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COMPUTERISED BLOOD PRESSURE MONITORING IN OUTPATIENT SETTINGS

The paper presents the measurement of a normal 24-hour heart rate and blood pressure analysis of an anonymous patient. The object of study in this paper is the computer processing of outpatient blood pressure monitoring. The goal is to mathematically model the data as a sum of relatively smooth trends and detrended fluctuations. Tasks: decomposition of the primary series by two independent methods, stability and spectral analysis of the shifted fluctuations using the Wiener-Hinchin theorem, and proving the self-similarity of such fluctuations. The methods used are: singular spectrum analysis, exponential smoothing of the simulation, and analysis of autocorrelation functions. The following results are obtained. The dataset is a sum of relatively smooth trends and detrended fluctuations; blood pressure trends have certain nighttime minima; detrended fluctuations are fractional Gaussian noise with a Hurst index of about (0.80 ± 0.016), the energy spectra of detrended fluctuations were found for the first time. Scientific novelty of the results: 1) the measured 24-hour heart rate and blood pressure analyses are decomposed into relatively smooth trends and detrended fluctuations; 2) trends allow for a more reliable assessment of 24-hour, nightly and daily average blood pressure values, which are the leading indicators of a series of blood pressure measurements and monitoring; 3) detrended fluctuations contain other valuable diagnostic information, such as short-term blood pressure variability or persistence index. 4) fluctuation analysis provides information about the power spectra of the blood pressure monitoring series and their similarity to the spectra of fractional Gaussian noise; 4) knowledge of short-term changes in blood pressure is the basis for constructing informative repeatability graphs for blood pressure monitoring; 5) detrended fluctuations are identified as fractional Gaussian noise, which is a self-similar stochastic process.

Keywords: mathematical modelling, computing technologies, singular spectrum analysis, fluctuation analysis, stochastic process, computer blood pressure monitoring.

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КОМП'ЮТЕРНИЙ МОНІТОРИНГ АРТЕРІАЛЬНОГО ТИСКУ В АМБУЛАТОРНИХ УМОВАХ

В роботі представлено вимірювання звичайного 24-годинного пульсу і аналіз артеріального тиску анонімного пацієнта. Об'єктом вивчення в статті є комп'ютерна обробка амбулаторного моніторингу артеріального тиску. Метою є математичне моделювання даних, як сума відносно плавних трендів і детрендованих флуктуацій. Завдання: розкладання первинного ряду двома незалежними методами, стійкість та спектральний аналіз зміщених флуктуацій, використовуючи теорему Вінера-Хінчина та доведення самоподібності таких флуктуацій. Використовуваними методами є: сингулярний аналіз спектру, експоненціальне згладжування моделювання та аналіз автокореляційних функцій. Отримані такі результати. Набір даних являє собою суму досить плавних трендів і детрендованих флуктуацій; тренди артеріального тиску мають певні нічні мінімуми; детрендовані флуктуації - це дробові гаусові шуми з показником Херста близько (0.80 ± 0.016), енергетичні спектри детрендованих флуктуацій були знайдені вперше. Наукова новизна отриманих результатів: 1) виміряний 24-годинний пульс і аналізи артеріального тиску розкладаються на досить плавні тренди і детрендовані флуктуації; 2) тренди дозволяють більш надійно оцінювати 24-годинні, нічні та добові середні значення артеріального тиску, які є головними індикаторами серії вимірювання та моніторингу артеріального тиску; 3) детрендовані коливання містять іншу цінну діагностичну інформацію, таку як короткочасна варіабельність артеріального тиску або показник персистенції. 4) флуктуаційний аналіз надає інформацію про спектри потужності серії моніторингу артеріального тиску та їх подібність до спектрів часткового шуму Гауса; 4) знання короткочасових змін артеріального тиску є основою для побудови інформативних графіків повторюваності для моніторингу артеріального тиску; 5) детрендовані флуктуації ідентифікуються як фракційний гаусовий шум, який є самоподібним стохастичним процесом.

Ключові слова: математичне моделювання, технології виконання обчислень, сингулярний аналіз спектру, флуктуаційний аналіз, стохастичний процес, комп'ютерний моніторинг артеріального тиску.

Introduction

Ambulatory blood pressure monitoring (ABPM) is a widely recognized technique for diagnosing hypertension. From a clinical perspective, the most valuable information is the 24-hour average and nocturnal blood pressure readings. Other derived indices of ABPM also have clinical significance, albeit to a lesser extent [1]. Routine ABPM involves a few dozen trials over 24 hours that are more or less regular, often averaged within each hour [2]. This ordinary and cheap test solves a pretty lengthy and impressive list of diagnostic problems [3]:

1) Identify "white coat" hypertension.
2) Identify masked hypertension.
3) Detect standard 24-hour blood pressure patterns (dipping, daytime, and nocturnal hypertension).
4) Assess hypertension treatment.
5) assessing hypertension in the elderly, children/adolescents, pregnancy, and high-risk patients.
6) Identify ambulatory hypotension.
7) Identify blood pressure patterns in Parkinson's Disease.
8) endocrine Hypertension.

The authors [4] presented statistical data from five prominent medical centers known for their work in ambulatory blood pressure monitoring (ABPM). This data indicates a trend in the increasing use of ABPM, suggesting that its growth is primarily due to its clinical benefits rather than reimbursement incentives. The statistics show a steady rise in ABPM testing over time.

The use of ABPM to monitor treatment can be notably facilitated by software capable of providing a trend report [4]. Although the adverse cardiovascular consequences of hypertension primarily depend on average blood pressure values [1], evidence from observational studies and clinical trials has shown that these outcomes may also depend on increased short-term and long-term blood pressure variability (see [5] and [6]).

Trend analysis in ABPM helps identify long-term blood pressure patterns, including sustained hypertension and nocturnal dipping patterns. Such information is crucial for diagnosing conditions like nocturnal hypertension, which often go unnoticed in clinical settings [7].

Detrended fluctuation analysis (DFA) is increasingly being explored in ABPM to reveal subtle, long-range correlations in blood pressure variability, particularly those associated with cardiovascular risk and autonomic regulation [8]. However, recent studies specifically applying DFA to ABPM remain relatively niche. The contribution of our research may be defined as an extention og this niche.

Related works

It is reasonable to break down ABPM readings into at least two components: smooth trends and pure fluctuations free of trends. The first component reflects low-frequency signals, which indicate averaged parameters. The second component relates to high-frequency signals associated with short-term variability. We are only referring to short-term variability, as there are valid concerns about whether long-term variability can be accurately determined from standard ABPM readings [5,7].

Research has also been conducted on the multifractal multiscale analysis of detrended fluctuations using the DFA method [8,9]. The goal is to enhance clinical procedures for more accurate cardiovascular risk assessment. Additionally, this research could aid in analyzing day/night variations in blood pressure. The application of real-time heart rate variability as a predictor of hemodialysis efficiency in patients with end-stage kidney disease is detailed in [10].

However, attempts to decompose ABPM data are still relatively rare [7, 8, 11, 12]. The issue arises because commonly used digital filters, such as wavelets, typically involve two-fold downsampling, which is undesirable for short series like those in ABPM [12]. Meanwhile, innovative methods, such as ABPM registration using computer vision techniques [13], enable continuous blood pressure monitoring, allowing data series to be as lengthy and detailed as needed. Nevertheless, traditional ABPM methods will continue to produce short series.

It is essential to note that methods are available that do not require downsampling of short time series. For instance, Principal Component Analysis (PCA) is closely related to the Poincaré Plot technique, especially when considering these plots for embedding short ABPM series in a two-dimensional space [12, 14].

Another method, Singular Spectrum Analysis (SSA), is often considered more suitable for more extended series [15]. However, its effectiveness for short series should also be evaluated. A third method that might be utilized is Exponential Smoothing Modeling (ESM) [16, 17], which involves decomposing the studied series. An attempt to apply ESM to DFA can be found in [18]. Nonetheless, the authors are not aware of any examples of the ESM technique utilizing ABPM data, which inspired us.

Aim and tasks

Express-analyze of publications hints at two principal different, but mutually ancillary, approaches to ABPM:

1. Usage of advanced but more expensive registration techniques ([13])
2. Usage of advanced but more complex processing methods ([11] and [12])

Based on the abovementioned point, one can formulate the article's primary purpose. The aim is to predict the reliable separation of the ABPM series on smooth trends and fluctuations, free of trends (detrended ones), for deeper insight into the ABPM structure and more reliable diagnostics.

Trends shall reflect the average features of the ABPM series, including nocturnal dipping. At the same time, the detrended fluctuation analysis (DFA) will inform us about the series' persistence and self-similarity if they exist.

The following tasks were formulated to achieve the stated goal:

a) Data Decomposition: Divide the ABPM time series into smooth trends and detrended fluctuations using SSA and ESM. Compare and validate the results obtained from these two independent methods.

b) Persistence Analysis: Perform Detrended Fluctuation Analysis (DFA) to evaluate the persistence and self-similarity of the detrended fluctuations. Estimate the Hurst exponent to quantify the memory effect in blood pressure variability.

c) Variability Characterization: Apply Principal Component Analysis (PCA) to quantify short-term variability in ABPM data. Construct recurrence plots to visualize and analyze patterns within detrended fluctuations, including their recurrence ratios and entropy.

d) Clinical Relevance Assessment: Analyze trends to determine 24-hour, nocturnal, and diurnal average blood pressure values. Assess the significance of nocturnal dipping and identify diagnostic indicators derived from trends and fluctuations in blood pressure.

Theory and Experiments Origin and Brief Description of Data

CardiacDirect (https://www.cardiacdirect.com/) is a US-based medical equipment supplier specializing in cardiac devices and accessories. They released a report on the ABPM trial [2] involving an African American female patient with severe hypertension but not currently taking any active medication. This test was conducted to determine the appropriate treatment and was performed by the Oscar 2™ automatic blood pressure monitor.

The report included 60 automated measurements and was created using AccuWin Pro 4. This user-friendly Windows application allows for the configuration, analysis, interpretation, and reporting of ABPM studies. The test started at 16:13 and finished the next day at 16:30. The sleeping time was in the range (23.00 - 7.00). The trials were hourly during sleeping; the diurnal ones had 20-minute intervals.

Exponential Smoothing Models

Exponential Smoothing Modeling (ESM) emerged in the second half of the last century as a forecasting method for time series data [16, 17, 19]. It posits that recent observations have a greater influence on the future values of a series than older ones. This method applies to time series that exhibit trends, seasonality, or both, as well as to those that lack these characteristics.

One of the branches of ESM is called "state space models," which includes Error-Trend-Seasonality (ETS) modeling. Each ETS model consists of a measurement equation that describes the data and some state equations that describe unobserved components or states (such as errors, level, trend, and seasonality) that change over time [17].

There are about 30 distinct ETS models, the details of which are described in the recently published book [16], resources [17], and paper [19]. Thus, any time series may be approximated by one of those. Various information criteria can be used here to determine which of the ETS models is most appropriate for a time series [14]. These are often the Akaike's Information Criterion, or the Bayesian Information Criterion. The method is programmed and implemented in many software, particularly Excel (since 2016), Maple (since 2018), and Python (since 2020) [17]. It is included in the "Time Series Analysis" package within Maple.

There are three main types of exponential smoothing. A simple method assumes no essential trends or seasonality, an extension that accounts for trends, and the most advanced approach supports both trends and seasonality [16]. Short series like ABPM exclude seasonalities.

Singular Spectrum Analysis

In [15], Singular Spectrum Analysis is explained in detail, especially its theoretical and computational foundations. SSA is viewed as a digital filter bank for biomedical signals [20]. SSA implementation within Maple was developed in [20] for a series with a short length of N = 128 points. However, the authors aim to apply SSA to ABPM, a much smaller series with only N = 24 samples.

A window length of $2 \le L \le 0.5N$ has a crucial meaning in this method. The point is that L defines the accuracy of trend extraction, and it is desirable to choose maximal $L = 0.5N$ [20].

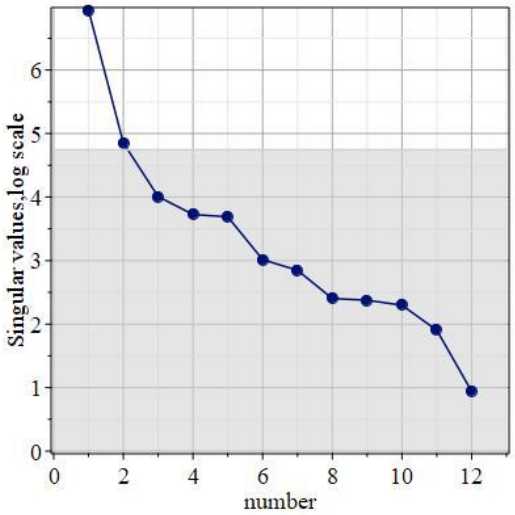

Fig. 1. Singular values of trajectory matrix for diastolic blood pressure series in the semi-logarithmic axes; those in a shadowed area are less than the mean value of the complete array

In Fig. 1, an array of singular values is displayed for the trajectory matrix corresponding to the series of diastolic blood pressure measurements from the ABPM. Similar diagrams are observed for the systolic and cardiac series. According to Kaiser's heuristic rule [15], ignoring all singular values and their right and left eigenvectors is recommended if the particular values are less than the mean of the array. For the diastolic and systolic blood pressure series, it is suggested that only the two highest singular values be considered. Aside from heart rate, even the highest singular value is enough.

Let $1 \le n \le L$ be the number of accounted singular values and $\{s\}_{i=1,\dots,L}$ the array of singular values. After that, the part of the total dispersion that ensures these selected values could be estimated as follows:

$$0 \le \alpha = \frac{\sum_{i=1}^{n} s_i^2}{\sum_{i=1}^{L} s_i^2} \le 1 \qquad (1)$$

The evaluations using expression (1) give 0.988, 0.998, and 0.993 for the heart rate, systolic, and diastolic pressure series of ABPM. One should remember that the quantities of accounted singular values (n) are equal to 1, 2, and 2, respectively. The highest singular values within SSA usually define the trends [9].

To characterize a complex system based on time series, trends, and fluctuations, these aspects should be studied separately. Detrended Fluctuation Analysis (DFA and similar methods [16, 17, 19]) enables the reliable detection of long-range (auto-) correlations and self-similarity in data, provided they exist. Their investigations help to find the series's persistence (or sometimes anti-persistence) and estimate their Hurst exponents [21].

Principal Component Analysis: short-time variabilities and recurrence plots

Blood Pressure (BP) is a highly dynamic parameter characterized by continuous fluctuations, including short- and long-term variability. Short-term variability within 24 hours can be readily assessed using ABPM [5], for instance, through the use of Poincaré Plots or Principal Component Analysis (PCA) [11, 12]. Different evidence from observational studies and post hoc analyses of data from clinical trials has indicated that cardiovascular events may also depend on increased short-term BP variability [5].

Estimating short-time BP variability can be a natural threshold for building informative recurrence plots for the ABPM series. These plots reflect the fundamental property of any life process, its relapsing (cycling) [22].

Trends

Trends enable us to estimate the average values required for clinical diagnostics more accurately (see Table 1). Note that the average values attained via different methods are almost identical. The heart rate unit is in bpm, while the BP unit is in mmHg.

Table1

Average values for ABPM series

Method	24-hours		Nocturnal	
	Heart rate	BP ratio	Heart rate	BP ratio
SSA	70	136/90	69	118/74
ETS	70	135/89	70	116/72

The night dipping of Table 1 is statistically significant at a confidence level of 0.99, as determined by a standard two-sample Z-test for 24-hour and nocturnal trials. The one exception is the heart rate trend, obtained via the ETS method, which shows no nighttime decrease in heart rate.

The similar results [2] concerning the night dipping are somewhat questionable. The dip in blood pressure observed in this report bordered on the respective standard deviations, which were overestimated in this method due to the impact of mixed fluctuations that were not separated from the sought signal. Meanwhile, our trends are free of such volatility.

Figure 2 illustrates the trends in heart rate and blood pressure ABPM series obtained using the SSA and ETS methods. They look similar but not identical. In particular, the SSA trends for blood pressure are much smoother than the analogous ETS trends. Besides, the SSA heart rate trend is not trivial compared to the ESM prediction

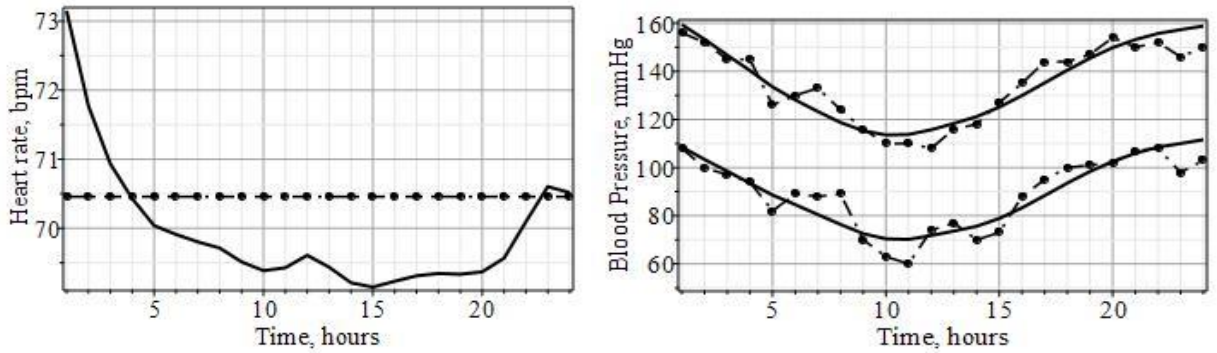

Fig. 2. Trends for heart rate (upper graph) and blood pressure (lower one); point lines show ETS trends, solid lines - SSA ones

Most trends in Fig. 2 have minima at nighttime. The one exception was mentioned above. Heart rate trends and BP ones have periodograms that show only one peak that matches the periodicity of about 24 hours. The SSA trends for blood pressure appear smoother than those of the ETS (Fig. 2).

Detrended fluctuations

The separation of detrended fluctuation allows for estimating their contribution to short-term heart rate and blood pressure variabilities. According to our SSA results, the heart rate, systolic blood pressure, and diastolic blood pressure show fluctuations of 6.5 bpm, 5.4 mmHg, and 6.0 mmHg, respectively. Similarly, ESM results indicate fluctuations of 6.7 bpm, 6.6 mmHg, and 7.7 mmHg, respectively. Comparing these results with the standard deviations reported in [2] of 7.0 bpm, 14.7 mmHg, and 13.2 mmHg, we can see that the fluctuation causes almost all of the heart rate variability and about half of the blood pressure uncertainty.

Detrended fluctuations reveal specific correlograms (autocorrelation functions); examples are shown in Figure 3. Results for BP are displayed there, but the correlogram for heart rate is similar to them.

All correlograms, regardless of whether obtained via SSA or ETS methods, exhibit decay with a power-law dependence on lags (L). It was confirmed in [22].

$$C(L) \sim L^{-\gamma}. \qquad (2)$$

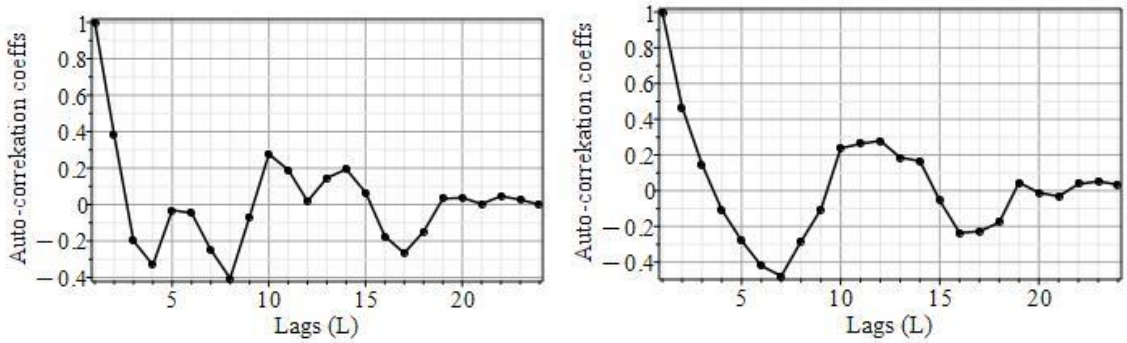

Fig. 3. Normalized correlograms for systolic (upper chart) and diastolic (lower diagram) arterial blood pressures; detrended fluctuations attained via the SSA method

Two other DFA exponents [22] are linearly connected with γ :

$$\alpha = 1 - \gamma / 2, \quad \beta = 1 - \gamma. \qquad (2)$$

The relations (3) are the straight consequences of the well-known Wiener-Khinchin theorem. At that, β defines the slope of power spectra ($P(f) \sim f^{-\beta}$), while α is an index of the noise "color."

The decay laws were found to be highly linear when examined on double-logarithmic axes. This excellent linearity is supported by the determination coefficients (R-squared values shown in Table 2). The DFA scaling exponents (α) are closely aligned across different series and methods of detrended fluctuation analysis. The inequality $\alpha \geq 0.5$ indicates that these series are fundamentally self-correlated, persistent, and exhibit "long memory."

Autocorrelation functions (correlograms) enable us to determine the power spectra of detrended fluctuations using the Wiener-Khinchin theorem, as demonstrated in the above-cited papers [20]. The power density is close but not identical for Detrended fluctuations attained via the SSA and ETS methods (see Figure 4). Spectra testifies that the series exhibits fluctuations with periods shorter than 24 hours, in contrast to the trends.

Table 2

DFA exponents and linearity estimators of the scaling power law in double-logarithmic axes

Meth.	SSA			ETS		
	HR	**SBP**	**DBP**	**HR**	**SBP**	**DBP**
α exp.	0.79	0.82	0.80	0.78	0.79	0.78
R^2	0.998	0.993	0.998	0.998	0.998	0.998

Note: HR, SBP, and DBP in Table 1 mean heart rate, systolic, and diastolic blood pressures, respectively.

Poincaré plots for the ABPM series have been examined in [11]. Our calculation, based on the method [12], confirms the earlier findings of [11]: short-term variabilities (SD1) are 6.5 bpm, 4.9 mmHg, and 5.7 mmHg, respectively. These thresholds enable the construction of matrices of similarity and recurrence plots. Fig. 5 displays examples of such plots for the detrended fluctuations of BP. One can see that SSA and ETS recurrence plots are alike but not identical.

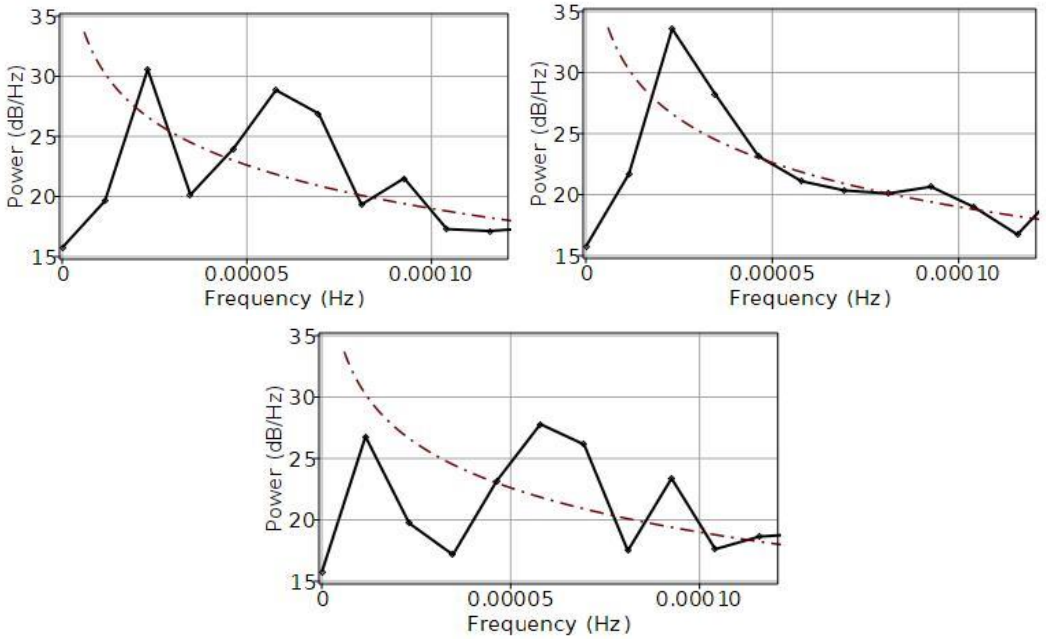

Fig. 4. Power spectra for blood pressures: systolic BP (left side) and diastolic one (right side); the upper row reflects the SSA method, while the lower one - ETS; solid lines are the power densities, dash-dot lines show the power-law decaying of power spectra with β=0.6, following (3) and data of Table 2

First, we can note that the results of two conceptually different methods (SSA and ETS) turned out so close. Similes within Section 3 demonstrated this convergence, which was not guaranteed a priori.

SSA does not predict specific time series structures ([15] and [20]) in contrast to ETS ([16, 17] and [19]. As a result, the partition of a time series strongly depends on the procedure of "singular triples grouping", which is partly an art based on experience and partly a technique.

The Kaiser's rule, used in this paper, is essentially a "rule of thumb." Another similar "thumb rule," the Cattell scree plot test [18], demands, for example, accounting for the first five singular values instead of two by Kiser's rule for Fig.1. We checked such a variant. As a result, some fluctuations are transferred to the trend, thus losing smoothness.

Perhaps the higher reliability of Kaiser's rule is due to the specific structure of the ABPM series. ETS claims that these series have the simplest possible model with additive noise, known as "simple exponential smoothing" [16]. There is no seasonality, but maybe a simple, smooth, undamped trend or no trend. Thus, the first few "singular triples" (one or two) might be enough to extract such a trend. Therefore, ETS modeling hints at "triples grouping" within SSA. They are excellent at working in "a couple."

The partition of the ABPM series into trends and fluctuations free of trend is possible via both methods, yielding close results. Note that SSA provides smoother trends, although it is slightly more labor-intensive. Purified trends, for instance, allow for a more reliable evaluation of 24-hour and nocturnal averages and night dipping because the noise-like components have been excluded from the valid signal.

Estimating the persistence of time series within ABPM is possible by analyzing detrended fluctuations. These time series have a long memory and are autocorrelated. However, it is not accurate to consider these fluctuations as Fractal Gaussian Noise (FGN) based solely on DFA exponent evaluations from Table 2. That is because FGN must have stationary increments and a power-law decay of its power spectra. In the best case, real power spectra (as shown in Fig. 4) are asymptotically close to the power-law decay.

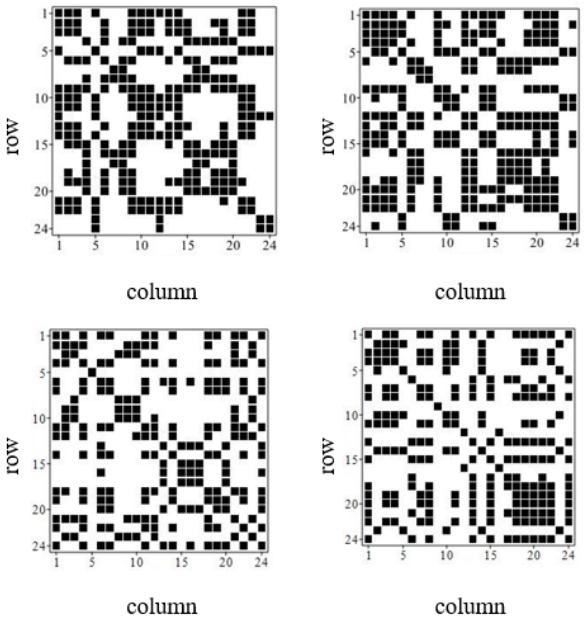

Fig. 5. Recurrence plots for detrended fluctuations: systolic BP (left-hand side) and diastolic one (right side); the upper row holds the SSA results, while the lower one – ETS: recurrence ratios are 0.451, 0.483, 0.389, and 0.402, respectively

Cleaned trend fluctuations also allow us to estimate short-range variabilities, which are the operative reactions of the blood circulatory system in an inconsistent habitat. Such variabilities can serve as the natural thresholds for the recurrence analysis of fluctuations.

The recurrence plots offer a range of exciting conclusions when one follows the qualitative analysis of [23]:

a) Many single isolated "pixels" testify to the dominance of heavy fluctuations or that ABPN is even partly stochastic and noisy.

b) Vertical and horizontal lines forming rectangles mean some states do not change or change slowly for some time (laminar states), or the process is halted at a singularity in which the dynamics are stuck in paused states.

c) Periodic patterns indicate that the process has characteristic cyclic ties, with periods corresponding to the time distance between periodic structures, which a circadian rhythm may cause.

d) SSA predicts a few higher recurrence rates than ESM concerning the ABPM systolic BP series.

Reliable SSA requires high-resolution data collected at least 30 minutes to one hour to monitor physiological responses effectively. The higher the temporal resolution of the time series, the more precisely we can distinguish the rapidly changing physiological components.

This limitation applies to ESM even more, as seen in Fig. 2, where this method demonstrates the lack of trend smoothness. Revising the standards for automated ABPM to shorten the intervals between consecutive tests may help overcome this limitation.

Discussion

As shown in Table 1, our results indicate a significant overestimation of the nocturnal pulse dip, with traditional processing reporting a seven-bpm increase compared to our measurement of no more than one bpm. Furthermore, the processing without partitioning [2] also notably exaggerates the 24-hour average blood pressure ratio (146/99 vs. our 136/89) and the nocturnal blood pressure dip (37-30 mmHg vs. 16-18 mmHg).

Detrended fluctuations provide additional valuable diagnostic information, including short-range BP variability [21] and persistence exponent. In particular, the Hurst Exponent evaluation testifies that it falls within the (0.5 – 1.0) range, with the most likely value being approximately 0.8. It indicates the persistent behavior of detrended fluctuations in the ABPM series, as well as some similarity with Fractional Gauss Noise, notably self-similarity and a power-law decay.

Additionally, fluctuations analysis offers insights into their power spectra and their similarity to fractional Gaussian noise (FGN). Understanding the nature of noise may improve the accuracy of ABPM trials in the future, for example, by employing noise filtering techniques. Knowledge of the short-time variabilities of BP became the basis for creating informative recurrence plots for the ABPM series.

Reliable SSA requires high-resolution data collected for at least 30 minutes to one hour to monitor physiological responses effectively. The higher the temporal resolution of the time series, the more precisely we can distinguish the rapidly changing physiological components.

This limitation applies to ESM even more, as seen in Fig. 2, where this method demonstrates the lack of trend smoothness. Revising the standards for automated ABPM to shorten the intervals between consecutive tests may help overcome this limitation.

Finally, the authors confidently assert that the primary objective of this research – reliably distinguishing between smooth trends and trend-free fluctuations in the ABPM series has been successfully achieved. The tasks specified in subsection 1.3 (a, b, c, and d) were executed with thoroughness and attention to detail, as supported by the preceding text.

Conclusions

Let us summarize the conclusions with a few points:

1. The ESM and SSA trends are truly close, but SSA ensures smoother curves
2. DFA analysis indicates the persistent behavior of detrended fluctuations in the ABPM, as well as similarity with Fractional Gauss Noise, notably self-similarity and a power-law decay/ ABPN are the series with "long memory"
3. The recurrence analysis reveals a relatively high recurrence rate for ABPM.
4. It would be helpful to decrease the intervals of measuring within standard ABPM to 30 minutes instead of one hour, and the number of trials increases to 48 per 24 hours.

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