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► **To cite this version:**

Jérôme Diaz, François Kimmig, Fabrice Vallée, Arthur Le Gall, Romain Kirszenblat, et al.. Modeling-based Radial Pressure Waveform Reconstruction Using Photoplethysmography Signals. CinC 2024 - 51st international Computing in Cardiology Conference, Sep 2024, Karlsruhe, Germany. 10.22489/CinC.2024.332 . hal-04870802

HAL Id: hal-04870802

<https://inria.hal.science/hal-04870802v1>

Submitted on 7 Jan 2025

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Modeling-based Radial Pressure Waveform Reconstruction using Photoplethysmography Signals

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Abstract

This study introduces a model linking photoplethysmography (PPG) dynamics to radial pressure waveform (RPW), which could be integrated into digital twins, that enables the reconstruction of RPW from PPG measurements using pulse pressure extrema. Built upon existing literature and supervised symbolic regression on anesthesia data, the model was validated on 581 continuous 10 seconds subsequences from 24 patients. Calibration through an unscented Kalman filter ensured patient-specific accuracy, yielding an averaged Pearson correlation coefficient of 0.955 for the reconstructed signal. The model's ordinary differential equation (ODE) with three parameters showed consistency with existing models. The stable, identifiable parameters underscore the model's robustness. The proposed model gives some insights into the physiology hidden behind the PPG and paves the way for RPW reconstruction using non-invasive measurements.

1. Introduction

PPG is a non-invasive optical technique used to explore vascular functions [1]. It involves emitting light onto the skin surface and measuring the light that either reflects back (reflection PPG) or passes through the tissue (transmission PPG). The tissue's optical properties vary with its composition, and at the heartbeat timescale, the PPG signal reflects the blood volume changes in both macro- and micro-circulation.

The PPG signal is affected by measurement modalities such as sensor contact pressure, sensor geometry – particularly its position with respect to the main arteries – the light wavelength used, and the choice between transmission and reflection PPG. By adjusting these modalities, PPG-based tools can be tailored for a wide range of applications.

In a clinical setting, PPG is utilized for heart rate monitoring, rhythm analysis, blood oxygen saturation measure-

ment, pulse wave velocity measurement, arterial stiffness estimation, breathing monitoring [1, 2]. Additionally, over the past decade, PPG has been increasingly integrated into wearable devices for daily cardiovascular health monitoring [2, 3], which paves the way for new applications such as atrial fibrillation detection [4], cardiovascular state assessment [5, 6], sleep stage classification [7] or hypertension assessment [8].

With its widespread use, including in commercial applications, research on PPG is very active [2]. Understanding the physical content of the PPG signal continues to be a significant challenge. New sensors are being designed to improve signal quality or target new features. Additionally, innovative analysis methods are being developed to extract more information from the signal, mostly relying on either signal feature extractions or machine learning technics using the entire PPG waveform as input.

A prominent challenge in PPG analysis is the estimation of blood pressure from the PPG signal. While many attempts have been made to estimate systolic, diastolic or mean arterial pressure [9–17], few methods successfully reconstruct the complete waveform [18].

In this work, we propose a method to dynamically link RPW and PPG, paving the way for the integration of PPG into cardiovascular digital twins. As a first validation, we use it in a standalone fashion to reconstruct the RPW from the PPG signal within the context of vital sign monitoring during anesthesia. PPG signals are collected from the finger using a transmission setting, the calibrated RPW used for the model validation is measured invasively at the wrist and regular cuff blood pressure measurements providing systolic and diastolic pressure values are available.

2. Material and methods

The proposed method relies on an explicit model formulated as a dynamical system that connects the tempo-

ral evolution of pressure with the PPG signal. Following a patient-specific parameter personalization phase conducted using an unscented Kalman filter [19], the model reconstructs the RPW from PPG measurements based on pulse pressure extrema.

2.1. Model formulation

The proposed model reads

$$\dot{P}PG(t) = \alpha PPG(t) + \beta \frac{(P(t) - P_{\min})}{\Delta P} + \gamma \frac{\dot{P}(t)}{\Delta P}, \quad (1)$$

where α , β and γ are model parameters that can be calibrated and $\Delta P = P_{\max} - P_{\min}$ corresponds to the pressure range over which the PPG measurements are taken. In this model, the pressure and its time derivative are taken as source terms in order to reconstruct the PPG. It is worth noting that the signs of the parameters are critical to the model's consistency: α is negative in order to avoid exponential growth of PPG while β and γ are positive such that the dynamics of the pressure source terms drive the evolution of PPG. We also recovered this dynamics through supervised symbolic regression [20], amongst other ODE of varying complexity. The aim of this symbolic regression was to find an ODE able to reproduce the dynamics of the PPG by combining operations on RPW and its time derivative. It minimized the following functional C_j with respect to f_j in a chosen functional space:

$$C_j(f_j, \mathbf{x}, \mathbf{u}, g) := \int_0^T f_j(\mathbf{x}(t), \mathbf{u}(t))g(t)dt + \int_0^T \mathbf{x}(t)\dot{g}(t)dt, \quad (2)$$

where $\mathbf{x}(t)$ is the target dynamics (PPG in our case), $\mathbf{u}(t)$ the source terms (P and \dot{P}) and $g(t) \in \mathcal{C}^1$ being a test function.

By rewriting (1) such that \dot{P} appears at the left-hand side, we can get an expression for the dynamics of the pressure as a function of the PPG, as shown hereafter

$$\dot{P}(t) = c_1(P(t) - P_{\min}) + \Delta P(c_2 PPG(t) + c_3 \dot{P}PG(t)). \quad (3)$$

As the PPG's signal intensity cannot be used quantitatively, the subsequence's maximal systolic and minimal diastolic pressures (through ΔP) are needed to rescale the RPW.

2.2. Data preprocessing

The data used to perform the symbolic regression procedure and the parameter estimation was taken from a partner hospital anesthesia database of patients. The PPG data was filtered using a band-pass filter with 0.5 Hz and 8 Hz cut-off frequencies in order to get rid of baseline drift as well as high frequency noise [18]. We then segmented the data for RPW and PPG signals using a random forest based algorithm to highlight each heartbeat. Any sequence of data

that did not contain continuous aggregations of heartbeats (which happens when either of the signals flatlines) was removed from the dataset. Furthermore, we looked at duration outliers and discarded any heart rate sequence with a frequency lower than 20 beats per minute (BPM) or higher than 200 BPM. Finally, the signals were resynchronised with one another using cross-correlation [18]. RPW being measured at the wrist while the PPG is taken at the fingertip induces a small lag between the signals due to wave travel time, which can be identified by looking at the location of the maximum value for the cross-correlation. The resulting data was then split into 10 seconds of continuous subsequences of RPW and PPG, with no overlap. The PPG data was normalized over each subsequence (not each heartbeat) such that it varies between 0 and 1 while retaining some features of the respiration. At the end of the pre-processing procedure, the data used in our study amounts to 24 patients split into 581 subsequences, which corresponds to 97 minutes of signal in total.

3. Results

3.1. Model validation

The derived model (1) was first validated in its ability to reconstruct the PPG dynamics using the RPW as its source term. We calibrated the model through an unscented Kalman filter. The PPG reconstruction is done by splitting the 10 seconds signal sequence into two parts: the first 5 seconds are used to calibrate the parameters, and then the PPG is predicted using only the RPW and its time derivative as source terms for the remaining 5 seconds. As a metric to compare the similarities of the two waveforms, we used Pearson's correlation coefficient (r) [18], as well as the Mean Absolute Error (MAE). Its averaged value as well as the means and standard deviations of the model's parameters can be found in Table 1a.

3.2. RPW reconstruction

We used the same calibration procedure as for the PPG model. An example of the parameter estimation procedure and the resulting predicted RPW can be seen on Fig 1. The model's parameters are identified sequentially during the estimation phase, which can be seen through the narrowing of their covariance. The averaged parameters' value over the different time sequences for (3) and their standard deviations can be seen in Table 1b, as well as the averaged Pearson's correlation coefficient.

4. Discussion

The performance of RPW reconstruction achieved with our newly proposed model is comparable to that reported in [18], with an average correlation coefficient of 0.993 (versus 0.955). However, our explicit dynamical system

(a)	α (s^{-1})	β (s^{-1})	γ	r	MAE	(b)	c_1 (s^{-1})	c_2 (s^{-1})	c_3	r	MAE (mmHg)
	-7.1 ± 2.5	7.0 ± 2.6	1.0 ± 0.15	0.961 ± 0.03	0.07 ± 0.04		-17 ± 17	17 ± 18	0.95 ± 0.27	0.955 ± 0.03	5.04 ± 2.47

Table 1. Mean values and standard deviations for the parameters estimated by the Kalman filter, mean Pearson correlation coefficient and MAE over the 581 subsequences used for the reconstruction of (a) PPG and (b) RPW.

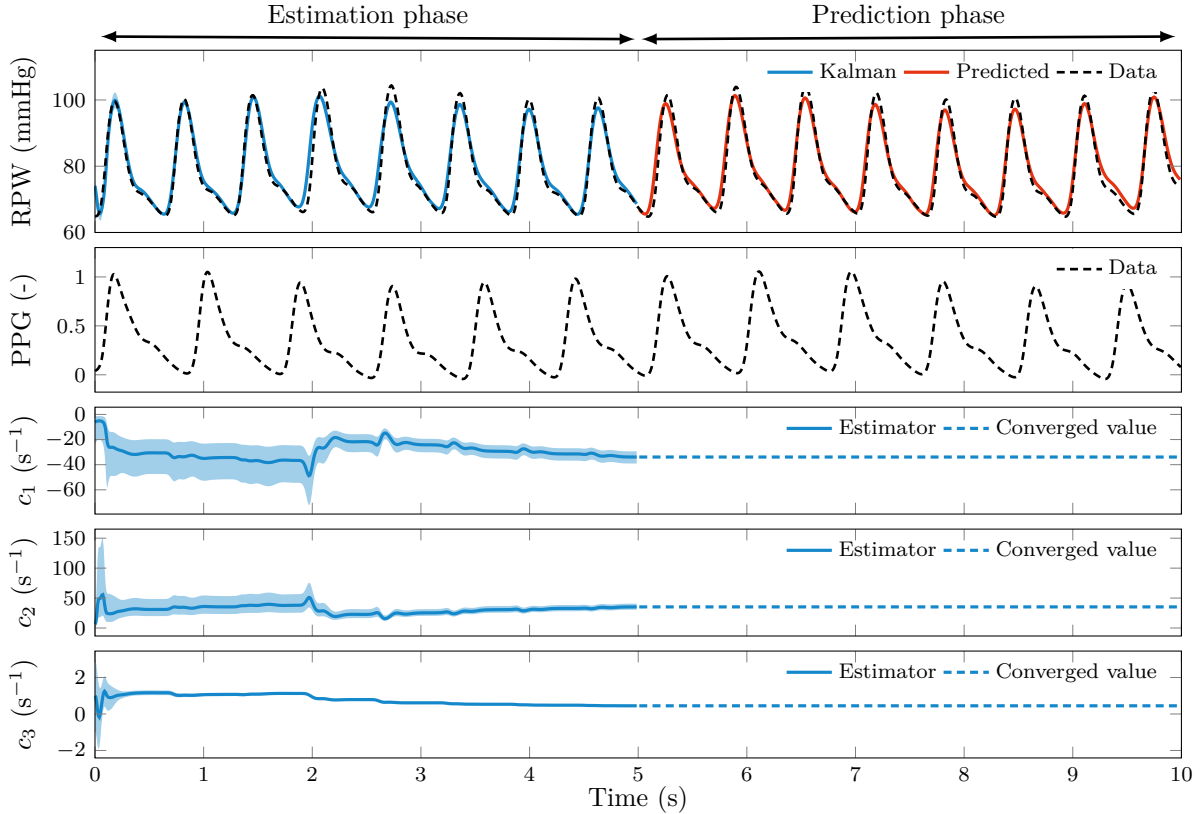


Figure 1. RPW reconstruction and parameter estimation for the model linking pressure and PPG defined in (3). Covariances for the estimation phase are represented in light blue around the estimated trajectories.

formulation offers several advantages over black-box approaches. It can be used, as demonstrated here, as a standalone modality for RPW reconstruction, but more importantly it can also be integrated into larger cardiovascular dynamical models that serve as the core element of a patient's digital twin, enabling the use of PPG measurements to inform and update the digital twin. This newly developed model is consistent with the existing literature [21] and expands on it, serving as a valuable tool to interpret the physiology encoded by the PPG waveform. Indeed, the formulated model in (1) can be linked to a one-stage Windkessel circulation model between the wrist and the fingertip. Assuming that the time derivative of the PPG is proportional to the variations of blood volume measured at the fingertip, $\frac{\beta}{\Delta P}$ plays the role of a resistance and $\frac{\gamma}{\Delta P}$ of a capacitance. The contributions of the pressure term and its time derivative correspond to the blood flux entering the wrist, whereas the PPG term corresponds to the blood flux going to the fingertip with α being a decay

constant. The calibration procedure for both (1) and (3) showed that the parameters were identifiable and had a reasonable overall variability (within 100% of their averaged value), following Gaussian-like distributions. In addition, the reconstructed signals showed high Pearson correlation coefficients, highlighting the potential of the two models for clinical use. However, our method has some shortcomings: the pressure range over which RPW is predicted must be known – typically via a cuff, which is mandatory during anesthesia – and the parameters of the model need a patient specific calibration, which requires a RPW over a few seconds. The requirement for RPW could be mitigated by instead using Doppler ultrasonography at the wrist in order to measure blood flow which could be used to calibrate a local Windkessel model [22]. This personalized circulation model would then be used to generate a RPW suitable for the calibration of (3). The practicability of this calibration procedure will depend on the parameters' intra-patient variability, which remains to be investigated in detail when

the RPW morphology is subject to change.

5. Conclusion

Our dynamical PPG model has been established and tested on a small cohort of patients and offers an explicit form, with interpretable parameters and behavior. The results showed that the reconstructed signals were in agreement with the patient data for both models, with high Pearson correlation coefficients. The literature on this model-based approach to PPG signal analysis remains limited [21] despite its advantages over purely signal-based analysis methods. Our model can be used as a bridge between standard cardiovascular models and PPG measurements, thus enhancing digital twin frameworks. Future work may involve enriching the model by incorporating additional terms in order to reconstruct RPW over a wider range of waveforms found in other databases, such as MIMICS-IV. In terms of clinical use, this model may enable the reconstruction of RPW from non-invasive measurements, for instance using a PPG device and a blood pressure cuff during anesthesia where both measures are readily available or with a wearable device embedding both sensors.

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