Ambulatory Blood Pressure Monitoring: Modeling and Data Mining

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Abstract. We use here the non-conventional means of study and modeling for ambulatory blood pressure monitoring (24-hours test). Poincaré Plots, their fractal index, the analysis of principal components and time series, statistics tools are in use as one complex toolbox. Such an approach allows deeper insight into and recognizing of the information that is brought with these trials. It allows making more sure and reliable medic decisions. We found the fractal index of Poincaré Plots for heart rate, systolic, and diastolic blood pressures in the range (0.69-0.79) with an accuracy of about 10 %. That allows considering all series as the "pink" noise. The "negative" memory, or anti-persistency, is inherent in all these series. If the measured values had been up in the previous time, it is more likely that it will be down in the next time, and vice versa. Similar series are often termed as "mean value returning. All three series of monitoring admit the forecasts. Meantime, we confirm the clear difference between day and night trials. The circadian rhythm is the reason for the series clustering.

Keywords: Ambulatory blood pressure monitoring, ant-persistent series, Poincaré Plots, circadian rhythm.

1 Introduction

1.1 Rationale of actuality

Ambulatory blood pressure monitoring (ABPM), shortly termed as a 24-hours test, is a standard and wide-spreading medical procedure [1-5]. This test is in use for hypertension diagnostics. Modern tolerant to motion devices with memory, Bluetooth and client-server support [4], with detail protocols of the readings processing [5], allow medics the accurate testing anywhere and every time.

Why such testing is so actual nowadays? Because high blood pressure (BP) puts you at risk for heart disease and stroke, which are leading causes of death in many countries of the world. One-third of adult Americans, for example, need permanent BP control due to hypertension [6]. That is quite enough to reckon the ABPM as an actual object despite its studies have a rather long history (about 50 years).

Meanwhile, ABPM ensures highly effective diagnostics indexes. The so-called "white-coat effect", masked hypertension, nocturnal hypertension, and sustained hypertension, seems to be most prominent among them [1]. The obvious advantages ABPM regarding the episodic tests have been pointed out in [1, 3]. Besides, ABPM is a useful annex to cure of hypertension, especially with medications [1,2].

Therein, the search for new models of ABPM processing and data mining still can be useful and actual.

1.2 Poincaré Plots as models and data mining with them.

Let consider an ABPM reading as three mutually connected and unified time series of the same capacity (24 trials is a typical length). Poincaré Plots (PP) seems to be a handy tool for the presenting and study of variabilities inherent in these series [7-12]. Yet, we do not know any papers using PP for ABPM data. Perhaps, data analysts had some doubts regarding the little length of series? In spite of this, we intend to check PP`s validity for short enough series of ABPM.

PP analysis was first applied to the heart rate [7,9, 11,12]. However, its sphere of using may be wider [8, 10]. PP analysis, initially tuned to the evaluation of short-term and long-term variabilities of the heart rate [7,11], is now out these bounds [8,10,12]. The fractal nature of a PP [12] allows using its fractal index for the deeper insight in the persistency of each series [13]. That is vital for diagnose and clinical decision making.

The PP is an embedding of a time series into the two-dimensional (2D) space if one is looking from the mathematics point of view [14]. It can be described by simpler words. PP is a dependence of successive time series terms on the previous ones [9,10,11]. Each pair of time series members (successive and previous term) corresponds to a point on the 2D-plane. PP is just the "cloud" of such points.

Pay attention, this object has the fractal properties [11,12]. It means that a fragment is statistically equivalent to the complete PP. If so, then one can count that PP involving 24 points is equally well as another PP with a larger capacity.

1.3 Motives and aims

The last paragraph of the previous subsection explains our motives. We want to apply PP to ABPM data mining. Indeed, fractal nature can give the virtually equal rights for lengthy and shorty series like ABPM. Thence, the doubts as for the little length of the ABPM series might be an excess fear.

The first of our goals is to show the validity and usability of PP analysis concerning the ABPM short series. The second aim is the study of series persistence and predictability on this base. Our third aim is the study of the diurnal changes (the rhythm) of BP if exists.

We are going to determine the ordinary descriptors for both short-term (SD1) and long-term (SD2) variabilities besides. It will be realized within a case-study.

2 Data provenance, modeling, and data mining

2.1 Data provenance and the chart of an ABPM series

One anonymous patient had had hypertension with a night-time dip of B. Oscar 2 Ambulatory Blood Pressure Monitor [4] was in use for his/her ABPM. Data of this case study was published in [5].

These data include the hourly trials of systolic BP (SBP), diastolic BP (DBP), and heart rate (HR) during 24 hours, performed by a certain protocol. Start date: 04-Apr-2002 16:13. End date: 05-Apr-2002 16:30. Duration of test: 24:17. The patient had had hypertension with a night-time dip of BP.

The initial data had all series with a length of 60 samples. The downsampling to the length of 24 samples was performed by hourly averaging.

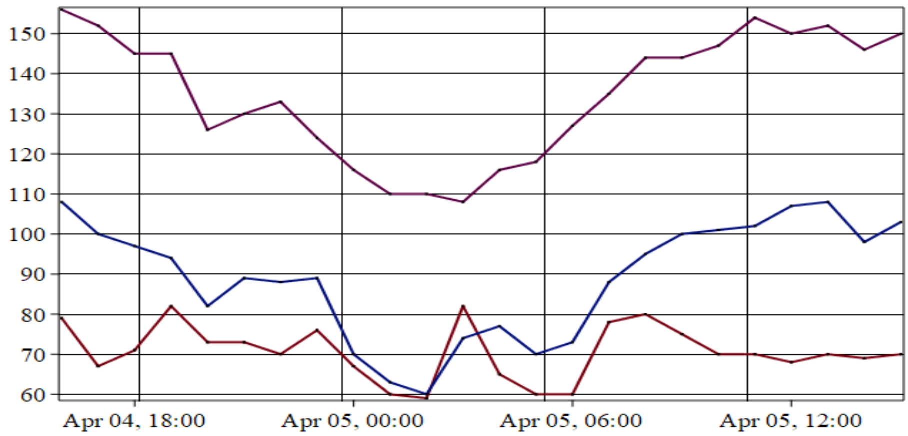

Fig. 1. The chart of the ABPM. Two upper curves illustrate SBP and DBP respectively, measured in mmHg. The lowest curve reflects HR in beats per minute (bpm). The sleep-time dip of BP is especially visible on the SBP series.

Fig.1 shows all the time series of ABPM. Note, the vertical scale of Fig1 is graduated in mmHg for SBP and DBP, but in bpm for HR.

2.2 Poincaré Plots as a data model and data mining

Let consider a time series with the length N. Its Poincaré Plot can be presented as a data matrix [14]:

$$D_N = \begin{pmatrix} x_1 & \cdots & x_{N-1} \\ x_2 & \cdots & x_N \end{pmatrix} \tag{1}$$

Here x_n is a term of series. This matrix has Hankel's type and the rank equal to 2. Taking the first row as the vector of arguments and the second one as the vector of dependent variables (a function) one can build the PP of the series. Such a plot is an embedding (or a projection) of the time series into 2D space(into a projective plane).

Let present the Poincaré plot for the SBP series. That shows Fig.2. The HR and DBP plots are similar to this plot

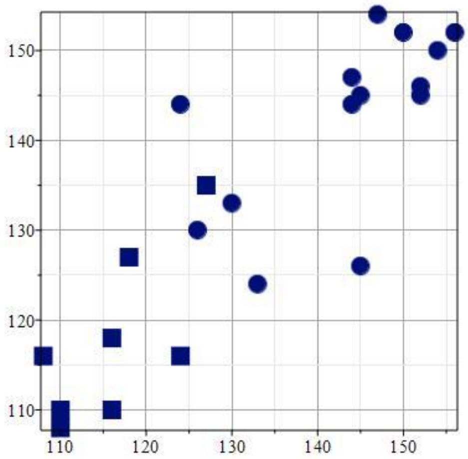

Fig. 2. The PP of systolic blood pressure series (SBP). Solid circles show the day trials, solid boxes - the night ones. Note, both axes are graduated in mmHg.

Fig.2 shows typical Poincaré Plot, elongated in the quadrant bisectrix direction. The scatter of points along the bisectrix and along the normal to that defines two standard descriptors SD2 and SD1 which were mentioned above. They and their ratio R are presented in Table 1.

Table 1. Variability descriptors and their ratios for ABPM data series.

	SD2	SD1	Ratio
Heart rate (in bpm)	6,3	7,4	0.86
SBP (in mmHg)	4.9	21.6	0.23
Dbp (in mmHg)	5,7	19.7	0.29

The ratios in the last column estimate the randomness of the series. One can see this ratio is much larger for heart rate. Meanwhile, these are close each to an-other having much lesser values if we speak about blood pressures. It means the heart rate is presented by the more random time series. Long-term variabilities are dominant for both BP series. Both variabilities are comparable for heart rate series.

We suggest here another indicator for PP. That is the fractal index (d) [14] or the fractal dimension [16,17]. The set of points lying on a single line segment or around that (see Fig.2) is quite similar to the generalized Cantor set [18]. That give us rights to expect

$$0 < d < 1 \ and \ HE = 1 - d \tag{2}$$

where HE is known as Hurst exponent [14].

The above expectations are confirmed by our results collected in Table 2.

Table 2. Fractal indexes, their standard deviations, Hurst exponent, and adjusted determination coefficients (R squared) to ABPM data.

	d, fractal index	Standard deviations	HE, Hurst exp.	R squared
Heart rate	0.72	0.09	0.28	0.91
SBP	0.69	0.07	0.31	0.94
DBP	0.79	0.08	0.21	0.94

The determination coefficients are close to 1. It means, the scaling law as the main trait of fractals [14, 15], is fulfilled well enough for each PP.

Besides, the values of fractal indexes are obviously above the critical value of 0.5. This border divides the persistent and anti-persistent time series [14]. Our data contain only anti-persistent ones. That means the lacking of clear trends first. The curves of-Fig.1 might be considered as the "pink" noise. It is characterized by the "negative" memory: if positive increment was registered in the past interval, it will be probably followed by a negative increment and vice versa [14]. Such series are often termed as "returning the mean value" ones. Since they are predictable enough.

It is useful to test the above conclusions via another independent method. There are many various ways to forecasting time series [18]. We have selected one based on the Exponential Smoothing Model first implemented in one of the program packages of Maple18, namely in Time Series Analysis [19].

This software allows us to pick up an optimal "Error-Trend-Seasonality" (ETS) model for each time series separately at several or several dozen possible. Then, one can make a short-time (a few steps) forecast for future behavior of series on the base of the ETS model [19].

We found a uniform ETS-model for all our series as most probably. It predicts additive undammed errors (noise), no trends, and no short-time seasonality. That is in accord with the previous results about anti-persistency, getting from fractal index estimations.

Table 3. The 8-hours forward forecasts and mean values of ABPM series.

	Forecasts	Mean values	Standard Dev.
HR (bpm)	70	70	7
SBP (mmHg)	150	135	16
DBP(mmHg)	103	89	15

The 8-hours forward forecasts are presented in Table.3 each series. The reader can see, the divergences between forecasts and mean values do not exceed the standard deviations.

2.3 Circadian rhythm affects blood pressure

The reader could note the nocturnal dips in Fig.1 and two clusters of nocturnal and day-time points in Fig. 2. Clusters are localized at lower left and upper right corners of PP. These phenomena are the result of circadian rhythm [20, 21] and connected.

Here we are going to confirm the statistical significance of this effect. To do that one can to perform the standard statistical two-sample test regarding the difference of two means. Each sample was presented either day-time trials (16 samples) or nocturnal ones (8 samples).

The Null hypothesis was: sample drawn from populations with the difference of means equal to 0. An alternative hypothesis was: sample drawn from populations with the difference of means not equal to 0. The confidence level was equal to 0.99.

Performed statistical tests provide evidence that the null hypothesis is false for both blood pressure series (SBP and DBP). However, the Null Hypothesis is acceptable for heart rate series. Thus, the nocturnal dips are statistically significant for the BP series only. Nocturnal heart rate dip lefts under a doubt.

Let's visualize the above result. Fig. 3 shows a box-plots for SBP and DBP.

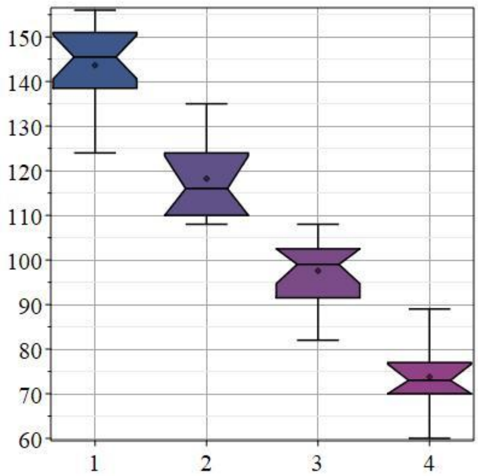

Fig. 3. The statistical box-plot for blood pressures. Here horizontal axis labels are 1— SBP-day, 2—SBP-night, 3—DBP-day, 4—DBP-night. The vertical axis is graduated in mmHg.

Statistical analysis confirms the effect of circadian rhythm on the blood pressures at least. Thus, two clusters of the PP for SBP, which were evident from Fig. 2, are not random. They reflect the circadian rhythm and its impact on blood pressure and can be the diagnostic sign for medics. Note, a certain association between dip of blood pressure of asleep and increased incidence of cardiovascular events forces to search the medications inhibiting these dips [20].

2.4 Principal components of the data matrix for the Poincaré Plot.

Poincaré Plot in the arbitrary system of coordinates. Matrix's rows are strongly correlated. Principal component analysis (PCA) allows finding such rotation of the coordinate system, after which the rows of the transformed data matrix will be decorrelated [14]. Such a rotation is termed as a transition to the main axes. Data matrix (1), transformed into the main axes, contain two independent rows. Both are so-called principal components. One of them presents a signal, while the second one is noise.

Thus, the principal components of the data matrix (1) show us the purified signal and the independent noise. Both principal components of the heart rate series are shown in Fig.4.

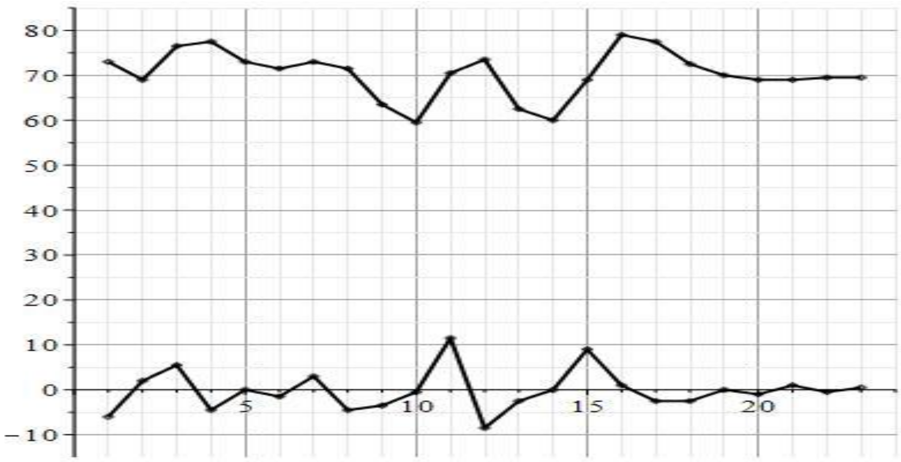

Fig. 4. Two principal components for heart rate series. The horizontal axis is graduated in samples, the vertical one – in beats per minute (bpm).

One can see upper principal components fluctuate around the mean value (or forecasted one, see Table 3) without a visible trend. Meantime, the noise has the zero-mean value, is undamped and additive, in accord to the Exponential Smoothing Model (see above section 2.2). The standard deviation for the noise of Fig, 4 is close to the presented in the first row of Table 3 (4.5 versus 7).

The doubts about nocturnal dip look like as if grounded if considering the behavior of the upper curve in the asleep range (from 8 to 16 samples). We will yet return to this question below.

The like graphs for SBP and DBP show the similar properties of the noise. The noises were additive and undamped alike to Fig. 4. However, the nocturnal dips were clearly visible for both the pressure series.

Therefore, PCA partitioning is in agreement with the results of the previous subsections. We mean the results about anti-persistence of series, absence of trends, noise features and effects of the circadian rhythm, if do not take into account a little problem with the heart rate for now.

Note, that the PCA rotation matrix was virtually corresponding to the simple rotation on the angle 45 grades clockwise. For all series.

3 Discussions

3.1 What about heart rate nocturnal fall?

We could not prove the presence of any nocturnal drop in the heart rate frequency neither statistically nor via PCA. Meantime, such fall off have to exist as it was proven in the wider investigation [21]. Let try the PP once more (see Fig.5).

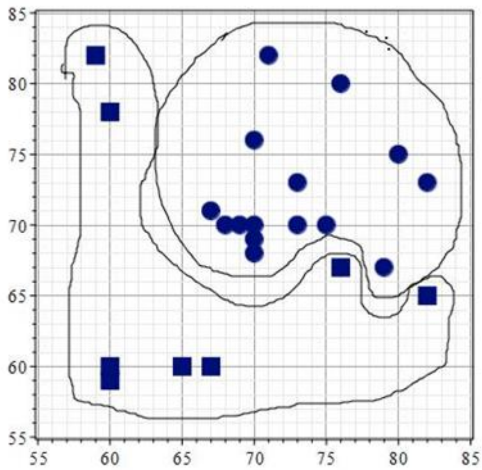

Fig. 5. The PP heart rate series (HR). Solid circles show the day trials, solid boxes - the night ones. The bounds of two clusters are shown, Note, both axes are graduated in beats per minutes.

The Poincaré Plot in Fig. 4 clearly shows two clusters, day-time one and nocturnal ones, al-located according to the same principle as the clusters of Fig. 2. There are only more complicated bounds between clusters in Fig. 5. Thus, the problem has got salvation. Clustering of PP, hence and nocturnal drop, is inherent in all ABPM series, including heart rate, in accord with [20, 21].

Moreover, we can now understand the reason for occurring this problem in our case study. It is a specific variability of heart rate series for the anonymous patient [5], reflected in Fig. 5 (compare with Fig. 2) and in Table 1.

3.2 Efficacy of Poincaré Plots for ABPM readings processing

Let us list the results, often non-trivial or even hidden in data, which were mined with Poincaré Plots at the ABPM case study. Those are followed results:

1. The estimation of descriptors of variability and their ratios (see Table 1). It allows us to conclude about the dominance of long-term variability for ABPM data.
2. The evaluation of the fractal indexes and Hurst exponents for Poincaré Plots (Table 2). It allows the conclusion about the “negative" memory for all series, which defines the anti-persistence of data. It permits the short-time prognoses for series.
3. Visible two-cluster structure of Poincaré Plots (Fig. 2 and 5) allows detecting the circadian rhythm effect for ABPM data.
4. Principal component analysis of the Poincaré Plot data matrices allows us a simple partition of data on two parts: signal and noise.

The time-series analysis, particularly the Exponential Smoothing Model, and Principal component analysis (PCA) were needful for the confirming of the conclusion of point 2 of the list. Meanwhile, it was unlucky to trace the impact of circadian rhythm on the heart rate neither statistically, nor via PCA. Only the Poincaré Plot clustering suggests the conclusion of point 3. The simple and handy way of the moist extracting also uses the PP data matrix (see point 4).

The reader can see, that point 1 of the list, for that the method of PP is tuned, does not far exhaustive. The efficacy of the PP method of ABPM data mining seems to be quite suitable.

3.3 Is the length of the ABPM series enough to rely on Poincaré Plot analysis?

Our position is “quite enough”. We are asserting it because of the following main arguments:

1. All Poincaré Plots of the ABPM series have fractal properties.
2. The main trait of fractals, the scaling law, or the double logarithmic bond between the scale of covering element and their number, is fulfilled rather good.
3. Any fragment of the fractal structure is statistically equivalent to the whole one. Hence, the PP with 24 points in the cloud is as good as its self-similar “brother” with 240 or 2400 points.

Indeed, a short series, so and the limited number of points in PP, drops the accuracy of the estimations fractal indexes. Table 2 shows the relative tolerance of 10-12% for the fractal indexes. However, such accuracy is not critical, that is rather enough for sure conclusions in the case study.

The short length of the ABPM series is one of the reasons for the trends and short-time seasonality lack of. It simplifies the common analysis, Home blood pressure monitoring (HBPM), working with much longer series, showed recoverable trends and long-term seasonality [22, 23]. On the other hand, ABPM data are more convenient for studying circadian rhythm and its disorders.

4 Conclusions

Let us summarize all the above said as a set of short asserts.

1. Poincaré Plots turned out an excellent way of ABPM data mining.
2. All ABPM series were anti-persistent and so allowing the short-time forecasts.
3. One can divide each series into the signal and noise transforming its Poincaré Plot data matrix to the principal axes.
4. Circadian rhythms reflect themselves into the two clusters of Poincare Plots of ABPM data series
5. ABPM series have no clear trends or short-time seasonality.

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