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Original Research Article

Real-time estimation of the spectral parameters of Heart Rate Variability

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ABSTRACT

Spectral Heart Rate Variability (HRV) parameters, LF (low frequency) and HF (high frequency), have an important role in interpreting slower and faster heart rate modulations. An online analysis method of HRV spectral parameters based on the modified Hilbert–Huang Transform (HHT) is proposed in the paper. A number of novel methods have been put forward to meet the demand of causal pre-processing of interbeat time intervals (IBI) series prior to application of HHT. Also in the real-time implementation of the HHT which is the combination of the Empirical Mode Decomposition and Hilbert spectral analysis an original extrapolation method of intrinsic mode function related to LF and HF spectral parameters was applied. The proposed algorithm allows temporal estimation of HRV spectral parameters in real-time with delays being reduced up to 60% with respect to the Short Time Fourier Transform (STFT) analysis. Such reduction in analysis delay can have an important significance in a number of cardiologic invasive procedures, e.g. in cardio-resynchronisation therapy (CRT).

1. Introduction

Combined efforts of clinicians and engineers have made it possible to use the data extracted from the Heart Rate Variability (HRV) to aid the diagnosis and prediction of various heart illnesses as well as ailments originating from different human organs but indirectly influencing the Autonomous Nervous System (ANS). A comprehensive review of HRV analysis techniques and their significance in diagnosing health status is available in [1]. A large number of computer analysis methods defined in the time-domain or the frequency-domain have been proposed to attain a more complete characterisation of HRV parameters and their diagnostic validity [2,3].

Time-domain methods are predominantly based on statistical analysis of the RR time series. The RR time series is obtained by detecting consecutive R waves in ECG recordings and noting time distances between them. The R waves are large amplitude ECG signal peaks of short duration that delineate the onset of the contraction of the cardiac ventricles, hence they are straightforward to detect (see Fig. 1). Variations over time in RR intervals allow to estimate the Heart Rate Variability (HRV). Example statistical parameters characterising RR time series are: the mean and standard deviation of the series, the root mean square of differences between consecutive RR time intervals and a number of geometric indices derived from the histogram of the RR intervals.

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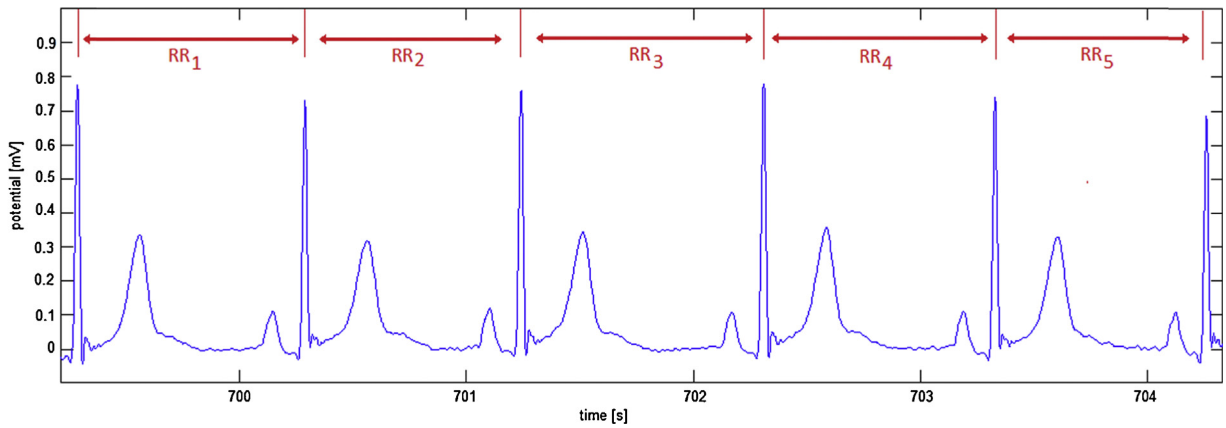

Fig. 1 – Derivation of RR intervals from an ECG (ECG recorder: Medea Kardio PCMu, lead II).

Two groups of methods are applied for estimating the HRV spectrum: the non-parametric spectrum estimates are the power spectrum density (PSD) or the Welch's periodogram [4] and the parametric approaches are autoregressive (AR) modelling, moving average (MA) modelling and combination of the both (ARMA) [5]. The frequency-domain methods allow for a better assessment of the fluctuations in HRV as a result of the modulation influence of the ANS. These fluctuations have been subdivided into low rate fluctuations characterised by the low frequency (LF) spectrum components (0.04–0.15 Hz) and by the higher rate fluctuations termed high frequency (HF) components (0.15–0.4 Hz) in the HRV spectrum [6]. According to the clinical interpretation, the sympathetic ANS control is related to the LF band and the parasympathetic ANS control is related to the HF band of the HRV spectrum. Thus, to quantify these two antagonistic regulatory mechanisms of the HRV the key spectral index characterising HRV is the LF/HF power ratio.

It is important to note that both the time-domain methods and the frequency-domain methods require an analysis of sufficiently long sequences of RR time intervals to provide reliable estimates of the HRV parameters. Such analyses perform poorly in an online HRV analysis tasks that are aimed at the assessment of instantaneous coupling variations between the heart and the ANS. Such variations occur during functional tests like tilt tests, body position changes, deep breathing, handgrip etc. Also, the results of recent research [7] indicate a new potential application of temporal HRV analysis. Namely, for patients who underwent cardio-resynchronisation therapy (CRT) it is possible to assess whether the resynchronising electrodes were properly placed. The anticipated improvement can be observed in the temporal variations of the LF and HF parameters.

In order to detect temporal changes of HRV parameters during the CRT procedure, real-time HRV analysis is necessary. There have been very few documented attempts to analyse HRV in real-time [8]. In this paper an online analysis method of HRV spectral parameters based on the modified Hilbert–Huang Transform is proposed.

In the standard off-line analysis, prior to estimation of HRV spectral components, the series of interbeat intervals (IBI) requires proper preprocessing. As shown in Fig. 2, for real-time HRV analysis standard methods for off-line analysis available in the literature [1] are not suitable. The major limitation of the online methods is that they need to be causal. Another problem hindering instantaneous analysis of the HRV spectral parameters comes from slow HRV signal variations, i.e. at the rate of fractions of cycles per second. Hence, derivation of reliable estimates of a spectral parameter requires processing of at least several entire cycles of the signal. In this paper both the analysis and necessary preprocessing steps in real-time are addressed, what results in a complete algorithm for real-time HRV analysis.

2. Preprocessing of HRV for real-time analysis

Prior to HRV analysis, a series RR time intervals also termed heart inter-beat intervals (IBI) needs to be properly preprocessed. This is because the elements of the HRV series are not uniformly spaced in time. There are also signal events that need to be corrected before further processing, e.g. occurrences of premature ventricular beats and false positive or false negative beat detections. Preprocessing consists of artefact correction, interpolation and uniform resampling.

In real-time processing and analysis the future samples are unknown. Therefore, artefact detection can only be based on analysis of previous samples. In many cases, it is much more difficult to distinguish between an artefact and an actual physiologic, sudden change in the heart rhythm. Hence the methods available for off-line analysis cannot be successfully adapted to real time processing.

In case of artefact deletion and interpolation into the gap, the interpolation can only be performed when the artefact has terminated and several valid samples have been measured. This introduces a significant delay as well as erroneous results since there are fewer nodes for interpolation.

Finally, a critical problem in real-time preprocessing of HRVs is the signal interpolation method itself. In many earlier works [6,9] cubic splines have been suggested as the most convenient interpolation method. In our case, the interpolated series is constantly updated by newly arriving samples and the new value significantly influences the recent part of the interpolation curve.

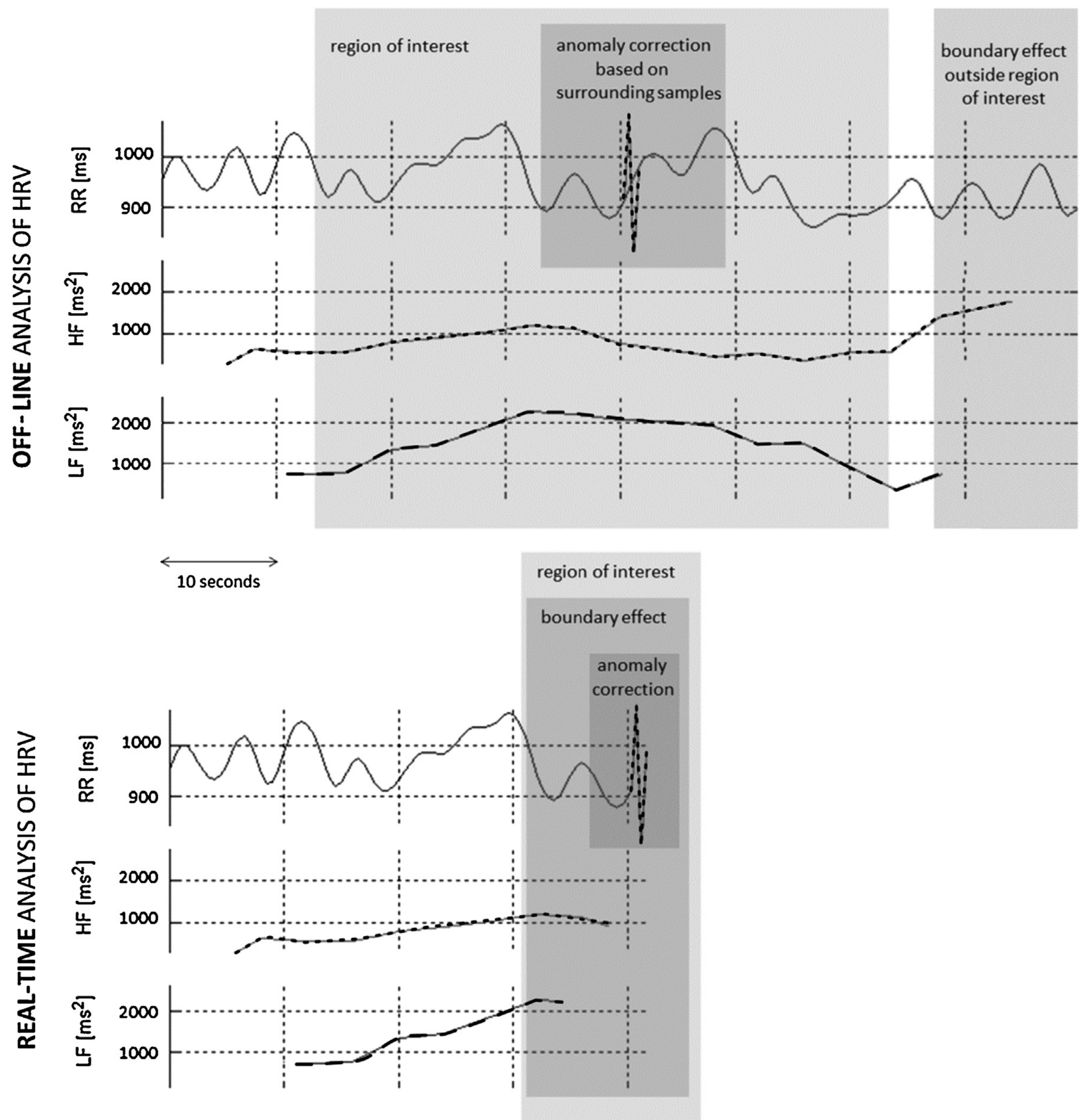

Fig. 2 – Overview of the approaches to HRV analysis: in an off-line analysis (upper panel) estimation of the LF and HF power spectral parameters can be implemented in a non-causal manner, i.e. the entire RR series can be accessed for processing, whereas in an online analysis (lower panel) the causality requirement complicates the analysis (see Section 2).

2.1. *Artefacts elimination*

In the approach suggested by the authors of this paper, every incoming sample is immediately checked for the artefacts using the criterion proposed in [10] and specified in Eq. (1).

$$\left|\frac{t_{k-1} - 2t_k + t_{k+1}}{(t_{k-1} - t_k)(t_{k-1} - t_{k+1})(t_k - t_{k+1})}\right| < U \tag{1}$$

where t_k is the time instance of the kth beat occurrence.

The value of the threshold U is chosen empirically. As seen from the equation the artefact occurrence is detected basing on two consecutive IBIs. In case of real-time processing these are the two last determined intervals. According to [10], if Eq. (1) is not fulfilled, either t_k or t_{k+1} can be corrupted, which means in practice that the IBI sample can be approved as correct only if a following sample is available.

Therefore, the delay introduced by artefact removal is not constant throughout the record. In the best, artefact-free case the sample can be further analysed after the arrival of the next sample (0.5–2 s depending on heart rate). If an anomaly occurs, it can affect the heart rhythm in a certain period of time. The delay introduced by the correction algorithms is proportional to this period. Since our aim is to look for changes (often unexpected) in the rhythm, filling such gap with samples generated by any model based on previous samples only is not an appropriate solution.

2.2. Interpolation

In most approaches to HRV analysis the series is interpolated and evenly resampled prior to spectral analysis. In real-time analysis, this problem cannot be neglected. In the cubic spline interpolation, encouraged for use in HRV [9], the interpolant between two points is determined on the basis of a long set of neighbouring points. However, for the real-time interpolation case, however, with the arrival of a new IBI sample the previously determined interpolant would no longer be valid. Therefore, we propose an alternative interpolation approach, in which every point is derived on the basis of 5 points only with the point of interest being the one in the middle. This approach was introduced by Akima [11] in 1970. In Fig. 3, it is shown how far backward a new value influences the interpolant for the Akima and classical cubic spline methods. This example clearly demonstrates, that the classical cubic spline interpolation would introduce a significant delay. By applying the Akima interpolation, the introduced delay is equal to the time of the two last registered IBIs only.

The demonstrated, theoretical example is very improbable and most of such cases would be considered an artefact anyway. In practice, the two interpolation techniques give similar results. Still, the clear advantage of the Akima spline is its low computational cost compared to that of the cubic spline method.

To check the validity of the Akima method, the frequency spectra of a set of HRV signals interpolated using the Akima and the classical cubic spline are determined and compared. The results show that the Akima application causes insignificant decrease in the power of the HF components and an increase in the power of the frequency components above the HF limit.

According to the research on errors introduced by beat replacement and resampling [12] the classical spline interpolation also introduces an error in the spectrum. It overestimates the low frequency components. In the cited work, the authors suggest using the Lomb Scale Periodogram computed on a series with unevenly spaced samples to avoid the problem [13]. What is more, in the presence of artefacts the error introduced by interpolating the gap with cubic splines results in even greater overestimation. This is because there are no interpolation nodes inside the long gap left after artefact removal and at the same time there are numerous points outside of the gap to which the interpolating function has to be adjusted. The use of the suggested Akima interpolation technique, where only 4 nodes are being considered at any time, solves this interpolation problem as shown in Fig. 4.

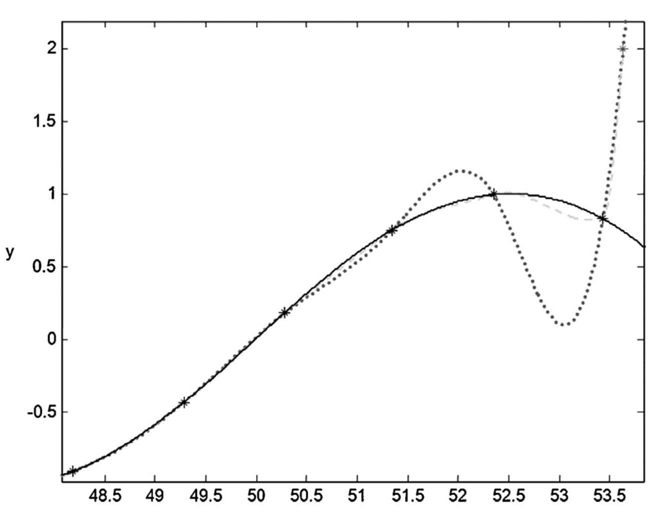

Fig. 3 – Influence of new sample introduction on the shape of the interpolating curve. Solid line – interpolation for the set of points denoted by asterisks. Dotted line – interpolation using classical cubic spline after introducing to the data set a new point marked with an asterisk in the upper right hand corner of the plot. Dashed line – interpolation using the Akima spline method after introducing the new point to the data set.

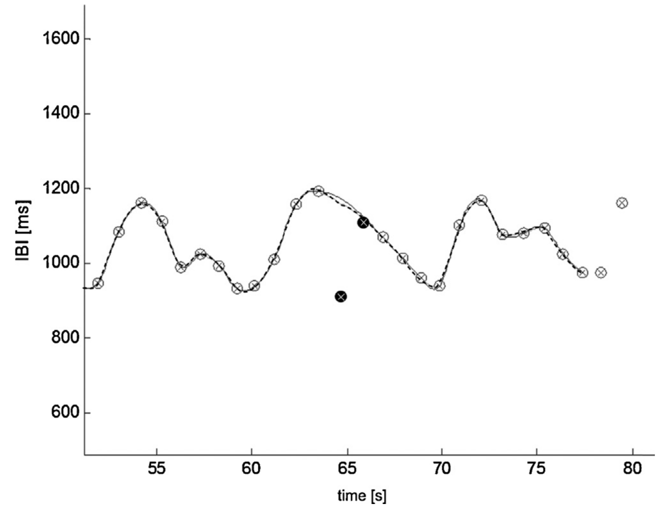

Fig. 4 – IBI series after elimination of artefacts (black circles), the Akima interpolation (dashed line) and the non-causal bicubic spline interpolation (solid line). The interpolating curve is delayed by two interbeat intervals – see the right side of the plot.

3. Review of time–frequency methodologies in HRV and their adaptability to real-time analysis

Frequency analysis methods for estimating the power contained in the LF and HF bands include nonparametric periodograms and their modifications as well as parametric models [14]. In case of analysis of highly non-stationary recordings time–frequency methods are required. They include the Short Term Fourier Transform, the Wavelet Transform and the Wigner-Ville Distribution. Recently, relatively good results have also been obtained by applying the Kalman Filtering of Autoregression Coefficients [15,16] and the Hilbert–Huang Transform [17].

3.1. Kalman filtering of Autoregression Coefficients

Application of sequential data techniques seems to perfectly fit to the real-time analysis requirements. Online estimation of autoregressive coefficients can be performed using a Kalman filter. The updates of the vector of autoregressive coefficients' estimates are made after the arrival and preprocessing of every new sample (i.e. inter-beat interval). However, in real-time analysis the problem of the lack of smoothness cannot be solved using the methods suggested in the literature [18,19] as the smoothing is performed off-line with the knowledge of the entire recorded series. Another problem encountered in real-time processing is related to the choice of the model order. In practice the samples arriving at the beginning of the recording have a decisive effect on the choice of the model type and order. However, for a non-stationary HRV the chosen model may be no longer valid, while the updating process is rational only under the assumption that the type of the model does not change [16].

3.2. *The Hilbert–Huang Transform*

According to recent studies [17], the Hilbert–Huang Transform (HHT) algorithm can be used to identify the low-frequency and high-frequency bands of HRV more efficiently and accurately through the Hilbert spectrum than using the Fourier spectrum.

The key part of the HHT [21] is the so-called Empirical Mode Decomposition (EMD) procedure which decomposes any complicated signal or time series into a small number of intrinsic mode functions (IMF). As the name implies the decomposition method is empirical, i.e. no basis functions are defined a priori, but, instead, the decomposition is dependent on the analysed data set. The process of IMF determination is called sifting and it is described in the following flowchart (Fig. 5).

In a single step of the so called ''sifting'' process (Fig. 6) a local mean is determined as the difference between upper and lower envelope of the series and it is subtracted from the series. This process is similar to traditional high-pass filtering with such a difference, that here the filter cannot be predefined as the process depends on the distribution of local extrema in the analysed series.

By repetition of the sifting process up to the point when the mean is approximately zero at all times, the component of the highest locally observed frequency is obtained. At this point, the obtained component is assumed an IMF, it is subtracted from the original signal and the residue signal is being sifted again until the next IMF is found. The process is continued until the sifted signal cannot be decomposed any more as it possesses no more extrema.

Having decomposed the series into the IMFs, owing to their properties, it is possible to apply the Hilbert transform on each of them. The Hilbert Transform is used to determine a conjugate pair of the given series:

$$H(x(t)) = \frac{1}{\pi} PV\left\{\int_{-\infty}^{\infty} \frac{x(\tau)}{(t-\tau)} d\tau\right\} \qquad (2)$$

where operator $PV\{\cdot\}$ denotes the Cauchy principle value [14]. The algorithms for the discrete time Hilbert Transform can be found in [14] and [22]. Thanks to the application of the Hilbert

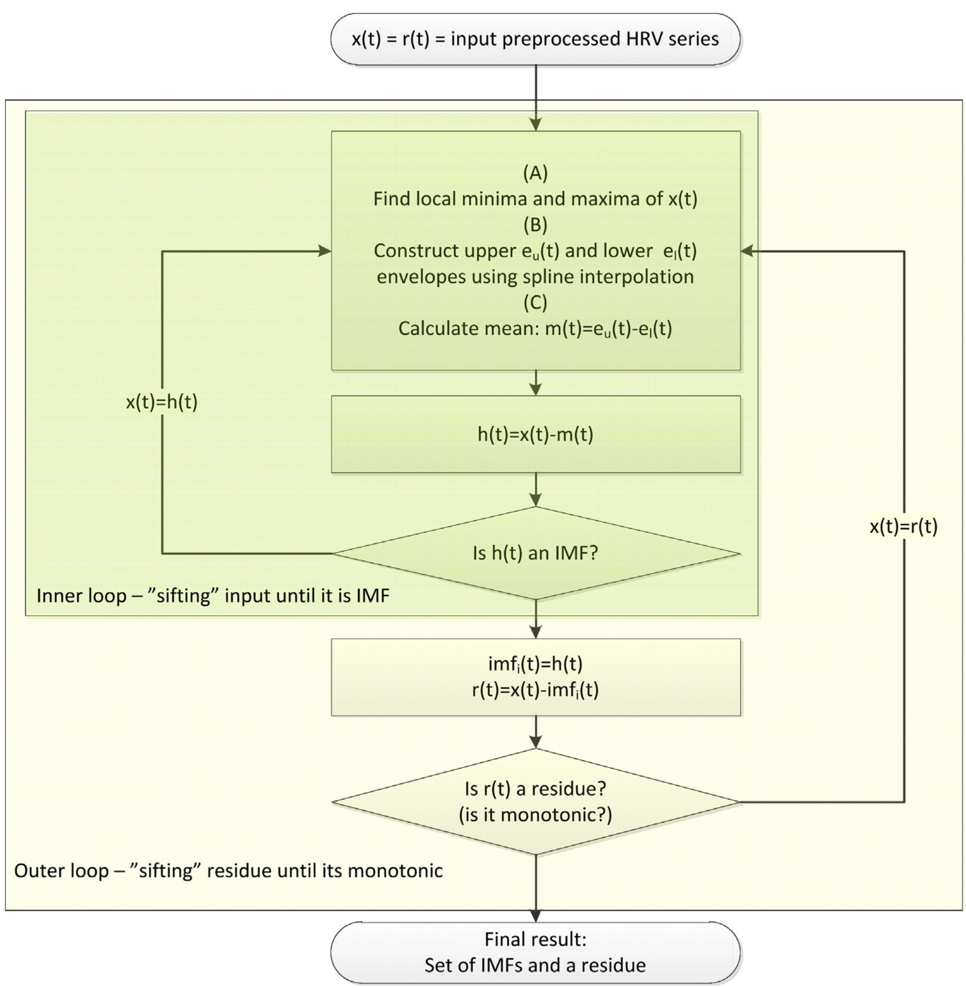

Fig. 5 – The flowchart of the algorithmic implementation of the Empirical Mode Decomposition.

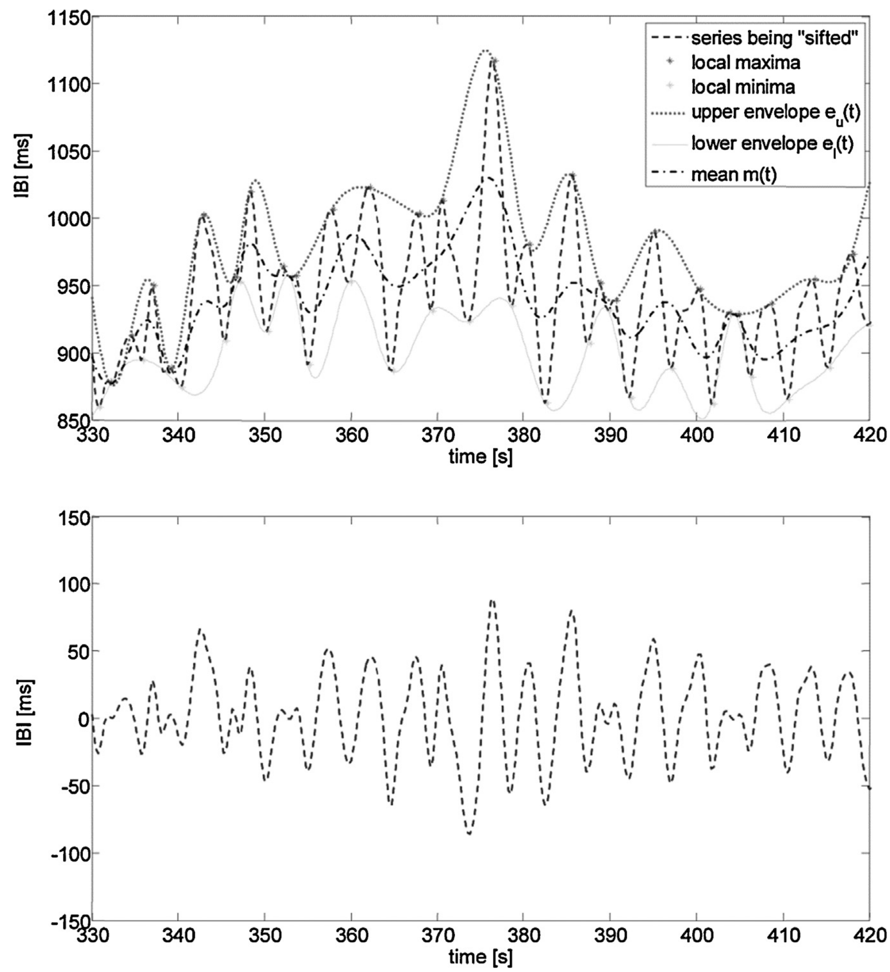

Fig. 6 – A single step of a "sifting" process; finding lower and upper envelopes and determining the local mean (upper panel); the result of subtraction of the mean from the original series (lower panel) – plots obtained from the authors' own EMD implementation.

transform an analytic signal can be built, whose real part is the original data, and an imaginary part contains the Hilbert transform. Extraction of instantaneous amplitude a and frequency f is possible using the following equations:

$$a(n) = \sqrt{[x^2(n) + H^2(n)]} \tag{3}$$

$$f(n) = \frac{\Delta\left(\arctan\frac{H(n)}{x(n)}\right)}{T_s} \tag{4}$$

where H is the Hilbert transform of the signal x (in this case an IMF) and T_s is the sampling period.

The HHT is a powerful decomposition method for HRV analysis. However, it is not destined for real-time analysis. First, the sifting process of the Empirical Mode Decomposition (EMD) algorithm involves a large number of nested iterations, which results in high computing demand impeding real-time application. Secondly, boundary effect exists in the course of EMD. When performing off-line EMD, divergence will occur at the two ends of data series, and with successive iterations of the sifting process this divergence propagates further into the centre of the analysed series (Fig. 7). In real-time analysis the boundary effect is unacceptable because each incoming sample of interest is on the boundary of the series.

From the very few papers on the topic of real-time EMD implementation [20], none gives a solution to the boundary effect elimination. A suggested tip to reduce distortion of

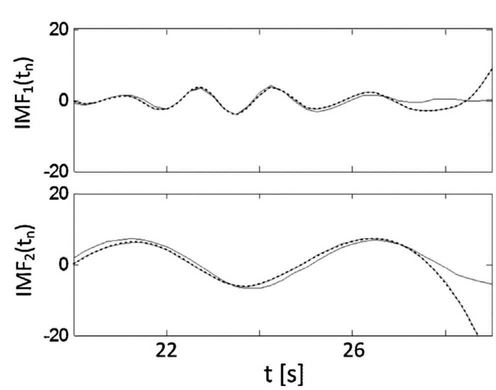

Fig. 7 – The right boundary of the two first Intrinsic Mode Functions (IMFs) of an IBI series (dotted lines) and the modified shape of the same IMFs determined after the arrival of the successive IBI samples (solid lines).

decomposition at the end of measurement intervals is to estimate the future course of IMFs and their future local extrema using the currently known courses of IMFs [20]. The authors of the cited work dealing with environmental data did not specify how to address the problem. In our case the problem of distorted decomposition at the end of the analysed intervals is especially difficult as we are trying to detect the unexpected change in the signal nature. Therefore, the projection of extrema on the basis of the actual measurement is not valid.

4. The method for real-time estimation of the HRV spectral parameters based on the Hilbert–Huang Transform

The mentioned limitations indicated in the reviewed literature are addressed in our algorithm that is specially designed for real-time analysis of HRV series. The steps of the algorithm with their short descriptions are shown in Fig. 8. The details

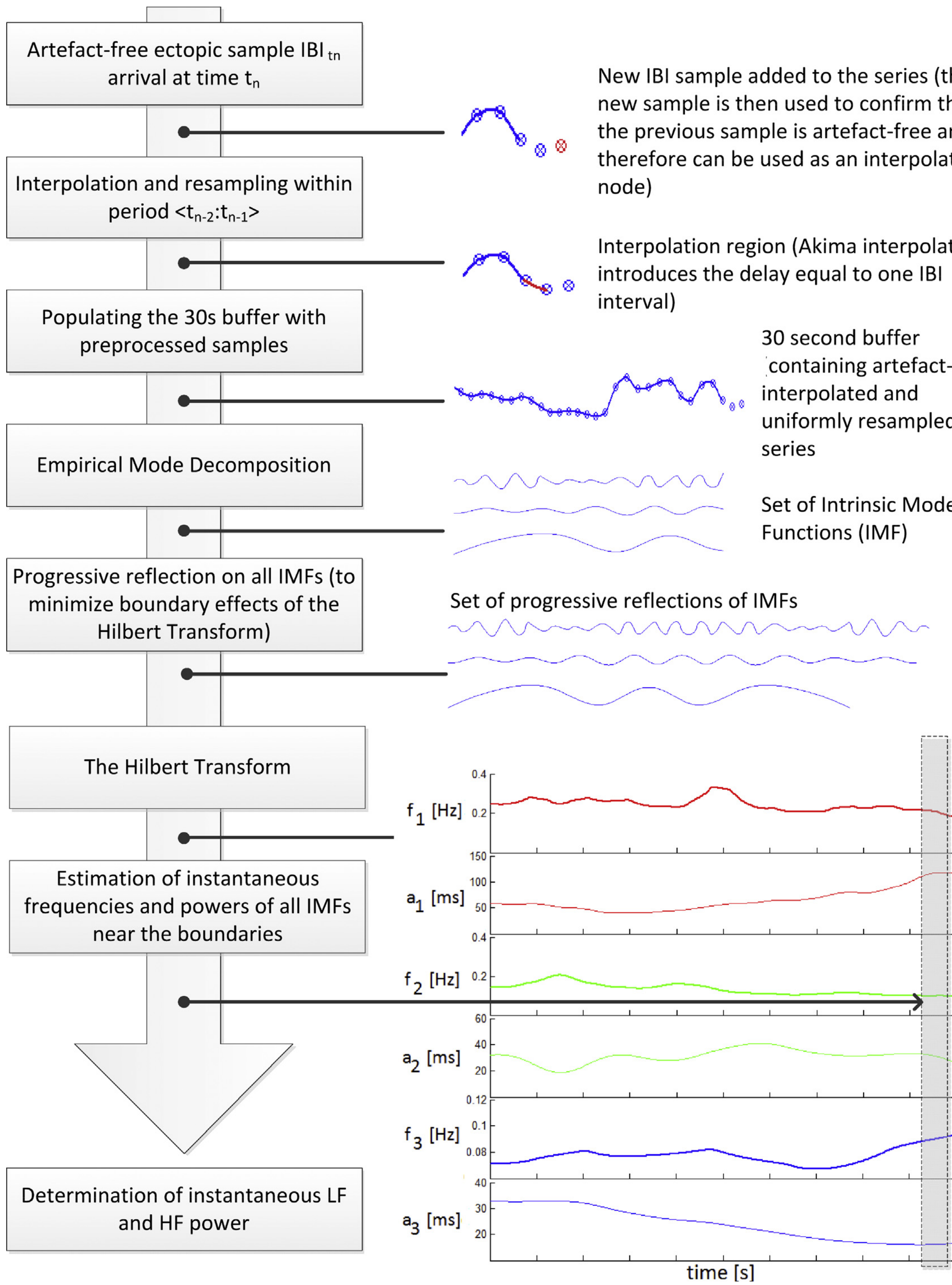

Fig. 8 – A flow chart diagram illustrating the steps of the proposed algorithm for real-time estimation of the HRV spectral parameters based on the Hilbert–Huang Transform.

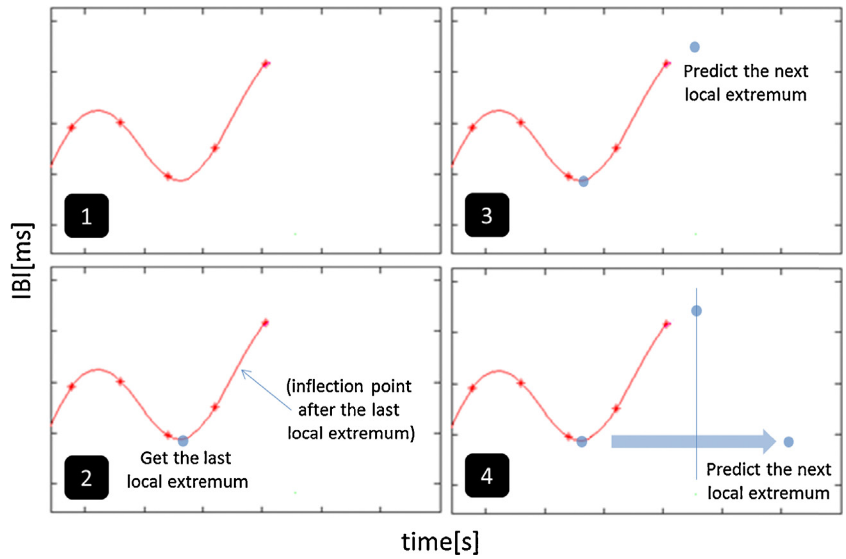

Fig. 9 – Extrema prediction in case the inflection point occurred after the last extremum (the order of processing indicated by numbered labels).

concerning each step are explained in the following subsections.

4.1. *The sliding buffer and extrema progression*

In the proposed algorithm, with each new sample of the HRV series, a sliding buffer is filled with the preprocessed samples of the last 30 s. Such duration being longer than 25 s enables detection of components of 0.04 Hz being the slowest possible influences of the LF band.

To the extrema found at each sifting iteration, two successive extrema predictions are added. Without such extrapolation, the boundary effect would be very significant. The closest extremum prediction is based on the shape of the ending of the interpolated curve. From the values of the first and second derivatives it is determined whether the curve has passed its inflection point or not (i.e. the point at which the curve changes from being convex to concave or vice versa). If it has, the second derivative is extrapolated with the constant value and the prediction of the first derivative and then the original curve is reconstructed until the extremum is smoothly attained. The following extremum is assumed to have the same value as the last existing extremum and occurs at time t_2:

$$t_2 = t_1 + (t_1 - t_0) \tag{5}$$

where t_0 – time of the last local extremum, t_1 – time of the first predicted extremum (Fig. 9).

If the inflection point did not yet occur after the last extremum, it is assumed there is no strong basis for prediction of the future extremum and therefore both extrema are the reflections of the two last extrema determined in the series (Fig. 10).

4.2. *Real-time EMD*

In HRV, the frequency of heart beats is small in comparison to the dynamics of the measured physiological influences. It is therefore impossible to estimate the future course of IMFs and their future local extrema using the currently known courses of IMFs, as it was proposed in the studies on meteorological time-series data [20]. It has to be accepted, however, that the prediction of future extrema does not yield current envelopes that will stay valid when the new samples will be added to the series. Therefore, the authors' conclusion is that the only possibility to obtain acceptable results in real-time, is to recompute new IMFs with new extrema predictions at every time instance of the analysis.

Although, the computational payload of EMD is high, the computations for each step were performed within tens of a second on a standard desktop computer (Dualcore, 3 GHz, 8 MB RAM, 1666 MHz). Considering a typical heart rate of 60–80 bpm, this is a sufficient computing speed for real-time processing of HRV.

4.3. *Progressive reflection for the Hilbert Transform*

After the sifting processes, the instantaneous frequencies and amplitudes can be computed for each IMF. The Hilbert Transform which best serves this purpose also suffers from the boundary conditions.

The most desirable signal decomposition results are obtained for the two conditions: first, there is an equal and infinite number of points at both sides of the point of interest and second, the series at the starting and the ending point features the same phase. The two conditions cannot be satisfied in case of HRV real-time measurement because we are bound to a buffer limited in time, and we are always interested in the result on its right boundary corresponding to current series' samples.

The proposed approach to deal with this problem benefits from the fact that the IMFs obtained during the EMD process are single frequency components and therefore their local mean is approximately 0 at any time and they are quasi symmetric with respect to the time axis.

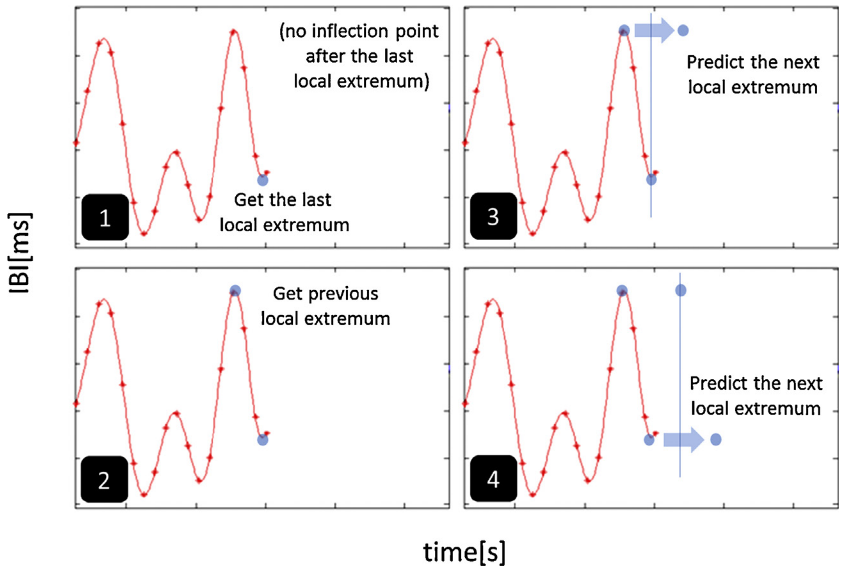

Fig. 10 – Extrema prediction in case the inflection point did not yet occur after the last extremum (the order of processing indicated by numbered labels).

For each intrinsic mode function *imf*(*t*), the last local extremum and the last inflection point are detected. We determine time *t* = *T*:

$$T = \max(T_E, T_{IP}) \tag{6}$$

where T_E and T_{IP} are the occurrence times of the last extremum and the last inflection point, correspondingly. All samples occurring after *T* are dropped. Therefore, the domain of *imf*(*t*) function becomes $<0,T>$.

Then the cropped function *imf*(*t*) is merged with its reflection according to the formula:

$$imf'(t) = \begin{cases} imf(t) + imf(2T - t) & if\ \ T = T_E \\ imf(t) - imf(2T - t) & if\ \ T = T_{IP} \end{cases} \tag{7}$$

The length of the resulting series is approximately twice as long as that of the original series. The Hilbert Transform can now be performed. The computed instantaneous frequency and amplitude still suffers from the boundary effects, but the point of interest is located approximately in the middle of the boundaries (see Fig. 11).

The interval of the dropped fragment which is interpreted as the delay is less than a fourth of the IMF period it was taken from. In case of a typical HF component this time interval is about 4 s/4 = 1 s, for a typical IMF belonging to the LF band the interval is about 10 s/4 = 2.5 s.

4.4. *Instantaneous LF and HF power determination*

After the preprocessed series is decomposed (via EMD) and the Hilbert Transform of every IMF is computed, their instantaneous frequency and power are known. Then, after artefact removal, the functions of the instantaneous power and frequency estimates are filtered with a simple moving average filter.

The values of powers of each IMF whose frequency are within the LF range are summed resulting in the instantaneous LF power. The HF power is computed analogously and the whole procedure is repeated for the next IBI sample.

5. Results

The performance of the elaborated real-time algorithm was assessed in several ways. First, simulated IBI series were generated with the use of the IPFM (Integral Pulse Frequency Modulation) model [9]. The author's software tool written for this purpose enables generation of IBI series whose LF and HF components can vary in time. Changes of the LF and HF parameters detected by the two proposed algorithms and the real-time implementation of the STFT were compared to each other and to the reference time instances available from the controlled IPFM input. Finally, the methods were verified on a set of ECGs recorded during various exercise tests and clinical procedures.

5.1. *HRV analysis on simulated records*

The IBI series used for validating the proposed methods were generated from the IPFM model whose input was a sum of two sinusoids of varying frequencies close to 0.1 Hz and 0.25 Hz reflecting simplified influences from sympathetic and parasympathetic nervous systems. To test the real-time performance of analysis of nonstationary HRV series, the model input was changed in time. The values of the LF and HF power and frequency were controlled by the user so that they are known at all times (Fig. 12).

In the validation process the instantaneous values of the four parameters: frequency of the LF component, power of the LF component, frequency of HF component and power of HF component were compared.

5.1.1. *IBI series generated from stationary IPFM model*

Before analysis of nonstationary HRVs, the validity of the proposed method for estimation of spectral parameters of HRV series was tested on stationary series. For this purpose, a set of IBI series with parameters kept fixed were generated using the

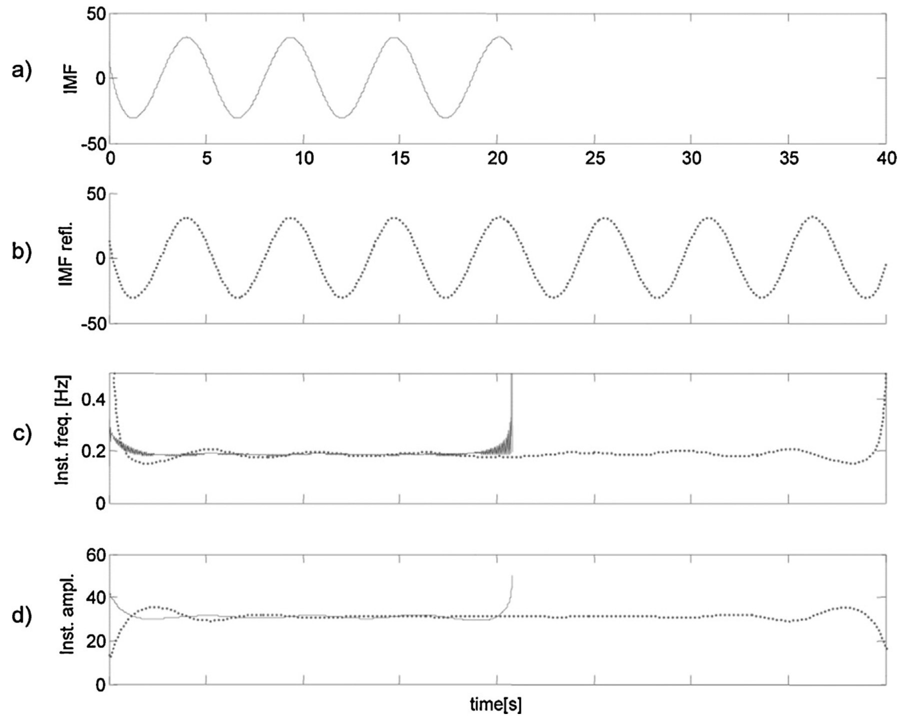

Fig. 11 – Graphical explanation of the proposed progressive reflection scheme: IMF (a), IMF progressive reflection up to a 40 s time interval (b), instantaneous frequency (c), and instantaneous amplitude (d) obtained by computing the Hilbert Transform of the IMF. For comparison, the corresponding solid lines shown in panels (c) and (d) illustrate the boundary effects if the progressive reflexion scheme is not applied.

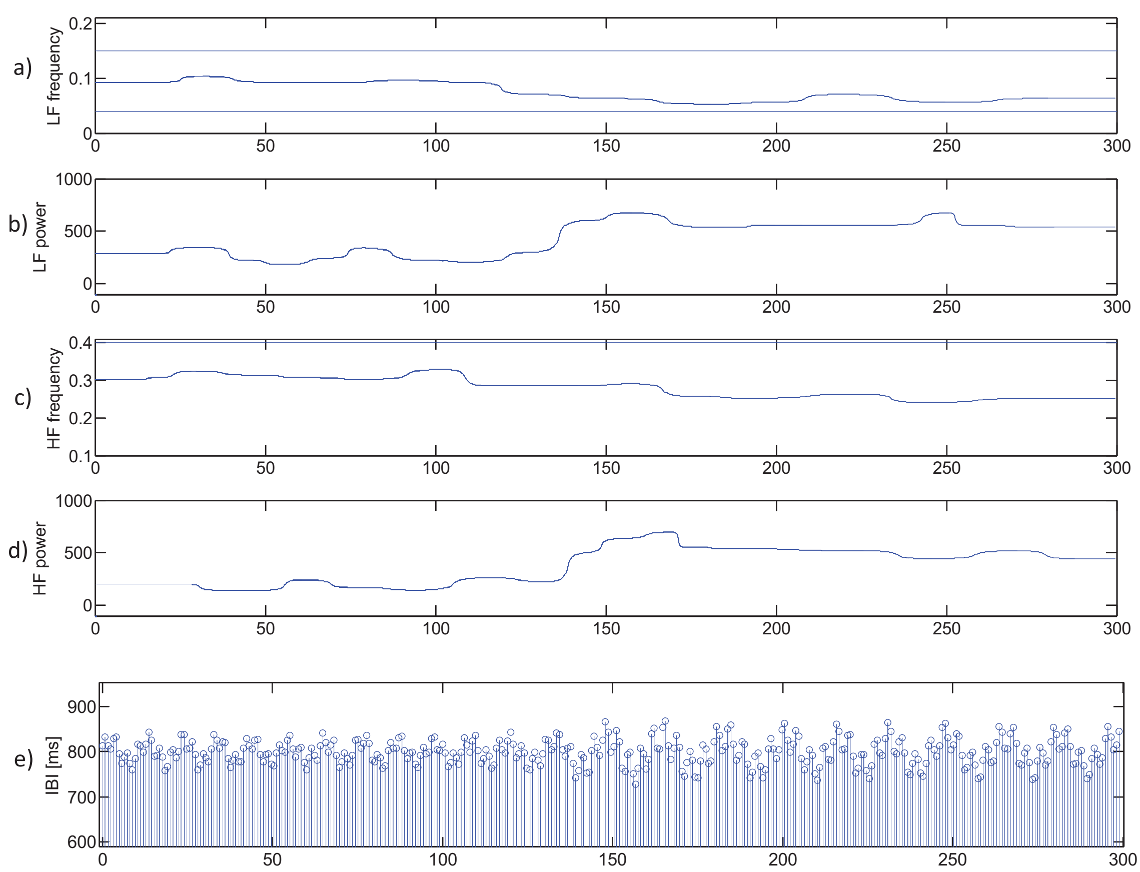

Fig. 12 – The values of power and frequency of LF components (panels (a) and (b)) and HF components (panels (c) and (d)), correspondingly and the resulting, generated HRV series (panel (e)).

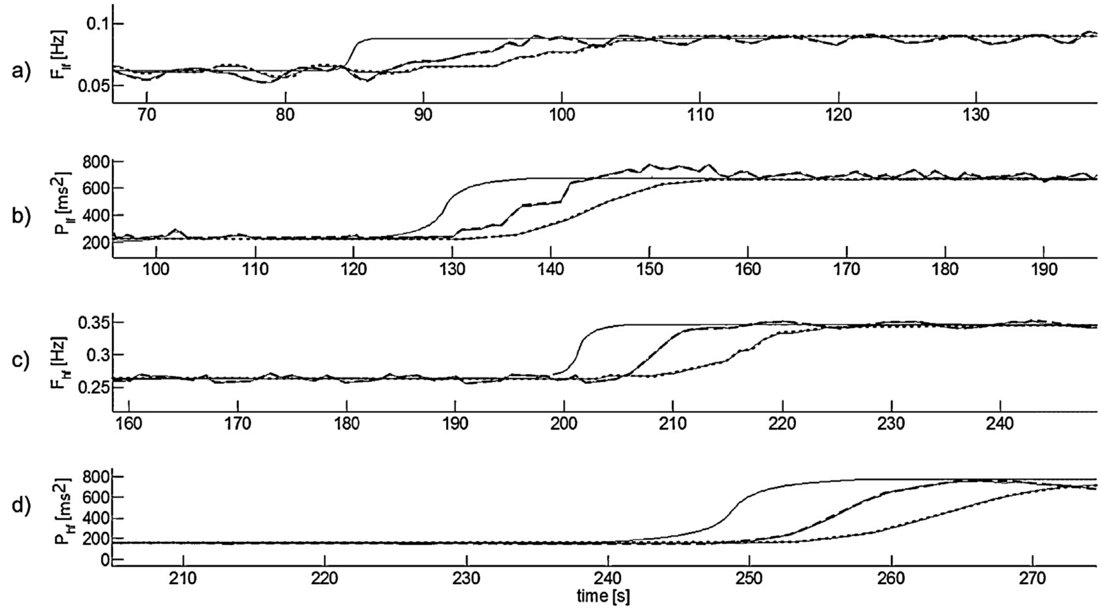

Fig. 13 – The changes of parameters of the LF and HF components driving the IPFM model (solid line) and their estimation using the two compared real-time methods: STFT (dotted line) and the modified EMD-HHT method (dashed line), where F_{lf}, F_{hf}, P_{lf} and P_{hf} denote frequencies and powers of the LF and HF components correspondingly.

IPFM model. Then each series was analysed using the real-time STFT implementation and the designed method. Three measures were used to assess the performance of the method. They included root mean squared error (RMSE), the displacement of the mean of the estimation with respect to the generated input and the standard deviation.

A set of 10 stationary HRV series was generated and the three mentioned values were computed. The relative error measures are all below 3%, with STFT being equally precise as the modified EMD method.

5.1.2. *Time varying IPFM model based scenarios*

A very significant feature from the point of view of this work is the ability of the proposed method to detect a spectral change in instantaneous powers occurring in real-time. In order to assess it, a testing set of HRV series was generated. It included 100 IBI series generated automatically with the use of the IPFM model. The values of LF and HF frequency and power amplitude were drawn randomly (within physiologically justifiable ranges). For each generated IBI series at a single time instance only one change (either frequency or power) occurred in time. The example results are shown in Fig. 13.

In this case, the detection of series parameters was assumed to occur when the value of the estimation reached half of the destination level of the reference. The average delays of detections defined in such a way are presented in Fig. 14.

We can summarise that using the STFT, we have to wait almost twice as long for the detection of the change than in case of the HHT based method.

5.2. *HRV analysis on ECG recordings*

In the second verification run the designed real-time algorithm was applied to HRV series derived during various functional

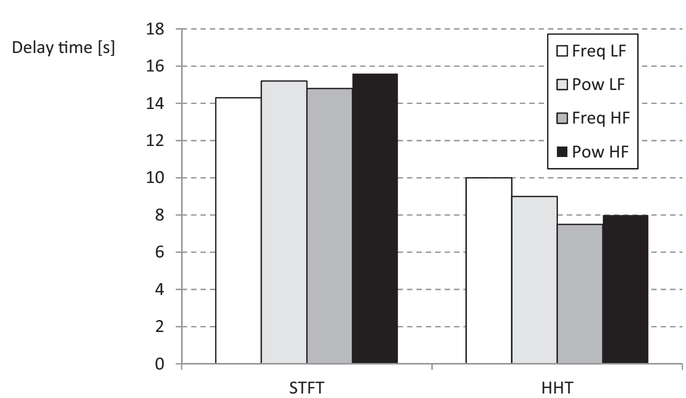

Fig. 14 – Comparison of delay times of the compared STFT and HHT based methods in detecting simulated changes of the frequency and power values of the LF and HF components correspondingly (measured at the middle point of the simulated change).

Table 1 – Comparison of the performance of the proposed method and the real-time implementation of the STFT in detecting time changes of HRV spectral parameters.

		Average delays of detection in seconds				Reduction of delay time with reference to STFT	
		Using STFT		Using modified HHT		Using modified HHT	
		LF	HF	LF	HF	LF (%)	HF (%)
Simulated change	of frequency	16.5	16.3	10.5	7.8	36	53
	of power	17	17.3	11.3	8.5	34	51
Registered change of power during standing to sitting transition		28.2	25.8	15.6	20.2	45	22
Registered change of power during sitting to supine transition		11.1	25.1	4.7	18.5	58	26

tests. Most of the tests included a sudden activity potentially engaging either sympathetic or parasympathetic nervous system or both. The recordings were analysed and detection times of the events were established using the compared HRV analysis methods. A group of 40 recordings including various exercise and activity tests were performed by 10 healthy subjects. The test included hand-grip, body position change (from standing to sitting, from sitting to supine) and deep breaths. The test group consisted of healthy people of age between 20 and 59 years. The analysis of the results were done in cooperation with the Department of Electrocardiology of the Clinical University Hospital in Lodz and with the Department of Biophysics of the Medical University of Lodz. The results are shown in Table 1.

The STFT based method requires at least 17 s to detect changes in the HF and LF power. Whereas, a modified HHT enables detection of the same changes in approximately 11.3 s and 8.5 s, correspondingly. For the both methods the relative root mean square error (RMSE) of the results with respect to the parameters driving the simulation is less than 3%.

6. Summary and discussion

According to the authors' best knowledge, there have been few reported attempts in which the problem of temporal estimation of HRV spectral parameters has been undertaken. In our study, we have proposed a novel method for online estimation of HRV spectral parameters based on the Hilbert–Huang Transform which is a combination of the Empirical Mode Decomposition and Hilbert spectral analysis. Novel, causal pre-processing procedures of the IBI series were proposed to make the implementation of this transformation technique possible for an online estimation of HRV spectral parameters. The achieved interpolated result of the IBI series (with the use of the Akima interpolation) is continuous up to the 2nd derivative with a delay of only 2 heart beat intervals in comparison to classical spline interpolation in which the processing delay is larger than 5 heart beat intervals. Also, a special modification scheme was proposed for extrapolation of the frequencies and amplitudes of intrinsic mode functions prior to application of the Hilbert–Huang Transform. This processing step has enabled determination of the instantaneous LF and HF powers. The proposed algorithm for real-time estimation of HRV spectral parameters was verified both for the simulated IBI sequences and IBI sequences derived from patients ECGs performing functional tests.

Time delays of the detected transient changes of the instantaneous LF and HF powers for the simulated HRVs were reduced with the use of the proposed methods by approx. 50% (for the HF power estimate) and by approx. 35% (for the LF power estimate) in comparison to the real-time adaptation of the STFT method (see Table 1). Similarly to LF and HF components, the LF/HF ratio will be inaccurate in the transient state. The length of the transient state of the LF/HF ratio will be equal to the time interval within which both the LF or HF become stable. For the temporal HRVs analysis performed during the functional tests, the corresponding reduction in the detection time was no worse than 45% (for the LF estimate) and 22% (for the HF estimate). For the functional tests, these percentage values correspond to approx. 12 s shortening of the detected transients in the LF power and almost 7 s shortening of the detected transients in the HF power. Such seemingly small values, however, can be of high significance in detections of temporal changes of the HRV parameters during the cardio-resynchronisation therapy procedures or other invasive cardiologic procedures.

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REFERENCES

[1] Acharya UR, Joseph KP, Kannathal N, Min LC, Jasjit SS. Heart rate variability: a review. Med Bio Eng Comput 2006;44:1031–51.

[2] Tarvainen MP, Niskanen JP, Lipponena JA, Ranta-ahoa PO, Karjalainen PA, Kubios HRV. Heart rate variability analysis software. Comput Methods Prog Biomed 2014;113:210–20.

[3] Kudrynski K, Strumillo P, Ruta J. Computer Software tool for heart rate variability (HRV), T-wave alternans (TWA) and heart rate turbulence (HRT) analysis from ECGs. Med Sci Monit 2011;17(9):MT63–71.

[4] Marple SL. Digital Spectral Analysis with Applications. Prentice Hall, Inc; 1987.
[5] Broersen PMT. Automatic spectral analysis with time series models. IEEE Trans Instrum Meas 2002;51(2):211–6.
[6] Task Force of the European Society of Cardiology and North American Society of Pacing and Electrophysiology. Heart rate variability: standards of measurement, physiological interpretation and clinical use. Eur Heart J 1996;17:354–81.
[7] Urbanek B, Ruta J, Kudryński K, Cygankiewicz I, Ptaszyński P, Kaczmarek K, et al. Influence of etiology of left ventricular dysfunction on heart rate variability parameters in short-term frequency domain analysis in patients qualified for cardiac resynchronization therapy. Pol J Cardiol 2011;13(1):5–9.
[8] Kudrynski K, Strumillo P. Real-time estimation of heart rate variability parameters from passband filtered interbeat interval series. Comput Cardiol 2011;38:297–300.
[9] Tkacz E. New diagnostic possibilities of heart rate variability (HRV) analysis;Habilitation dissertation, Gliwice [in Polish] 1996.
[10] Mateo J, Laguna P. Analysis of heart rate variability in the presence of ectopic beats using the heart timing signal. IEEE Trans Bio-Med Eng 2003;50(3):334–43.
[11] Akima H. A new method of interpolation and smooth curve fitting based on local procedures. J Assoc Comput Mach 1970;17(4):589–602.
[12] Clifford GD, Tarassenko L. Quantifying errors in spectral estimates of HRV due to beat replacement and resampling. IEEE Trans Bio-Med Eng 2005;52(4):630–8.
[13] Lomb NR. Least-squares frequency analysis of unequally spaced data. Astrophys Space Sci 1976;39:447–62.
[14] Marple SL. Computing the discrete-time analytic signal via FFT. IEEE Trans Signal Process 1999;47(9):2600–3.
[15] Tarvainen MP, Georgiadis S, Lipponen JA, Hakkarainen M, Karjalainen PA. Time-varying spectrum estimation of heart rate variability signals with Kalman smoother algorithm. Engineering in Medicine and Biology Society. EMBC Annual International Conference; 2009.
[16] Kudrynski K, Strumillo P. Estimation of instantaneous values of parameters of autoregressive heart rate variability model with the use of Kalman filtering. Biocybernetics and Biomedical Engineering Conference Proceedings; 2011 [in Polish].
[17] Li H, Kwong S, Yang L, Huang D, Xiao D. Hilbert–Huang transform for analysis of heart rate variability in cardiac health. IEEE/AC. Trans Comput Biol Bioinform 2011;8 (6):1557–67.
[18] Welch G, Bishop G. An introduction to the Kalman filter. Chapel Hill: UNC; 2006, TR 95-041.
[19] Sangkatumvong S, Coates TD, Wood JC, Meiselman HJ, Kato R, Detterich JA, et al. Time-varying analysis of autonomic control in response to spontaneous sighs in sickle cell anemia. Conf Proc IEEE Eng Med Biol Soc 2010;1626–9.
[20] Trnka P, Hofreiter M. The empirical mode decomposition in real-time. 18th International Conference on Process Control; 2011.
[21] Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc R Soc Lond 1998;A454:903–95.
[22] Oppenheim AV, Schafer RW. Discrete-time signal processing. 2nd ed. Prentice-Hall; 1998.