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Development of an intelligent remote control system for heart rate biomonitoring

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The paper proposes a new method for remote biomonitoring based on recording a pulse curve. A relevant algorithm was developed, and video images of biological tissues were processed by machine learning methods for the subsequent time-frequency analysis of the received signal having the goal to determine physiological parameters. The model training was accomplished.

Keywords: remote photoplethysmography, computer vision, heart rate, biomonitoring.

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Human health and performance are largely determined by the blood microcirculation and transport which are fundamental physiological processes governing vital activity of the body as a whole. By determining indicators of the body vital functions, including the heart rate, one can systematically assess the body functional state. To date, the issue of remote (with the aid of information and communication technologies) monitoring of the human body vital functions remains open. Development of the theoretical basis for optical flow conversion in a video system implementing a new method for noninvasive express diagnostics of pathological conditions, as well as its practical implementation, is an urgent research and technical problem whose solution will lead to an increase in efficiency and accessibility of medical interventions.

In recent years, active research has been performed in the field of remote photoplethysmography [1]. This is a new technique for measuring human pulse, which is based on analyzing the light reflected and backscattered from the surface of biological tissues. Remote photoplethysmography involves analyzing the changes in human skin tone in video images of various body parts using the computer vision and machine learning algorithms.

An algorithm for remote biomonitoring was developed based on remote heart rate measurement. The first stage of the developed remote monitoring system was finding a human face in the image. The next stage was searching in the face for regions of interest (under-eye area, forehead). At the third stage, the color of pixels corresponding to the selected regions was measured for a certain time period. The result of this stage was a harmonic signal of changes in the colors of selected pixels in accordance with the human pulse variations in time. After that, the obtained data were clustered so as to reduce their amount and extract the useful information. At the final stage, analysis of the received harmonic signal was performed. Fig. 1 illustrates the main operating stages of the remote biomonitoring system.

The first stage of analyzing a video image of human biological tissue was searching for the faces in it. The search results were coordinates of the rectangle bounding the image region containing the face. This task was solved by using the YOLOv7-Tiny neural network [2]. The model was trained on the WIDER-Face training dataset [3] containing about 12 000 training data and 5 500 validation data. The monitored metrics were recall, precision, and Mean Average Precision (mAP) (Table 1).

The next stage of the algorithm for the contactless human condition monitoring was recognizing the regions of interest in the human face. Regions most informative for the analysis are the forehead and under-eye areas. These regions were searched for by using the algorithm for finding facial points. After that, the necessary regions were identified geometrically.

In searching for the facial points in the image, a computer vision algorithm was used. The result of the algorithm was a vector representing a set of coordinates of each point from two-dimensional space $LM = \{x_1, y_1, x_2, y_2 \ldots x_n, y_n\}$. The algorithm for finding facial points is based on coordinate regression which is used to find coordinates of a fixed number of points [4]. Coordinate regression was performed by using a convolutional neural network. As the basis, the MobileNetV2 architecture was taken [5]. Table 2 describes the neural network architecture realized based on the MobileNetV2 modules. To train the neural network, the 300-W dataset was used [6].

Table 3 lists the results of the neural network training versus epochs; the input batch size was 16. The results of testing the model in the process of training are presented

Table 1. Results of training the YOLOv7-Tiny model

mAP, %	Recall, %	Precision, %
68.7	62.2	86.2

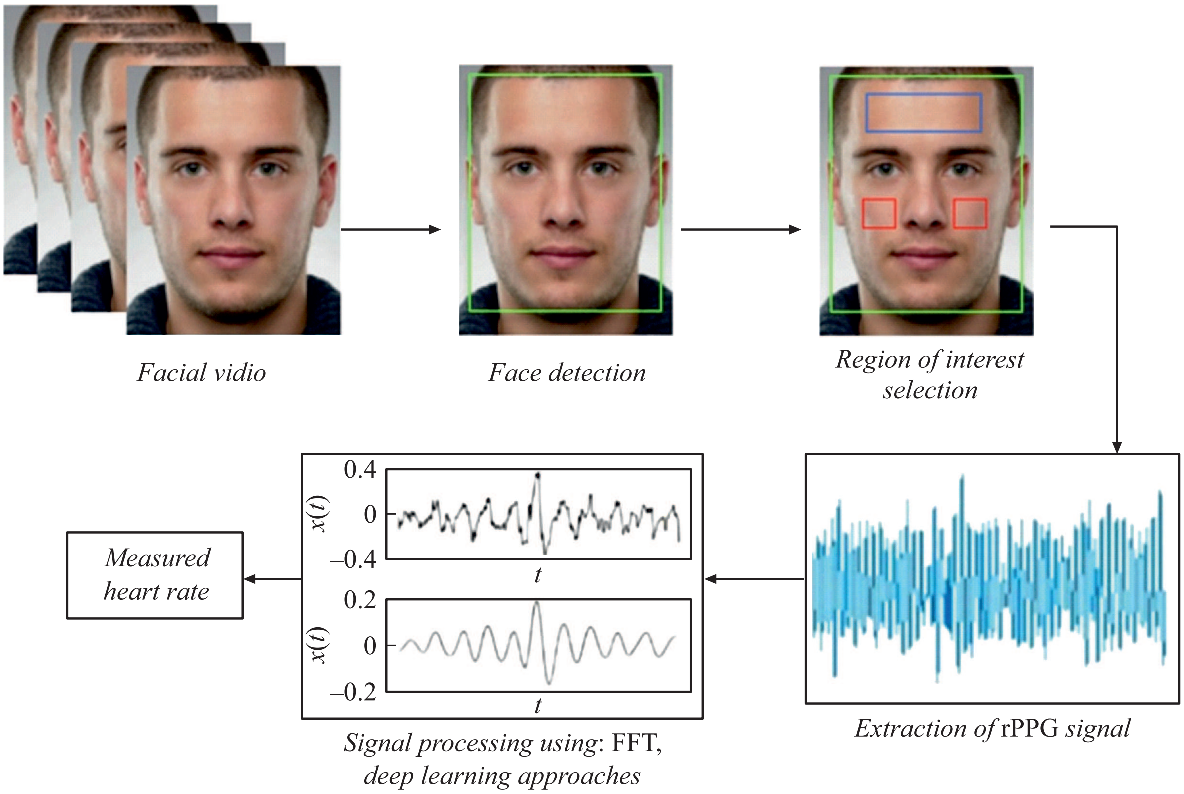

Figure 1. Main operating stages of the biomonitoring system based on remote photoplethysmography.

Table 2. Architecture of the neural network used in the study

Input tensor size	Operation	Expansion coefficient of the Bottleneck module e	Number of channels at the operation output c	Number of the layer repetitions n	Reduction coefficient of the tensor spatial dimension s
$224^2 \times 3$	Conv 3×3	–	32	1	2
$112^2 \times 32$	Depthwise Conv 3×3	–	32	1	1
$112^2 \times 32$	Bottleneck	2	32	5	2
$56^2 \times 32$	Bottleneck	2	64	1	2
$56^2 \times 64$	Bottleneck	2	64	5	2
$28^2 \times 64$	Bottleneck	4	128	1	1
$14^2 \times 128$	Bottleneck	2	128	6	1
$(L1)14^2 \times 16$	Conv 3×3	–	32	1	2
$(L2)7^2 \times 32$	Conv 7×7	–	128	1	1
$(L3)1^2 \times 128$	–	–	128	1	–
$L1, L2, L3$	Full connection	–	68×2	1	–

in Fig. 2. As the most tangible examples to be used in demonstrating the detection results, epochs 3, 4, 5, 7 were chosen.

The results obtained show that, when the minimum mean-square error (MSE) was reached, the neural network succeeded in finding location of the facial marks. Thus, we have implemented the most important stages of the remote biomonitoring algorithm, namely, computer vision algorithms for detecting in the image faces and keypoints necessary to identify important areas. The face detection accuracy reached 86.2%. The minimum mean square error in detecting facial keypoints was 2.69%. The research results evidence for high efficiency of the new approach to solving the problems of noninvasive human health and performance

Epoch 3 MSE = 5.25 | *Epoch* 4 MSE = 4.20 | *Epoch* 5 MSE = 3.64 | *Epoch* 7 MSE =2.69

Figure 2. Results of determining the facial keypoints using the neural network.

Table 3. Neural network training

Epoch	MSE
1	10.13
2	6.01
3	5.25
4	4.20
5	3.64
6	3.15
7	2.69
8	3.30

monitoring by contactless methods. The results obtained may be applied in creating a new generation of medical diagnostic systems.

This article does not contain any studies involving human subjects.

Conflict of interests

The authors declare that they have no conflict of interests.

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