Application of Approximation Methods to Identify Sinusoidal Chronostructures in Healthy Individuals and Patients with Cardiovascular Pathology

Artur Vardanyan
Institute for Informatics and Automation Problems of the National Academy of Sciences of the Republic of Armenia
Yerevan, Armenia
e-mail: artur.vardanyan@iiap.sci.am

Lyusya Babayan
Armenian Medical Institute, Republic of Armenia
Yerevan, Armenia
e-mail: babayan.lucia@gmail.com

Vladimir Sahakyan
Institute for Informatics and Automation Problems of the National Academy of Sciences of the Republic of Armenia
Yerevan, Armenia
e-mail: vladimir.sahakyan@sci.am

Naira Atoyan
Armenian Medical Institute, Republic of Armenia
Yerevan, Armenia
e-mail: atoyannaira@gmail.com

***Abstract*—This study presents a mathematical and computational approach for identifying sinusoidal chrono-structures in physiological data collected from healthy individuals and patients with cardiovascular pathology. Using a nonlinear least squares approximation based on the Levenberg–Marquardt optimization algorithm, it is estimated rhythm parameters such as mesor, amplitude, acrophase, and period for various biological signals, including blood pressure, heart rate, glucose levels, and blood oxygen saturation. The classification of biological rhythms followed the international chronobiological standard into ultradian, circadian, and infradian categories. A single patient's clinical data over three days was analyzed as a test case to validate the method. The results confirmed the presence of circadian rhythms in most features and demonstrated the reliability and feasibility of the proposed method for detecting rhythmicity in biomedical data. This approach offers potential for broader chronobiological diagnostics and rhythm-based assessment of pathological conditions.**

***Keywords*— Chronobiology, sinusoidal approximation, nonlinear least squares, Levenberg–Marquardt algorithm, circadian rhythms, physiological monitoring, cardiovascular pathology.**

I. Introduction

The effects of fluctuations in the natural environmental factors (geomagnetic fields, cosmic rays, and hydrometeorological factors) on human homeostasis and chrono-periodic systems remain a topic of global research, but there is no clear consensus. Chrono-periodic systems and the dynamics of human rhythm have evolved under the influence of natural environmental factors. The circadian temporal structure had been regarded as a leading system of human organisms. The circadian chrono-periodic system was formed under the influence of light variations, having a daily frequency due to Earth's rotation with accompanying gravity. The discovery of the Earth's magnetosphere, the solar wind (solar plasma), and the interplanetary magnetic field made it obvious that the biological rhythms and magnetic factors have similar fluctuations. Logically, this gives reason to talk about the participation of natural magnetic factors in their formation. Malfunctions of biological rhythms [1, 2, 3, 4, 5]. This paper discusses mathematical methods for detecting sinusoidal chrono-structures in healthy individuals and patients with cardiovascular pathology. The rhythms were classified according to the International Glossary [6, 7] with some modification [8, 9]. Rhythms with periods ranging from 3 to 20 hours were considered ultradian, from 20 to 28 hours - circadian, and from 28 to 96 hours - infradian.

II. Approximation Method

To analyze the temporal structure of physiological features, a nonlinear least squares approximation technique is employed to detect sinusoidal rhythms in patient data. This approach is aligned with the rhythmological analysis described by Babayan et al. [5], where the core model takes the form:

$$y(t) = g(t) + x(t),$$

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where

$$g(t) = M + A\cos\left(\frac{2\pi}{T}t + \phi\right).$$

Here, M is the mesor (mean level), A is the amplitude (half-range of oscillation), ϕ is the acrophase (phase shift in radians), and T is the period of oscillation. The residual term $x(t)$ represents normally distributed white noise, implicitly accounted for by the least squares minimization framework. This model is nonlinear concerning both the phase and the period, and thus requires iterative numerical estimation.

Physiological data were extracted from clinical measurements recorded over three consecutive days at regular intervals. The following features were analyzed: body temperature (BT), pulse rate, systolic and diastolic arterial pressure (APS, APD), arterial difference pressure (ADP), mean arterial pressure (APM), blood oxygen saturation (SpO_2), and glucose levels. Measurements with missing data were excluded or interpolated conservatively to preserve signal integrity.

For each feature, the rhythm parameters (M, A, ϕ, T) were estimated using a developed Python algorithm that applies the Levenberg–Marquardt optimization method [10, 11] via the `curve_fit` function from the SciPy library [12]. Based on the estimated period T, rhythms were classified as:

- **Ultradian (U):** $3 \leq T < 20$ hours
- **Circadian (C):** $20 \leq T \leq 28$ hours
- **Infradian (I):** $28 < T \leq 96$ hours

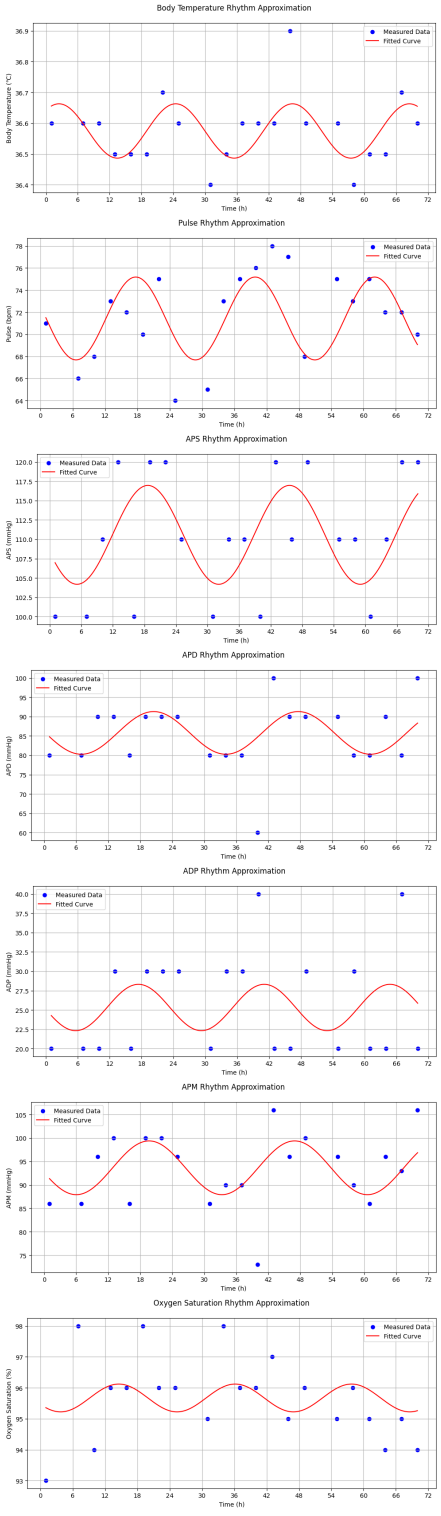
following the international chronobiological classification system [7, 8, 9]. The acrophase (ϕ) was converted to the time of day representation in hours.

Each rhythm was visualized by fitting the cosine curve over the original time domain, and residuals were assessed to validate the suitability of the model under Gaussian noise [13] assumptions.

III. Results

The nonlinear sinusoidal approximation was applied to the time series data of a single patient recorded over a 3-day period; an illustrative example is presented in Table I.

The objective was to detect and classify the chronostructures of physiological features using nonlinear least squares estimation. The results for each measured variable are summarized below through visualizations and Table II presenting rhythm classifications and computed acrophase values where applicable.



All features exhibited circadian rhythms, confirming the presence of intrinsic temporal structure in physiological parameters. No ultradian and infradian rhythms were detected. All circadian acrophases were calculated

TABLE I
MEASURED PHYSIOLOGICAL PARAMETERS OF THE PATIENT OVER THREE DAYS

Day	Hour	BT (°C)	Pulse (bpm)	APS (mmHg)	APD (mmHg)	ADP (mmHg)	APM (mmHg)	SpO_2 (%)
1	01:00	36.6	71	100	80	20	86	93
	07:00	36.6	66	100	80	20	86	98
	10:00	36.6	68	110	90	20	96	94
	13:00	36.5	73	120	90	30	100	96
	16:00	36.5	72	100	80	20	86	96
	19:00	36.5	70	120	90	30	100	98
	22:00	36.7	75	120	90	30	100	96
2	01:00	36.6	64	110	90	30	96	96
	07:00	36.4	65	100	80	20	86	95
	10:00	36.5	73	110	80	30	90	98
	13:00	36.6	75	110	80	30	90	96
	16:00	36.6	76	100	60	40	73	96
	19:00	36.6	78	120	100	20	106	97
	22:00	36.9	77	110	90	20	96	95
3	01:00	36.6	68	120	90	30	100	96
	07:00	36.6	75	110	90	20	96	95
	10:00	36.4	73	110	80	30	90	96
	13:00	36.5	75	100	80	20	86	95
	16:00	36.5	72	110	90	20	96	94
	19:00	36.7	72	120	80	40	93	95
	22:00	36.6	70	120	100	20	106	94

TABLE II
RHYTHM PARAMETERS FOR VARIOUS PHYSIOLOGICAL FEATURES

Feature	Mesor	Amplitude	Period (h)	Rhythm Type	Acrophase (h)
BT (°C)	36.57	0.09	22.02	Circadian	2.44
Pulse (bpm)	71.43	3.75	22.17	Circadian	17.70
APS (mmHg)	110.57	6.39	26.94	Circadian	18.64
APD (mmHg)	85.77	5.52	27.09	Circadian	20.53
ADP (mmHg)	25.32	2.99	23.68	Circadian	17.42
APM (mmHg)	93.65	5.73	27.28	Circadian	19.66
SpO_2 (%)	95.67	0.45	21.61	Circadian	14.55

in hours, accounting for waveform inversion where applicable.

These results support the utility of nonlinear rhythm analysis in characterizing chrono-structures in physiological signals and may offer diagnostic value in distinguishing normal and pathological temporal patterns. Although this approximation was conducted on a single patient's data, it demonstrates the methodological feasibility for future chronobiological assessments across a broader patient population.

IV. CONCLUSION

In this study, a nonlinear approximation method is applied to analyze the chrono-structures of physiological signals from a patient with cardiovascular pathology. The method is based on fitting a cosine model using the Levenberg–Marquardt optimization algorithm and accounts for white noise through a least squares framework. The classification of rhythms into ultradian, circadian, and infradian types was performed based on the estimated periods. For the examined patient, all physiological features exhibited circadian rhythms, with reliable mesor and acrophase estimations. An area-based reliability metric is also introduced to quantify the consistency of the rhythm within clinically defined normal ranges. The results support the applicability of the method for rhythm detection in clinical data and show promise for its use in broader chronobiological diagnostics. Future work will focus on validating this methodology on a larger dataset across multiple patient groups to assess its generalizability and diagnostic value.

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