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The Photoplethismographic Signal Processed with Nonlinear Time Series Analysis Tools.

- José Luis Hernández Cáceres.
  Centro de Cibernética Aplicada a la Medicina (**CECAM**). Instituto Superior de Ciencias Médicas de La Habana.
  E-mail: caceres@cecam.sld.cu
- Karelia Cabañas.
  Policlínico " 5 de septiembre". Santa Fé, Ciudad Habana.
- Jersys O. Falcón Rodríguez. Centro de Cibernética Aplicada a la Medicina (**CECAM**). Instituto Superior de Ciencias Médicas de La Habana.
- Rolando Hong.
  Centro de Cibernética Aplicada a la Medicina (**CECAM**). Instituto Superior de Ciencias Médicas de La Habana.
- Abel García Lanz. Centro de Cibernética Aplicada a la Medicina (**CECAM**). Instituto Superior de Ciencias Médicas de La Habana.
- Luis García Domínguez. Centro de Cibernética Aplicada a la Medicina (**CECAM**). Instituto Superior de Ciencias Médicas de La Habana.

RESUMEN

Este trabajo aborda el análisis de las señales fotopletismográficas digitales (PPG) con herramientas no-lineales de serie de tiempo. Para esto se aplicaron las siguientes técnicas analíticas:

I- Estimación polinomial de alto grado para la corrección de la línea base.II- Análisis espectral mediante transformada rápida de Fourier.III- Estimación de la dimensión fractal mediante el método propuesto por Higuchi para el dominio del tiempo. IV- Estimación no paramétrica por núcleos para la reconstrucción de los atractores libres de ruido y de los componentes estocásticos de las señales.

La señal PPG puede ser dividida en los tres componentes siguientes:

1. Una tendencia no-estacionaria, no-lineal dependiente del tiempo que se relaciona con la mayor parte de la no-estacionaridad de la señal PPG.

2. Un componente no-lineal de ciclo límite determinístico invariante que corresponde a la generación de ondas pulsátiles que reflejan el punto más relevante de la señal PPG en los estudios clínicos.

3. Un componente estocástico que sea, por lo menos, fractal parcialmente. Este componente soporta menos del 5 % de la varianza de la señal corregida básica.

La suma de la base (1) más los componentes estocásticos (3) puede explorar las propiedades fractales de la señal PPG original.

Se considera que la separación de la señal PPG en tres componentes diferentes posibilita la obtención de nueva información, tanto para las investigaciones básicas, como para propósitos clínicos.

ABSTRACT

Finger photoplethismography (PPG) signals were submitted to nonlinear time series analysis. The applied analytical techniques were: (i) High degree polynomial fitting for baseline estimation; (ii) FFT analysis for estimating power spectra; (iii) fractal dimension estimation via the Higuchi’s time-domain method, and (iv) kernel nonparametric estimation for reconstructing noise free-attractors and also for estimating signal’s stochastic components.

The PPG signal could be separated into the following 3 components:

1) A baseline, nonlinear-time-dependent nonstationary trend, which accounts for most of the nonstationarity of the PPG signal.

2) A nonlinear, time invariant deterministic limit-cycle component, which corresponds to the generation of pulsatile waves, the most relevant point of the PPG signal in clinical studies.

3) A stochastic component, which is at least partially fractal. This component bears less than 5% of the variance of the baseline-corrected signal.

The sum of the baseline (1) plus the stochastic (3) components accounts for the fractal-like properties of the original PPG signal.

We consider that the separation of the PPG signal into three distinguishable components opens the possibility for extracting new information both for basic research and for clinical purposes.

INTRODUCTION

Finger photoplethismography (PPG) is a commonly used technique in medical services. In most of the cases it is used for measuring the heart rate. A recent research suggests the possibility to use plethismography for measuring blood pressure and other indices of peripheral vascular activity [2,4,14,15,17]. However, it has been pointed out that there may be difficulties related to wrong data interpretation [3,6].

Nevertheless, several groups suggest that the plethismographic signal carries very rich information about cardiovascular regulation, which commonly is not obtained by using the available methods [1, 13,16].

Thus it seems to be justified the use of advanced signal analysis techniques for the study of plethismographic signals.

In this work, we applied a high-degree polynomial detrendening technique in combination with a kernel nonparametric method for evaluating plethismographic signal dynamics.

Our results indicate that the detrendened plethismographic signal is a very stable, highly nonlinear signal with a very small stochastic contribution. Application of the kernel nonparametric estimator revealed that the purely deterministic nonlinear component corresponds to a low dimensional limit cycle resembling the original appearance of the phase portrait from original data. The stochastic component of this signal, however, is not a white noise. At least an important contribution of 1/f noise may be detected. Regarding its spectral properties, the noise component shares some of the properties of heart rate variability signals reported in literature. Thus, the application of nonlinear techniques allowed separating three distinct components of the plethismographic signal:

A slow non-stationary component probably related to recording artifacts.

A non-linear deterministic component carrying information about the waveform features, and corresponding to a limit cycle.

A noise non-stationary component with 1/f dynamics, suggesting at least partial fractality. This component seems to share important aspects of the R-R signal described in literature.

The two last components may carry important information both, about the cardiovascular and the autonomic nervous system. Thus, we may expect that the previously mentioned methodology may open new possibilities both for research as well as for diagnostic purposes.

MATERIALS AND METHODS

Subjects

Transmission plethismography (PG) recordings were obtained from six healthy volunteers (three female and three males), aged 24-46 years (average age 32 years). The subjects were seated during examination, with their hands laid comfortably on the table at the level of the heart. Recording time was 5 min after a rest period of 10-min. Room temperature was 25 oC.

PPG Recordings

The transmission PPG probe of the commercial pulse oxymeter (OXY9800-COMBIOMEQ, Cuba) consisted of a light emitting diode (LED) of 865 nm and a PIN photodetector (peak spectral response 865 nm) placed on different sides of the probe, so that they were attached to the two contralateral surfaces of the finger.

The PPG probe was attached to the right hand. The computerized system allowed to optimally adapting the amplification level for obtaining a nonsaturated signal. The PPG signal was digitized (75 Hz) and stored in ASCII format. All the statistical processing was performed off-line.

Data analysis.

Signal processing included:

- Power spectrum estimation.
- Baseline correction.
- Correlation, dimension, estimation.
- Fractal Dimension estimation.
- Nonlinear Dynamics identification.

Power spectrum estimation was performed through the FFT algorithm applied to the original signal [20]. The power spectrum was estimated as the square of the absolute value of the FFT. Linear fit was performed to log-log transformed power spectra for obtaining an estimate of the fractality index a

Baseline correction was performed by adjusting the whole signal to a polynomial of the type:

where S_t is the plethismografic signal evaluated at time t; $a_0,a_1,\ldots,a_k$, are real constants, corresponding to the model's coefficients. The order of the model was set at k=22, since this value better warranties stationarity of the corrected signal without affecting the shape of the pulsatile waveforms.

The aim of this procedure is to correct the signal for nonstationarities, while preserving the original features of the waveform.

Three experts independently checked for the preservation of the waveform's shape after the detrendening procedure.

Correlation dimension estimation a Grassberger Procaccia algorithm [10], was applied to the detrendened signals. In each case the estimated value was compared with that of a surrogate signal obtained via inverse FFT analysis with phase randomization, as described in [10]. Two-dimensional projections of the reconstructed phase portraits were obtained applying the Taken's vector method [8].

Nonlinear Dynamics identification. Kernel nonparametric analysis was applied to the trend-corrected signals. In kernel autoregression, the signal is fitted to a model of the type:

$$S_t = F(S_{t-1}, S_{t-2}, \ldots S_{t-r}) + \varepsilon_t$$

The function nonlinear F is obtained as a weighted average of the observed points in the phase space, the nearest points bearing the highest contribution. A detailed description of the method appears in the references [7-11, 18].

During the application of the kernel procedure, the following information was obtained:

- Order of the autoregressive model (r). It reflects the number of past values necessary to optimally describe the autoregressive function.

Nonlinear correlation coefficient expressed as:

$$\eta = \sqrt{\left(1 - V_{ne}/V_{tot}\right)}$$

- where Vtot corresponds to the signal's variance and Vne is the unexplained variance after applying the model.
- In the linear case, this expression is equivalent to the linear correlation coefficient [10].
- Noise free realization generation (NFR). The noise free realization [9,18] is obtained via sequential estimation of the function F to previously estimated data points of the time series. The first points of the series are set at random. The 100 first points of the NFR are discarded for assuring the absence of transients in the NFR.

The phase portrait reconstructed from the NFR gives information about the noise free dynamical system.

RESULTS

General features of the signal.

An original, untreated recording is shown in fig 1.

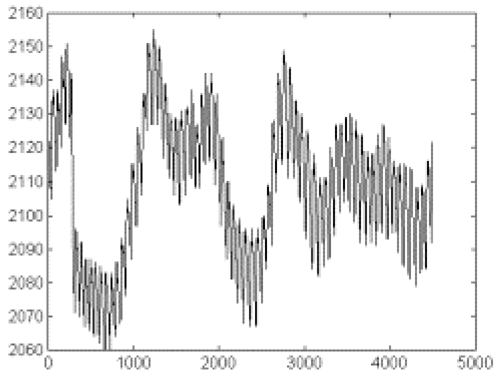

Fig 1. Photoplethismographic (PPG) signal obtained from a female healthy subject (age 30 years). Legend: Abscissas-time, expressed in 13,33-ms time units. Ordinates- PPG signal amplitude in arbitrary units.

As appreciable, significant baseline shifts are present in this signal. It is possible that this is a consequence of recording difficulties (fixation fails, subject's movements, etc), though it is not possible to exclude some physiological influences. A detailed look up at the signal shows the presence of quite stable waveforms, whose appearance is relatively little influenced by baseline shifts.

In the literature, most of the attention is paid to pulsatile waveforms ([1,13,19]).

It could be plausible to suppose that this signal is a more or less periodic component affected by random influences. However, some evidences may not support this view.

In fig 2 a log-log plot of the signal's power spectrum is shown. As appreciable, a linear component with a negative slope could be appreciated. The estimated slope from the power spectrum is 1.83, close to that of fractal Brownian process [12].

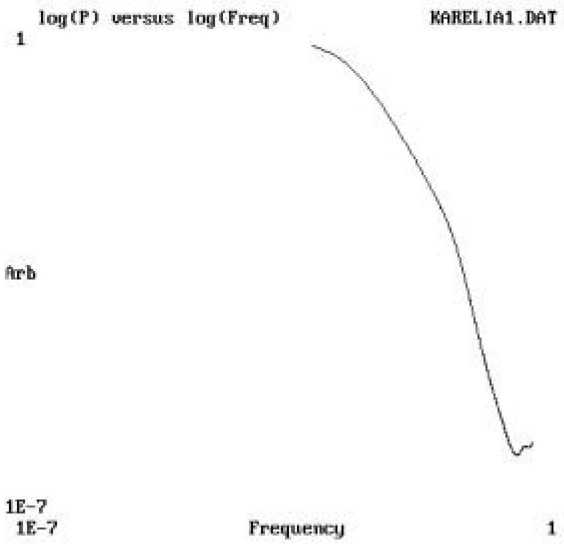

Fig 2. Log-Log plot of the power spectrum estimated from the recording in 1-a. Legend: Abscissas, frequency in arbitrary units; Ordinates-Power spectral density. Notice the presence of a relevant negative slow linear

component. The peak corresponds to the periodic pulsatile waves.

We applied a time domain algorithm proposed by Higuchi for the estimation of the fractal dimension [12]. Higuchi's method also allows the estimation of the power-spectral slope in log-log coordinates (a).

The signal’s dimension was 1.65, which correspond to a fractal process. The spectral log-log slope (a) estimated by Higuchi’s method was 1.70, close to that estimated from the power spectrum (1.83, see above).

Since these observed features of the original signal may not be explained by its periodic component, nor by its perturbations with Gaussian noise, it has sense to try to find out what components may be responsible for different properties of the PG signal.

Base Line Correction

Fig 2a. shows an original signal and the estimated 22-degree-polynomial. As appreciable, the procedure applied gives a satisfactory estimate for a time-dependent base line for the original signal.

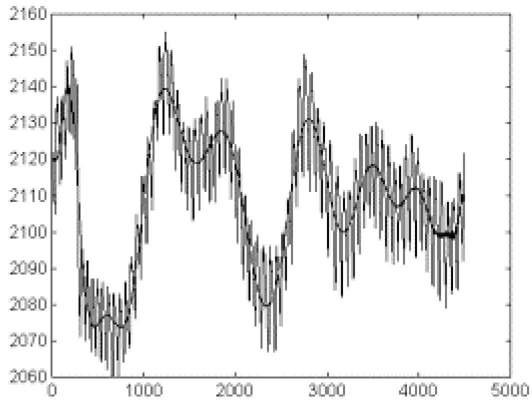

Fig 2-a. The recording from fig in 1-a and its time-dependent trend estimated by fitting to a 22-degree polynomial. Legend: as in fig 1a

After base line substraction, a detrendened signal was obtained (fig 2b).

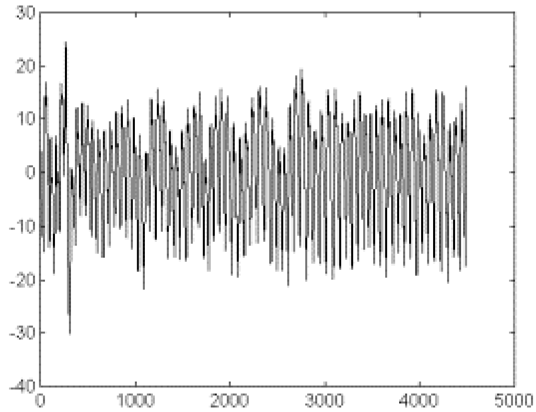

Fig 2-b. The result of subtracting the estimated trend in fig 2a from the signal in fig 2. This is the trend-corrected component. Legend: as in fig 2.

Visual appreciation suggests that the detrendened signal seems to be much more close to a stationary one than the original signal. This may also be supported with quantitative data. Fig 2c represents the dependence of the standard deviation of the signal for both, the original and the detrendened signal. This dependence for the original signal is typical for nonstationary time series, included fractal ones ([12,20]).

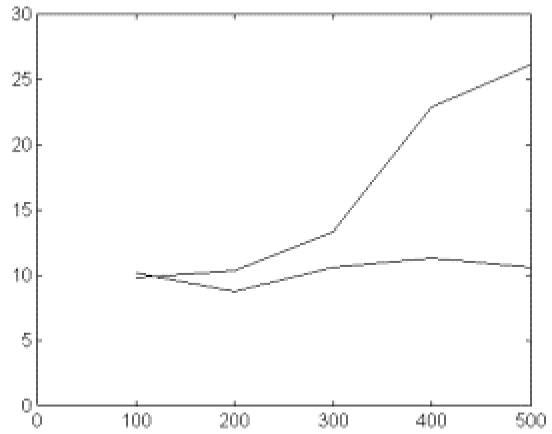

Fig 2-c. Dependence of the signal's standard deviation upon segment's length for the original trace in fig 2 (upper line) and for the trend-corrected signal from fig 2b. Legend: abscissas-time-segment duration in 13.3 ms sampling units. Ordinates: standard deviation.

At the same time, the detrendening procedure did not affect the appearance of the pulse waveforms.

Fig. 3a shows a 2-dimensional projection of the reconstructed phase portrait.

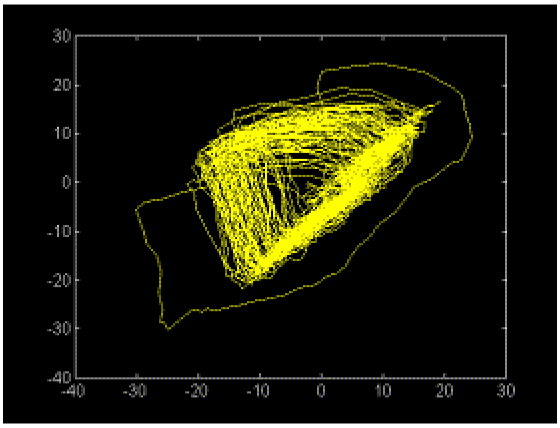

Fig 3a. S-D projection of the reconstructed attractor, using the Takens method. Abscissa St. Ordinates St-10.This picture corresponds to the trend-corrected signal in fig 2b.

In figure 3b is represented the same phase portrait obtained from another record taken from the same subject 3 days after. The high stability of the picture may be suggested from both pictures.

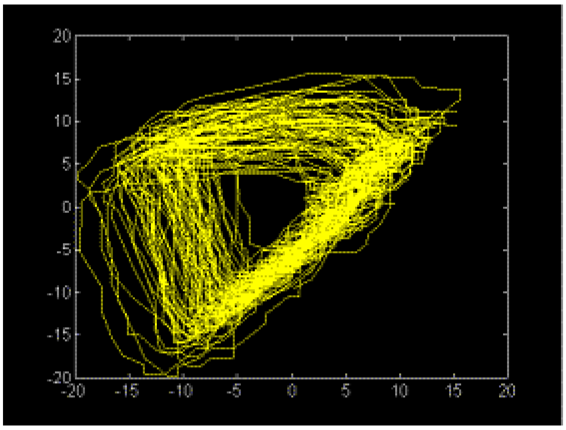

Fig 3b. The same as in fig 3a, applied to another recording from the same subject taken three days after. Notice that the difference in scales accounts for very similar attractor geometry.

The appearance of this signal could suggest about a low dimensional chaotic dynamics, very similar to the Rossler attractor.

However, as shown previously for EEG signals, an alternative explanation may be that of a limit cycle perturbed by noise [9].

We estimated the correlation dimension of the detrended signal. For that we applied the Grassberger-Procaccia algorithm. The value of correlation dimension corresponding to the detrended signal was D=4.694 ± 0.662 for an embedding dimension of ED=10. This value may suggest about a low dimensional chaotic attractor. However, for the phase surrogate of the detrended signal this value was 3.64 ± 0.51. Thus correlation dimension value does not support the hypothesis of a chaotic attractor.

Nonlinear identification techniques allow to separate deterministic and stochastic components from a nonlinear stochastic time series. One of the most powerful methods of nonlinear identification is the kernel nonparametric autoregressive estimation. However, this method works satisfactorily only for stationary signals. Thus the detrendening procedure allowed us to apply a nonlinear identification method to detrended data.

Application of this method to 1000-points segments of the original time series revealed that the order of the autoregressive model was equal to 3 in more than 85% of the segments analyzed. The nonlinear correlation coefficient was higher than 0.99 in all cases, suggesting the presence of a low-dimensional nonlinear deterministic component in the detrended signal.

Fig. 4 shows a phase portrait obtained from the noise-free realization. The comparison to figs. 3a and 3b supports the idea of the plethismographic signal modeled as a limit cycle perturbed by random contributions.

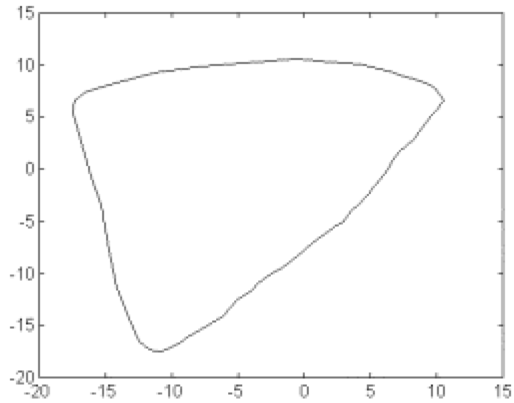

Fig 4. The same as in fig 3a, applied to a noise-free realization obtained from applying kernel nonparametric autoregression to the first 1000 points of the trend-corrected recording in fig 2b. Notice the limit cycle structure of the noise-free attractor.

Though the generated noise free realization may carry information about the nonlinear dynamics of pulse wave generation, it obviously may not account for the fractal-like properties of the original recording.

Properties of the Residuals

From the application of the kernel autoregression there still remain the residuals of the estimation. The residual's signal may give a good estimate of the noise component in the model. If we compare the variance of the noise component to that of the original signal we may observe that this component seems to be negligible compared to the original signal or even to the noise free realization (it's value never reaches 5% of the variance of the detrendened signal).

However, the residual's signal also may contain interesting information.

In particular, the residuals' signal (fig 5a) does not seem to be a white noise signal. Is spectral slope in log-log coordinates is a=1.3 (r=0.73; n=450). Though it is lower than the value of the original signal this suggests about the presence of fractal components in the residual's signal (see fig 5b).

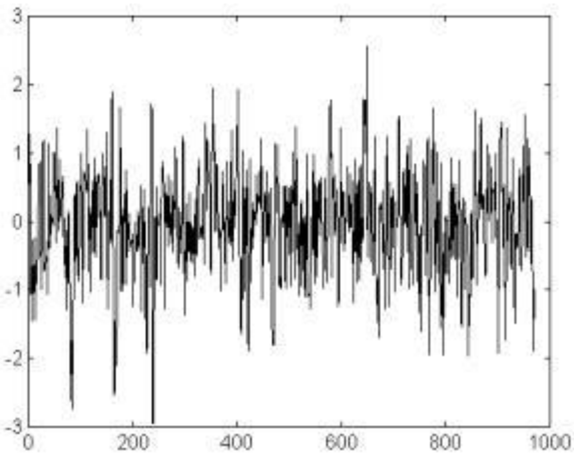

Fig 5a Residuals after the estimation of the expected values in the recording from fig 2b. according to the nonlinear nonparametric autoregressive model. Legend, as for fig 2. Notice the small amplitude of the signal, compared to fig 2b, or 2a.

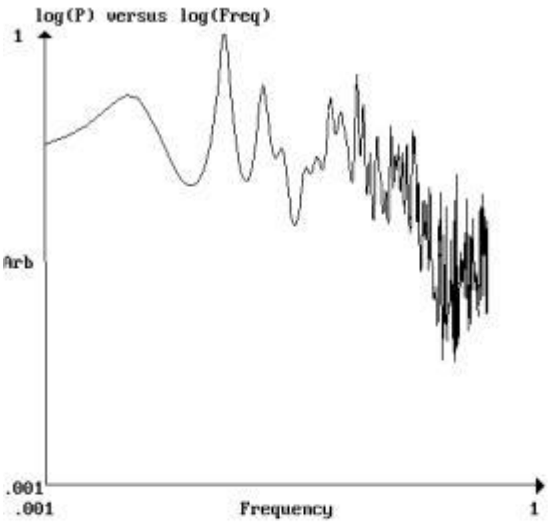

Fig 5b. Log-log power spectrum of the residual's signal in fig 5. Legend, as in fig 2. After discarding the first 15 points on the left part of the trace, the curve fits to a straight line with a = 0.83 and the linear correlation coefficient r=0.76 (N=450 data points).

Finally, we decided to reconstruct a signal composed by the sum of both residuals and the estimated base line. This signal will carry information about the original signal with exception of the part corresponding to a deterministic nonlinear dynamics.

After submitting this signal to the f Higuchi's algorithm, the estimated signal's fractal dimension was D=1.65, which corresponds to a value of a=1.71, almost identical to the 1.70 value obtained from the original data (see above).

Fig. 6 represents the log-log spectral plot of the baseline-added residual signal.

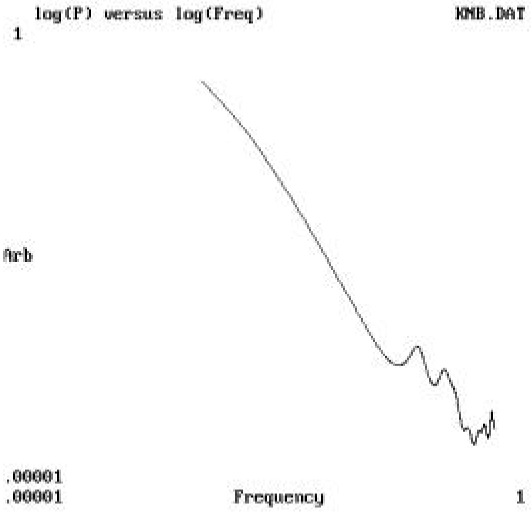

Fig 6- The log-log power spectrum of the sum of the signal in 5 and the trend component from fig 2a. Similarity to fig 2 is appreciable.

DISCUSSION

The main results obtained in this research may be summarized as follows:

The PPG signal can be represented as a sum of at least three processes, including:

- A low dimensional nonlinear component with a periodic attractor, which accounts for the plethismographic signal waveform, commonly studied [13].
- A more or less regular high-amplitude-baseline signal, which may be, approximates as a polynomial function of the time. The baseline is likely to include both artifacts (patient's movements, sensor's fluctuations, etc) and physiological components (tissue replenishing with blood, respiration, etc. [16]).
- A low-amplitude random component with fractal-like properties.

The original signals present not only periodicities due to the presence of the pulse waves, but also fractal-like properties. The sum of the baseline and the residual's signal (after applying a kernel nonparametric method) may account for the fractal-like properties of the original signal.

Thus our results suggest that it is possible to separate the plethismographic signal, via nonlinear filtering, into components carrying different types of information.

In our opinion, our results open new possibilities, and, at the same time, give birth to new questions.

Thus the fact that the nonlinear deterministic part of the signal may be modeled with a nonparametric function of order 3 opens the possibility to find an analytical model for this component generation. Since this component is related to arterial compliance and resistance, as well as other factors contributing to blood volume increase during systole [16], this may open new possibilities for research and diagnosis of blood pressure regulation.

It seems difficult to determine the possible physiological components of the baseline signal. Though literature data refer to the baseline as inversely related to the blood volume in the tissue under examination [16], it is not excluded the contribution of recording artifacts to this signal. Thus, as described in [1] minor movements of the arm may change the signal baseline. It seems reasonable to suppose that physiologically-conditioned factors contribute to the fractality of the original signal, which could not be expected from low frequent trends in the signal.

At the same time, it seems difficult to ignore the physiological implications of the fractality of the low amplitude residual (noise) signal.

A considerable experimental material supports the idea of a partially fractal nature of heart rate variability signals [5,20].

However, the HRV signal is contained in the electrocardiogram, and, as assumed also in the plethismographic signal [16].

The signals analyzed were relatively short in terms of HRV analysis, and lasted fractions of a minute. However, if we believe in the truly fractality of a process, it must be present not only at long-range time scale, but also at microscopic scales [5].

On the other hand different authors have claimed the fractal nature of ECG complexes [5]. Thus it would not be surprising to find a physiologically conditioned fractal component in the PPG signal.

A major task remains to identify the physiological bases of these processes. In literature, several attempts have been made, as for example those related to interpret the fractal nature of the QRS-complex in the ECG as emerging from the fractal nature of the Hiss bundle [5].

Experimental research by Yamamoto suggested that the HRV fractal component is not affected by beta blocking, which suggests involvement of factors different from the autonomic nervous system in this process [20].

The possible diagnostic utility of these results also open new perspectives. Some of these questions are subject of further analysis by our group.

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