Heart rate intellectual analysis by structural decomposition methods of photoplethysmography signals

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Abstract. In this paper, various algorithms for the analysis of photoplethysmography signals are considered. The sequence of performing the intelligent analysis of the measured signals is presented. The study of heart rate variability was carried out, based on the assessment of the instantaneous frequency and the instantaneous period of the pulse wave. The estimates of heart rate and indicators of variation pulsometry were obtained.

Keywords: Photoplethysmography, Multiresolutional analysis, Signal processing, Heart rate variability.

1 Introduction

An important subject area of data mining (ADM) is the development of medical decision support systems (DSS) for recognizing a patient's diagnosis based on a presented set of symptoms [1-2]. One of these promising areas is photoplethysmography is a remote PhotoPlethysmography - rPPG. This method allows you to quickly identify abnormalities in the physical state of a person and is also an effective methodology for remote express diagnostics in the telemedicine format. Of practical interest is the analysis of biological wave processes in the human body - pulse, respiratory, myogenic, etc.

In solving the problem of identifying biological wave processes, an important role is played by the formation of the space of informative features based on the measured initial data. The basis for solving this problem is the use of artificial intelligence methodology in the form of a natural symbiosis of methods for structural and spectral analysis of the dynamics of non-stationary time series (TS).

Remote PhotoPlethysmography monitors changes in the intensity of light reflected from a subject's skin. An RGB video camera is used as a sensor, and the area of interest is most often the face, less often the palm or wrist.

The aim of this work is the intellectual analysis of heart rate variability (HRV) by various algorithms for processing photoplethysmography signals. It is important to note that HRV analysis refers to the pre-medical stage, i.e. does not make a diagnosis, but forms the basis for its statement.

2 Materials and methods

2.1 Dataset description

As the initial data for the study, we took a database recorded by volunteers of the Eindhoven University of Technology (Netherlands), and designed to study the methods of photoplethysmography [3]. The database (DB) contains a set of video recordings, as well as reference HRV indicators, taken simultaneously with a photoplethysmogram. There are videotapes of the facial area of three subjects with different skin colors. For each participant in the experiments, a recording was carried out after physical activity, a set of recordings in a calm state, but under different lighting intensities, as well as recording with head turns (movement). Thus, based on this database, it is possible to study the operation of algorithms under various conditions, that is, their adaptability.

In this work, we analyze relatively short recordings of rPPG data - recording duration no more than 15 minutes at a frequency of 30 frames / sec. Such a measurement mode is typical for mass prophylactic examinations or during preliminary outpatient and clinical examinations, which allows registering the general state of health of the subject and finding out some significant indicators.

An area of the face is selected from the current frame - the so-called. the area of interest of certain areas of the skin of the face. Based on the results of measuring the degree of light scattering, the initial signals are formed in the form of TS. Each pixel in the image represents the red (R), green (G), and blue (B) color components. Thus, the face area can be represented as an array, the rows of which are frames, and the columns are color components. To obtain a pulse signal, which, in turn, does not depend on the spectral characteristics of a stationary illumination source and its brightness level, it is necessary to normalize each color channel by dividing the TS realizations by their average values (trends).

The paper considers promising methods for analyzing the dynamics of indicators of non-stationary TS - stabilization of the pulse and respiration after physical exercises.

2.2 Methods

To determine a person's health status, an rPPG signal is required, which can be compared with a cardiogram or rhythmogram. This is due to the need to isolate the sequence of RR intervals for HRV analysis. ADM models and algorithms are a reliable methodological basis for the formation of an informative component, i.e. an aggregated signal based on a set of RGB signals. The general algorithm for analyzing a photoplethysmogram consists of the following steps:

- For each frame, a face area is selected according to the Viola-Jones algorithm [4] and skin pixels according to the skin tone. The intensity value in each color channel is calculated as the average of the pixel intensity of the region of interest.
- Structural decomposition of RGB non-stationary TS is performed using multiresolution analysis (MRA) in the discrete wavelet transform basis [5]. Removes color channel trend estimates.
- An informative pulse wave frequency range from 0.667 to 4 Hz is identified according to the Analysis Mode Decomposition (AMD) method [6].
- An informative pulse wave signal is generated in the form of a combination of color signals according to the algorithms.
- Estimate the instantaneous phase and frequency of the pulse wave based on the Hilbert-Huang transform.
- Assess the indicators of heart rate variability.

Allocation of the frequency range of the pulse wave using the AMD method. AMD extracts informative harmonic components from a wideband signal as follows:

$$x_s(t) = sin(2\pi f_b t) \cdot H[cos(2\pi f_b t) x_0(t)] - cos(2\pi f_b t) \cdot H[sin(2\pi f_b t) x_0(t)] \quad (1)$$

$$x_f(t) = x_0(t) - x_s(t) \quad (2)$$

Where $x_0(t)$ is the original signal; f_b - boundary frequency; $x_f(t)$ - fast changing signal; $x_s(t)$ is a slowly changing signal.

Extraction of photoplethysmogram from TS color channels. CHROM algorithm - provides invariance of informative signals to the spectral composition of lighting as a result of aggregation of components based on color difference, i.e. chrominance, signals. The idea of the method consists in orthogonal projection of TS samples of color channels onto the plane specified by the orts **X** = (3, -2, 0)/√13 and **Y** = (-1.5, -1, 1.5)/√5.5 in RGB-space, informative orthonormal basis (**X**, **Y**, **Z**) [7], where **Z** = (1, 1, 1)/√3 is the unit of skin tone [8]:

$$CHROM = X_f + \frac{\sigma(X_f)}{\sigma(Y_f)} Y_f. \quad (3)$$

Here $X_f = (3R - 2G)/\sqrt{13}$ and $Y_f = (-1.5R - G + 1.5B)/\sqrt{5.5}$ are two orthogonal chroma signals at the output of the FIR filter with a bandwidth equal to the frequency range of the pulse wave; σ is the operator of a robust estimate of the standart deviation (MSD).

In the POS algorithm, the unit vectors of the informative plane orthogonal to the skin tone unit **Z** in RGB space are chosen as follows: **X** = (0, 1, -1)/√2 and **Y** = (-2, 1, 1) / √6. Accordingly, the projections of the readings of the TS-centered color channels $X = (G - B)/\sqrt{2}$ and $Y = (-2R + G + B)/\sqrt{6}$ onto this plane form an estimate of the pulse wave [8]:

$$POS = X + \frac{\sigma(X)}{\sigma(Y)} Y, \quad (4)$$

Where σ(X) and σ(Y) are robust standard deviations of nonstationary TS X and Y.

Estimates of the instantaneous phase and frequency of the pulse signal based on the Hilbert - Huang transform. The Hilbert transform provides adaptive estimates of the instantaneous envelope, phase, and frequency of a signal. The total phase of the analytical signal is:

$$\varphi_s(t) = \arg\big(z(t)\big) = arctg\,\frac{\hat{s}(t)}{s(t)} \tag{5}$$

The instantaneous frequency is defined as the time derivative of the total phase:

$$\omega_s(t) = \frac{\mathrm{d}}{\mathrm{dt}} arctg\,\frac{\hat{s}(t)}{s(t)} = \frac{\hat{s}'(t)s(t) - \hat{s}(t)s'(t)}{\hat{s}^2(t) + s^2(t)}, \tag{6}$$

Where $s(t)$ is a pulse signal; $\hat{s}(t)$ - the signal obtained as a result of the Hilbert transformation of the pulse signal.

The energy of the Hilbert - Huang spectrum is the square of the pulse signal envelope $E(t) = s^2(t) + \hat{s}^2(t)$.

Assessment of indicators of heart rate variability. The RR time sequence of the pulse wave intervals is very informative. Based on this characteristic of the pulse wave, various HRV indicators are calculated, one of which is heart rate. It is defined as the number of samples for the total recording time.

$$HR = 60 \cdot 1000 \cdot \frac{n}{\sum_{i=1}^{n} NN_i(\textit{мс})} \tag{7}$$

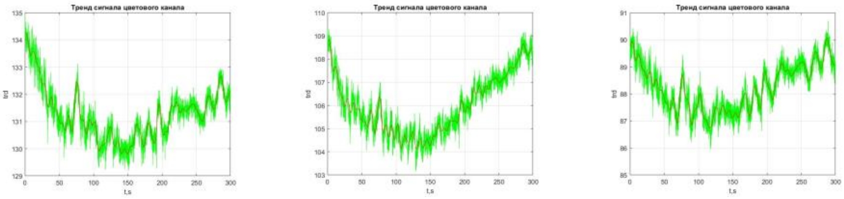
Where NN is the normal RR interval.

3 Results

3.1 Allocation of the informative component of color channels

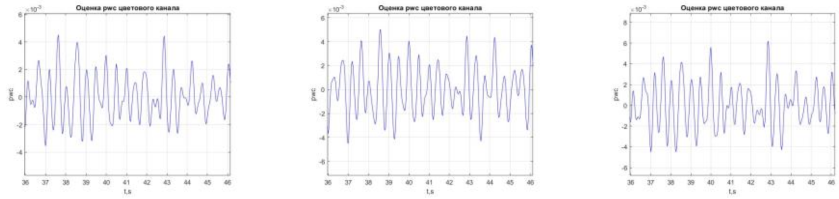
The TS extracted from the RGB video are subjected to multiresolution analysis (MRA). In our computational experiments, the 40th order Debeschy wavelets were used as a basis for the expansion. Ten levels of decomposition made it possible to form an expert model of the structural components of non-stationary TS color channels of rPPG, namely:

- Trends (Figure 1) as the sum of the eighth, ninth, tenth detailing and tenth approximating components of the MRA;
- Respiratory, myogenic and other wave processes with frequencies not exceeding 0.667 Hz in the form of the sum of the slow part of the fifth, sixth and seventh detailing components of the MRA;
- Centered pulse waves of each color channel (Figure 2) in the frequency range from 0.667…4 Hz as the sum of the slow part [6] of the second, third, fourth and fast parts of the fifth detailing components of the MRA normalized to the trend value;
- Noise components with frequencies of at least 4 Hz as the sum of the first and fast parts of the second detailing components.



a) b) c)

Fig. 1. Time series of RGB channels and their trends: R - a), G - b), B - c).



a) b) c)

Fig. 2. Fragments (10 c) of centered pulse waves of color channels: R - a), G - b), B - c).

Figure 3 demonstrates the topology of a 3D scatter diagram of the TS samples of centered pulse waves (Figure 2) in RGB space in projections onto the coordinate planes R-G, R-B and G-B, respectively.

It is important to note that the absence of anomalous values in the dynamics of the TS of the centered pulse waves of the color channels makes it possible to obtain an effective assessment of the aggregated pulse wave and its correlation - spectral characteristics according to the corresponding algorithm. In particular, the implementation of the non-stationary TS of the pulse wave pw and its averaged periodogram estimates Psd of the Schuster and Thomson power spectral density (PSD) obtained using the POS algorithm are shown in Figure 4.

The presence of dominant harmonics at frequencies of 2.50 is characteristic; 2.08; 1.71; Hz, (Figure 4, b), demonstrating the dynamics of stabilization of instantaneous frequencies and, accordingly, heart rate after physical exercises of the subject.

For a more detailed analysis of this dynamics, the time interval of measurements with a duration of 300 s, containing 9000 TS counts, was divided into 200 overlapping segments of 1024 counts each. Figure 5 illustrates the dependence of the sample estimates of autocorrelation functions (ACF) and Thomson periodograms of the pulse wave pw on the segment number ns.

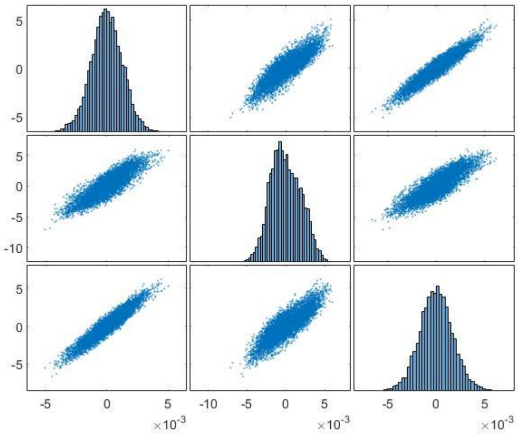
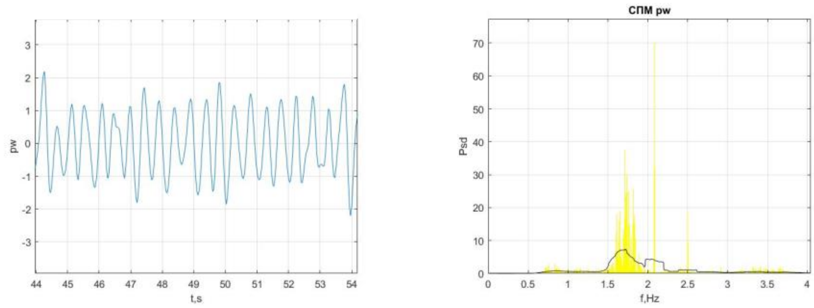
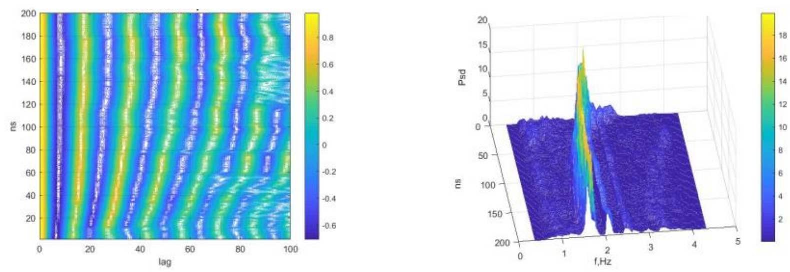


Fig. 3. Projections of the 3D scattering diagram of the TS counts of the centered pulse waves onto the coordinate planes of the RGB space.



a) b)

Fig. 4. Fragment (10 s) of the pulse wave - a) and its PSD - b), averaged over the entire implementation of TS.



a) b)

Fig. 5. ACF of overlapping segments of the pulse wave - a) and their Thomson periodogram - b).

It is clearly seen that as ns increases, the intervals between the zeros of the ACF increase, and the largest values of the PSD of the segments shift to the region of lower frequencies.

3.2 Assessment of indicators of heart rate variability

A simplified version of the heart rate assessment for a subject in a static state does not require the restoration of the pulse waveform by the rPPG method. The frequency range, including the fundamental heart rate harmonic, is 0.8 ... 1.6 Hz [11]. Also, considering this simplification, the values of the instantaneous periods are taken as R-R intervals, which are the basis for the HRV analysis. Average heart rate values for each algorithm are shown in Table 1. Reference values are presented in Table 2.

Table 1. Heart rate values for each algorithm.

Algorithm	POS	CHROM
HR, bpm	133	131

Table 2. HR ground truth values.

	Mean	Standart deviation	Minimal HR	Maximum HR
Value, bpm	107	7.69	90	134

The shift of the heart rate to the region of high frequencies is associated with the peculiarity of the TS example chosen for the study.

The data in Table 3 demonstrate the dynamics of heart rate for 5 non-overlapping video segments.

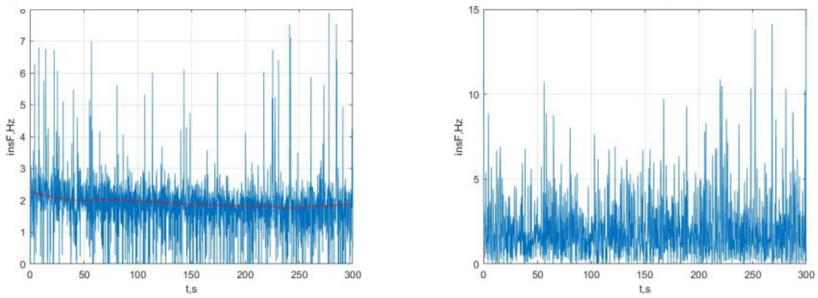
Table 3. HRV indices for video with division into intervals.

Algorithm	No.	HR, bpm	R-R, s
CHROM	1	141	0.42
	2	142	0.42
	3	147	0.40
	4	138	0.43
	5	150	0.40
POS	1	133	0.45
	2	131	0.45
	3	138	0.43
	4	138	0.43
	5	146	0.41

There is a significant correlation between the heart rate values, the instantaneous frequency values and their correspondence to the visual assessment of the subject's condition on video.

One of the significant disadvantages of estimating (1) using the Hilbert transform hilbert(pw) is, as is known, the presence of negative values of instantaneous frequencies. The physically non-interpretable result is due to errors in the calculation of the accumulated instantaneous phase (unwrap phase). In our opinion, this drawback can be easily eliminated by dividing the accumulated instantaneous phase into two components. The first is a continuous, differentiable, and monotonically non-decreasing function of time. The second component contains discontinuities of the first kind, i.e. is a non-decreasing "step function", thus taking into account the errors in the estimates of the accumulated instantaneous phase.

Within the framework of this approach, the continuous component of the accumulated instantaneous phase is described using shape-preserving piecewise cubic interpolation by Hermite polynomials [12]. The numerical estimate of the instantaneous frequency is the first derivative of this model (Figure 6, a).



a) b)

Fig. 6. Dynamics of instantaneous frequency - a) and energy - b) pulse wave.

The solid line in Figure 6.a represents the nuclear robust locally weighted quadratic regression of Cleveland [13] and demonstrates the stabilization of the average instantaneous frequency of the pulse wave in time after the end of physical exercise of the subject.

4 Discussion

Correct determination of HRV and heart rate indices requires a chronological sequence of RR intervals, similar to ECG data [14, 15]. Otherwise, there is a significant deviation of the indicators from the norm. To solve this problem, it is necessary to restore the shape of the pulse wave using the rPPG method.

5 Conclusion

The paper describes algorithms for extracting an informative component - a pulse signal from noisy data. For the pulse wave, its main characteristics, required for HRV analysis, were identified, and an example of analysis for one video sequence was given. In the example, both a complete record and its splitting were considered to identify the dynamics of indicators.

Based on the results obtained, it can be concluded that a structural decomposition is necessary in the analysis of rPPG signals, since interference at extraneous frequencies has a high-power relative to the required spectral range. This will allow restoring the shape of the pulse wave, obtaining a cardiogram, excluding contact with the patient.

It should be noted that the problem of reducing the degree of mixing of modes because of signal decomposition is essential for reconstructing the pulse waveform.

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