Remote Photoplethysmography Application to the Analysis of Time-Frequency Changes of Human Heart Rate Variability

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Abstract—**In this article we present the possibilities of using remote photoplethysmography (rPPG or imaging PPG) technology to estimate time-frequency changes of human heart rate variability. We propose improvements for algorithm presented in our recent study. Algorithm modification allows to exclude skin areas with highly variable levels of lighting, thus reducing noise level and increasing duration of signal suitable for processing. Twenty healthy volunteers (males and females) aged from 20 to 25 took part in this investigation. The blood volume pulse rate estimated from the rPPG rhythmogram and cardiac pulse rate estimated from the electrocardiogram are compared. The results showed that the very low frequency hemodynamic oscillations of blood volume pulse rate estimated from the rPPG rhythmogram in the [0.04-0.003] Hz frequency band can be used to monitor functional changes of a human.**

I. Introduction

The increasing pace of life in big cities raises the importance of the impact of psycho-emotional overload on the physical, mental and social health. Modern society makes more and more demands for the cognitive status of the population to meet working, social and everyday challenges. Furthermore, in the areas of human activity the threshold of sound and electromagnetic background is very exceeded. All this leads to the decrease in stress tolerance and adaptive capacity.

These processes result in people's neuroticism with the gradual accumulation of mental disorders. People in metropolitan areas often suffer from anxiety, panic attacks, depression [1].

Pathophysiological basis of such phenomena is associated with reduced functional personal reserves. The human body experiences the lack of adequate resources necessary to achieve adaptation.

Thus, the development of methods that can quickly determine the impaired functional state of the human may significantly improve the system of detection and prompt prevention of psycho-emotional disorders in modern society.

The autonomic nervous system (ANS) is responsible for the implementation of psychosomatic interactions within the human body. A lot of stress-related diseases are the result from impairing body function regulated by ANS [2].

Consequently, the assessment of the ANS performance may be an indicator of the stress affecting the individual functions and the whole body [3].

One of the physiological systems most sensitive to the ANS regulatory influences is the cardiovascular system. Any changes in the regulatory processes of ANS can be quickly detected in a change of vessel tone of different caliber, the frequency, power and other heart characteristics.

In this case heart rate variability (HRV) based on a cardiointervalography study is used as the information indicator [4].

In the clinical practice, electrocardiography data (ECG) are used for the analysis of HRV systems. In recent years the systems of hemodynamic changes based on photoplethysmography (PPG) are actively developed. This method of investigation is based on the analysis of the parameters of backscattering radiation from the body as a result of hemodynamic changes. The dynamic characteristics of such systems based on PPG allow to remotely monitor the following parameters: heart rate, blood flow volume, respiration rate, cardiac output, blood oxygen saturation, and others.

II. Remote Photoplethysmography

Most of the recent research has focused on the new technology of heart rate estimation by using the remote photoplethysmography (rPPG), also known as imaging photoplethysmography (IPPG).

A pioneer in this area is Vladimir Blazek [5] who was the first to introduce the principles of remote photoplethysmography systems. rPPG is based on the photoplethysmography. Therefore the first examples of such systems were created with near-infrared camera with LED light sources. The recent works have used rPPG in usual life conditions.[6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [18], [19]. They used video cameras and web-cameras to detect a visible light reflection. Basically the light source is sunlight or ambient light with sunlight.

The process of working remote photoplethysmography is still not fully investigated. It is known that the rPPG signal is composed of several components. One of the main parameters of forming useful rPPG signal is backscattered radiation from the human tissue. Yu Sun and Sijung Hu described this process as blood volume variations in the microvascular bed of tissue [12]. Such signal allows to monitor the same parameters as the PPG method, for example blood oxygen saturation and respiration rate.

In recent studies, Kamshilin et al. presented a new model of rPPG signal formation which indicates that the rPPG signal is based on arterial transmural pressure deformation of the connective-tissue components of dermis [9]. That shows that the signals in areas above the arteries can have a phase shift component compared with nearby areas. This explains the complex structure of the signal and confirms that defining moment of systole is challenging.

Usually to estimate the HRV, the maximum peak of spectrogram local changes in dermal perfusion was used. Such estimate is determined on the basis of approximately 10 seconds of the rPPG signal, thus it can change a real signal. In the present study to determine the HRV signals the peak detection method was used.

A detailed review of rPPG technology was introduced by Yu Sun et al.[16] and Daniel McDuff et al.[17]. This papers present a summary of many existing works and provide the short review of existing methods.

The aim of this work is to establish the ability of the developing method of remote photoplethysmography for detecting physiological patterns in the HRV parameters.

III. MATERIALS AND METHODS

This work is performed at the Research Medical and Biological Engineering Center of High Technologies, IRIT-RTF, Ural Federal University (Russia) with participation of employees of the Department of Psychiatry, Ural State Medical University (Russia). Twenty healthy volunteers (males and females) aged from 20 to 25 took part in this investigation. Ethical committee approved this study. Informed consent was obtained from each subject. The assessment of neurological and mental status did not reveal any neurological and mental pathology.

A. *Experiment*

The studies were all conducted indoors without sunlight. Each subject sat at a distance of 3 meters in front of the camera with their face visible and illuminated by two fluorescent light sources. Each experiment was recorded and took 20 minutes. The subjects were asked to keep still during the experiment.

B. *Camera*

All images were recorded by using an IP-network video camera. Video images were downloaded to a personal computer via the Ethernet. The camera allows to capture frames approximately at 30 frames per second (fps) in color (24-bit RGB with 3 channels $\times$ 8 bits/channel). The camera resolution is 640×480 pixels. Each image frame (with the capture time in filename) was saved in the uncompressed png format on the personal computer.

C. *Contact measurements*

The cardiac pulse rate and cardiac HRV was obtained by electroencephalograph-analyzer EEGA-21/26 "Encephalan-131-03" (model 11) from MEDICOM MTD (Russia). It provides real-time registration of the electrocardiogram signals for I-lead at a sampling rate 250 Hz and automatically stored the signals in personal computer. To analyse and compare HRV all data were saved as a text file in the local database.

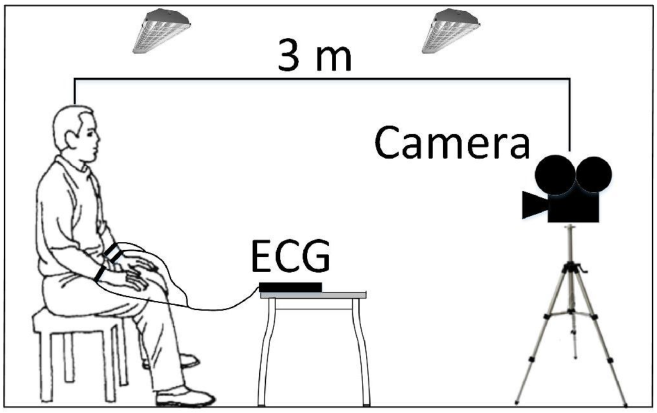

Fig. 1. Experimental set-up. Blood volume pulse was measured by video camera. Camera is placed 3 m from the subject, and captures images at 30 Hz, 640×480 resolution

D. *Software*

Software for video capturing and data processing was performed in the Python computer programming language with using popular open-source libraries and packages such as OpenCV, scikit-learn, Pandas, Jupyter, Matplotlib and others.

Each image frame was saved in the local database with filenames which contain the time of frame capture. Filename format is : "image[%d]_yyyy-MM-dd_hh-mm-ss.msec". For example "image000000000_2015-02-19_09-48-51.944000.png". This allows to accurately determine the rPPG signal points as compared with normal video.

Set of images for each study was processed by application which uses the algorithm described below. The developed application allows to work with video, webcam and streaming video. The heart rate estimate is obtained in real time.

E. *Algorithm*

The analysis of the published works shows that the main problems in rPPG registration are noisy signal and ensuring repeatability of its real-time processing. In this case, the algorithm time should not exceed the images sampling period.

The block diagram of the proposed algorithm of rPPG rhythmogram formation is shown in Fig. 2.

The sequence of proposed algorithm of rPPG rhythmogram formation is based on our previous work [19]. But it has some differences in signal formation:

1) We used the face detecting method proposed by Akshay Asthana et al. in 2014 [20]. This tracking method allows to detect global head motions of human and determine facial landmark positions. For detecting original images were converted into gray color and resized to 320×240 pixels. It provides high accuracy with real-time processing.
2) We chose the square region of interest (ROI) located on the forehead above eyebrows and between inner corners of eyes. The forehead is less influenced by local nonrigid motions such as blinking and has the highest signal-to-noise ratio [6], [15]. We track ROI

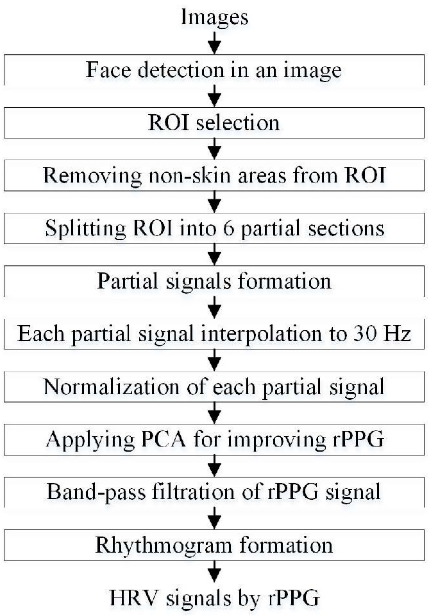

Fig. 2. Block diagram of the proposed algorithm of rPPG rhythmogram formation

in time using the information about face landmark positions and pitch, roll and yaw movements of head.

3) Non-skin areas were removed from the ROI. In this case all ROI were converted into the two formats – HSV and YC_bC_r [13], [14]. HSV space was used to determine skin areas in ROI. All non-skin areas were excluded by using the criteria of color. YC_bC_r was used to determine changes of light intensity in ROI. The YC_bC_r criteria allowed to exclude skin areas which change the color due to movements. Criteria for HSV and YC_bC_r are automatically determined based on information about the facial landmark position and colors.
To convert frames to HSV and YC_bC_r, we used the $cvtColor$ (convert color) OpenCV function with parameters $cv2.COLOR\_BGR2HSV$ and $cv2.COLOR\_BGR2YCR\_CB$, respectively. The YC_bC_r coordinates are calculated from BGR space as defined in OpenCV:

$$\begin{aligned} Y &= 0.299 \cdot R + 0.578 \cdot G + 0.114 \cdot B \\ C_r &= (R - Y) \cdot 0.713 + 128 \\ C_b &= (B - Y) \cdot 0.564 + 128 \end{aligned} \quad (1)$$

To calculate the HSV coordinates R,G,B are converted to the floating-point format and scaled to fit the 0 to 1 range.

$$\begin{aligned} &V = max(R, G, B)) \\ &S = \begin{cases} \frac{V - min(R,G,B)}{V}, & \text{if } V \neq 0 \\ 0 & \text{otherwise} \end{cases} \\ &H = \begin{cases} 60\frac{G-B}{V-min(R,G,B)}, & \text{if } V = R \\ 120 + 60\frac{B-R}{V-min(R,G,B)}, & \text{if } V = G \\ 240 + 60\frac{R-G}{V-min(R,G,B)}, & \text{if } V = B \end{cases} \end{aligned} \quad (2)$$

if $H < 0$ then $H = H + 360$.
The result values were converted to 8 bit HSV data type as follows: $V = 255 \cdot V$, $S = 255 \cdot S$, $H = H/2$. To exclude single point areas the erode and dilate methods with kernel 3×3 was used.

4) After that, the selected ROI was split into 6 equal-sized (with same shape) partial sections.

5) It is shown that spatial averaging signal contains more powerfull rPPG signal. Also it is well-known that the rPPG pulse wave in neighboring areas of skin changes simultaneously in the same direction. Thus, in each partial section partial signals were formed, by means of the spatially averaged pixel values. So, the number of analyzed signal sources was reduced. Kavan Mannapperuma conducted the study of minimal rPPG skin size of face [15]. Based on this research we have choosen the areas containing more than 8 skin pixels.

6) Each partial signal was fitted into 30 Hz by using linear interpolation because during the recording process some frames are lost. It is possible to use other methods of interpolation.

7) After that partial signals are normalized as follows:

$$x_{norm} = \frac{x_i - \bar{x}}{\sigma^i} \quad (3)$$

where σ^i is the standard deviation of the partial signal, $\bar{x}$ – the average value of the partial signal.

8) Because in neighboring areas of skin changes appear simultaneously in the same direction we can use the blind source separation techniques (BSS) to determine the rPPG signal in different areas. Typically, the BSS is presented by means of two techniques: the principal component analysis (PCA) and independent component analysis (ICA). The PCA method has been chosen in this paper because of the running time and accuracy. The Magdalena Lewandowska [6] was the first to use the PCA method for assessing rPPG signal. She showed that the PCA and ICA have similar accuracy, but the PCA running time for forehead ROI is about 1.2 msec that is approximately 100 times faster then the ICA (FastICA).
The matrix of partial signals is the following:

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,N} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,N} \end{bmatrix} \quad (4)$$

where n is the number of partial signals, N – number of elements in each partial signal.
We define the matrix of mean values as M. Each new element M_k of this matrix can be calculated as follows:

$$M_k = \frac{1}{N} \sum_{i=1}^{N} x_{k,i}, \quad (5)$$

where $k = 1...n$.
The covariance matrix S is defined as:

$$S = \frac{1}{N-1}((X - M) * (X - M)^T) \quad (6)$$

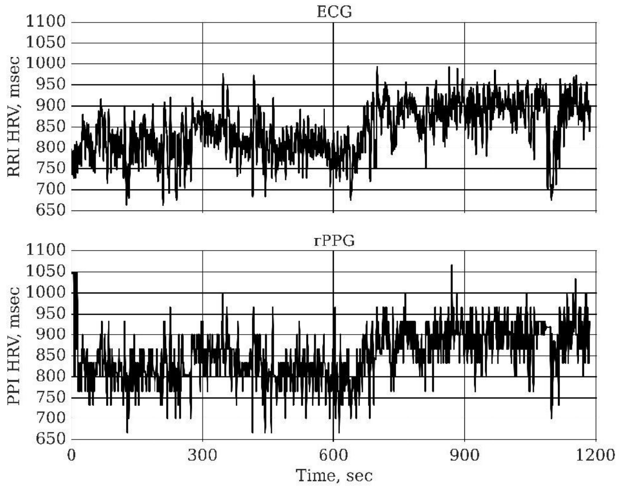

Fig. 3. Comparision the HRV signals obtained by rPPG and ECG

Then we calculate eigenvalues λ and eigenvectors $\vec{v}$ of the covariance matrix S, where $S\vec{v} = \lambda\vec{v}$, under the condition that:

$$|S - \lambda I| = 0 \quad (7)$$

After that we calculate eigenvectors $\vec{v}^i$ for each eigenvalues λ_i as:

$$\vec{v}^i(S - \lambda_i I) = 0 \quad (8)$$

We determine the relevance of eigenvector to rPPG signal as a value of eigenvalue. To get the most relevant data the eigenvectors $\vec{v}^i$ were sorted in ascending order by eigenvalues λ_i and the first eigenvector was chosen. In our case $j = 1$.

Resulting "demixing matrix" is denoted as:

$$W = \begin{bmatrix} v_1^1 & \cdots & v_n^1 \\ \vdots & \ddots & \vdots \\ v_1^j & \cdots & v_n^j \end{bmatrix} \quad (9)$$

The next stage is the source separation:

$$Y = X \cdot W \quad (10)$$

In our case Y contains only one row with values of rPPG signal.

9) The rPPG signal was filtered by using 5-th order Butterworth bandpass filter with cut-off frequencies set at [0.667, 2.5] Hz, which corresponds to the heart rate frequency from 40 to 150 beats per minute.
10) The rPPG rhythmogram was formed.

IV. Results and discussion

Fig. 3 shows the HRV signals obtained by rPPG and ECG. It can be seen that for long term variations the signals have the similar shape and direction. These signals are typical for this study.

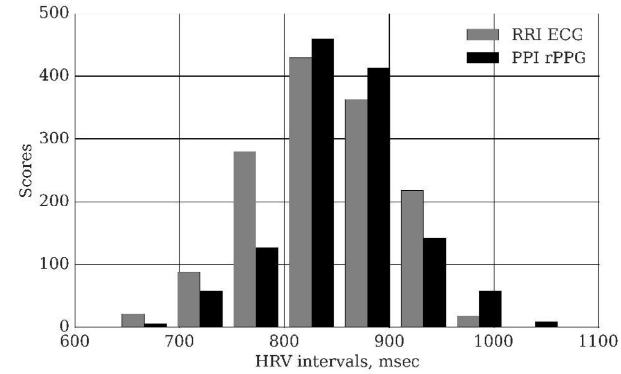

Fig. 4. Histogram of heart rate periods obtained by rPPG and ECG.

Fig. 4 shows the heart rate histograms of selected HRV signals. Let us denote the HRV periods obtained by ECG as R-R intervals (RRI) and peak-to-peak intervals (PPI) obtained by rPPG rhythmogram. To calculate the PPI, we used the peakdet algorithm (our implementation is the same as that of Eli Billauer for MatLab Mathworks). RRI is calculated using Encephalan software (MEDICOM MTD).

The subjects were not locked in the chair, so they make movements during the study. Fig 5 shows typical patient head motions. It is seen that the subject rarely changed the position of their head with their face visible. The presence of noise is caused by an error of face landmark detection algorithm. To ensure the stability of the ROI location we used the error threshold of head movements.

Fig. 4 histograms are similar, then have asymmetrical shape and not normal distribution. The median value for RRI obtained by the ECG equals 840 ms. For PPI obtained by the rPPG rhythmogram, the median value equals 833 ms. In both cases, the mode of distributions is located in the same interval (800-850 msec). The average values of RRI and PPI were 839 ms and 850 ms, respectively. The maximum error of the heart rate estimation by the rPPG compared to the heart rate by the ECG is less than 1.2 %. These results are similar to known methods of heart rate measuring, for example by PPG.

The analysis of graphs presented in Fig. 3 and histograms in Fig. 4 shows that the HRV signals obtained by the ECG and rPPG rhythmogram are quite similar. The similarity was assessed by changes of power spectral density (PSD) and Spearman correlation coefficient in high frequency (HF) [0.4-0.15], low frequency (LF) [0.15-0.04], very low frequency (VLF) [0.04-0.003], and total frequency (total power – TP) [0.4-0.003] Hz bands. PSD was measured in selected frequency ranges for 60 second time intervals.

We calculated the Spearman correlation coefficient to check the correlation of measured HRV signals in our recent work [19] as:

$$r_s = 1 - \frac{6\sum d^2}{m^3 - m} \quad (11)$$

where d is the difference between ranks for each element of signals, m – number of elements in signals.

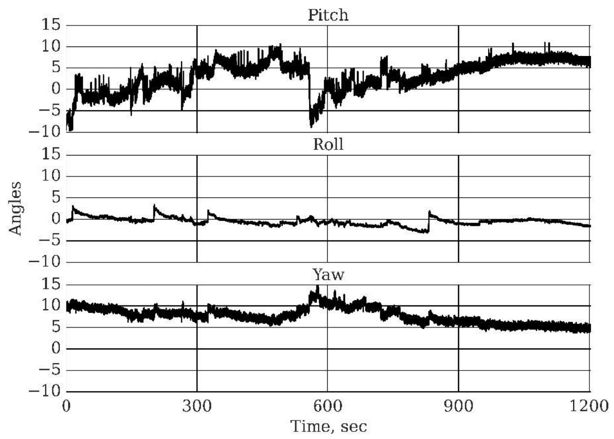

Fig. 5. Subject head motions during the study

The PSD defined as the power in the selected frequency range. Let us denote PSD as P_{psd}. It can be calculated as follows:

$$P_{psd} = \int_{t_{start}}^{t_{end}} f(t)\mathrm{d}t \tag{12}$$

where t_{start} and t_{emd} are the selected time interval boundaries (in this case time interval = 60 sec), $f(t)$ is the filtered signal in the selected frequency range.

Before filtration, the HRV signals linearly interpolated with 10 Hz sampling frequency. We used the same wavelet basis as gaus8 in MatLab Mathworks. The filtered signal is multiplied by gain coefficient obtained from amplitude frequency response of wavelet filter.

The analysis of data shows that total duration of the time intervals with Spearman correlation coefficient above 0.9 for [0.15-0.04], [0.04-0.003] Hz frequency bands is several times longer than for [0.4-0.15] Hz frequency band. That is consistent with the data presented in Fig. 6. It shows the changes of PSD of HRV signals obtained by the ECG and rPPG rhythmogram in a) HF [0.4 - 0.15], b) LF [0.15 - 0.04], c) VLF [0.04 - 0.003], d) TP [0.4 - 0.003] Hz frequency bands. Each column in graph defines the PSD value in 60 sec time interval.

The data presented in Fig. 6 show that in [0.4-0.15] Hz frequency band the PSD changes of HRV signal obtained by the rPPG rhythmogram are slightly bound with HRV obtained by the ECG. The intensity of PSD of HRV obtained by rPPG significantly exceeds the intensity of the PSD of HRV obtained by the ECG in the same frequency band. These signals are more correlated in [0.15-0.04], [0.04-0.003] Hz frequency bands. The connections of PSD in all HRV frequency ranges can be found in d)

The significance of HRV oscillations obtained by the ECG in [0.04-0.003] Hz frequency band for analyzing physiological changes was shown in studies [21], [22], [23], [24], [25], [26]. This frequency band contains information about baroreflex, central and myogenic regulatory mechanisms, and is directly

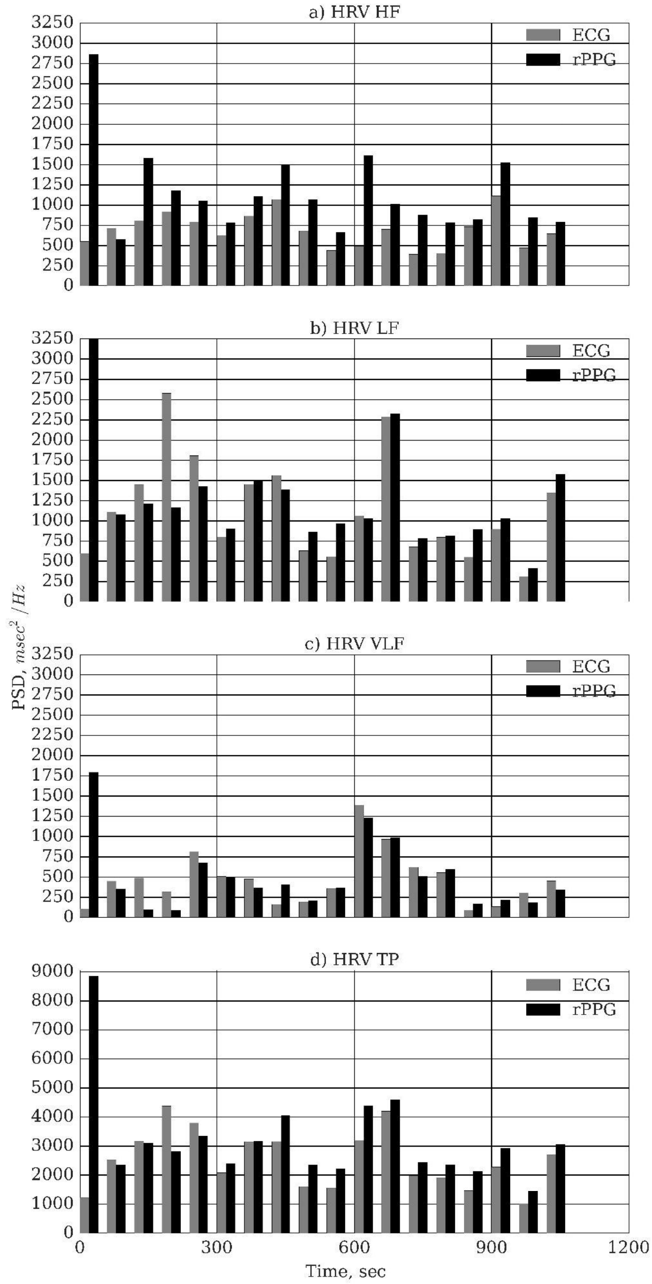

Fig. 6. Power spectral density of HRV signal obtained by rPPG and ECG in a) HF - [0.4-0.15], b) LF - [0.15-0.04], c) VLF - [0.04-0.003], d) TP - [0.4-0.003] Hz frequency bands for 60 sec time intervals.

related to postganglionic fiber activity. Very low frequency oscillations have linear relationships with suprasegmental part of the vegetative nervous system, endocrine and humoral factors and are connected with the metasympathetic nervous system of the heart.

V. Conclusion and Future Work

As a result of the study the ability of the developing method of the remote photoplethysmography for detecting physiological patterns in the heart rate variability parameters was established.

The most important part of the work is the development of image processing algorithm for receiving rPPG signal. rPPG signal detection algorithm mentioned in the article is an updated version of the algorithm described in the previous article [19]. There was the assumption of non-uniformity of illumination of the part of human body at motion of the subject. Algorithm modifications allow to exclude areas of the skin where color changes are the result of light levels change due to movements of the subject or light sources from the processing. Defining and excluding these areas from the processing allows to reduce the noises in the rPPG signal and to increase the duration of the original rPPG signal included in the processing.

As a result of comparing the HRV parameters derived from the ECG and rPPG data, the correspondence in VLF range Algorithm modifications allow to exclude areas of the skin the frequency range [0,04-0,003] Hz can be used for remote monitoring of the current state of the ANS. It allows to indicate functional changes in the human body.

Conformity of the HRV parameters derived from ECG and rPPG data in HF and LF bands were not high. In the frequency range [0,15-0,04] Hz rPPG data can be verified by additional information. In future work we plan to analys these HRV signal components and to develop methods for determining breath parameters, such as breath rate, depth and to compare them with existing methods.

The development of remote registration method of human body physiological parameters is a major challenge in improving the health system and the health of modern society.

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