31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Improved HRV Characterization Using OCDWT

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Abstract— **In this paper an over-complete discrete wavelet transform (OCDWT) algorithm, obtained by blending two wavelet transform implementations that is redundant wavelet transform and the Mallat's multiresolution decomposition, has been proposed to retrieve the time-varying characteristics of HRV under two different postures, supine and standing. The OCDWT algorithm is critically sub-sampled to a given level of decomposition, below which it is then fully sampled. Five subjects were included to investigate posture-related HRV. The results showed that the high frequency fluctuations are larger in supine and get significantly reduced in standing in comparison to low frequency variations. Moreover, the very low frequency heart beat fluctuations during supine were greater than during standing. Further a comparative analysis has also been made between the Mallat's and OCDWT implementation in order to show the superiority of proposed algorithm.**

I. Introduction

THE period of heart beat is not constant and changes over time. These variations in heart rates and their respective periods are called heart rate variability (HRV). The heart beat fluctuations in low frequencies is jointly mediated by the sympathetic and parasympathetic nervous systems and the fluctuations in high frequencies are mediated by the parasympathetic nervous system and are synchronized with respiration [1]. With the increase in popularity of HRV studies, it has become a subject of interest in biomedical and clinical research in the past years [2]. A great number of tools and new methods of processing are continuously emerging to indirectly access the biological mechanisms underlying the cardiovascular activity under normal and pathological conditions. Out of all these the wavelet transform (WT) has been rapidly finding application as a tool for the analysis of non-stationary biomedical signals, data compression and fast computations [3]. However, the most commonly used implementation of the WT: the critically sampled discrete wavelet transform (DWT), is shift variant or aliased transform and so it is unsuitable for many signal analysis applications. More narrowly, it may introduce undesirable artifacts for the analysis of biomedical signals and images [4]. Therefore, to enable applications such as signal analysis, texture analysis, and edge detection, a redundant wavelet transforms have been used in the literature [3]-[6]. In this paper critically sampled DWT and redundant WT are blended together to utilize an OCDWT for deciphering postural related changes in HRV. The OCDWT method used in this paper has not been assessed for HRV studies earlier. Further, a comparative study has also been made between DWT and OCDWT algorithms using DB-6 and DB-3 basis functions, to illustrate the dominance of OCDWT in reflecting the changes in HRV during supine and sitting postures, related to physical activity [7], [8]. Moreover, from the earlier work it has been observed that such comparative performance evaluation of different wavelet transform algorithms (DWT and OCDWT), for deciphering postural related changes in HRV, has not been reported in literature.

Manuscript recieved: April 7th , 2009.

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II. Methodology

The study was performed on the five sets of RR-interval time series of 10 minutes duration of healthy subjects, obtained from the standard Eurobavar data base available on internet (http: // www. cbidongnocchi.it / glossary/ eurobavar.html) (subject no. 2 to 5) and ECG data of standard lead-II, recorded in our own laboratory, using a BIOPAC® MP100 system (subject no. 1).

A. Theory of Redundant Wavelet Transform

In critically sampled DWT, most commonly referred to as Mallat's algorithm, the decimation of the wavelet coefficients at every decomposition stage is its intrinsic property. This decimation step removes every other coefficient of the current level. Thus the computation of the wavelet transform is faster and more compact in terms of storage space. But at the same time it makes the transform susceptible to aliasing and shift variant [4]-[6]. Here in Mallat's implementation, the input signal is first convolved with the high pass and low pass filters and then further the output of these filters are sub-sampled by a factor of two. While in redundant wavelet transforms, firstly the filter is stretched, to take into account the rescaling and then the convolution is performed without any sub-sampling. This procedure is named as *algorithme`a trous* [4]. This method makes the transform bulky and is said to be redundant or over complete, in the sense that superfluous coefficients are retained in the transform and successive coefficient metrics are of the same size as the input data. This property of redundant wavelet transform makes the transform shift-invariant and aliased free. In addition to shift-invariance it gives an increased amount of information about the transformed signal as compared to Mallat's algorithm. This added information can be very useful for the better analysis and understanding of the signal properties under estimation. The earlier studies prove the superiority of *algorithme`a trous* over Mallat's algorithm in variety of research applications like in biomedical signal analysis, for feature extraction, in the image denoising applications where the discrimination between the noise and the real data is improved by using redundant wavelet transform [5], [6].

B. Implementation of Mallat's Algorithm

For discrete time signals, the Mallat's algorithm shown in Fig. 1 can be implemented to decompose them into eight wavelet scales ($J=8$) with sampling interval T=1/4.8 sec using, with DB-6 and DB-3 wavelets. This resulted in the following set of bandlimits for the filter bank: 0.01875, 0.0375, 0.075, 0.15, 0.30, 0.60, 1.2 and 2.4 Hz. The decomposed low-frequency (LF) and high-frequency (HF) signals were obtained by merging the detail signals at scales 6 and 7 (0.0375-0.15 Hz: LF band) and at scales 4 and 5 (0.15-0.60 Hz: HF band), respectively. The very-low frequency (VLF) component corresponded to the detail signal at scale 8 (<0.0375 Hz: VLF band) [10]. The spectral power values for each band are computed by merging together the corresponding square wavelet coefficient values [9]-[12].

C. Over-complete Discrete Wavelet Transform

The Mallat and *`a trous* algorithms are both special cases of the same filter bank structure. Therefore in principle it is possible to combine both these algorithms in the same decomposition structure, called an OCDWT, and thus gaining the benefits of both of these approaches [3], [6]. That is, the computational efficiency and sparse representation of Mallat, and shift-invariance along with aliased free spectrum of *`a trous* algorithms. The generalized representation of OCDWT algorithm is shown in Fig. 2. In this section the approach which has been used to construct an OCDWT is that, we choose an eight level decomposition tree and apply the Mallat's algorithm to the first three stages of 8-level decomposition and then apply *`a trous* algorithm to the remaining five levels. This algorithm can be viewed as an initial down sampling of the signal prior to a fully sampled DWT decomposition. This study has been made using DB-6 and DB-3 wavelets. The values of power in VLF, LF and HF bands were computed in the same manner as in Mallat's algorithm.

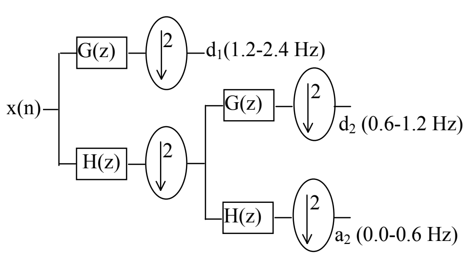

Fig. 1. Two filter bank implementation of Mallat algorithm for frequency bands of HRV signals. Where G(Z) and H(Z) are high and low pass filters, d's and a's are detail and approximation coefficients.

III. RESULTS AND DISCUSSION

It is now a well established fact that not only the autonomic nervous system, but the external factors, likes body posture and physical activities also influence the spectral characteristics of HRV. In terms of vertical positioning, HRV is significantly reduced from supine to sitting and further decreased from sitting to standing [7]. Thus, the heart rate varies during different physical activities and postures (sitting, standing, and supine). In this paper, the study has been carried out for two different body postures (i) Supine, and (ii) Standing using Mallat and OCDWT algorithms. To access the performance of these algorithms in capturing the dynamics of varying postures, RR-interval recordings of five subjects in supine and standing postures were included.

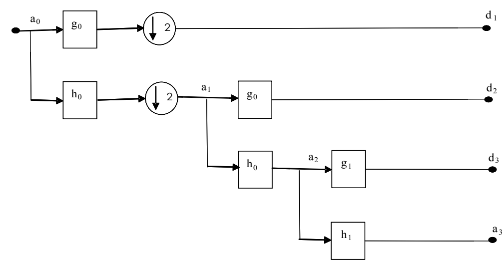

Fig. 2. Over complete discrete wavelet transform algorithm consisting of single level of Mallat algorithm and two levels of *`a trous* algorithm. Where g is representing the high pass filter, h is the low pass filter, d_j is the detail signal at jth level, and a_j is the approximation signal at jth level.

To quantify the modulation of the autonomic nervous system, four parameters are calculated: (i) VLF power, (ii) LF power, (iii) HF power, and (iv) LF/HF ratio. The LF and HF powers are used to represent the nerve activity of sympathetic and parasympathetic nervous system. But the physiological significance of VLF power is not well understood. The LF/HF ratio behaves as an index of autonomic balance. A low LF/HF ratio represents a dominant modulation of parasympathetic nervous system, and a high ratio justifies the dominance of sympathetic nervous system. The results in the form of LF/HF ratios and values of power in VLF, LF, and HF bands, are given in Table I and II. The values of power in Table I, obtained using OCDWT algorithm for DB-6 wavelet demonstrate that the HF power is the largest in the supine position. Further, it decreases in the standing position for all the five subjects. The percentage reduction of HF power is always higher as

TABLE I

QUANTIFIED VALUES OF POWER IN SUPINE AND STANDING POSTURES USING DB-6 WAVELET

	Sub. no.	Postures	PVLF	PLF	PHF	LF/HF Ratio
OCDWT Algorithm	1	Supine	652.613	169.131	14.157	11.947
		Standing	427.001	107.775	7.149	15.073
	2	Supine	539.564	148.682	16.980	8.756
		Standing	324.540	121.252	9.584	12.652
	3	Supine	518.753	195.441	26.65	7.332
		Standing	310.224	102.195	9.529	10.724
	4	Supine	531.975	151.010	14.736	10.247
		Standing	415.015	135.617	11.075	12.245
	5	Supine	770.946	279.900	18.983	14.744
		Standing	722.203	206.227	11.812	17.459
Mallat Algorithm	1	Supine	12.143	9.293	2.612	3.557
		Standing	8.272	7.750	1.957	3.960
	2	Supine	13.942	8.929	3.466	2.576
		Standing	6.107	7.173	2.471	2.902
	3	Supine	9.963	10.019	7.444	1.346
		Standing	6.585	6.238	3.498	1.783
	4	Supine	10.224	8.657	2.859	3.027
		Standing	7.460	7.167	3.392	2.113
	5	Supine	16.265	13.683	3.747	3.652
		Standing	14.571	10.948	3.157	3.467

PVLF: Power of very low components, PLF: Power of low frequency components, PHF: Power of high frequency components, LF/HF Ratio: Power ratio of low to high frequency components.

TABLE II

QUANTIFIED VALUES OF POWER IN SUPINE AND STANDING POSTURES USING DB-3 WAVELET

	Sub. no.	Postures	PVLF	PLF	PHF	LF/HF Ratio
OCDWT Algorithm	1	Supine	808.010	207.757	19.001	10.934
		Standing	459.479	156.770	10.529	14.888
	2	Supine	767.864	191.303	20.644	9.266
		Standing	474.839	140.484	11.251	12.486
	3	Supine	621.558	214.433	31.186	6.875
		Standing	404.616	128.944	11.635	11.083
	4	Supine	667.695	175.533	19.376	9.058
		Standing	500.693	169.096	14.507	11.655
	5	Supine	1123.20	267.031	23.262	11.479
		Standing	846.841	248.300	16.632	14.929
Mallat Algorithm	1	Supine	23.607	16.932	4.968	3.407
		Standing	15.291	14.034	2.888	4.858
	2	Supine	21.296	16.032	5.291	3.030
		Standing	11.213	12.453	2.313	5.372
	3	Supine	19.396	15.022	10.383	1.446
		Standing	11.466	11.511	5.256	2.190
	4	Supine	18.854	15.906	4.651	3.420
		Standing	14.758	11.782	5.183	2.273
	5	Supine	30.106	23.401	5.205	4.496
		Standing	23.379	18.215	5.619	3.241

PVLF: Power of very low components, PLF: Power of low frequency components, PHF: Power of high frequency components, LF/HF Ratio: Power ratio of low to high frequency components.

compared to that of LF power for all the subjects. This reflects the changes of the parasympathetic modulation. In addition, a shift in the autonomic balance is seen in all the subjects as shown in Fig. 3(a), i.e., the LF/HF ratio is increased from supine to standing postures. This implies that there is an increased sympathetic response in the standing position. But when the Mallat algorithm for DB-6 wavelet is used, a marginally reverse trend is seen in LF/HF ratio for supine and standing postures for subject no. 4 and 5 as shown in Fig. 3(b). Further, when these two algorithms of wavelet transform were implemented using DB-3 wavelet, same trend in the results were obtained given in Table II and shown in Fig. 3(c) and (d), as obtained for DB-6 wavelet. Here also the OCDWT algorithm performs better than Mallat algorithm in representing true HRV. In addition, the VLF power has been found to be greatest during supine posture in all the results. Moreover, this study was also performed on the ECG records acquired in our own laboratory settings from 20 healthy volunteers, and the same trends in the observations were obtained.

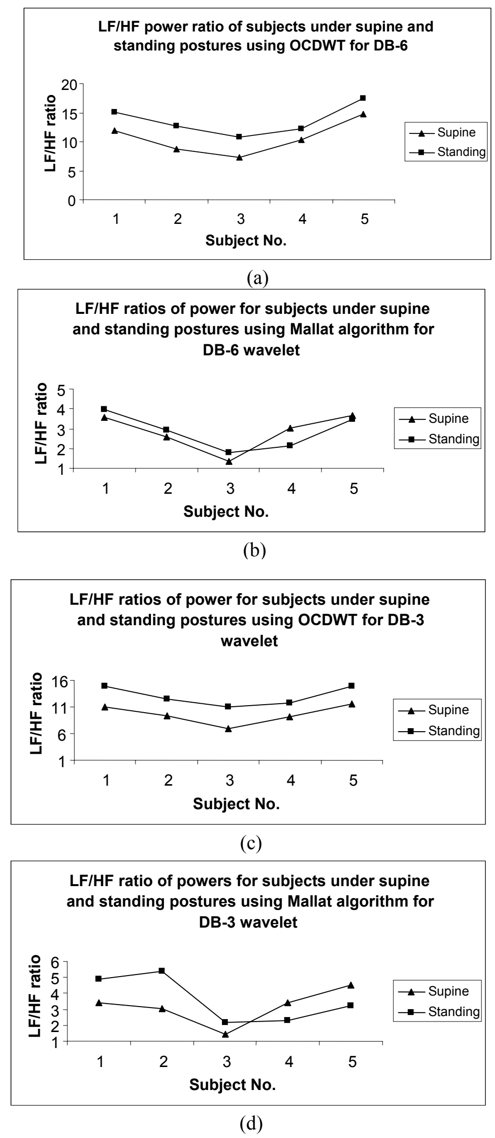

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Fig. 3. Plots of LF/HF ratios (a) Using over-complete discrete wavelet transform for DB-6 wavelet (b) Using Mallat algorithm for DB-6 wavelet (c) Using over-complete discrete wavelet transform for DB-3 wavelet (d) Using Mallat algorithm for DB-3 wavelet.

purpose of the study which we performed here is to present WT based analysis techniques of HRV and to obtain better quantification of autonomic nervous system. It was found that an OCDWT algorithm has performed well in representing fast autonomic nervous system adaptations in changing postures in comparison to Mallat algorithm. Although there are still many applications and developments which remain to be explored regarding the OCDWT algorithm but based upon the results this algorithm may prove to be useful for dynamic modeling of cardiovascular regulation in supine and standing postures.

IV. Conclusion

Although there are several postures and physical activities in daily life, but we have used only supine and standing postures as activity indicators for HRV. It is because of that HRV has specific autonomic implications in these activities. In this paper an over complete discrete wavelet transform has been proposed for separating the HRV of different postures for understanding the role of postural related changes in mechanisms of HRV. The OCDWT achieves various levels of sparsity of representation, shift-invariance, approximately same temporal resolution with an aliased free response, by controlling the amount of sub sampling that is applied at each decomposition level. The results support the hypothesis that a decreased HF power and increased LF/HF ratio in supine to standing postures. Further, the efficacy of the OCDWT has been demonstrated by performing the comparative analysis with Mallat algorithm. The proposed algorithm could be the start for future wavelet transforms based analysis of HRV aimed at the prediction of various episodes of heart rate time series, which has been found to be more consistent and convincing with previous time- and frequency domain studies. In future more clinical investigations are needed for both short-term HRV and long-term HRV to study the role of postures in heart rate modulation.

Acknowledgment

The authors are thankful to the Department of Electronics and Communication Engineering, Department of Instrumentation and Control for providing the necessary laboratory support to carry out a research work.

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