## Parametri Fisiologici

BVP**: Blood Volume Pulse**

RR: **Respiratory Rate**

HR: **Heart Rate**

HRV: **Heart** **Rate** **Variability** (indice per attività cardiaca autonoma)

## Techniques

PPG: Photoplethysmography  
PPG is a lowcost and noninvasive mean of sensing the cardiovascular BVP through variations in transmitted or reflected light [9]. Although PPG is typically implemented using dedicated light sources, Verkruysseshowed that pulse measurements from the human face are attainable with normal ambient light as the illumination source [10].

However, the study lacked rigorous physiological and mathematical models amenable to computation; it relied instead on manual segmentation and heuristic interpretation of raw images with minimal validation of performance characteristics.

Recently, we developed a robust method for automated computation of HR from digital color video recordings of the human face [11]. In this letter, we extend this methodology to quantify multiple physiological parameters. **Specifically, we extract the BVP for computation of HR, RR, HRV.**

### ICA: Indipendent Component Analysis

ICA is a relatively new technique for uncovering independent signals from a set of observations that are composed of linear mixtures of the underlying sources [12]. **The underlying source signal of interest in this**

**study is the BVP that propagates throughout the body.**L’analisi delle componenti indipendenti è una tecnica relativamente nuova per la determinazione di una base di segnali indipendenti da un set di osservazioni (o fotogrammi) composto da combinazioni lineari della suddetta base. Il segnale indipendente d’interesse in questo caso è il BVP che si propaga attraverso il corpo.

During the cardiac cycle, volumetric changes in the facial blood vessels modify the path length of the incident ambient light such that the subsequent changes in amount of reflected light indicate the timing of cardiovascular events.

Durante il ciclo cardiaco, cambiamenti del volume dei vasi sanguigni facciali modificano le lunghezze d’onda della luce ambientale incidente, in modo che i consecutivi cambiamenti della luce riflessa forniscano informazioni sugli eventi cardiovascolari.

By recording a video of the facial region with a webcam, the red, green, and blue (RGB) color sensors

pick up a mixture of the reflected PPG signal along with other sources of fluctuations in light due to artifacts.  
Nella registrazione di un video della regione facciale, i sensori Red Green e Blue prelevano anche una composizione del segnale fotopletismografico riflesso, insieme ad altre sorgenti di fluttuazione luminosa d’origine artificiale.  
Given that hemoglobin absorptivity differs across the visible and near-infrared spectral range [13], each color sensor records a mixture of the original source signals with slightly different weights.  
Siccome l’assorbività dell’emoglobina differisce tra gli intervalli visibile e invisibile dell’asse spettrale, ogni sensore di colore ha registrato una combinazione dei segnali originari con pesi leggermente differenti.

These observed signals from the RGB color sensors are denoted by vector y(t), which components are the amplitudes of the recorded signals at time point.

We assume three underlying source signals, represented by vector x(t).

The ICA model assumes that the observed signals are linear mixtures of the sources, like y(t) = A x(t).  
Il modello ICA assume che la combinazione lineare sia modellizzabile secondo y=Ax.

**The aim of ICA is to** find a demixing matrix W that is an approximation of the inverse of the original mixing matrix A; output is an **estimate of the vector x(t) containing the underlying source signals.**   
To uncover the independent sources, **W must maximize the non-Gaussianity of each source.   
In practice, iterative methods are used to maximize or minimize a given cost function that measures non-Gaussianity.**

Lo scopo dell’ICA è determinare una matrice W che sia un’approssimazione della matrice inversa dell’originale matrice di miscela lineare A; l’output è quindi una stima del vettore contenente i sottostanti segnali indipendenti.  
W deve esser scelta in modo da massimizzare la non-gaussianità di ogni sorgente: nella pratica dei metodi iterativi sono usati per raggiungere l’estremo di una data funzione di ottimo misurante la non-gaussianità.

## Algorithm

## I - Recording Phase

All videos were recorded in:

* 24-bit RGB
* 3 channels
* 8 bits/channel
* 15 fps
* for 1 min
* pixel resolution of 640 × 480
* saved in AVI format.

We also recorded their BVP and spontaneous breathing using an FDA-approved finger BVP sensor and chest belt respiration sensor, respectively at a sampling rate of 256 Hz.

### II - Recovery of BVP from Webcam Recordings

(II\_1)  
We utilized the Open Computer Vision library [14] to automatically **identify the coordinates of the face location in the first frame of the video** recording using a boosted cascade classifier [15].

The algorithm returned (*x*, *y)* coordinates along with the height and width that define a box around the face. We selected the center 60% width and full height of the box as theregionofinterest (ROI) for our

subsequent calculations.

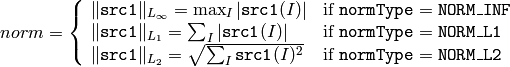
(II\_2)

**The ROI was then separated into three RGB channels and spatially averaged over all pixels in the ROI**

**to yield a R,G,B measurement point for each frame and form the raw signals y**1 (t), y2 (t), and y3 (t), respectively.

(II\_3)

**The raw traces were detrended** using a procedure based on a smoothness priors approach [16] with the smoothing parameter λ = 10 (cutoff frequency of 0.89 Hz) **and normalized** as follows. <normalization>

By the way, the program uses cv::norm(src1,NORM\_L2) as described here  
  
 

(II\_4)

The normalized raw traces are **then decomposed into three independent source signals using ICA** based on the Joint Approximate Diagonalization of Eigenmatrices (JADE) algorithm [17].

ICA is able to perform motion-artifact removal by separating the fluctuations caused predominantly by the BVP from the observed raw signals [17].   
However, the order in which ICA returns the independent components is random. Thus, **the component whose power spectrum contained the highest peak was then selected** for further analysis.

### III - Quantification of Physiological Parameters

(III\_1)

The **separated source signal was smoothed** using a five-point moving average filter and bandpass filtered (128-point Hamming window, 0.7 – 4 Hz).

(III\_2)

To refine the BVP peak fiducial point, the signal was i**nterpolated** with a cubic spline function at a sampling frequency of 256 Hz.

(III\_3)

We developed a custom algorithm to **detect the BVP peaks in the interpolated signal** and applied it to obtain the interbeat intervals (IBIs).

(III\_4)

To avoid inclusion of artifacts, such as ectopic beats or motion, the **IBIs were filtered** using the noncausal of variable threshold (NC-VT) algorithm [18] with a tolerance of 30%.

(III\_5)

**HR was calculated from the mean of the IBI time series as 60/avg(IBI)**.

(III\_8) seems not done by Luky

**Analysis of HRV was performed by** **power spectral density** (**PSD**) **estimation** using the Lomb periodogram. The low-frequency (LF) and high frequency (HF) powers were measured as the area under the PSD curve corresponding to 0.04–0.15 Hz and 0.15–0.4 Hz, respectively, and quantified in normalized units

(n.u.) to minimize the effect on the values of the changes in total power.

The LF component is modulated by baroreflex activity (one of the body's homeostatic mechanisms for maintaining blood pressure) and includes both sympathetic and parasympathetic influences [19].

The HF component reflects parasympathetic influence on the heart through efferent vagal activity and is connected to respiratory sinus arrhythmia (RSA), a cardiorespiratory phenomenon characterized by IBI fluctuations that are in phase with inhalation and exhalation.   
We also calculated the LF/HF ratio, considered to mirror sympatho/vagal balance or to reflect

sympathetic modulations.

(III\_8) seems not done by Luky

Since the HF component is connected with breathing, the **RR can be estimated from the HRV power spectrum**. When the frequency of respiration changes, the center frequency of the HF peak shifts in accordance with RR [20]. Thus, we **calculated RR from the center frequency of the HF peak** fHFpeak **in** **the**

**HRV** **PSD** derived from the webcam recordings as 60/fHFpeak.

The respiratory rate measured using the chest belt sensor was determined by the frequency corresponding to the dominant peak fresppeak in the PSD of the recorded respiratory waveform using 60/fresppeak .

### IV - Results

We extracted the BVP waveforms from the webcam recordings via ICA. A typical example of the recovered BVP recordings is shown in Fig. 2(a) along with the BVP recorded with the Flexcomp sensor. **It is evident that the two signals are in close agreement and their respective IBI signals are comparable** [see Fig. 2(b)]. **Since the IBI series is irregularly time-sampled, we utilized the Lomb periodogram to obtain the PSD to avoid resampling and inferring probable replacement values for excluded samples**. The resulting spectra are presented in Fig 2(c). Both spectra are comparable and exhibit a dominant HF component. A second example of HRV assessment is shown in Fig. 2(d)–(f). Once again, the BVP and IBI signals are similar and the HRV power spectra both exhibit a dominant LF component. We were able to determine RR from the HRV power spec-trum by locating the center frequency of the HF peak. Fig. 3(a) presents an IBI time series and its corresponding PSD [see Fig. 3(b)]. The center frequency of the HF peak was 0.23 Hz (14 breaths/min) and corresponds to the fundamental breathing rate computed from the PSD [see Fig. 3(d)] of the measured respiratory signal using a chest belt sensor [see Fig. 3(c)].  
The level of agreement between the physiological measure-ments by our proposed method and reference sensors was accessed using Pearson’s correlation coefficients (n=12). Corre-lation scatter plots for each measured parameter are shown in Fig. 4. The webcam-derived physiological measurements were strongly correlated across all parameters withr=1.0 for HR, r=0.92 for HF and LF,r=0.88 for LF/HF, andr=0.94 for RR (p<0.001 for all). The root-mean-squared error of the HR, HF, LF, LF/HF, and RR was 1.24 beats/min, 12.3 and 12.3 n.u., 1.1, and 1.28, respectively.

## Program Procedure Scheme

main() {

cvCapture\* openVideo(char\* path) //and check if it’s valid

setROI {}

? searchFace(Mat frame\_gray) // and normalize faces[0] size

? splitChannels(?) // getting the three raw signals. one signal is an array of doubles

? detrendTraces(?) //and standardizes

}