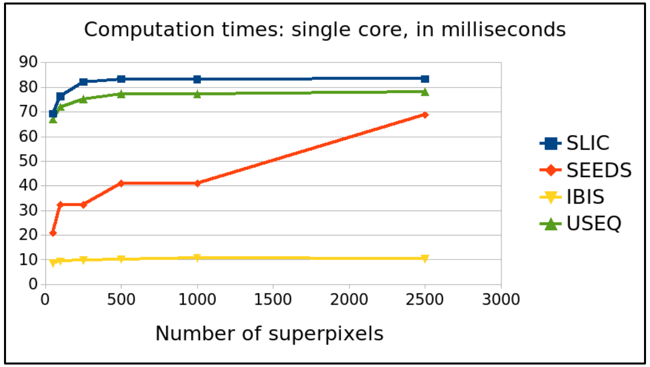




Segmentation quality evaluation



Computation time evaluation



IBIS: Iterative Boundaries implicit Identification for Segmentation

S. Bobbia et al., "Real-Time Temporal Superpixels for Unsupervised Remote Photoplethysmography", CVPR workshop, 2018
https://github.com/xapha/IBIS

Remote photoplethysmography

Spatial ROI selection and tracking → Spatial averaging → **Color channel selection - combination** → Denoising → Physiological parameters estimation

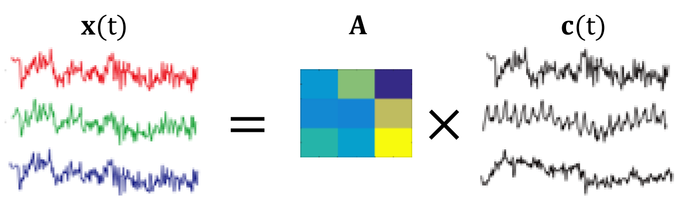
Channel combination formulated as a semi-blind source extraction problem

Remote photoplethysmography

rPPG as a semi-blind source separation problem

Why does it work?

The measured RGB time traces are a mixture of several independent components, i.e. the rPPG signal, movements, light variations, noise, etc.



$$\mathbf{x}(\mathrm{t}) = \mathbf{A} \cdot \mathbf{c}(\mathrm{t})$$

$$\mathbf{y}(\mathrm{t}) = \mathbf{W} \cdot \mathbf{x}(\mathrm{t})$$

ICA decomposes a multivariate signal into independent signals by optimizing an objective function

Originality of our approach: For the PPG measurement, we are not totally blind
We have prior information about the signal we are looking for

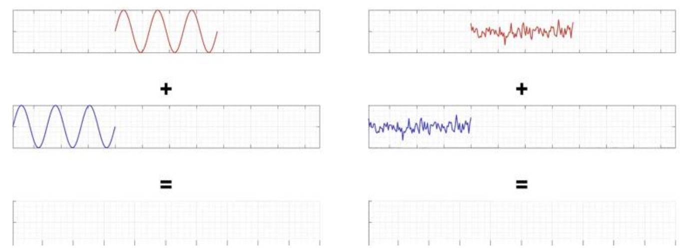
Remote photoplethysmography

rPPG as a semi-blind source separation problem

Multi-objective optimization using Autocorrelation and ICA (MAICA)

$$\text{Maximize} \;\; J(\text{y}), R(\text{y})$$

Mean of squarred autocorrelation

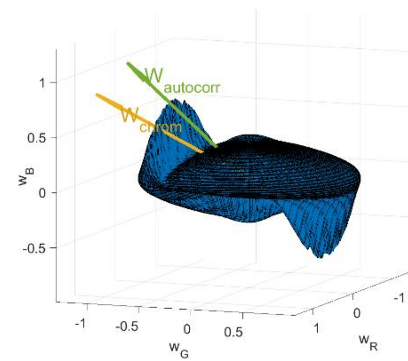


Semi-Blind Source Separation / Constrained ICA

$$\text{Maximize} \;\; J(\text{y})$$

$$\text{Subject to: } g(w) \leq 0$$

Constraints on periodicity and on chrominance

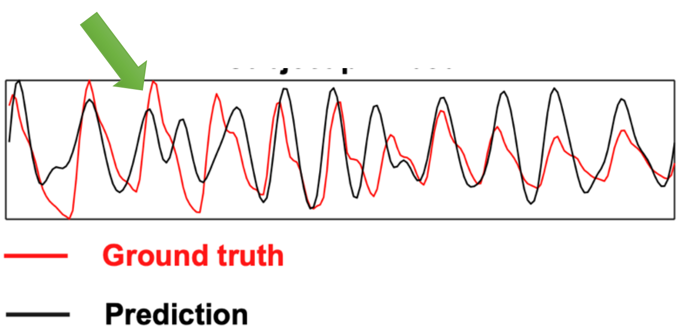


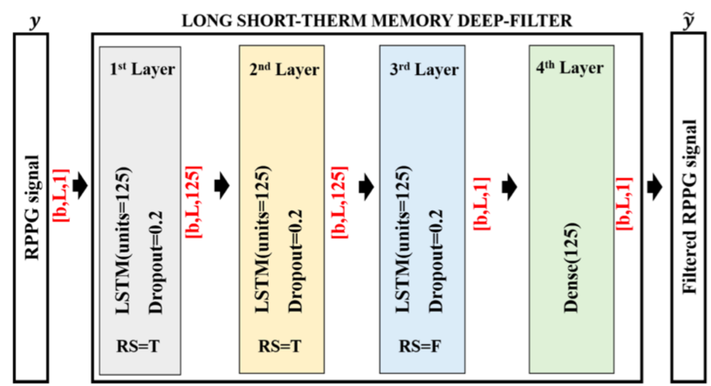
R. Macwan et al., Heart rate estimation using remote photoplethysmography with multi-objective optimization, BSPC, 2019

Remote photoplethysmography

Deep Learning-based physiological signal filtering

Spatial ROI selection and tracking → Spatial averaging → Color channel selection - combination → **Denoising** → Physiological parameters estimation





D. Botina-Monsalve et al. Performance analysis of remote photoplethysmography deep filtering using long short-term memory neural network, Biomed Eng, Springer Nature, 2022

Remote photoplethysmography

RT-RPPG: Multi-task light-weight 3D-CNN for fast physiological measurements

Spatial ROI selection and tracking → Spatial averaging → Color channel selection - combination → Denoising → Physiological parameters estimation

→ 3D CNN →

Heart Rate

Breathing Rate

rPPG signal

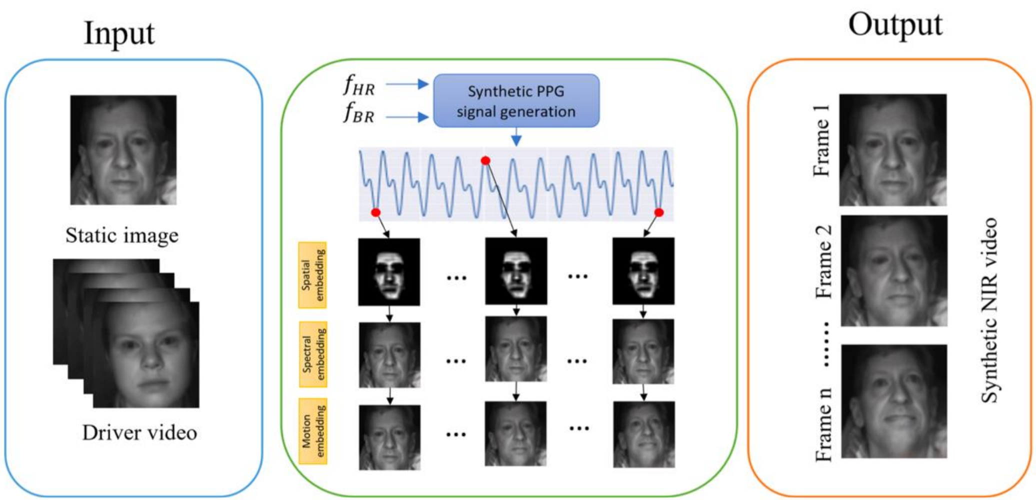
Introduction of non-linearity
Better management of the temporal and spatial dimensions

3D convolutions are computationally expensive

D. Botina-Monsalve et al. RTrPPG: An Ultra Light 3DCNN for Real-Time Remote Photoplethysmography, CVPR workshop, 2022

Remote photoplethysmography

rPPG from challenging scenarios using synthetic video generation



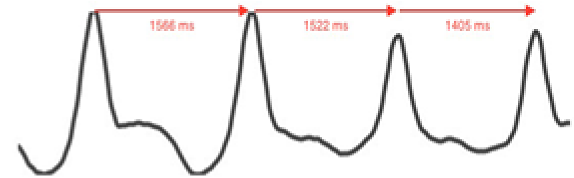
Synthetic videos are used to train large DL models on cases where the number of videos are not sufficient (NIR, fitness, …)

Y. Benezeth et al., Video-based heart rate estimation from challenging scenarios using synthetic video generation, *BSPC 2024*

Remote cardiac variability estimation and applications

We can measure Pulse Rate Variability (PRV) from the video stream

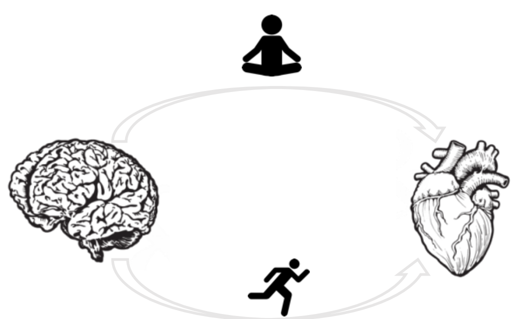
PRV/HRV represents variation of the time intervals between consecutive pulses



Autonomic Nervous System (ANS)

ANS controls the unconscious bodily processes (heart rate, body temperature, digestion, ...)

Parasympathetic Nervous System



Sympathetic Nervous System

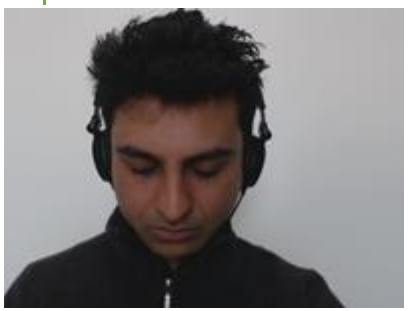
> Heart Rate Variability is an interesting measure of the Autonomic Nervous System. It has been used in many psychophysiological research.

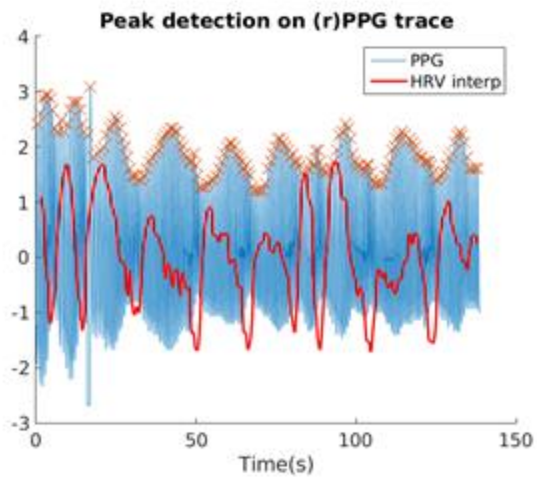
Remote cardiac variability estimation and applications

Correlation between emotional states and remote PRV

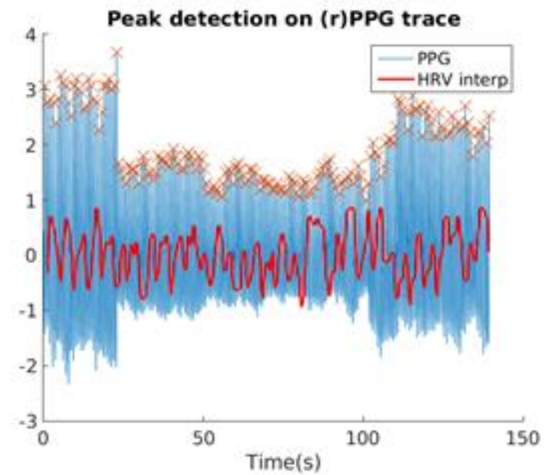
Positive emotions increase coherence in heart rhythms while negative emotions increase disorder in the heart rhythms.

Impact of music on PRV ?





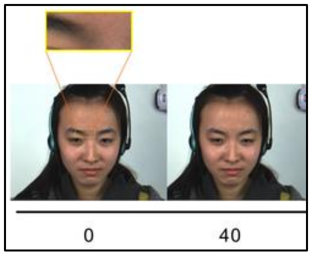
Relaxing music



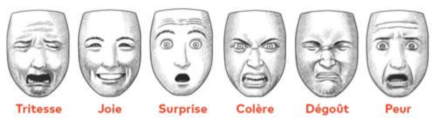
Disturbing music

Remote cardiac variability estimation and applications

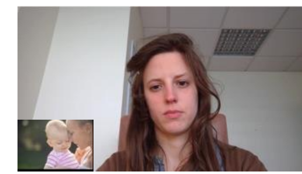
Example of projects using remote PRV

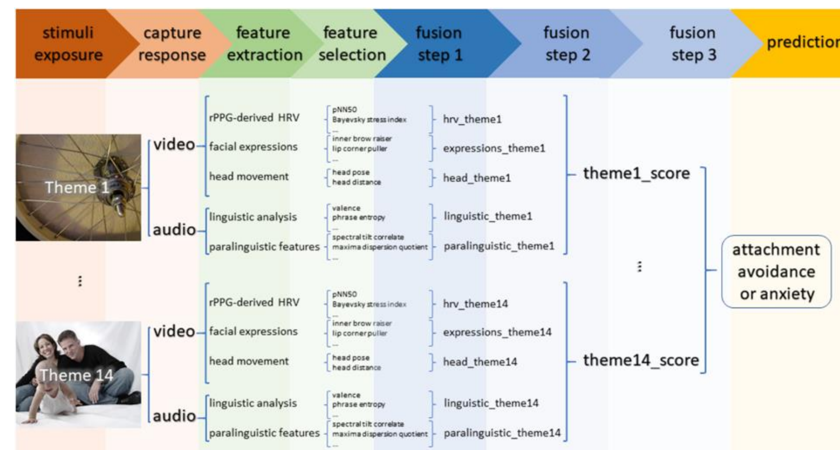


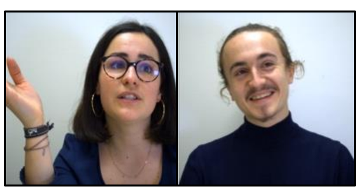
Emotion recognition



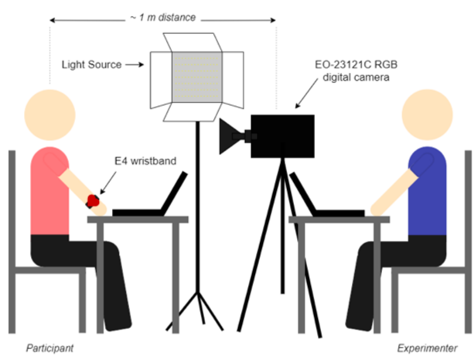
Automatic psychometric test







Stress estimation



Remote cardiac variability estimation and applications

Emotion recognition

CAS(ME)^2 dataset

A dataset for micro facial expressions recognition and spotting

22 participants, 19 to 26 years old

3 types of emotion inducing videos: *disgust, anger, happiness*

97 videos with durations of 1min to 2min30s

Leave One Subject Out (LOSO) cross-validation protocol

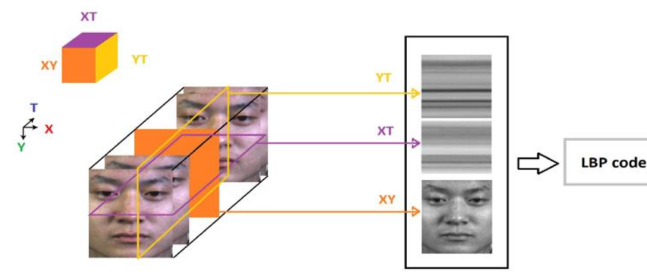
Comparison of emotional states recognition based on facial-expression vs remote PRV

We consider micro and macro facial expressions

LBP TOP features + SVM/RBF for classifier

Mixture of temporal, frequency and geometric features of PRV signals

→PRV features surpass facial features in that context



R. Belaiche et al., Emotional State Recognition with Micro-expressions and Pulse Rate Variability. ICIAP 2019

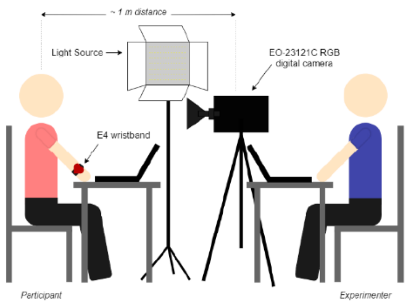
Remote cardiac variability estimation and applications

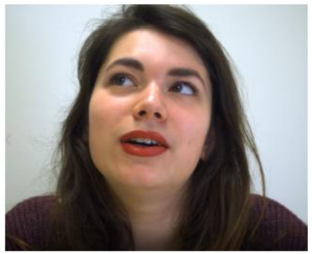
Stress recognition

The UBFC-Phys dataset is a public multimodal dataset

56 participants underwent an experiment inspired by the well-known Trier Social Stress Test (TSST) with three stages: a rest, a speech, and arithmetic tasks with different levels of difficulty.

Acquisition of different modalities: Video and physiological signals - blood volume pulse (BVP) and electrodermal activity (EDA) signals.





→ PRV features can be used to estimate stress levels
→ Remote estimation of PRV features demonstrates comparable reliability to data acquired using a contact sensor

R. Meziati Sabour et al. "UBFC-Phys: A Multimodal Database For Psychophysiological Studies Of Social Stress", IEEE Trans. on Affective Computing, 2021

Remote cardiac variability estimation and applications

Multimodal data analysis: the *Biometric Attachment Test*

Automatic psychometric test powered by multimodal fusion and machine learning.

Multimodal feature extraction from audio and video: facial expressions, head pose, gaze direction, rPPG derived HRV features, linguistic and paralinguistic features.

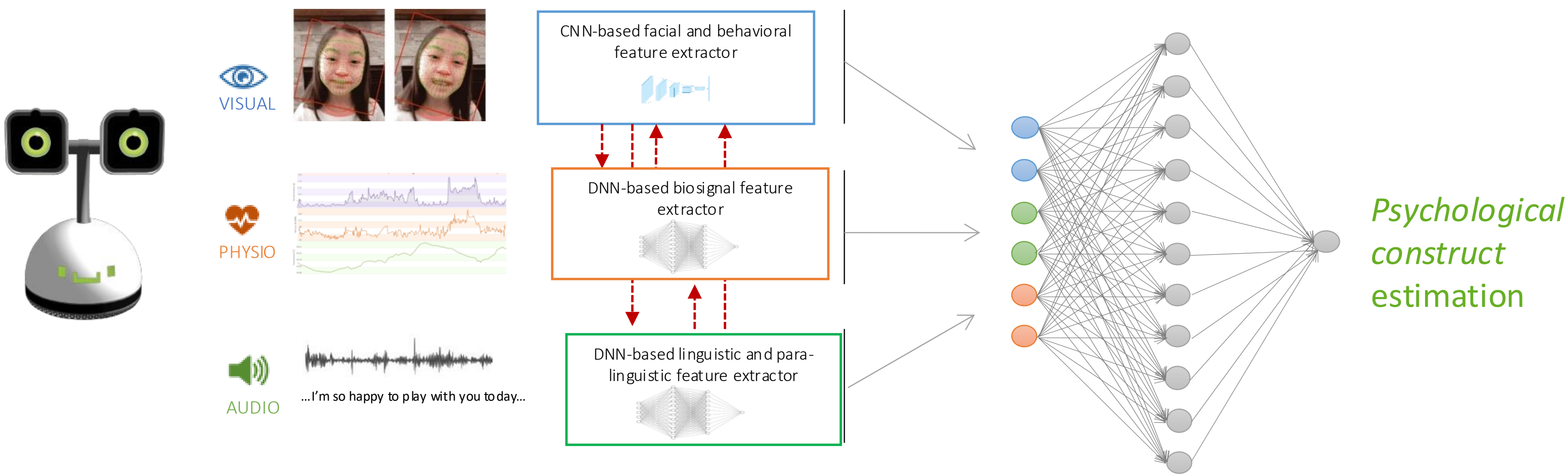
Multimodal fusion and classification with a small dataset (57 francophone participants and 19 anglophone).

→We obtain good correlation with the Adult Attachment Questionnaire (AAQ)

F. Parra et al., Development and cross-cultural evaluation of a scoring algorithm for the Biometric Attachment Test: Overcoming the challenges of multimodal fusion with “small data”, IEEE Trans on Affective Computing, 2019

Remote cardiac variability estimation and applications

Multimodal *psychological construct* estimation from a very **small** multimodal dataset



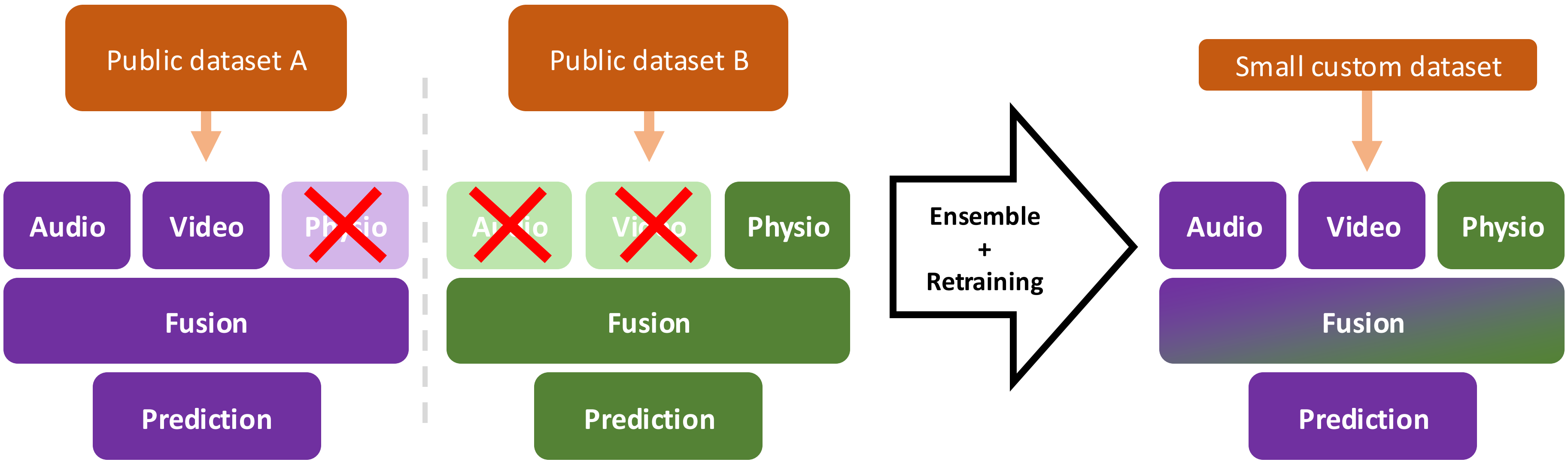
Notable aspects of our approach

1. exploit the correlations between modalities
2. target any relevant psychological construct with pre-training on large public dataset and model specialization on a small target dataset

Remote cardiac variability estimation and applications

Multimodal *psychological construct* estimation from a very **small** multimodal dataset

- Machine learning model for multimodal time series analysis
- It is possible to use retraining techniques when the custom dataset is too small
- No single public dataset contains all modalities, so multiple datasets and ensembling methods are needed



Remote cardiac variability estimation and applications

Large homemade dataset of physiological signals

Dataset description

Physiological data (heart rate, heart rate variability, skin temperature, accelerometer)

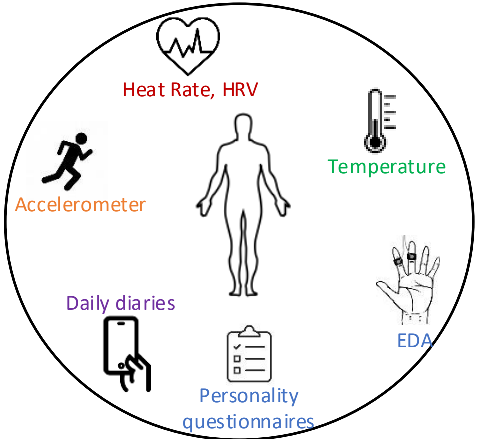
Pre-study data (age, sex, personality questionnaires)

Daily-diary data (stress perceived, mood, physical health)

Dataset objectives

Investigate how accurately we can measure and predict stress, mood and health in an uncontrolled environment

Pre-study data used to personalize AI models according to groups of individuals with homogeneous characteristics



Some figures

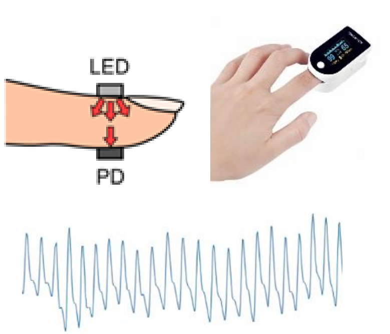
- 115 people participated in the study (13 dropped out)
- 7116 daily diaries
- 49,064 hours of physiological data

→Image-based physiological signal processing
→Advanced personalization strategies
→Self-supervised models for model pre-training
→...

Spatio Temporal rPPG

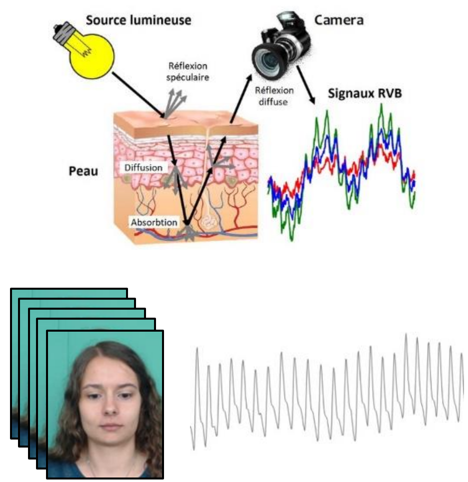
Evolution de la technologie PPG

PPG



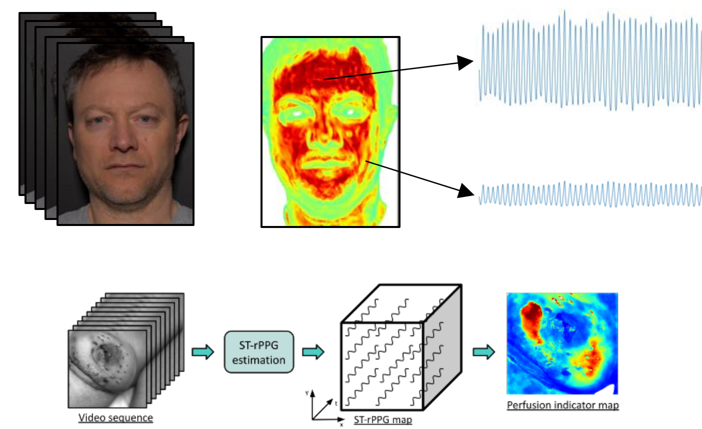
Mesure au contact d'un signal

Remote PPG (rPPG)



Mesure sans contact d'un signal

Remote PPG Map (rPPG Map)



Mesure sans contact d'un signal pour chaque pixel

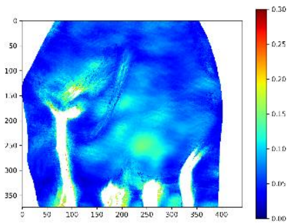
Spatio Temporal rPPG

Exemples de résultats de rPPG Map

Vasodilatation induite par la chaleur

FROID

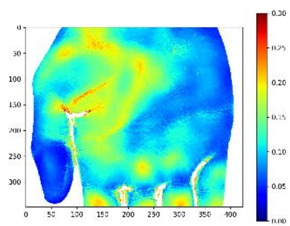
Image sequence



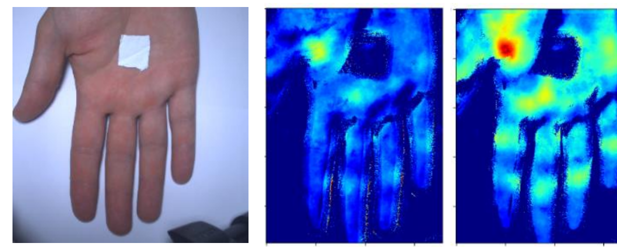
Amplitude Map (Time-averaged)

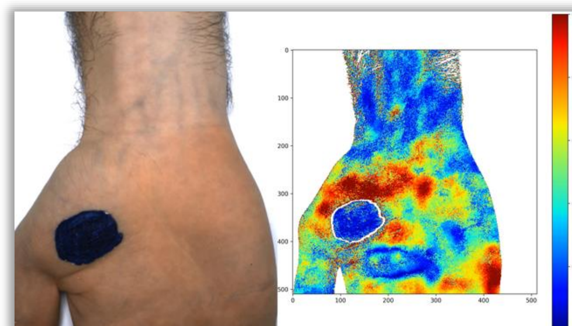
CHAUD

Image sequence



Amplitude Map (Time-averaged)





Exemples de résultats de rPPG Map

Etude de la distribution spatiale des signaux

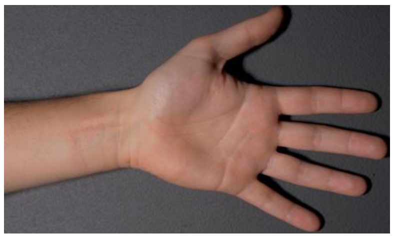
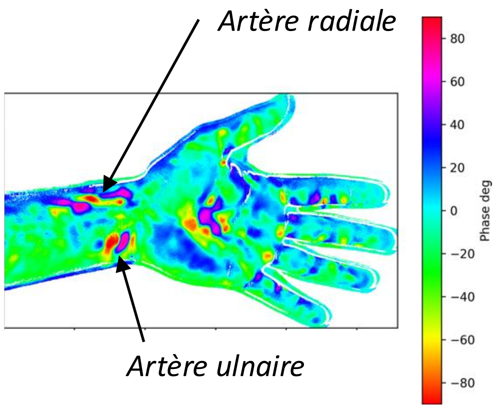
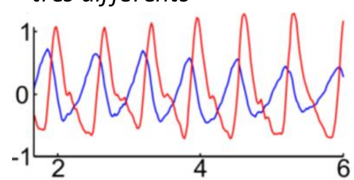
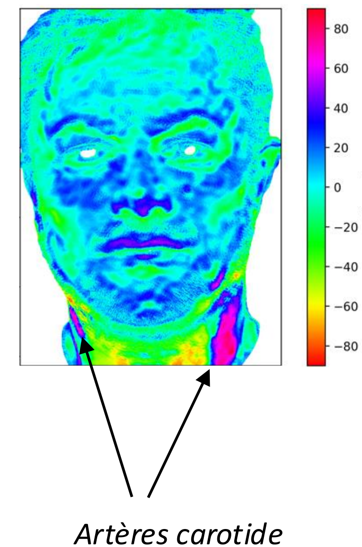


Image sequence



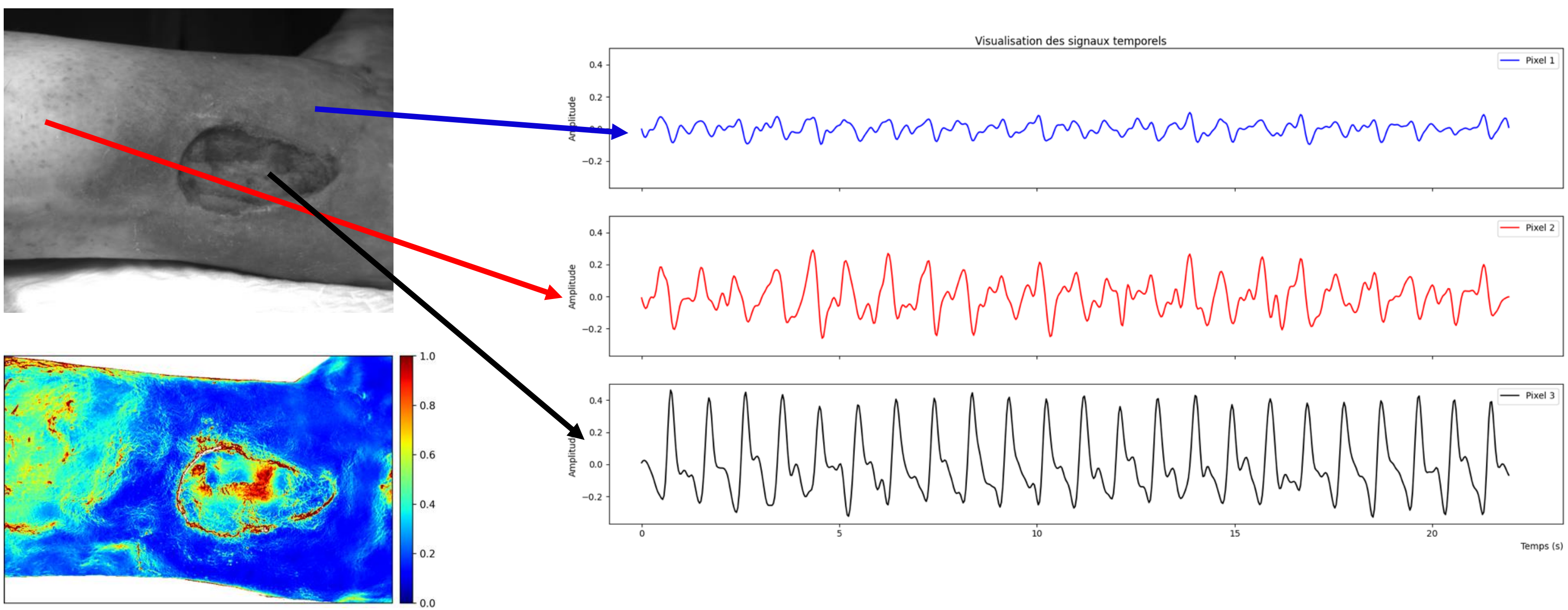
2 signaux très proches peuvent être très différents





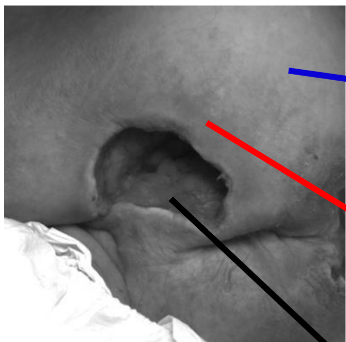
Exemples de résultats de rPPG Map

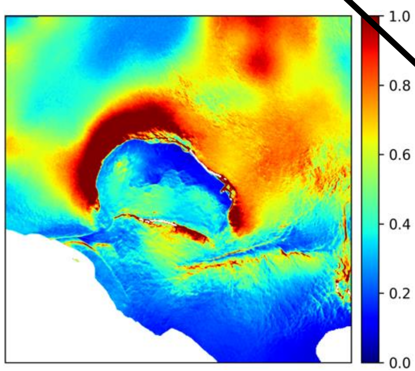
Application au suivi des plaies – ulcère mixte

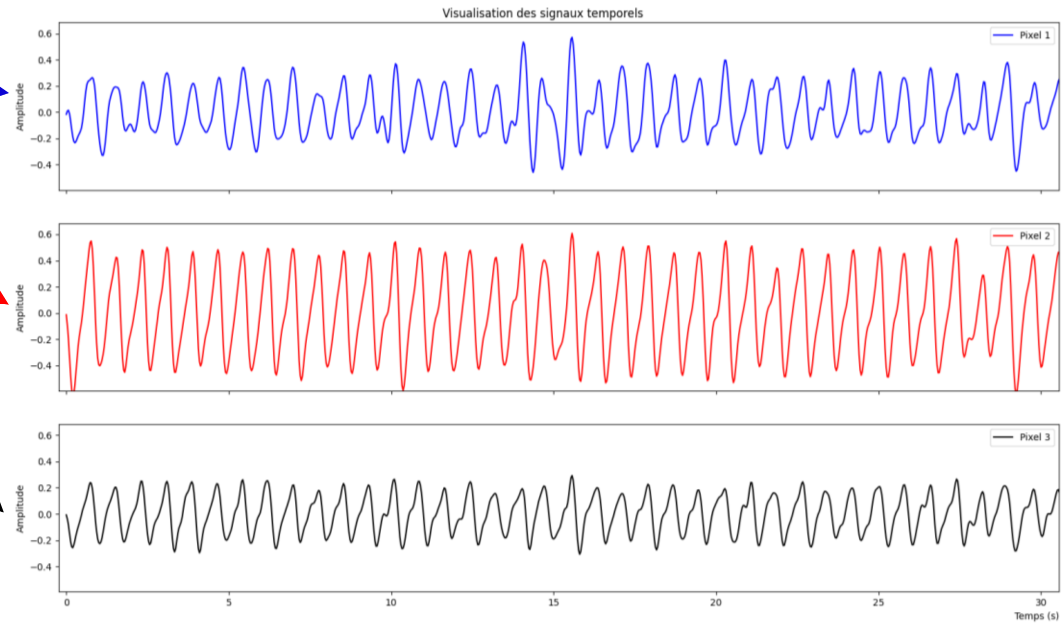


Exemples de résultats de rPPG Map

Application au suivi des plaies – Escarre

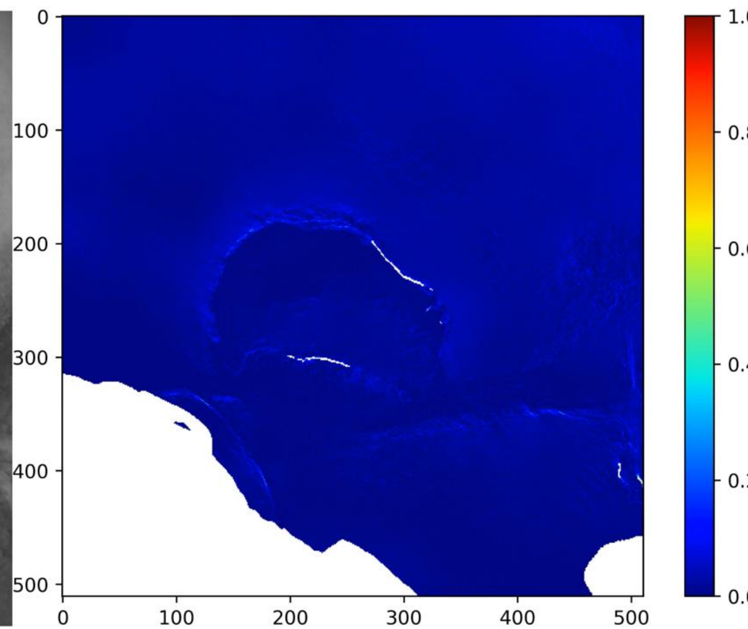






Exemples de résultats de rPPG Map

Application au suivi des plaies – Escarre



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