PHYSICS AND CHEMISTRY OF SOLID STATE
V. 26, No. 1 (2025) pp. 105-110
Section: Technology

DOI: 10.15330/pcss.26.1.105-110

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ФІЗИКА І ХІМІЯ ТВЕРДОГО ТІЛА
Т. 26, № 1 (2025) С. 105-110
Технічні науки

UDC: 612.117.5.

ISSN 1729-4428 (Print)
ISSN 2309-8589 (Online)

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Software processing features of photoplethysmography signals

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The study explores the potential of using photoplethysmography to analyze human health. This method is considered a promising non-invasive technique for monitoring biomedical indicators such as heart rate, respiratory rate, cardiovascular system condition, and blood oxygen saturation.

The study analyzes methods for processing photoplethysmography signals and develops an algorithm for signal analysis. This algorithm compensates for respiratory signal modulation, quickly identifies key extremum points, and determines heart rate, respiratory rate, cardiovascular system indicators, and blood oxygen saturation. The application of this algorithm places minimal load on the microcontroller, enabling the development of a low-power human health monitoring system.

Keywords: non-invasive monitoring, heart rate, saturation, computer system, signal processing, thermoelectric generator.

Received 07 January 2025; Accepted 07 February 2025.

Introduction

Photoplethysmography has been increasingly used in recent years as a non-invasive method for monitoring cardiovascular activity indicators. Both portable and stationary devices are utilized for this purpose [1,2]. Many authors in their publications [3-5] have attempted to apply these methods for non-invasive monitoring of hemoglobin and glucose levels in human blood. A prototype portable device has even been proposed, but using only a single frequency of 940 nm to determine blood glucose levels does not provide the necessary accuracy due to the similar absorption coefficients of water and glucose at this frequency. The accuracy of blood component measurements can be improved through computational methods using spectral analysis [5].

Continuous monitoring of critical parameters such as heart rate, respiratory rate, and blood oxygen saturation is essential for biomedical applications. These parameters can be obtained non-invasively through the software and hardware processing of optical signals from photosensitive sensor elements at various wavelengths. The analysis of the pulse wave can provide indicators for diagnosing the condition of the cardiovascular system, including vascular stiffness index, heart rate, pulse wave reflection time, reflection index, and more [6]. The widespread use of non-invasive methods for diagnosing cardiovascular diseases is due to their simplicity of implementation, non-destructive nature, and the absence of infection risk [7].

Hardware methods for acquiring and processing photoplethysmography signals have been developed in previous works [8,9]. This study presents the results of analyzing software filtering methods for photoplethysmography signals and the development of methods and algorithms for determining pulse wave and respiratory parameters. The concepts for creating integrated photodetectors are described in the publication [10].

I. Analysis of software filtering methods for photoplethysmography signals and determination of respiratory parameters

The blood pulsation signal obtained using a photosensitive sensor is quite weak, contains a large DC component and noise, and is not suitable for direct analog-to-digital conversion and subsequent software processing. To eliminate the DC component of the signal, a differential circuit on an operational amplifier [9] is proposed, with the ability to dynamically adjust the compensation level using the microcontroller's digital-to-analog converter. This allows for compensation of the DC component regardless of its magnitude, and the useful signal can be pre-amplified and expanded across the entire dynamic range of the analog-to-digital converter. The overall structural diagram of the developed hybrid microsystem for biomedical applications based on photoplethysmography is presented in the publication [8]. When using the developed system, several challenges arise. Specifically, the level of the signal obtained after hardware processing fluctuates synchronously with breathing. Additionally, to achieve low power consumption, a low-power microcontroller was selected, but its resources are insufficient for applying universal real-time signal processing algorithms.

Since the photoplethysmogram signal is modulated by breathing, it allows for the determination of respiratory frequency and parameters.

Attempts to use classical filters such as moving average, median and Kalman filters do not yield sufficiently good results (Fig. 1), but they are adequate for quickly determining heart rate and respiratory rate.

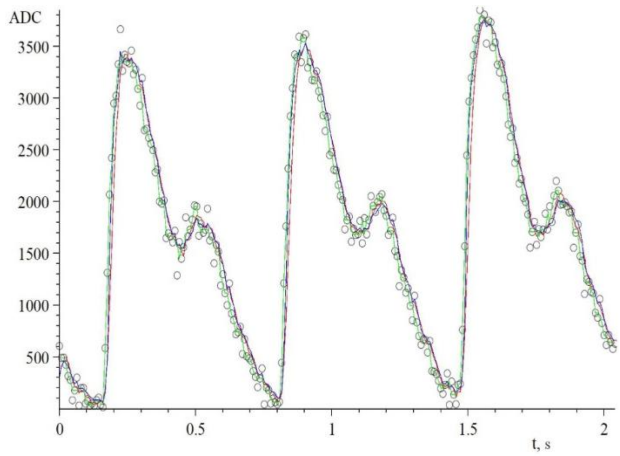

Fig. 1. Software filtering methods for digitized signals using the moving average method (red curve), median method (green curve), and Kalman filter method (blue curve).

The fastest filter is the moving average filter, after which, the data is easier to process programmatically, but there is a delay and some clipping of the peaks, leading to the loss of some information contained in the original signal. The most flexible in terms of settings is the Kalman filter, although it requires significantly more microcontroller resources. Depending on the noise level of the signal obtained after hardware processing using the developed integrated signal converter, the parameters of software filtering can be flexibly adjusted to minimize the loss of useful information.

The photoplethysmography signal contains valuable information about the cardiovascular and respiratory systems, which has not yet been widely used due to noise and signal processing difficulties [11]. The ratio of the two main components of the photoplethysmography signal – heart rate and respiratory rate – provides another important diagnostic indicator of the interaction between the respiratory and cardiovascular systems – the Hildebrandt index. Deviations from the value of 4.0 indicate the degree of mismatch between the cardiovascular and respiratory systems. The study [12] demonstrates the possibility of determining the Hildebrandt index using photoplethysmography with an accuracy of up to three decimal places.

Fig. 2. shows the photoplethysmogram over several inhale-exhale cycles. The green curve represents data averaged over several heart rate periods.

Data is well described by a periodic function, which can be approximately represented by the formula:

$$Y=A\sin(2\pi\omega t+\varphi)+B, \tag{1}$$

The main parameter here is the respiratory frequency ω. All other parameters are independent of the respiratory frequency and are needed only to position the curve relative to the measurement period: B – sets the offset along the abscissa axis, approximately equal to the arithmetic mean of the sample; parameter A – determines the signal amplitude and depends on the gain coefficient, which can be estimated as half the difference between the maximum and minimum of the moving average curve; parameter φ – is the phase shift, which depends on the start time of data digitization relative to the respiratory period. By applying the least squares method to approximate the data with formula (1), determine the respiratory frequency. Subtracting the curve obtained by formula (1) from the original data can significantly reduce the influence of breathing on the original data (Fig. 3) and substantially improve the accuracy of pulse wave analysis.

II. Software analysis of pulse wave

The general appearance of the photoplethysmogram is schematically shown in Fig. 4. The photoplethysmogram signal is sensitive to several types of noise and includes motion artifacts, sensor attachment disturbances, and signal line interference. Additionally, the waveform is influenced by technical aspects such as the type of sensor used and the measurement location [13]. For software analysis of the pulse wave and diagnosing possible deviations, it is necessary to identify the key points on the photoplethysmogram (Fig. 4).

The first peak of the curve A_1, corresponds to the anacrotic period of the pulse wave, which is the phase of heart muscle contraction occurring during systole [13].

The amplitude value of the pulse wave A_2, corresponds to the stroke volume of blood, thus providing indirect information about the level of inotropic effect. The second peak of the pulse wave A_3, corresponds to the dicrotic period of the pulse wave. It is formed because, during the ejection of blood by the heart under increased pressure, the aorta and large arteries elastically stretch, and when the systolic pressure decreases, the vessels return to their initial state, ejecting the accumulated blood volume. This peak corresponds to the diastolic period of the cardiac

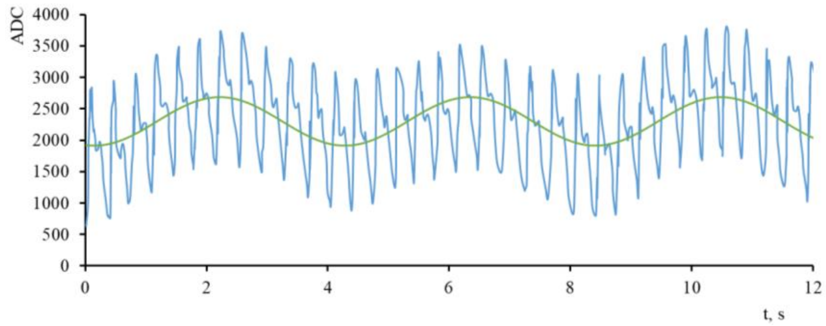

Fig. 2. Respiratory-modulated photoplethysmogram (blue curve) and its approximation by formula (1) (green curve).

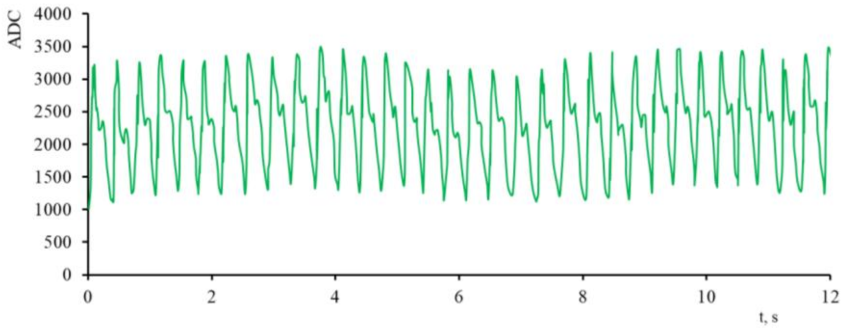

Fig. 3. Photoplethysmogram after alignment by subtracting the respiratory curve.

cycle and provides information about vascular tone. The frequency and duration of the pulse wave depend on the heart's functioning characteristics, while the magnitude and shape of its peaks depend on the condition of the vessel walls.

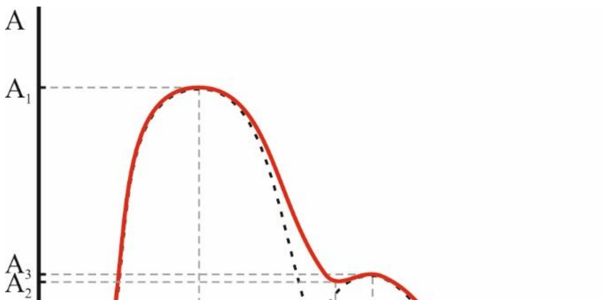

Fig. 4. Photoplethysmogram, which schematically representing the pulse wave.

The first step in analyzing the photoplethysmography signal is identifying individual pulse waves for analysis. This task is challenging because the pulse wave can show two distinct peaks, for example, in young healthy individuals, or it may lack a second peak entirely or have it at the noise level, such as in cases of vascular tone disorders [14-15]. Several methods for identifying pulse waves are known in the literature, most of which are based on detecting the systolic peak, as it is generally the most prominent feature [16]. The most common method for determining extremums is using the zero-crossing points of the first derivative [17]. However, due to noise, which is always present in real signals, this method can lead to random zero crossings of the first derivative, and even after smoothing the curve with software filters, it does not yield good results.

The application of more advanced methods, such as Wavelet transformation [18], is limited by the low computational resources of low-power microcontrollers. Threshold methods for peak detection are promising. Since the shape of one period of the photoplethysmogram is always characterized by the presence of main peaks, and the presence of the second peak depends on the condition of the vessels, it is worth dividing the task into two subtasks. At first, using relatively simple and fast algorithms, identify the main peaks and find the points A_0, t_0, A_1, t_1, A_0, t_4. Then, in the time interval t_1, t_4 use a similar algorithm to find the points A_2, t_2, A_3, t_3.

Using an analog-to-digital converter, measure and record photoplethysmogram data into a one-dimensional array ADCR, for example, every 8 ms, with $n = 256$ measurements. The algorithm for finding the main maxima in C language is presented below.

```
int Max_mas[9]; // result array
// looking for 3 points for each vertex of the maximum
int m=3;
Max_mas[0] = Max_index;
int  Grup_index1=0;  int  Grup_index2=0; int Grup_index3=0;
int Delta=30; int H=1000;

for (int j = 1; j < H; j++) {
 int max_line=ADCR[Max_index]-j;
 for (int i = 0; i < N; i++) {
```

```
      if (ADCR[i]>=max_line) {
       int Max_add=1;
       for (int j1 = 0; j1 < 3*m; j1++) {
        if  (i==Max_mas[j1])  {Max_add=0;}  //
check if it is a repeat
       }

       if (Max_add==1) { //if not repeat
        int Grup_index=Grup_index1;
        for  (int  j1  =  0;  j1  <=  Grup_index;
j1++) {
         if (abs(Max_mas[j1]-i)<=Delta) { //
check if it falls into the first round
          Max_add=0;
          if (Grup_index1<2) {Grup_index1++;
Max_mas[Grup_index1]=i; }
         } else {
          if (Grup_index2==0) {
           Grup_index2=3;
Max_mas[Grup_index2]=i;   Max_add=0;}   //
group 2 is empty
         }
        }
       }
       if (Max_add==1) { //_if not repeat
        int Grup_index=Grup_index2;
        for  (int  j1  =  3;  j1  <=  Grup_index;
j1++) {
         if (abs(Max_mas[j1]-i)<=Delta) { //
check if it falls into the second circle
          Max_add=0;
          if         (Grup_index2<5)         {
Grup_index2++; Max_mas[Grup_index2]=i;}
         } else {
          if (Grup_index3==0) {
          Grup_index3=6;
Max_mas[Grup_index3]=i;  Max_add=0;  }  //
group 3 is empty
         }
        }
       }
       if (Max_add==1) { //_if not repeat
        int Grup_index=Grup_index3;
        for  (int  j1  =  6;  j1  <=  Grup_index;
j1++) {
         if (abs(Max_mas[j1]-i)<=Delta) { //
check if it falls into the third circle
          Max_add=0;
          if         (Grup_index3<8)         {
Grup_index3++; Max_mas[Grup_index3]=i; }
         }
        }
       }
       if         (Grup_index1==m-1         &&
Grup_index2==2*m-1 && Grup_index3==3*m-1)
       {break;}
      }
      }
     }
```

Similarly, find the minima and obtain the main extremum points (Fig. 5).

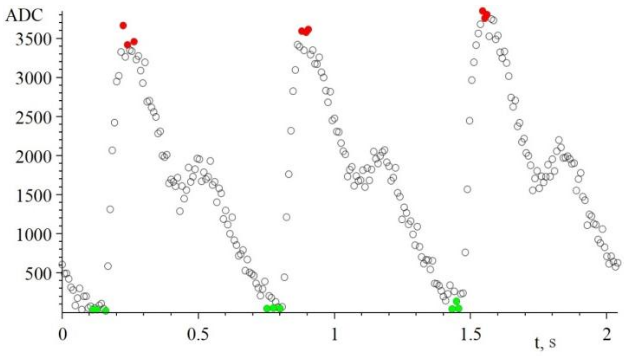

Fig. 5. Photoplethysmogram with software-detected maxima and minima (colored circles).

Having determined the coordinates of the main extrema, divide the photoplethysmogram into two parts. The first part, in the interval t_0t_1, contains a linear section. The second part has two more extrema, which can be found using standard methods or by slightly modifying the previous algorithm. In the interval t_1t_2, a linear section is also distinguished (Fig. 6).

III. Discussion of results and prospects for the development of the method

For further decoding of the photoplethysmogram, the coordinates of the points where the obtained approximation lines diverge from the averaged photoplethysmogram are also determined (points $t_{L1}A_{L1}$ and $t_{L2}A_{L2}$, Fig. 6).

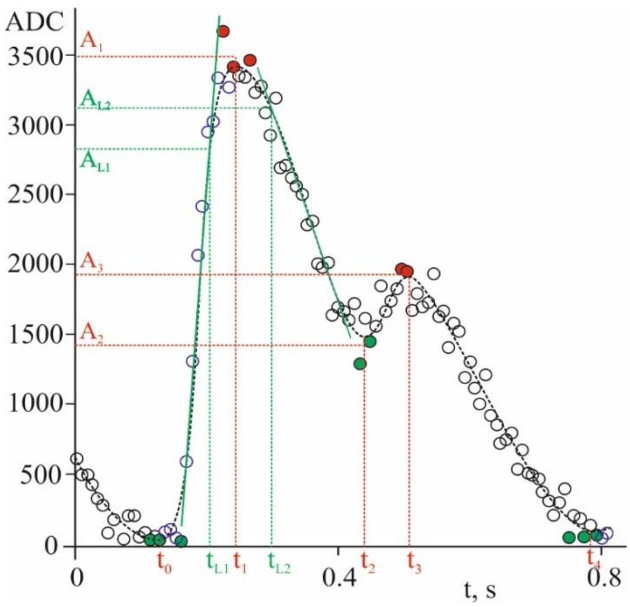

Fig. 6. Decoding of the photoplethysmogram. x and the elasticity index are determined.

In particular, the vascular tone inde

The vascular tone index is defined as the ratio of the time spent on the maximum rise of the pulse curve to the time taken for the entire pulse curve to pass until the beginning of the next period $T = t_4 - t_0$:

$$VTI=100\%\cdot(t_1-t_0)/(T).$$

The elasticity index is determined by the ratio of the amplitude of rapid blood filling to the amplitude of slow blood filling:

$$EI = 100\% \cdot A_{L1}/A_{L2}.$$

With normal vascular tone, the elasticity index is 70-80%. In the case of vasodilation, the elasticity index rises above 80%, and in the case of vasoconstriction, it falls below 70%.

Overall, the PPG method and the prototype device developed based on it showed good results. As seen in Fig. 1, a sufficiently clear and stable signal was achieved, from which, after compensating for the influence of breathing using the developed software algorithms, it was possible to accurately determine the parameters of the pulse wave. The implemented photoplethysmography method allows for non-invasive and rapid acquisition of information about heart function, the state of the cardiovascular system, changes in blood circulation parameters under the influence of various physical factors, and can become one of the options for solving the problem of quick and simultaneously accessible diagnostics and monitoring of human health parameters.

The low energy consumption of the developed system allows for the use of low-power alternative energy sources to extend the autonomous operation time. In particular, the authors are working on the development of a thin-film thermoelectric energy converter [19] from human body heat for an autonomous photoplethysmography system.

Conclusions

The possibilities of analyzing human health using the photoplethysmography method have been investigated. It has been shown that photoplethysmography is a promising method for non-invasive monitoring of human biomedical indicators such as heart rate, respiratory rate, cardiovascular system condition, and blood oxygen saturation.

An algorithm for analyzing the photoplethysmography signal has been developed, which compensates for signal modulation by breathing, quickly finds the main extrema points, and determines heart rate, respiratory rate, cardiovascular system indicators, and blood oxygen saturation.

It has been shown that the application of this algorithm places little load on the microcontroller, which contributes to the low energy consumption of the system and, in the future, will allow the use of low-power alternative energy sources, particularly thermoelectric ones, to extend the autonomous operation time.

The work was partially performed within the project of the Ministry of Education and Science of Ukraine "Multifunctional Sensor Microsystem for Non-Invasive Continuous Monitoring and Analysis of Human Biosignals" (State registration number 0124U000384).

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Особливості програмної обробки сигналів фотоплетизмографії

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В роботі досліджено можливості аналізу стану здоров’я людини методом фотоплетизмографії, як достатньо перспективного методу неінвазивного моніторингу біомедичних показників людини, зокрема, частота серцевих скорочень, частота дихання, стан серцево-судинної системи та насиченість крові киснем.

В роботі проаналізовано методи обробки сигналів фотоплетизмографії та розроблено алгоритм аналізу сигналу фотоплетизмографії, якій здійснює компенсацію модуляції сигналу диханням, швидко знаходить основні точки екстремумів, та визначає частоту серцевих скорочень, частоту дихання, показники серцево-судинної системи та насиченість крові киснем. Застосування даного алгоритму мало навантажує мікроконтролер та дало можливість розробити систему моніторингу стану здоров’я людини з низьким енергоспоживанням.

Ключові слова: неінвазивний моніторинг, частота серцевих скорочень, сатурація, комп’ютерна система, обробка сигналів, термоелектричний генератор.