

# **MATHEMATICAL MODEL FOR CALCULATING CARDIAC OUTPUT USING MULTI-PARAMETRIC DATA**

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*Abstract. This article proposes a mathematical model to calculate cardiac output by integrating multi-parametric data derived from electrocardiography and photoplethysmography signals. Recognizing the limitations of existing measurement methods, the model aims to leverage the complementary nature of electrocardiography and photoplethysmography signals to provide a more accurate, non-invasive, and continuous assessment of cardiac function. Through a detailed methodology that includes signal acquisition, preprocessing, and mathematical integration, this work outlines the theoretical foundation and potential application of combining these two modalities for enhanced cardiovascular monitoring.* 

*Keywords: electrocardiography, photoplethysmography, cardiac output, non-invasive, multiparametric data.* 

#### **Introduction**

Cardiovascular diseases are the most common cause of human death. An effective way to detect early signs of cardiovascular diseases is the continuous monitoring of the patient's critical physiological parameters during his full activity using a portable device. Most wearable devices available on the market can register only one or two types of biosignals, which are processed independently. On the one hand, the data obtained in this way is sufficient to see certain changes in the cardiovascular system, and on the other hand, it is not enough to evaluate isolated signals for a deeper analysis of the physiological state. One of the most promising methods of cardiovascular system research today is the combined use and analysis of multiparametric data, namely the combination of data obtained from electrocardiogram (ECG) signals, photoplethysmogram (PPG), signal position and acceleration from an accelerometer, etc. The use of this approach makes it possible to calculate, for example, such a parameter as cardiac output volume, which can be the greatest indicator of the level of cardiac muscle fatigue and an early predictor of the appearance of hidden pathologies of the cardiovascular system.

Cardiac output (CO), the volume of blood pumped by the heart per minute, is a critical metric of cardiovascular health. Traditional methods for measuring CO, such as thermodilution and echocardiography, are either invasive, costly, or require specialized skill, limiting their utility in continuous monitoring [1]. The advent of wearable technology offers a promising avenue for non-invasive, real-time cardiac monitoring through electrocardiography and photoplethysmography signals. However, the potential of integrating these signals into a cohesive model for CO estimation remains largely untapped. This article introduces a mathematical model designed to calculate CO using multi-parametric data, aiming to overcome the limitations of current methods and improve the accuracy and accessibility of cardiac monitoring.

### **Available methods**

Traditional methods for CO measurement have ranged from invasive techniques, such as the thermodilution method and the Fick principle, to non-invasive approaches, including Doppler echocardiography and impedance cardiography [2]. While these methods have been foundational



in cardiovascular medicine, they come with limitations, including invasiveness, the need for specialized equipment, and variability in accuracy under different clinical conditions.

In recent years, the focus has shifted towards developing more accessible, non-invasive, and continuous monitoring technologies. This shift has been largely driven by advancements in sensor technology and signal processing algorithms, enabling the detailed analysis of ECG and PPG signals [3]. ECG, the standard for assessing electrical cardiac activity, and PPG, a technique measuring blood volume changes in the microvascular bed of tissue, are both cornerstone technologies for non-invasive cardiovascular monitoring.

Research into the use of ECG and PPG signals for CO estimation has shown promising results. Studies have explored various aspects of these signals, from heart rate variability and Rwave amplitude in ECG to the systolic peak time and amplitude variations in PPG, as potential indicators of stroke volume and, consequently, cardiac output. For example, correlations between PPG signal features and blood pressure changes have been used to infer cardiac output changes, offering a less invasive and more patient-friendly approach [4].

However, despite these advancements, the integration of ECG and PPG signals into a unified model for CO estimation remains underexplored. The majority of existing research tends to focus on either signal in isolation, overlooking the potential synergies that could arise from their combination. The complex nature of cardiovascular dynamics, coupled with the inherent variability in physiological signals, poses significant challenges in developing a model that accurately reflects cardiac function across diverse patient populations.

Furthermore, the literature reveals a gap in methodologies that can effectively harness the complementary information provided by ECG and PPG signals. While machine learning and data fusion techniques have been proposed, their application in real-time, non-invasive CO monitoring requires further investigation [5]. The development of such models necessitates a deep understanding of the physiological underpinnings of ECG and PPG signals, as well as advanced signal processing and analytical techniques to extract and integrate relevant features.

In response to these challenges, this proposal aims to contribute to the field by presenting a novel mathematical model that not only leverages the strengths of both ECG and PPG signals but also addresses the limitations of current methods. By providing a comprehensive review of existing techniques and identifying areas for improvement, this research underscores the importance of innovation in non-invasive cardiac monitoring technologies.

#### **Methodology**

*Multi-Parametric Data Acquisition*. The foundation of the proposed model is the acquisition of high-quality ECG and PPG signals. ECG signals are obtained using standard electrode placements on the subject's body to record the electrical activity of the heart. PPG signals are captured through optical sensors that emit light into the skin and measure the amount of light either transmitted or reflected, providing data on blood volume changes. Both signals are subject to various sources of noise and artifacts, necessitating robust preprocessing techniques to ensure data integrity.

*Data Preprocessing*. Preprocessing steps include filtering, normalization, and artifact removal. For ECG, a band-pass filter is applied to remove noise outside the heart rate frequency band, while PPG signals are processed to eliminate motion artifacts and baseline drift. The preprocessing ensures that the signals accurately reflect the physiological parameters of interest without extraneous noise.

*Mathematical Integration of ECG and PPG Data.* The integration of ECG and PPG data into a cohesive model for estimating cardiac outpu is predicated on the relationship between the heart's electrical activity and the volumetric changes in blood flow Eq. (1). The mathematical model combines features extracted from both signals to estimate stroke volume (SV), which, when multiplied by heart rate (HR), yields cardiac output (CO):

$$
CO = SV \cdot HR. \tag{1}
$$



*Feature Extraction*. Feature extraction involves identifying and quantifying signal characteristics that correlate with SV and HR. From the ECG, the R-R interval is used to calculate HR, while the amplitude and shape of the QRS complex can provide insights into ventricular contraction strength. PPG signal analysis focuses on the systolic peak amplitude and the time interval between successive peaks, which are indicative of blood volume changes during the cardiac cycle.

*Model Formulation*. The mathematical model integrates ECG and PPG features using regression analysis or machine learning techniques to estimate SV Eq. (2). The model can be represented as:

$$
SV = f\left(ECG_{feature}, PPG_{feature}\right),\tag{2}
$$

where: *f* - is a function derived from the relationship between the selected features and SV, established through calibration with known CO measurements.

### **Implementation and Validation**

The implementation involves developing a software application that processes, analyzes, and displays the ECG and PPG signals in real-time. This application will incorporate the mathematical model to continuously estimate and display CO. The process requires robust algorithm development, including signal processing, feature extraction, and the application of the model to estimate CO.

Validation of the model will be conducted in two phases: initial calibration using data from a cohort of subjects with known CO measurements, followed by validation in a clinical setting with patients undergoing cardiac monitoring. The model's accuracy and reliability will be assessed by comparing its CO estimates with those obtained from standard methods, such as thermodilution or echocardiography.

#### **Conclusions**

This article introduces a mathematical model for estimating cardiac output using multiparametric data from ECG and PPG signals. The proposed model offers a promising approach to enhance the accuracy and accessibility of CO monitoring, with significant implications for clinical practice and health monitoring technologies. As the field progresses, further research will be crucial in refining the model and realizing its full potential in improving cardiovascular care.

#### **References**

- [1] Zhang Y, Wang Y, Shi J, Hua Z, Xu J (2019) Cardiac output measurements via echocardiography versus thermodilution: A systematic review and meta-analysis. PLoS ONE 14(10): e0222105. [https://doi.org/10.1371/journal.pone.0222105.](https://doi.org/10.1371/journal.pone.0222105)
- [2] Arya, V.K., Al-Moustadi, W., & Dutta, V. (2022). Cardiac output monitoring invasive and noninvasive. Current Opinion in Critical Care, 28(3), 340-347. doi: 10.1097/MCC.0000000000000937.
- [3] Bayoumy, K., Gaber, M., Elshafeey, A. et al. Smart wearable devices in cardiovascular care: where we are and how to move forward. Nat Rev Cardiol 18, 581–599 (2021). [https://doi.org/10.1038/s41569-021-00522-7.](https://doi.org/10.1038/s41569-021-00522-7)
- [4] Pereira, T., Tran, N., Gadhoumi, K. et al. Photoplethysmography based atrial fibrillation detection: a review. npj Digit. Med. 3, 3 (2020). [https://doi.org/10.1038/s41746-019-0207-9.](https://doi.org/10.1038/s41746-019-0207-9)
- [5] Ghasemi, Z., Lee, J.C., Kim, C.S., et al.: Estimation of cardiovascular risk predictors from non-invasively measured diametric pulse volume waveforms via multiple measurement information fusion. Sci. Rep. 8, 10433 (2018). https://doi.org/10.1038/s41598-018-28604-6