Comparison of Re-sampling Methods in the Spectral Analysis of RR-interval Series Data

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Abstract

The heart rate variability (HRV), refers to the beat-to-beat alterations in heart rate, is analyzed using RR-interval (RRI) series derived from the ECG signal as an interval between successive QRS complexes. For deciphering the true HRV spectrum using FFT, the RRI series should be re-sampled. But re-sampling often induces a noticeable distortion in the HRV power spectral estimates. Thus, the re-sampling operation should be accurate enough in reproducing the finest variation in the given signal. This paper compared three most widely used interpolation techniques: linear, cubicspline, and Berger's, as re-sampling methods, in an attempt to propose an optimal method of interpolation for HRV analysis. The linear and cubicspline methods based PSD estimates, for artificially generated non-uniformly sampled RRI series, introduce linear phase shifting, and thus lower the HRV frequencies. On the contrary, Berger's method efficiently reproduced the inherent frequencies in the underlying signal except some amplitude distortion. Further, similar trends in PSD estimates were obtained for real RRI series as well. Thus, it was concluded that at the expense of some increase in computational complexity, the spectral distortion has been significantly reduced using the Berger's interpolation based re-sampling method as compared to the linear and cubicspline methods.

Keywords: HRV, Interpolation, Re-sampling, Distortion, Phase-shift.

1. INTRODUCTION

The analysis of variations in instantaneous heart rate time series using normal-to-normal inter-beat intervals or RR-interval (RRI) of the heart is known heart rate variability (HRV). In recent years, the growing number of reports has shown that the analysis of HRV is a valid non-invasive tool capable of providing adequate information on autonomic modulation of the sinoatrial node in normal subjects and in patients with a variety of cardiac and non-cardiac diseases [1]-[5]. The availability of this tool to explore the changing dynamics of individual cardiovascular regulation profiles might lead to a deeper understanding of the role of the neural mechanisms in cardiovascular medicine, and help improve the efficiency of targeted medical treatment. With regard to this, the spectral analysis of HRV has gained an increasing attention and varieties of techniques have been proposed for its assessment. This analysis allows the estimation of location and strength of major oscillatory components of heart rate, which contribute to the signal variance, and it is now largely utilized in HRV studies [6]. Although theoretical properties and application methods of classical approach such as discrete Fourier transform (DFT), based on the

computation of periodogram, are extensively discussed in many books and articles on spectral analysis of time series [7], but yet there are several problems which are still encountered in practical analysis without definite guidelines to solve them.

The power spectrum of RRI fluctuations obtained using FFT [8]-[10] presents two principal components: a low-frequency (LF) component around 0.1 Hz (0.04–0.15 Hz), whose changes in power have been related to the sympathetic activity [1], [9], [11] and a high-frequency (HF) component, in synchrony with respiration rate (0.15–0.4 Hz), which is considered to be an expression of the respiration disturbances mediated by the vagal activity [10], [11]. A portion of the spectral power is also concentrated in a very low-frequency (VLF) band (from 0.001 to about 0.04 Hz), which is probably due to slow mechanisms of regulation such as humoral and thermoregulatory factors [1]. Further, for the accurate assessment of an HRV signal there are three main prerequisites that need to be taken care of (1) re-sampling frequency; (2) segment length; and most importantly (3) type of interpolation method used for re-sampling the RRI series. Out of these three, the first condition i.e. value of re-sampling frequency, has now almost got standardized to 4 Hz [12], secondly the segment length of 256 samples has also now become a standard [13]-[15]. But for the third requirement, after an extensive literature survey on ECG spectral estimation it has been observed that there is lot of inconsistency in the selection of an interpolating method for re-sampling the RRI series and also an adequate justification about which interpolating method is most suitable in HRV studies is usually lacking, and most of the studies are silent on this particular approach. Thus, to analyze the frequency domain measures of HRV using non-parametric techniques, there is an urgent need to optimize the interpolation method used for re-sampling the RRI time series.

Moreover, in general the re-sampling operation has been used for variety of purposes in many signal and image processing applications. When re-sampling a biomedical image or data, using interpolation, to a new set of coordinates there is often a significant loss in image or signal quality and it is reflected in terms of distortion in the spectral estmates. To preserve the signal quality, the interpolating function used for re-sampling (the RRI series) should be such that which induces the least distortion in the spectral estimates [16]. In spite of the fact that several interpolating functions have been used for re-sampling the discrete data but the functions which were most commonly used for re-sampling the RRI series are: linear interpolation [9], [10], [12]-[15], [17], [18], parabolic interpolation [19], [20], spline interpolation [18], [21]-[23], and Berger's method of interpolation [21], [24], [25]. The choice of an interpolating function to be used for re-sampling depends upon the task being performed. Its choice becomes more critical when the re-sampling process is used prior to further signal processing.

In this paper, to determine which interpolating method would provide the best re-sampling operation for RRI series, three methods were compared: A) linear, B) cubicspline, and C) Berger's. Moreover, such comparative performance evaluation has not yet been reported in the literature and no such systematic experiments were published earlier which could infer that how and in what sense, these interpolation based re-sampling methods affects HRV metric calculations. Consequently, a need was felt to carry out a thorough comparative study to demonstrate the most suitable interpolation based re-sampling method for RRI time series. This study was conceived to analyze the effect of various interpolations based re-sampling methods in HRV quantification. The focus has been on the selection of an appropriate interpolating function for the true representation of HRV. We selected for this study an artificially simulated, uniformly and non-uniformly sampled test signals for the predefined set of frequency components in the autonomic range (0 to 0.5 Hz) [1], owing to their completely known characteristics and nature. Here uniformly sampled test signals are generated at a uniform sampling interval of 250 msec (for FFT based spectral estimation of evenly sampled data) and non- uniformly sampled test signals are generated at a sampling instants of actual RRI records (for FFT based spectral estimation of unevenly sampled data after an interpolation based re-sampling), from a sine wave. The emphasis is on the comparison of spectra keeping in view the smoothness and accuracy of spectral estimates. After the validation of results on test as well as on real signals it has been found that the spectral estimates obtained using Berger's interpolation based FFT method are

more accurate in terms of reproduction of spectral peaks, resolution, smoothness and relative magnitudes of each spectral component, as compared to that of linear and cubicspline interpolation based PSD estimates.

2. RE-SAMPLING

Re-sampling is the process of transforming a discrete signal which is defined at one set of coordinate locations to a new set of coordinate points. It can be divided conceptually into two processes; interpolation of the discrete signal to a continuous signal and then sampling the interpolated signal. Frequently, re-sampling is used to increase the number of points in the signal to improve its behaviour for analysis. This process of filling in points between the data points is often thought of as interpolation. However, more accurately, the process of interpolation is fitting a continuous function to the discrete points in the signal. This continuous function can then be sampled at whatever points are necessary. In implementing re-sampling, interpolation and sampling are often combined so that the signal is interpolated at only those points which will be sampled.

Re-sampling to a larger matrix is often used prior to HRV signal processing in order to make the analysis more certain about the frequency variations in the signal. Increasing the matrix size by re-sampling cannot increase the resolution of the signal or the information in the signal. (Signal processing can only reduce the information in the signal.) The purpose of the re-sampling is to reduce the high-frequency artifacts in the signal analysis.

2.1. Interpolation and Sampling

A signal can be exactly reconstructed from samples if the signal is band limited and sampling is done at a frequency above the Nyquist frequency. But, however, that unlike the continuous signal, the sampled signal is not band limited. Sampling can be viewed as replicating the frequency spectrum at multiples of two pi times the sampling frequency. Interpolation, in contrast, is the opposite of sampling. It produces a continuous signal from a discrete signal. In order to reproduce a band limited function from a set of samples, the interpolating function should be an ideal low-pass filter. An ideal low-pass filter removes the replicates of the frequency spectrum introduced by the sampling. This suggests that the interpolating function which should be used for re-sampling is an ideal low-pass filter [26].

There are, however, practical considerations which make this theoretical re-sampling technique difficult in the context of HRV signal processing. First, the HRV signal which is to be analyzed is of finite extent. Therefore, this theoretical description which assumes that the signals are of infinite extent is only an approximation; and there will be variations from the theoretical results. Second, because of the computational burden in handling the RRI records, the filtering usually take place by convolving with the finite impulse response filters of short duration. For these reasons, an exact interpolation cannot be performed on heart rate series; and consideration must be given to tradeoffs between the accuracy and computational efficiency.

3. METHODS USED

The theory of three interpolation based re-sampling methods and the FFT method of power spectrum estimation that are implemented in this study are discussed below.

3.1. Interpolation Based Re-sampling Methods

The interpolation is a method of constructing new data points within the range of a discrete set of known data points. In order to convert the real RRIs into new values which are evenly spaced in time, the different interpolation functions that we used are as follows:

3.1.1 Berger's Method of Interpolation

In this method a local window is defined over each point t_i as the time interval extends from the previous sample to the next [24], [25]. Thus assigning each t_i a new RR-value coinciding with the

number of RRIs associated with the local window as shown in figure 1. If the time interval is located between two successive beats, then the new RR-value is given by the equation (1).

$$r_i = \left(t_{i+1} - t_{i-1}\right) * f_m / \left(2 * r_b\right) \tag{1}$$

where r_b is the value of RR-distance between two successive beats and f_m is the re-sampling frequency.
If the interval uncludes a beat, the r_i would be calculated using equation (2).

$$r_i = \left(\left(t_a - t_{i-1}\right)/r_a + \left(t_{i+1} - t_a\right)/r_b\right) * f_m / 2 \tag{2}$$

where r_a and r_b are the RRIs associated with that beat and the following beat, respectively.

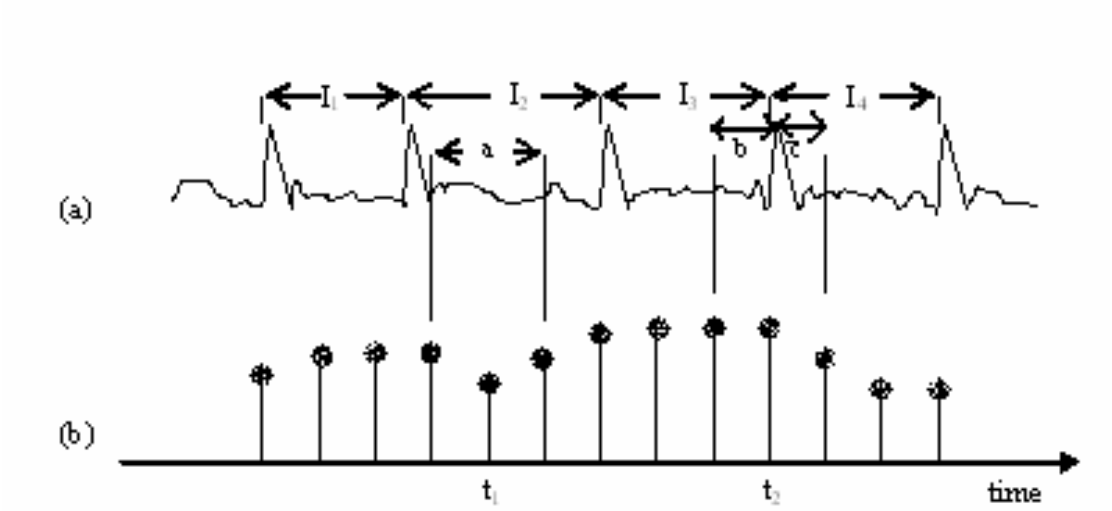

FIGURE 1: Berger's method of interpolation. Where a, b, and c are the local windows; I_1, I_2, I_3, I_4 are the distance between RR-peaks; t_1, t_2 are the time points.

3.1.2 Linear Interpolation

Linear interpolation also known by lerping - is a method of curve fitting using linear polynomials. It is one of the simplest methods of interpolation. With this method the new sequence of values which are evenly spaced in time are derived at each time instant t_i according to the re-sampling frequency of 4 Hz [25]. For each t_i its new associated RR-value is calculated using equation (3).

$$r_i = r_a + (t_i - t_a) * ((r_b - r_a)/(t_b - t_a)) \tag{3}$$

where t_a and t_b are the times associated with the beats before and after time t_i. r_a and r_b are their associated RR-values and r_i's are the new evenly spaced RR-values.

3.1.3 Cubicspline Interpolation

The basic idea behind cubicspline interpolation is based on the concept of drawing smooth curves through a number of data points. This spline consists of weights attached to a flat surface at the points to be interpolated. A flexible strip is then made to bend across each of these weights, resulting in a smooth curve. In mathematical spline, the weights are the coefficients of cubic polynomials used to interpolate the data. These coefficients bend the line so that it passes through each of the data points without any break in continuity. It uses the low degree polynomials in each of the intervals and chooses the polynomial pieces such that they fit together smoothly. Mathematically it can be expressed by the piece-wise function of the form given by equation (4) [21]-[23].

$$S(x) = \begin{cases} s_1(x) & if \quad x_1 \le x < x_2 \\ s_2(x) & if \quad x_2 \le x < x_3 \\ s_{n-1}(x) & if \quad x_{n-1} \le x < x_n \end{cases} \tag{4}$$

where s_i is the third degree polynomial defined using equation (5)

$$s_i(x) = a_i(x - x_i)^3 + b_i(x - x_i)^2 + c_i(x - x_i) + d_i \tag{5}$$

for $i = 1, 2, \ldots, n-1$

The first and second derivatives of these $n-1$ equations are fundamental to this process, and they are defined using equations (6) and (7).

$$s'(x) = 3a_i(x - x_i)^2 + 2b_i(x - x_i) + c_i \tag{6}$$

$$s_i''(x) = 6a_i(x - x_i) + 2b_i \tag{7}$$

for $i = 1, 2\ldots, n-1$

After solving the above defined generalized equations from (4)–(7), we get the new RR-values which are evenly spaced in time.

3.2. FFT Based Method

The FFT based technique has been used on Hann windowed data for the power spectrum estimation of the uniformly and non-uniformly sampled simulated test signal. The power spectrum which is computed using FFT is variance normalized [12]-[15] and is represented as amplitude spectral density functions defined using equation (8).

$$\left|X\left(k\Delta f\right)\right| = \sqrt{X_R^2\left(k\Delta f\right) + X_1^2\left(k\Delta f\right)} \tag{8}$$

$X_R(k\Delta f)$ and $X_1(k\Delta f)$ are the real and imaginary parts of complex spectrum $X(k\Delta f)$, computed according to equation (9) [14], [15].

$$X(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n) e^{-jkn(2\pi/N)} \tag{9}$$

4. POWER SPECTRAL ANALYSIS

The power spectral analysis of HRV provides an estimation of the variability, distributed as a function of frequency. In this paper, spectral analysis was first performed on uniformly sampled and non-uniformly sampled test signals generated using a sine wave model, in order to have control over the frequency variations, instead of on an actual data. Later on, the analysis was performed on actual RRI series data as well.

4.1. Generation of Test Signals

In order to induce desired frequency variations, uniformly sampled test signal $x_1(n)$, and non-uniformly sampled test signals $x_{11}(n)$, $x_{12}(n)$, $x_{13}(n)$, and $x_{14}(n)$ are generated for fixed set of frequency components: f_1=0.008 Hz, f_2=0.09 Hz, f_3=0.13 Hz, f_4=0.25 Hz, and f_5=0.4 Hz respectively in the autonomic range from 0 Hz-0.5 Hz, using a sine wave equation (10). For the generation of non-uniformly sampled test signals, actual RRI records of four healthy subjects have been used as sampling instants and the procedure that is adopted for acquiring the RRI data from healthy volunteers is as follows: The ECG data of standard Lead-II were obtained for the duration of 15 minutes, from selected healthy subjects using BIOPAC® MP100 system in a quiet room, in comfortable light and temperature levels. To achieve the good signal quality, the subjects were made to rest in supine position for 10 minutes prior to recording, so that the subject may stabilize to the laboratory environment. The recorded signals were A/D converted at 500 Hz sampling frequency, 12-bit resolution, and then stored and processed on an Intel PIV-processor. The recognition of the QRS complexes in the ECG and the detection of R-wave were performed by means of the software developed by our group [27]-[29]. Finally the RRI series is derived from R-waves of ECG records.

$$x_n = A\left[\sin\left(2\pi f_1 n\Delta t\right) + \sin\left(2\pi f_2 n\Delta t\right) + \sin\left(2\pi f_3 n\Delta t\right) + \sin\left(2\pi f_4 n\Delta t\right) + \sin\left(2\pi f_5 n\Delta t\right)\right] \tag{10}$$

where sampling frequency $f_s = 1/\Delta t = 4Hz$, amplitude A=2, and n is the time-index.

- Uniformly sampled test signal $x_1(n)$ is shown in figure 2(a).
- Non-uniformly sampled test signals from $x_{11}(n)$ to $x_{14}(n)$ are generated, by using the sampling instants of RRIs series shown in figures 2(b), (d), (f), and (h), using equation (10) shown in figures 2(c), (e), (g), and (i) respectively.

4.2. Spectral Estimation Results for Test Signals $x_1(n)$ and $x_{11}(n)$ to $x_{14}(n)$

The results in the form of comparative analysis between an idealized FFT based power spectrum of evenly sampled data (without any re-sampling) i.e. for signal $x_1(n)$, and an FFT based power spectrum of non-uniformly sampled data i.e. for signals $x_{11}(n)$ to $x_{14}(n)$, after re-sampling are as follows:

4.2.1 PSD Estimation of Uniformly Sampled Test Signal $x_1(n)$ Using FFT Method Without Re-sampling (idealized case)

The FFT- based PSD plot of signal $x_1(n)$ is shown in figure 3(a). Its power spectrum shows five distinct spectral peaks at exactly the f_1, f_2, f_3, f_4, and f_5 frequency locations, as given in test signal. The power values of frequencies in the pre-selected frequency bands are given in table 1,

which maintains approximately same magnitude in the entire power spectrum. The trend followed by these values of power in the PSD plot is shown by drawing a dotted black coloured trend line as in figure 4. The shape of this line is straight which signifies that all the frequencies have been resolved with equal strength and representing a high spectral resolution and accuracy.

4.2.2 PSD Estimation of Non-uniformly Sampled Test signal $x_{11}(n)$ Using Re-sampling Based FFT Method

The spectra obtained by using standard techniques of spectral analysis, such as FFT, may be distorted if the input data are not evenly sampled over time [30], [31]. This is due to the fact that when sampling is a function of beats, rather than seconds, the sampling rate will lack interindividual and intertask consistency due to differences in heart rate. In this part of work, when power spectrum estimation of raw RRI has been done using FFT without any re-sampling, then it has been observed that there is almost zero power contained in the spectral peaks at all the five preselected frequency bands corresponding to the five fixed set of frequency components. These values of power are given in table 1 and are also shown by plotting

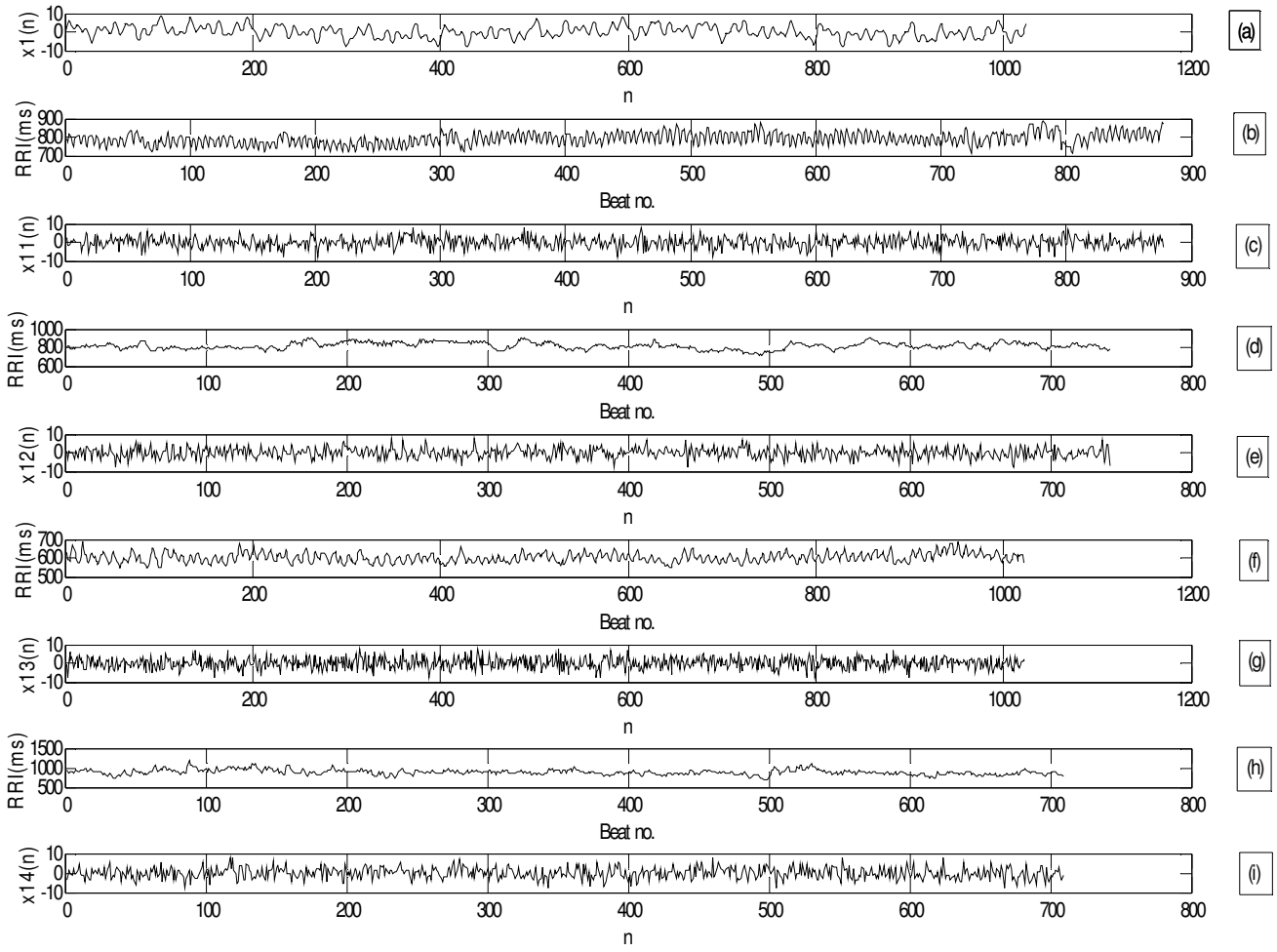

FIGURE 2: Test signals tachograms (a) Uniformly sampled test signal $x_1(n)$ (b) Timebase-I: actual RRI series from *Subject-I* (c) Non-uniformly sampled test signal $x_{11}(n)$ using sampling timebase-I (d) Timebase-II: actual RRI series from *Subject-II* (e) Non-uniformly sampled test signal $x_{12}(n)$ using sampling timebase-II (f) Timebase-III: actual RRI series from *Subject-III* (g) Non-uniformly sampled test signal $x_{13}(n)$ using sampling timebase-III (h) Timebase-IV: actual RRI series from *Subject-IV* (i) Non-uniformly sampled test signal $x_{14}(n)$ using sampling timebase-IV.

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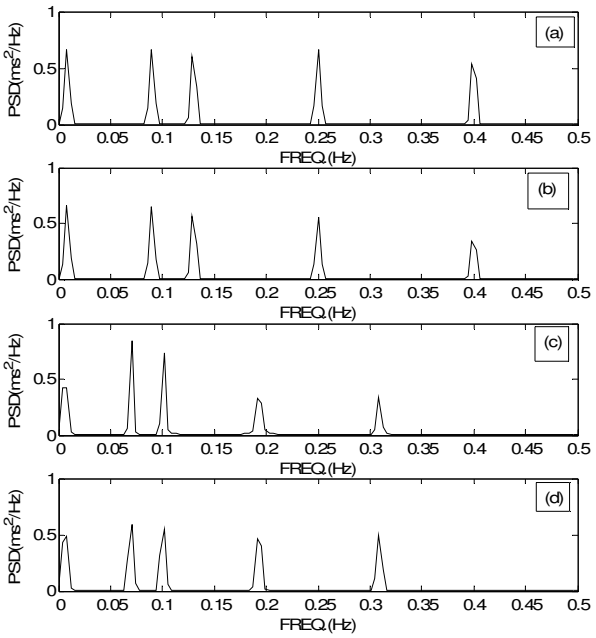

FIGURE 3: PSD plots of test signals $x_1(n)$ and $x_{11}(n)$ using FFT for fixed set of frequency components (a) For uniformly sampled test signal $x_1(n)$ (b) For non-uniformly sampled test signal $x_{11}(n)$ corresponding to *Subject-I* after Berger's interpolation based re-sampling method (c) For non-uniformly sampled test signal $x_{11}(n)$ corresponding to *Subject-I* after linear interpolation based re-sampling method (d) For non-uniformly sampled test signal $x_{11}(n)$ corresponding to *Subject-I* after cubicspline interpolation based re-sampling method.

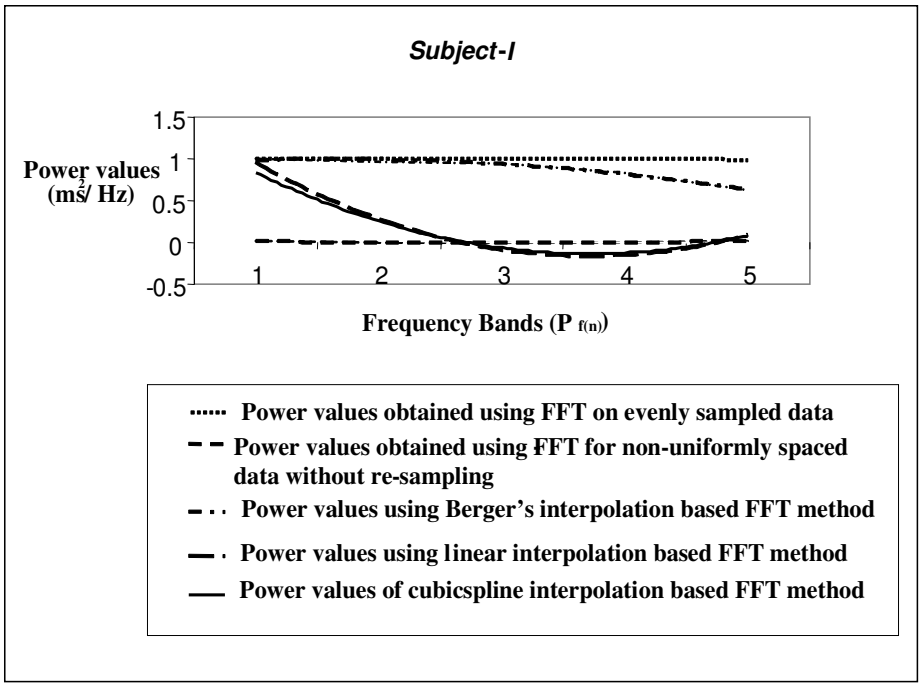

FIGURE 4: Trend line plot for the values of power obtained using FFT (i) For uniformly sampled test signal $x_1(n)$ (ii) For non-uniformly sampled test signal $x_{11}(n)$ corresponding to *Subject-I* without any re-sampling (iii) For non-uniformly sampled test signal $x_{11}(n)$ corresponding to *Subject-I* after applying Berger's, linear and cubicspline based re-sampling methods.

TABLE 1: Power values of test signals for fixed set of frequency components.

Subjects	Estimation Technique			P_{f1} (ms^2/Hz)	P_{f2} (ms^2/Hz)	P_{f3} (ms^2/Hz)	P_{f4} (ms^2/Hz)	P_{f5} (ms^2/Hz)
For signal $x_1(n)$	Spectral estimation using FFT on evenly sampled data (idealized case)			0.9981	0.9985	0.9948	0.9986	0.9883
Subject-I (For signal $x_{11}(n)$)	Spectral estimation using re-sampling based FFT method (for non-uniformly sampled data)	Re-sampling methods	No re-sampling	0.0009	0.0010	0.0001	0.0021	0.0026
			Berger	0.9944	0.9718	0.9416	0.8350	0.6242
			Linear	0.9412	0.0189	0.0162	0.0060	0.0018
			Cubicspline	1.0254	0.0117	0.0015	0.0002	0.0002
Subject-II (For signal $x_{12}(n)$)		Re-sampling methods	No re-sampling	0.0019	0.0021	0.0001	0.0006	0.0009
			Berger	1.0056	0.9860	0.9507	0.8318	0.6033
			Linear	0.9537	0.2224	0.0404	0.0110	0.0002
			Cubicspline	1.0037	0.0807	0.0161	0.0062	0.0003
Subject-III (For signal $x_{13}(n)$)		Re-sampling methods	No re-sampling	0.0011	0.0001	0.0016	0.0003	0.0005
			Berger	1.0002	0.9840	0.9698	0.8760	0.7175
			Linear	0.9989	0.9372	0.0133	0.5643	0.0004
			Cubicspline	1.0256	0.7300	0.0026	0.7495	0.0001
Subject-IV (For signal $x_{14}(n)$)		Re-sampling methods	No re-sampling	0.0002	0.0009	0.0021	0.0016	0.0013
			Berger	1.0231	0.9801	0.9232	0.7701	0.5465
			Linear	1.0147	0.9625	0.4230	0.1667	0.0280
			Cubicspline	0.9597	0.9168	0.8167	0.4846	0.1732

P_{f1} =0.000 Hz-0.01563 Hz, P_{f2} =0.08203 Hz-0.09766 Hz, P_{f3} =0.1211 Hz-0.1367 Hz, P_{f4} =0.2422 Hz-0.2578 Hz,
P_{f5} =0.3906 Hz-0.4064 Hz

a trend line in figure 4. This represents a very high spectral distortion and is the case of total spectral smearing. This justifies the need of re-sampling the RRI series prior to HRV analysis. Thus, to avoid spectral distortions, RRI series were transformed into evenly sampled signals using interpolation. This interpolation based re-sampling of the RRI data using equal intervals, before spectral estimation, has also been recommended in the literature [32], [33]. The results in the form of PSD estimates using FFT after three interpolations based re-sampling methods are as follows:

4.2.2.1 Berger's Interpolation Based Spectral Estimates

The PSD plot of test signal $x_{11}(n)$ after applying Berger's method of interpolation is shown in figure 3(b). This plot reproduces five distinct spectral peaks at f_1, f_2, f_3, f_4, and f_5 frequency locations as efficiently as in the case of FFT based method on uniformly sampled data (idealized case) and their relative amplitudes are also tallying to that of a plot of test signal $x_1(n)$. This means that the PSD plot obtained after applying this method on unevenly sampled data is almost the same as that for evenly sampled data, representing sufficiently smooth spectrum with negligible spectral leakage and distortion.

The power values for the test signal $x_{11}(n)$ using Berger's based FFT method, as given in table 1, are in close agreement to that obtained using FFT for uniformly sampled test signal ($x_1(n)$). These values are shown by a trend line in figure 4, representing nearly the same pattern as that obtained after FFT on uniformly sampled signal, except a slight deviation at the end representing an amplitude distortion in comparison to idealized case.

4.2.2.2 Linear Interpolation Based Spectral Estimates

After applying a linear interpolating function on test signal $x_{11}(n)$, the FFT based power spectra which are obtained is shown in figure 3(c). In the PSD plot the spectral peaks are shifted towards the low frequency regions i.e. to 0.007 Hz, 0.07 Hz, 0.10 Hz, 0.19 Hz and 0.3 Hz instead of remaining fixed at 0.008 Hz, 0.09 Hz, 0.13 Hz, 0.25 Hz and 0.4 Hz locations as specified in the test signal. This signifies that the linear interpolation method induces a distortion in the spectral estimates in terms of shifting of spectral peaks to low frequency regions of the autonomic band. In addition to shifting of spectral peaks, multiple peaks are also arisen in the PSD plot that further adds to the spectral distortion.
The frequency shift which is obtained here has been found to be linear and satisfies the mathematical relationship given by equation (11). The higher frequency components demonstrate a comparatively more frequency shift than the low frequency components.

$$\beta(f) = 0.25\Delta f \tag{11}$$

where $\beta(f)$ is the obtained linear frequency-shift and Δf is the frequency resolution.

Moreover, the values of power in P_{f2}, P_{f3}, P_{f4} and P_{f5} frequency bands, as given in table 1, shows a large deviation from the values of power obtained for evenly sampled signal as well as for non-uniformly sampled signal after Berger's based interpolation. Further, the trend line (representing the trend in the values of power in PSD plot) obtained after linear interpolation based FFT method of spectral estimation drifts largely away from the trend line obtained for an evenly sampled data and after Berger's based re-sampling method as shown in figure 4. That means, with this method of re-sampling the energy contained in the spectral peaks gets shifted into the neighboring side lobes due to the linear phase shifting effect.

4.2.2.3 Cubicspline Interpolation Based Spectral Estimates

After applying cubicspline interpolating function on test signal $x_{11}(n)$ the following are the observations:

- The frequency terms and the spectral peaks are linearly shifted towards the low frequency regions of the plot shown in figure 3(d), by the same amount and proportion as obtained in linear interpolation method.

- The values of power as per table 1 are further reduced from the values obtained using linear interpolation based FFT method. Thus the spectral distortion gets increases. These values of

power are also represented by drawing a trend line shown in figure 4, which exhibits a large deviation from even sampling or idealized case as well as from Berger's based method.

Further, this study was extended to test signals $x_{12}(n)$, $x_{13}(n)$, and $x_{14}(n)$. The results in terms of PSD plots are shown in figure 5, 6 and 7 and the values of power are given in table 1. These results demonstrate that the power values and PSD plots, obtained after Berger's re-sampling based FFT method on non-uniformly sampled data closely resembles with that obtained after FFT method on evenly sampled data. Thus, the Berger's interpolation based FFT method of spectral estimation for non-uniformly sampled data gives superior performance with clearly outlined peaks in predefined low- and high-frequency bands in comparison to other two variants (linear and cubicspline) in HRV studies. The same study was extended using the sampling bases of ten other healthy subjects with different sets of frequency components and the results support the earlier observations.

Although patterns of heart rate variability hold considerable promise for clarifying issues in clinical applications, the inappropriate quantification and interpretation of these patterns may obscure critical issues and may impede rather than foster the development of HRV in clinical settings. Thus keeping this thing in consideration, actual recordings of RRI series of twenty healthy volunteers were now analyzed. The series are selected to cover a variety of PSD estimate shapes. The results in terms of PSD plots for two such cases are shown in figures 8 and 9. From the visual analysis of these figures it is quite obvious that the type of an interpolation method chosen for re-sampling the RRI series, affects the HRV metrics in terms of resolution, spectral shift and smoothness, as well as power distribution among various autonomic frequency bands. After analyzing the actual signals, it is seen that the FFT based spectrum obtained using re-sampled RRI series data with linear and cubicspline methods of interpolation, are shifted to lower frequency regions as compared to that of Berger's re-sampling based FFT method. With this it is verified that the Berger's method provides an accurate and smooth spectral estimate with clearly prominent peaks in autonomic band. Thus, as established using synthetic signals and actual variability records, the Berger's interpolation based method for re-sampling the non-uniformly spaced RRI data has been used for accurate assessment, which has a direct bearing on the HRV interpretations.

5. CONCLUSION

The present paper lays considerable emphasis on (1) the algorithmic considerations of Berger's, linear, and cubicspline re-sampling methods for spectral estimates, and (2) their capabilities of resolving the frequency peaks in various bands leading to the ability to precisely discriminate between pathologies. In this study, the spectral estimates of the uniformly sampled data using FFT, which requires no re-sampling, is taken as a reference. Consequently, the non-uniformly sampled data was derived from the sinusoidal signal containing predefined set of frequency components. Using the sine wave based non-uniformly sampled data; it was found that the linear and cubicspline interpolation based re-sampling methods shift the spectral peaks towards the low frequency regions due to the linear phase shifting. This frequency shift is more for higher frequency components. But with Berger's interpolation no such linear shift is introduced and it provides most accurate results that closely match with that of spectral estimates of uniformly sampled test signal. Thus the Berger's based FFT method outperformed linear and cubicspline based FFT methods for spectral estimation of non-uniformly sampled data. Hence, the proposed Berger interpolation based re-sampling method in the spectral analysis of HRV signal is capable in providing accurate autonomic frequencies assessment.

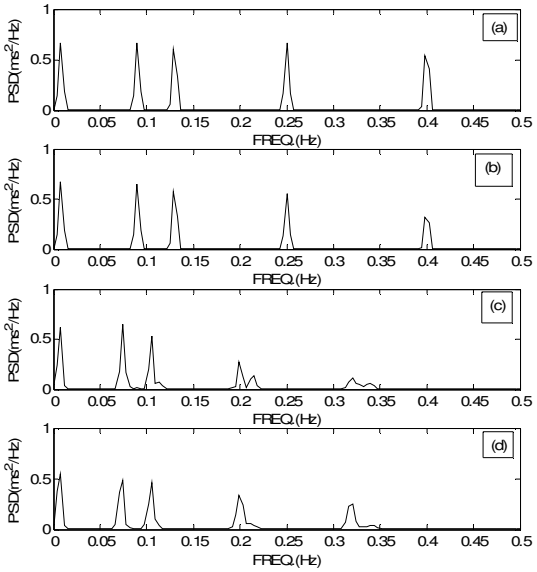

FIGURE 5: PSD plots of test signals $x_1(n)$ and $x_{12}(n)$ using FFT for fixed set of frequency components (a) For uniformly sampled test signal $x_1(n)$ (b) For non-uniformly sampled test signal $x_{12}(n)$ corresponding to *Subject-IV* after Berger's interpolation based re-sampling method (c) For non-uniformly sampled test signal $x_{12}(n)$ corresponding to *Subject-IV* after linear interpolation based re-sampling method (d) For non-uniformly sampled test signal $x_{12}(n)$ corresponding to *Subject-IV* after cubicspline interpolation based re-sampling method.

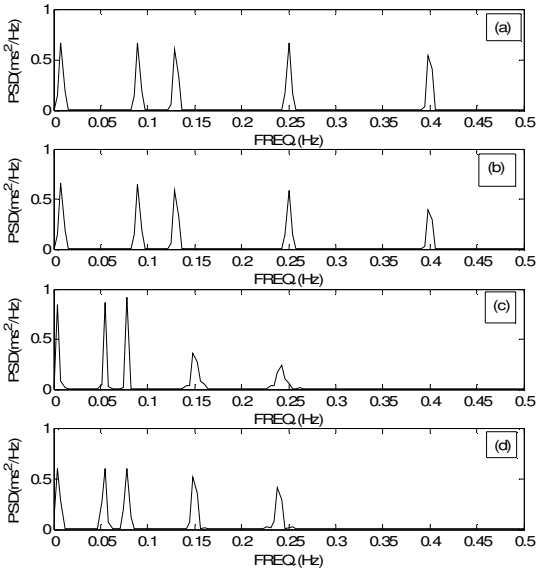

FIGURE 6: PSD plots of test signals $x_1(n)$ and $x_{13}(n)$ using FFT for fixed set of frequency components (a) For uniformly sampled test signal $x_1(n)$ (b) For non-uniformly sampled test signal $x_{13}(n)$ corresponding to *Subject-III* after Berger's interpolation based re-sampling method (c) For non-uniformly sampled test signal $x_{13}(n)$ corresponding to *Subject-III* after linear interpolation based re-sampling method (d) For non-uniformly sampled test signal $x_{13}(n)$ corresponding to *Subject-III* after cubicspline interpolation based re-sampling method.

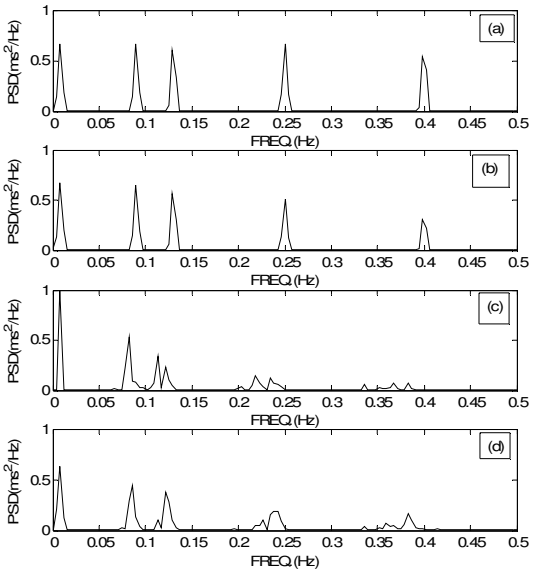

FIGURE 7: PSD plots of test signals $x_1(n)$ and $x_{14}(n)$ using FFT for fixed set of frequency components (a) For uniformly sampled test signal $x_1(n)$ (b) For non-uniformly sampled test signal $x_{14}(n)$ corresponding to *Subject-IV* after Berger's interpolation based re-sampling method (c) For non-uniformly sampled test signal $x_{14}(n)$ corresponding to *Subject-IV* after linear interpolation based re-sampling method (d) For non-uniformly sampled test signal $x_{14}(n)$ corresponding to *Subject-IV* after cubicspline interpolation based re-sampling method.

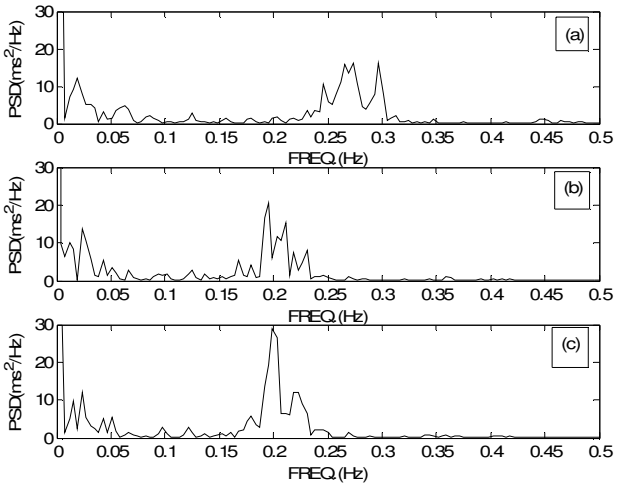

FIGURE 8: PSD plots of actual signal 1 using FFT (a) After Berger's interpolation based re-sampling method (b) After linear interpolation based re-sampling method (c) After cubicspline interpolation based re-sampling method.

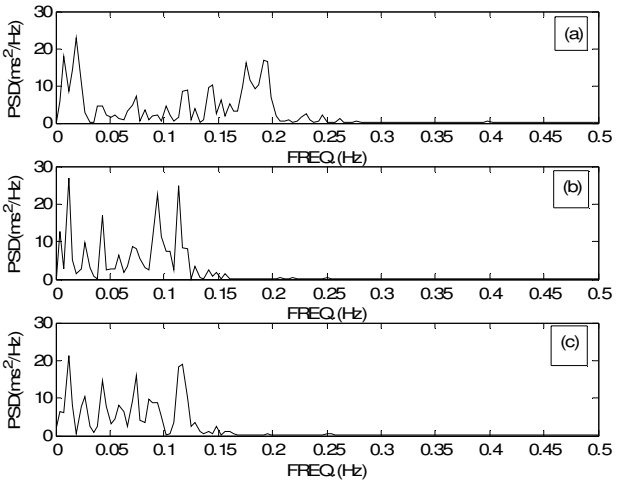

FIGURE 9: PSD plots of actual signal 2 using FFT (a) After Berger's interpolation based re-sampling method (b) After linear interpolation based re-sampling method (c) After cubicspline interpolation based re-sampling method.

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