A comparison between Walsh and autoregressive derived parameters of heart rate variability spectra in normal subjects and diabetics

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ABSTRACT

Objective: The objective of this study is to compare the fast Walsh transform with autoregressive method for spectral analysis of heart rate variability signals based on evaluating the quantitative and dynamic differences between the results of Walsh and autoregressive analysis of heart rate variability signals for healthy patients and diabetic patients who have suffered from diabetes more than 10 years and have autonomic dysfunction.

Methods: Electrocardiogram signals from 8 normal subjects and 8 diabetic patients were measured and recorded in the supine position for a 15 minute period. Heart rate variability signals extracted from electrocardiograms were recorded on FM recorder or digitized and recorded on floppy disk for future analysis. Walsh and autoregressive analyses were employed to compare the efficacy of both techniques.

Results: The study shows that there are quantitative differences of power spectra of heart rate variability signals between the two frequency techniques namely the autoregressive method and fast Walsh transform for both the healthy and diabetic groups. The efficiency of fast Walsh transform and the autoregressive method have been recognized due to the computionally superiority, supporting the use of both techniques instead of fast Fourier transform especially for heart rate variability signals. However, the autoregressive method may be superior over fast Walsh transform specially in short duration of heart rate variability signals as well as the low signal to noise ratio of heart rate variability signals.

Conclusion: The analysis of heart rate variability signals using autoregressive and fast Walsh transform methods based on evaluating the quantitative and dynamic differences seems promising to track the compilation of diabetic patients on autonomic function. Further investigation may be needed to use these indices for early diagnosis of autonomic dysfunction using this methodology.

Keywords: Heart rate variability, power spectra, autoregressive method, Walsh transform, autonomic nervous system.

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Starting from the 1970's great improvement in the analysis of arterial blood pressure (ABP) signal and heart rate variability (HRV) has resulted from extensive use of computerized techniques with autonomic detection of cardiac cycle fiducial points on the signals and further digital processing. Such spontaneous oscillations in time attributed to neural control mechanisms of blood pressure and heart rate (affected by way of sympathetic and parasympathetic systems) modulated by centrally mediated influences and very fast peripherial responses (ie baroreflex response) as well as by a direct mechanical influence of respiration.

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Since the papers of Hyndman[1], Sayers[2], Penaz[3], Ahmed et al[4], many authors have tried to extract more information from the variability signal of heart rate in order to obtain quantitative indices of the regulatory activities of both sympathetic and parasympathetic nervous systems. Kitney[5], Mearns et al[6] have used fast Fourier transform (FFT) method to estimate the power spectral of HRV signal. Also, Baselli et al[7] Pagani et al[8] have demonstrated how an autoregressive (AR) identification and power spectral estimation of the discrete series of HRV variability signal are significant methods.

The application of power spectral analysis derived from HRV signal for both normal subjects and diabetes following posture entrainment are reported [9,10]. Akker et al[9] found that low frequency in power spectrum (PS) of 13 diabetics with autonomic neuropathy was low. They ascribe depressed power of the power spectrum for HRV signal (PS/HRV) for diabetics to reduction of parasympathetic and sympathetic inputs to sinoatraial node. Also, Lishner et al[10] evaluated 23 diabetics with autonomic neuropathy, they marked reduction in the power of HR fluctuations throughout all the frequencies. Pagani et al[11] subjected 49 uncomplicated diabetics to supine and standing conditions while recording their PS/HRV. The PS/HRV have normal low frequency and high frequency ratio (LF/HF) ratio during supine state but during standing revealed a low LF/HF ratio compared to normal subjects. They referred that to the failure of augmentation of blood pressure control oscillation at 0.1 Hz/PS amplitude from supine to standing in cases of diabetes.

In recent years, the efficacy of using both the Walsh transform and autoregressive method for physiological signals specially electrocardiogram (ECG) has been examined by several authors[11-17]. Indeed, a controversy has arisen between advocates of each method.[13,14] The debate centers on the

Table 1 - Power distribution parameters definition of signal parameters extracted from Walsh and autoregressive spectra for comparison.

Parameter	Symbol	Definition
Lower corner frequency	FL	Frequency above which 90% of the power exists
Upper corner frequency	FU	Frequency below which 90% of the power exists
Algebraic mean frequency	FAC	(FL + FU)/2
Geometric mean	FGC	(FL * FU)1/2
Actual bandwidth	BWA	(FU - FL)
Total power	PT	Power presents between FL and FU

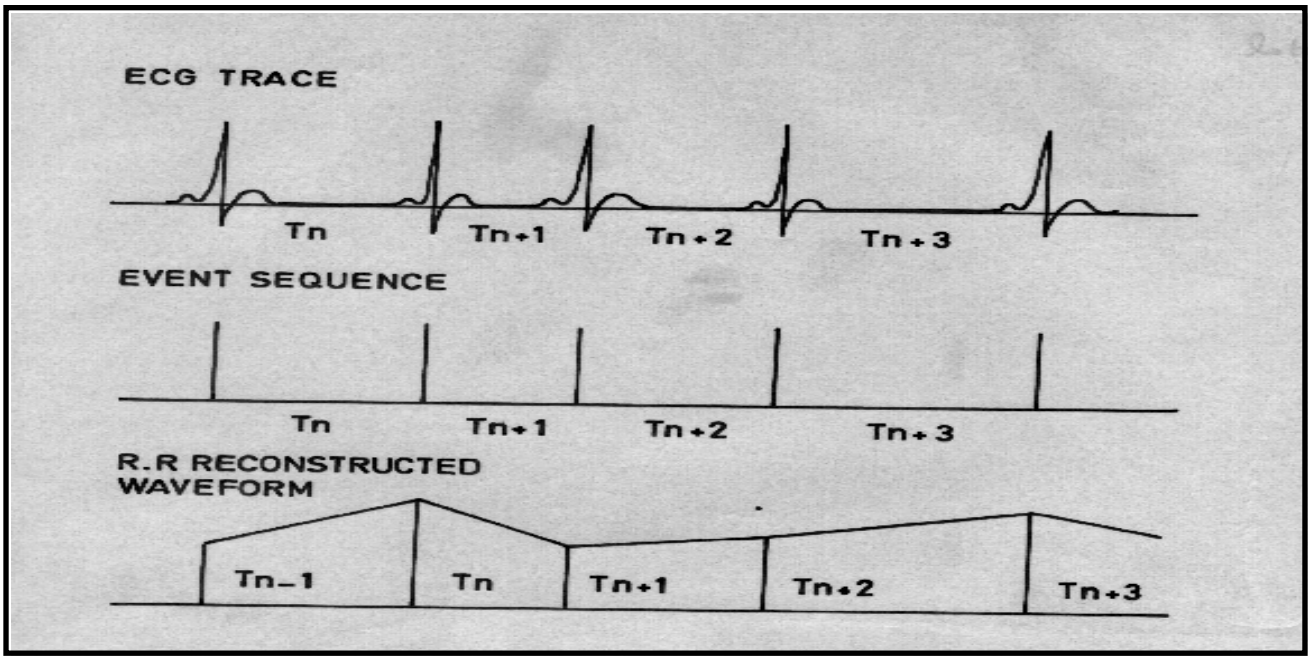

Figure 1 - Generation of heart rate variability signal.

Table 2 - Autoregressive derived parameters of high rate variability power spectra for normal subjects.

Subject	FL	FU	FAC	FGC	BW	PT
1	0.02	0.35	0.185	0.083	0.33	15.33
2	0.02	0.355	0.185	0.084	0.335	15.21
3	0.02	0.36	0.19	0.0848	0.34	14.95
4	0.02	0.365	0.1925	0.854	0.345	14.91
5	0.02	0.355	0.185	0.084	0.335	15.11
6	0.02	0.373	0.1965	0.087	0.353	14.81
7	0.02	0.38	0.20	0.0863	0.36	14.62
8	0.02	0.353	0.1865	0.084	0.0333	15.29

Table 3 - Walsh derived parameters of high rate variability power spectra for normal subjects.

Subject	FL	FU	FAC	FGC	BW	PT
1	0.02	0.44	0.229	0.093	0.42	16.15
2	0.02	0.445	0.2295	0.089	0.425	16.12
3	0.02	0.443	0.230	0.0892	0.423	16.1
4	0.02	0.45	0.234	0.09	0.430	15.995
5	0.02	0.46	0.24	0.0959	0.44	15.67
6	0.02	0.455	0.2375	0.091	0.435	15.84
7	0.02	0.453	0.03265	0.095	0.433	15.88
8	0.02	0.45	0.234	0.09	0.430	15.993

question of whether one can resynthesize a sinusiodal like signal as the majority of the physiological signals with summation of rectangular functions (Walsh series) and expect to derive the same information as is available from the AR method. Actually, Walsh functions are a class of orthonormal rectangular waveforms which have only two amplitude values of +1 and –1. A time series can be expressed in terms of the sum of a series of Walsh functions in sequency domain (sequency is defined as half the number of sign changes/unit time interval). Since Walsh functions can have two values a sequency spectrum can be computed more rapidly than other frequency spectrum. In fact fast Walsh transform (FWT) is attractive because it is computationally more efficient and thus faster to perform on a digital computer. On the other hand, the AR method has been broadly applied to many fields including speech system identification, image and biomedical signal processing.[8-10] A particular advantage of this approach is that it can result in a better estimation of spectral features, particularly in low signal to noise ratio.

This study was conducted to examine whether Walsh and AR analysis can be utilized to track the changes in the total power and distribution in the frequency spectrum of HRV signals in normal and diabetic patients. The signal parameters chosen to track these effects are listed and defined in Table 1. It may be noted that the power distribution parameters FL, FU, FAC, FGC, BWA are parameters commonly used in analog and digital filter design that describe the various characteristics of the frequency response of the filter when these parameters are applied to the power spectrum of HRV signals. They describe how the power is distributed by the fact they are defined in terms of power density. This is the basis for choosing them as power distribution parameters. In this study, these parameters were extracted from actual HRV signals for normal and diabetic patients at rest using Walsh and AR techniques. The resulting associated parameter records were compared statistically to evaluate their quantitative and dynamic differences.

Methods.

Experimental procedure. Electrocardiogram and peripheral blood flow (PBF) signals from 8 normal and 8 diabetic patients were used in this study. The volunteers (normal subjects and diabetic subjects) were male from the Boston Teaching University Hospital, Boston, USA. These ECGs and PBFs were measured and recorded in the supine position for a 15 minute period. During the recording session, the volunteers remained in a relaxed motionless supine position. The patients participated in the study with informed consent and with hospital approval.

Data collection. The ECG signals of 8 normal and 8 diabetic patients were amplified using instrumentation amplifiers and recorded on magnetic tape (Bioscience Co. Model 4A FM cassette or Model D FM reel to reel instrumentation recorder) for off-line analysis. The recorded ECG signals were processed with analog low pass filter (0-100 Hz, fourth order butterworth response). Heart rate variability signals were produced using hardware equipment to detect the R wave of the ECG and reconstruct the R-R interval wave as shown in Figure 1. The HRV signal were sampled at 400 msec. Then HRV signals were recorded for off-line analysis. Walsh and AR analyses were performed in 10 minute periods of 512 points epoch of each volunteer. The Walsh spectra was windowing with Hanning (cosine square) function. The AR power spectra had been accomplished by solving Yule-Walker equations by means of computionally efficient Levenson-Durbin algorithm[10,12]. Fast Walsh transform used by Larsen and Lai[18], and developed by the authors according to algorithm of Ohkita and Kobayashi[19] were used for the analysis using PC microcomputer. The sixth spectral parameters in Table 1 were extracted from

Table 4 - Summary of direct difference statistical analysis on corresponding Walsh and autoregresssive derived parameter records for high rate variability power spectra for normal subjects.

Subject	FL	FU	FAC	FGC	BW	PT
1	0	1	1	0	1	1
2	0	1	1	0	1	1
3	0	1	1	0	1	1
4	0	1	1	0	1	1
5	0	1	1	0	1	1
6	0	1	1	0	1	1
7	0	1	1	0	1	1
8	0	1	1	0	1	1
P>0.05	0	8	8	0	8	8
P>0.05	8	0	0	8	0	0

0 means p > 0.05 (no significant difference)
1 means p < 0.05 (significant difference)

Table 5 - Autoregressive derived parameters of high rate variability power spectra for diabetic patients suffering from neuropathy.

Subject	FL	FU	FAC	FGC	BW	PT
1	0.02	0.3	0.16	0.077	0.28	12.25
2	0.02	0.295	0.1575	0.0768	0.275	12.45
3	0.02	0.29	0.155	0.076	0.27	12.66
4	0.02	0.305	0.1625	0.078	0.285	12.08
5	0.02	0.285	0.1525	0.0755	0.265	12.91
6	0.02	0.275	0.1475	0.074	0.255	13.65
7	0.02	0.28	0.15	0.0748	0.26	13.21
8	0.02	0.27	0.145	0.0735	0.25	13.86

Table 6 - Walsh derived parameters of high rate variability power spectra for diabetic patients suffering from neuropathy.

Subject	FL	FU	FAC	FGC	BW	PT
1	0.02	0.33	0.175	0.08	0.31	12.9
2	0.02	0.325	0.1725	0.08	0.305	13.1
3	0.02	0.32	0.17	0.08	0.3	13.3
4	0.02	0.335	0.1775	0.081	0.315	12.7
5	0.02	0.305	0.1625	0.078	0.285	13.45
6	0.02	0.295	0.1575	0.0768	0.275	14.31
7	0.02	0.303	0.1615	0.0778	0.283	13.85
8	0.02	0.29	0.155	0.076	0.27	14.52

Table 7 - Summary of direct difference statistical analysis on corresponding Walsh and autoregresssive derived parameter records for high rate variability power spectra for diabetic patients suffering ffrom autonomic dysfunction.

Subject	FL	FU	FAC	FGC	BW	PT
1	0	1	1	0	1	1
2	0	1	1	0	1	1
3	0	1	1	0	1	1
4	0	1	1	0	1	1
5	0	1	1	0	1	1
6	0	1	1	0	1	1
7	0	1	1	0	1	1
8	0	1	1	0	1	1
P>0.05	0	8	8	0	8	8
P>0.05	8	0	0	8	0	0

0 means p > 0.05 (no significant difference)
1 means p < 0.05 (significant difference)

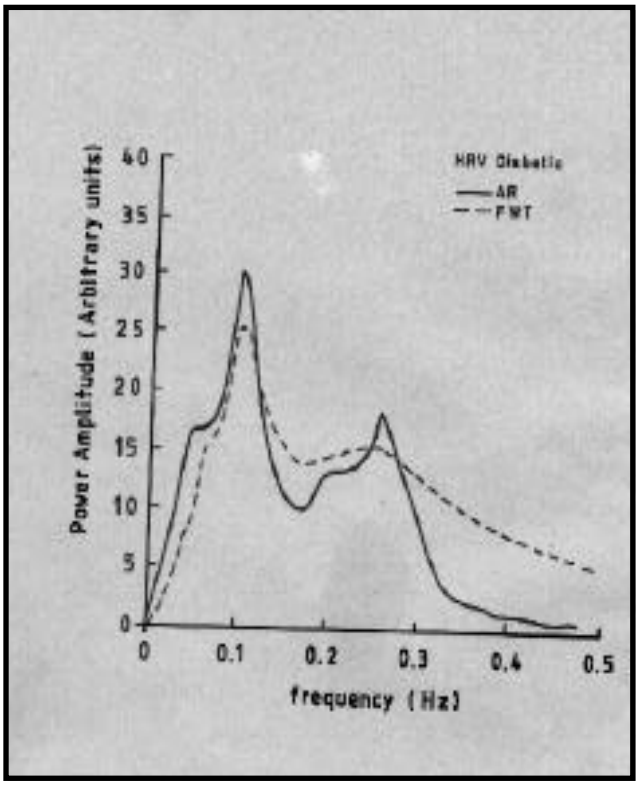

Figure 2 - Walsh and autoregressive average power spectra of heart rate variability signals for normal subjects in supine position.

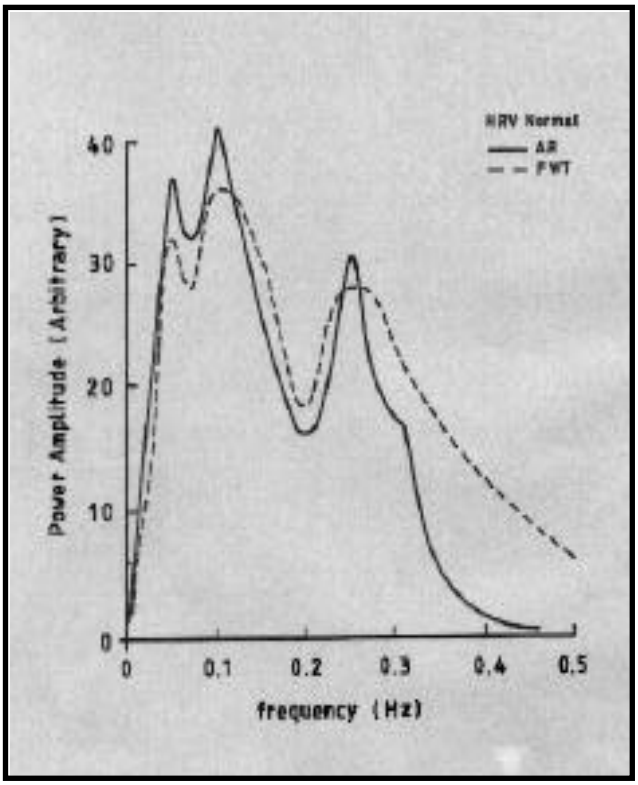

Figure 3 - Walsh and autoregressive average power spectra of heart rate variability signals for diabetic patients in the supine position.

each spectrum for normal and diabetic patients as shown from Table 2 to Table 7.

Statistical comparison. Table 1 shows the power distribution parameters definition of signal parameters HRV extracted from Walsh and AR spectra for comparison. The quantitative and qualitative (dynamics) differences between the results of Walsh and AR analysis were evaluated statisically. The level of significance for all statistical comparisons was assumed to be $p<0.05$. In all instances, the comparisons were made between corresponding Walsh and AR derived parameters records extracted from the same volunteers of normal subjects and diabetic patients of HRV signals. The quantitative differences in this study correspond to calculating the AR and Walsh derived parameters of HRV signals. On the other hand, the qualitative differences are demonstrated by the power spectra of HRV for normal and diabetic patients in the supine position. Under these circumstances, associated records of HRV signals were compared by calculating t-statistics using the direct-difference method in a correlated samples design study.

Results. ***Quantitative Difference Study.*** Tables 2-7 tabulate the results of the direct difference analysis for all groups with different HRV power spectra. There was, in general, a consistent significant difference between Walsh and Fourier estimates of FU, FAC, FGC, BW and PT. No consistant difference existed in corresponding FL estimates. The difference between the Walsh and AR derived estimates of the total power were found to be significant in all cases and groups.

Qualitative Difference Study. Figures 2 and 3 summarize the results of the qualitative (dynamics) difference study. Figure 2 and Figure 3 show the average based segments of 512 points epochs obtained of HRV spectra for 8 normal and 8 diabetic patients in Walsh and AR derived spectrum. Again all these figures demonstrate more diffusion of Walsh spectra and less peaked than the corresponding AR spectra.

Discussion. These results have confirmed the finding of Yeo and Smith[17], Larsen and Lai[18] and Sherebrin and Sherebrin[2], that Walsh power spectra are more diffuse and less peaked. These chracteristics appeared well in the power spectra of HRV signals. However, Figure 2 and Figure 3 show that Walsh power spectrum for HRV signal is more diffuse and less peaky while AR power spectra show sharp and more peaky harmonics. This may be interpreted from the nature of both HRV signal and Walsh function. Since HRV signal is nearly

constructed triangular waveform as shown in Figure 1 and Walsh functions are class orthonormal waveforms which have only two amplitude values +1 and -1, it leads to conclude that the perfect spectrum production is achieved by using FWT[21-25]. Actually, the characteristics of Walsh spectra explains the quantitative differences in the corresponding power distribution parameters seen in this paper. The higher degree of diffusivity of Walsh spectra for HRV signals for normal and diabetic patients has resulted in consistently higher Walsh estimates of FU and wider estimates of BW in comparison to the associated AR estimates. Although these results have shown that Walsh estimates of the total power in HRV signals are higher than AR estimates, these estimates should have theoretically been equal according to Parseval's theorem[26]. It has been found that the Walsh resynthesized HRV signals of both normal and diabetic patients accounted for essentially 100% of the power for the duration of 8 minutes of the original discrete signal. For duration of 4 minutes of original discrete HRV signals, the Walsh resynthesized HRV signal of normal subjects at 94% and for diabetic patients for 89% while the AR resynthesized signal accounted for 100% for HRV signal for normal subjects and 99% for diabetic patients for the duration of 3 minutes of original discrete HRV signals The variance between AR method and FWT arises from the nature of methodology used. The AR method is suitable for short periods of signals while the FWT method needs a longer time for the discrete HRV signals. This may lead to the recommendation of the AR method in place of FWT for HRV signals in both normal and diabetic patients specially for short periods of discrete. Actually, there is essentially no difference between the qualitative of the Walsh and AR derived set of parameters with slightly less peak in Walsh power spectra. This is an important point, since no standards exist with respect to the absolute values of any parameters derived from the power spectra. The effect of diabetes on AR and Walsh parameters for HRV spectra are shown from Table 4 to Table 6. It is clearly shown that diabetic patients exhibit lower PT, BW, FAC and FU in Walsh and AR method derived parameters (HRV spectra) with respect to normal subjects. At the same time, Walsh derived parameters of HRV spectra for diabetic patients show significant difference in PT, BW, FAC and FU as shown in Tables 5 and 7. These findings are important to track the effect of diabetes on the variation of HRV spectra in diabetic patients. Also, it is worth pointing out that FGC parameters are the geometric mean frequency which is very near to the blood pressure oscillation in HRV spectra and defined as Traube-Herring Mayer frequency[26-29] which oscillates at 0.1 Hz in normal subjects. However, there is no significant difference of this parameter (FGC) between Walsh and AR method for both normal and diabetic patients.

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