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Estimation of Heart Rate Variability Fluctuations by Wavelet Transform

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***Abstract*—Technique for separate estimation of fast and slow fluctuations in the heart rate signal is developed. The orthogonal dyadic wavelet transform is used to separate the slow heart rate changes in approximation part of decomposition and fast changes in detail parts. Experimental results using the recordings from persons practicing Chi meditation demonstrated the applicability of estimation heart rate fluctuations with the proposed approach.**

***Keywords*—Heart rate variability, HRV fluctuations, HRV wavelet analysis, time-dependent HRV estimation, wavelet transform.**

I. Introduction

CARDIOVASCULAR system is one of the most important in the human being, thus many researches are focused on the evaluation of its state and functioning. The "heart" of this system is the human heart, which is responsible for supplying whole body with blood carrying oxygen and nutrients. The main functions and features of the heart functioning are its automatism, conductivity and excitability: heart stresses and releases due to the influence of nervous system. The innervation of the heart allows the central nervous system to control the rate and periodicity of heart beats.

It is widely known, that time alternations between the sequential heart beats – phenomena of heart rate variability (HRV) – is inherent to healthy and sick persons [1]. These variations are due to the neurohumoral influences on heart functioning. The two parts of central nervous system, sympathetic and parasympathetic, affect the HRV thus investigating of HRV-derived parameters are useful for estimating the functional state of whole body, sympatho-parasympathic balance, neurohumoral regulation background, health reserve, stratification of sick person according to the degree of risk, forewarning therapy success, workload planning in the usual life and sport, overall quality of life.

Standard techniques of HRV analysis could be divided into three parts: frequency-domain (various types of power spectra estimation and parameters of HRV spectra), time-domain (statistical parameters of time intervals between adjacent cardiocycles' distribution) and nonlinear measures (estimation of chaoticity, unpredictability and coherence parameters of HRV).

The International Standard [2] is developed and widely used in clinical practice for measuring and analyzing HRV. It is prescribed to use the specific time duration of the HRV signal for analysis: only 5 min. and 24 hours signals are accepted. In most of investigations concerning the HRV analysis such intervals are used.

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The problem is that the heart rate could be investigated for the human under different conditions. For example, while analyzing drug influence on heart and nervous system, the effect can start earlier than in five minutes, thus the shorter time segments need to be used for calculation. The same situation is while the workload tolerance or adaptation is investigated: the reaction of the heart system can occur earlier. Contrariwise while investigating the long-term effects of adaptation, time segments of 1 or 2 hours can be useful. Thus, meaningful changes in HRV and HRV-derived parameters can occur during different time intervals.

Thereby when one uses 24 hours signals, all processes in heart and nervous systems could had been started and already finished while 5 minutes are often too short period for human body reaction to the influence to manifest. Moreover, in the same experiment the long- and short-term alternations of heart rate can be observed in the same signal. Using of short-time Fourier transform for detecting such fluctuations of different scales is limited because of the need to select the window type and duration, shifting step and overlapping parameters. Thus the technique for adequate estimation of the possible changes in HRV over various time intervals needs to be developed.

The focus of this paper is to propose the technique for evaluation of HRV fluctuations while taking into account only the changes originated over specific time periods. In the next Sections the wavelet transform-based technique of estimating the fluctuations of HRV parameters is proposed, and experimental results on separating the heart rate signal into parts with different time changes are presented.

II. Time-Scale Analysis of Heart Rate by Wavelet Transform

Wavelet transforms (WT) of various types are well-known techniques for nonstationary signal processing and has been thoroughly considered elsewhere in the literature [3]–[5]. WT gives the time-scale decomposition of signal to the components of different duration and spectral contents. In this work the orthogonal dyadic wavelet transform (ODWT) will be used [3], [5] because of existing of fast computation algorithms needed to process long signals in real time.

Let the discrete signal $S[n]$ be the time series of instant heart rate values with N samples. It can be presented in the framework of ODWT as consequent decomposition into two parts: signal details at different scales and signal approximation:

$$S[n] = A_m[n] + \sum_{j=1}^{m} D_j[n], \tag{1}$$

where m – the level of wavelet decomposition.

To obtain the approximation part for the level m (or at the dyadic scale 2^m), the orthogonal basis should be derived from mother wavelet function $\psi[n]$ using the equation:

$$\psi_{m,k}[n] = 2^{-m/2}\psi[2^{-m}n - k]. \quad (2)$$

After that signal $S[n]$ should be projected on the linear span of $\psi_{m,k}[n]$ to calculate the decomposition coefficients

$$a_m[k] = \langle S[n], \psi_{m,k}[n]\rangle = \sum_n S[n] \cdot \psi^*_{m,k}[n] \quad (3)$$

The approximation part of a signal could be obtained with these coefficients as the representation of $S[n]$ in wavelet basis

$$A_m[n] = \sum_k a_m[k] \cdot \psi_{m,k}[n]. \quad (4)$$

Each detalization part $D_j[n]$ of the signal $S[n]$ of level j from 1 to m could be obtained in the same way as

$$D_j[n] = \sum_k d_j[k] \cdot \varphi_{j,k}[n], \quad (5)$$

where

$$\varphi_{j,k}[n] = 2^{-j/2}\psi[2^{-j}n - k] \quad (6)$$

is the basis derived from the scaling function $\varphi[n]$, corresponding to selected mother wavelet $\psi[n]$ and

$$d_j[k] = \langle S[n], \varphi_{j,k}[n]\rangle = \sum_n S[n] \cdot \varphi^*_{j,k}[n] \quad (7)$$

It is known [3], [4] that the orthogonal dyadic wavelet decomposition could be considered as the subband filtering the signal with one low-pass filter (corresponding to the wavelet function) and a series of band-pass filters with scale-dependent bandwidth. Thus approximation part $A_m[n]$ (4) contains low-frequency signal components, thus representing the slow changes and giving rough approximation of a signal. The sum of details $\sum_{j=1}^{m} D_j[n]$ (5) keeps all remaining high-frequency content of the signal's spectrum and gives the detalization of comparatively fast signal fluctuations.

For any desired decomposition level m the basises (2) and (6) can be obtained and the decomposition coefficients (3) and (7) can be calculated. Thus for any desired level m the signal approximation of the scale 2^m and a series of details at scales from 2^1 to 2^m can be calculated. The graphical representation of such decomposition is presented on Fig. 1.

The time duration of wavelet $\psi_{m,k}[n]$ and scaling functions $\varphi_{j,k}[n]$ differs depending on the level m: if m is large then these functions are of long duration comparatively to the initial functions because of dilation equations (2) and (6). Thus while defining the coefficients (3) and (7) for different levels m, the duration of signal parts involved in calculations differs. This means that at each level of decomposition every component in (1) contains the information of fluctuations in the whole signal $S[n]$, occurring during different time ranges. Fast changes in hearing rate could be associated with details in decomposition (1), while slow changes corresponding to the low-frequency content of the heart rate signal are kept in the approximation part.

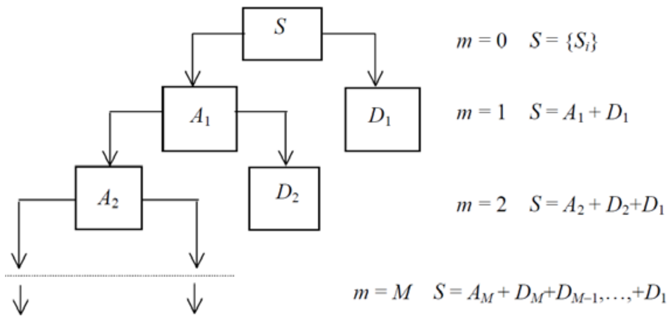

Fig. 1. Block diagram of signal $S[n]$ representation as the sum of approximation and details [5].

The higher the detalization (the larger is decomposition level m), the more details about heart rate fluctuations at different levels can be extracted from the signal in $D_j[n]$, $j = 1 \ldots m$, and the lower are residual spectral contents of approximation part in $A_m[n]$, giving the long-term fluctuations in the signal.

Thus analyzing separate components in the sum (1) one can obtain information about changes in the heart rate signal which occur at different time scales. This could be used for the separate analysis of fluctuations of various time durations and of the reasons influencing these effects.

III. Experimental Results and Discussion

During the experimental part of this work the application of proposed approach to separate analysis of fluctuations in heart rate signal was tested. Real heart rate signals from public available Physiobank Database [6] were used for experiments, performed in MatLAB. Two sets of 8 signals each containing heart rate fluctuations before and during performing Chi meditation were used, all having average duration of 1 hour 10 min. For calculation the wavelet decomposition maximum level $m = 5$ and Daubechies 4^{th} order mother wavelet function were selected just for proving applicability of proposed technique.

It can be seen that the properties of two heart rate signals are different, for instance the power spectral density differs substantially (Fig. 4a and Fig. 5a): most of energy shifted from low frequencies before to the higher frequencies during meditation. One of the tasks of experiments is to show the possibility to extract the fluctuations of different scales, and to see which components are responsible for contribution of which oscillations in the signal. The results are presented in Fig. 2 and Fig. 3.

After analysis of the results presented in Figs. 4 and 5 we can conclude that different components of wavelet decomposition are responsible for the fluctuations of various durations. Fast changes of heart rate could be extracted and further investigated (Figs. 4b, 5b) by using only detail components. Approximation components keep the slow-changing parts of heart rate which could be thus investigated after reconstruction (panels 4c and 5c). Also details of different scales could be added to the signals: the larger is the level of decomposition, the slower are the fluctuations included in reconstructed signal. Also signals before and during meditation could be compared

TABLE I
CORRESPONDENCE BETWEEN DECOMPOSITION LEVEL AND WAVELET DURATION

Decomposition Level m	1	2	3	4	5	6	7	8	9	10
Wavelet Duration, (Heart Beats)	15	29	57	113	225	449	897	1793	3585	7169
Wavelet Duration, (min)	0.25	0.5	1	2	3.75	7.48	∼15	∼30	∼60	∼120

TABLE II
HRV STANDARD DEVIATION BEFORE AND DURING MEDITATION

	Before	**During**
Initial Heart Rate Signal	13.0539	12.1329
Approximation	**58.8944**	**31.9583**
Detalization Coefficients for 5^{th} Level	19.1495	24.3879
Detalization Coefficients for 4^{th} Level	**16.0161**	**34.6372**
Detalization Coefficients for 3^{rd} Level	10.5106	13.1467
Detalization Coefficients for 2^{nd} Level	6.5411	4.8275
Detalization Coefficients for 1^{st} Level	3.4903	2.2978
Approximation + Detalization Coefficients for 5^{th} Level	11.1506	6.5859
Approximation + Detalization Coefficients for 5 and 4^{th} Levels	11.8437	10.8643
Approximation + Detalization Coefficients for 5, 4 and 3^{rd} Levels	12.4035	11.7921

and the parts which are similar and different could be recognized. For instance, while mean values of heart rate are similar for both cases, the slow fluctuations are much weaker during meditation than in pre-meditation period.

Table I shows wavelet duration in samples (which means heart beats for the case of HRV) and corresponding time duration of signal parts taken for calculation of one wavelet coefficient. Required time intervals for studying HRV fluctuations could be selected, i.e. if one use the decomposition level 3 then intervals of 1 minute long will be considered, and using level 8 one can analyze signals in frames of half an hour duration. The duration of signal part involved in calculations will depend on sample rate and thus decomposition levels for each signal should be adjusted and preliminary selected according to the aim of research.

From Table II the usefulness of proposed approach for analysis of HRV using standard deviation (STD) can be seen. Nevertheless the STDs of whole signals before and during meditation are nearly the same, while looking more precisely into decomposition one can see the differences inherent to the signals in two cases if we consider HRV fluctuations of different time components. In particular, for some components STD is twice larger in one state than in other, like for the case of analyzing only the detalization coefficients for 4^{th} level, or only approximation part. Thus for fixed level of decomposition the series of wavelet coefficients contains the information about signal fluctuations occurring only for corresponding time intervals but for all time shifts along the signal. After reconstructing the signal with only a few components the new information could be obtained and further analyzed.

IV. CONCLUSIONS

Orthogonal dyadic wavelet transform is used to decompose instant heart rate signal into parts containing approximation of the signal corresponding to slow heart rate fluctuations and the series of detalization parts which correspond to fast fluctuations each for different scale. Proposed technique is capable to extract signal components with fluctuations of various time durations from the heart rate signal.

Further work will be focused on finding the meaning of heart rate fluctuations of various scales, and two reverse tasks are to be considered. First, given the physiological reason of possible fluctuations find the appropriate scales and levels of decomposition at which these fluctuations should be investigated. The second task, given the various possible combinations of heart rate decomposition and observing possible fluctuations on different time periods, find whether or not there are physiologically and/or clinically proven causes of such changes. The results of first task solution will be further used for refinement of the proposed technique, first of all in the direction of connecting the levels of decomposition and the time duration of signal fluctuations being investigated. The second task is believed to be more challenging and most promising because the new possibilities for human body state estimation can be revealed this way and further used in clinical practice.

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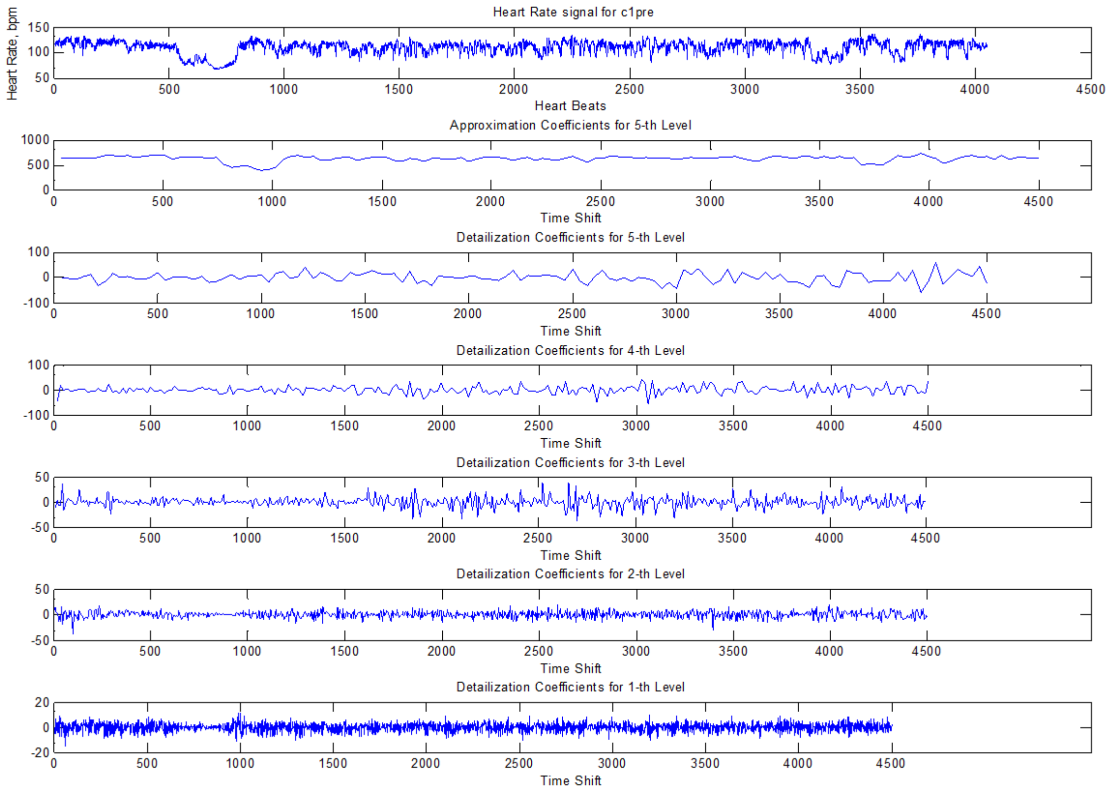

Fig. 2. Heart rate signal (top) before meditation and its wavelet decomposition coefficients for levels from 1 to 5.

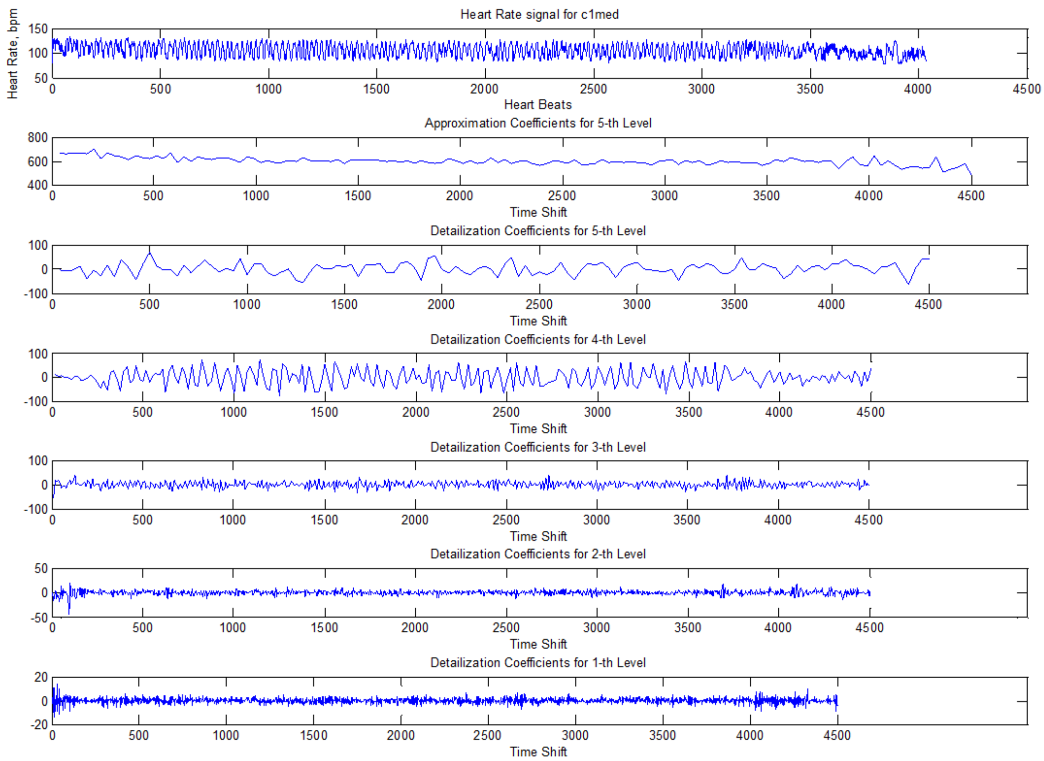

Fig. 3. Heart rate signal (top) during meditation and its wavelet decomposition coefficients for levels from 1 to 5.

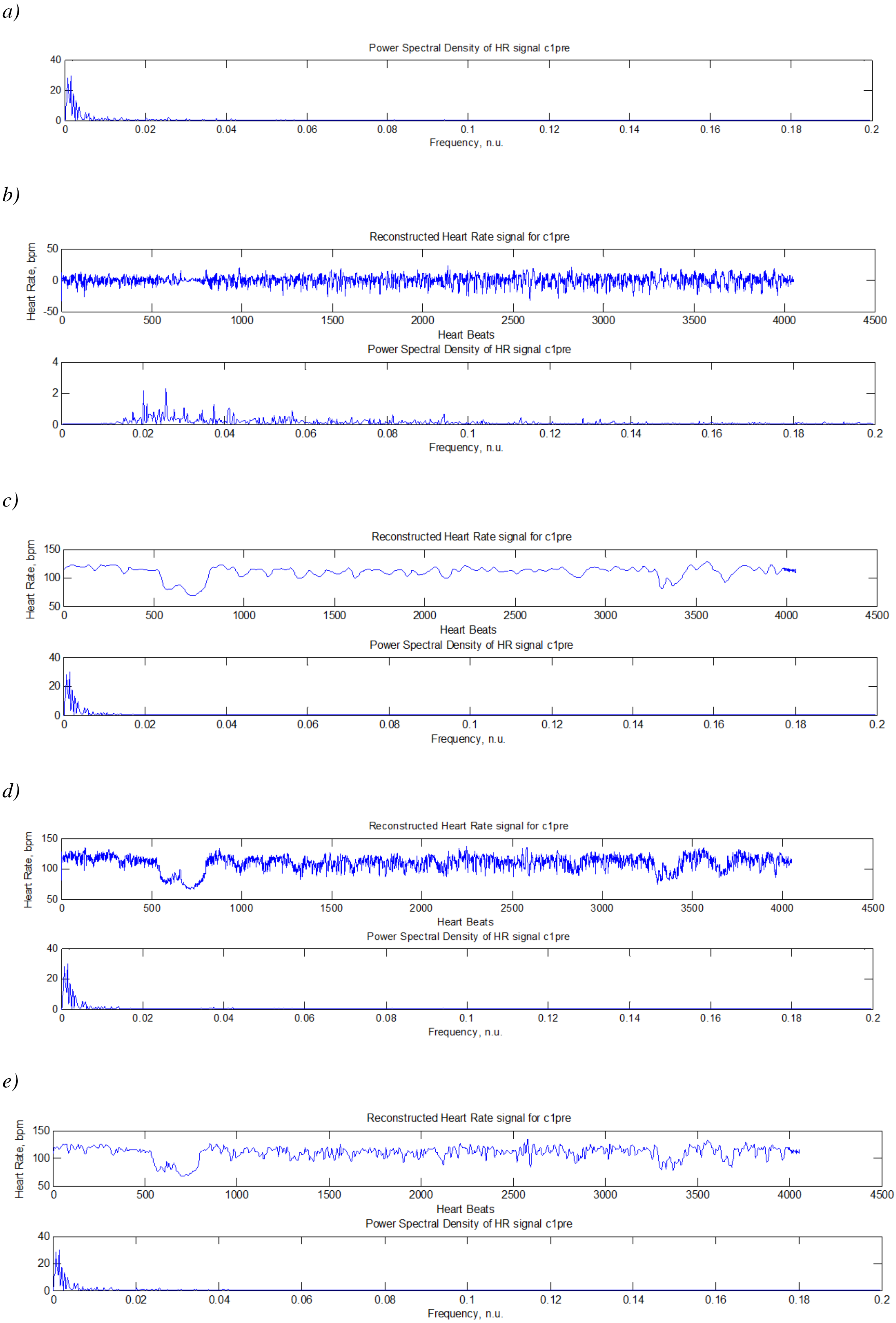

Fig. 4. Spectrum of reconstructed signal before meditation (a), partially reconstructed signal before meditation and its power spectra: without approximation coefficients (b), with approximation coefficients only (c), without 5^{th} level detail coefficients (d), without details from 1^{st} to 3^{rd} level (e).

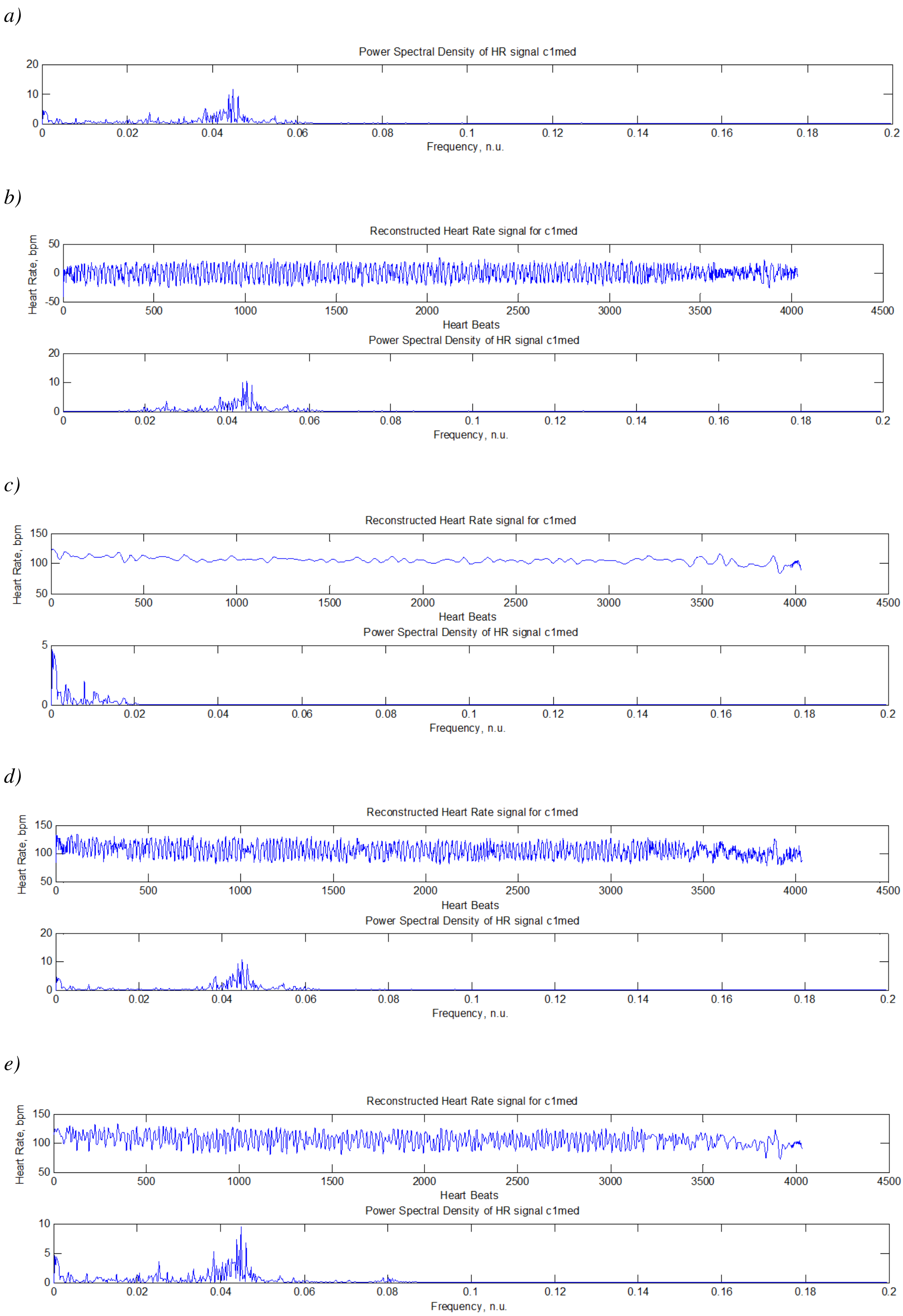

Fig. 5. Spectrum of reconstructed signal after meditation (a), partially reconstructed signal after meditation and its power spectra: without approximation coefficients (b), with approximation coefficients only (c), without 5^{th} level detail coefficients (d), without details from 1^{st} to 3^{rd} level (e)..