Wavelet Estimation of Pulse Rate Variability from Oscillometric Blood Pressure Measurements

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***Abstract*—We propose a wavelet-based spectral density estimation method for characterizing pulse rate variability of short duration oscillometric blood pressure signals produced by a digital blood pressure monitor during routine measurements. To validate our wavelet metric we compare its performance with other techniques by studying correlations of pulse rate variability with age and mean arterial pressure. Our results indicate that the proposed wavelet metric offers a superior and accurate characterization of variability of short duration oscillometric blood pressure signals.**

Keywords-electrocardiogram; peak-to-peak interval; pulse wave; variability; wavelet spectral density

I. INTRODUCTION

Heart rate variability (HRV) analysis performed on RR interval time series derived from electrocardiogram (ECG) signals is an important biomarker of health [1]. Researchers have shown HRV to correlate with physiologic and pathologic states as well as age [2], [3]. The analysis of pulse rate variability (PRV) performed on peak-to-peak interval time series derived from pressure waves or finger plethysmograph signals has also received much attention [4]. Most studies have found good agreement between ECG-based HRV and pulse wave based PRV for characterizing physiologic states and signal dynamics [5], [6].

Investigators have successfully characterized HRV and PRV using techniques ranging from time to frequency to fractal domain analysis of signals [7]. However, to our knowledge, these analyses have been performed on signals of duration 180 s or more based on experience and empirical results [8]. In this paper, we propose a wavelet-based spectral density estimation method to characterize PRV in short duration blood pressure (BP) oscillations (< 95 s). We propose the direct analysis of variability of oscillometric pulses produced by a digital blood pressure monitor during routine measurements.

To validate the proposed wavelet PRV metric, we compare its performance with mean, standard deviation (SD), root mean square successive difference (RMSSD), fast Fourier transform (FFT), and sample entropy (sampEn) measures of variability. To this end, we correlate these metrics with participant age and mean arterial pressure (MAP) derived from systolic and diastolic blood pressure measured using a classic sphygmomanometer. The wavelet PRV metric shows the highest and most significant inverse correlation with age and MAP, conforming to published work on similar analyses of longer signal durations [2], [3]. The SD metric achieves the next best performance but is not as consistent as the wavelet analysis across subjects and recordings. All other metrics fail to achieve significant correlations with age and MAP.

We conclude that the proposed wavelet PRV analysis metric offers a superior and robust method for accurately characterizing variability of short oscillometric pulses produced by digital BP machines during routine measurements. Incorporation of this metric into future BP devices promises quick tracking of physiologic changes. Moreover, the variability information gleaned may be used for fine-tuning algorithms for systolic and diastolic blood pressure estimation.

II. METHODS

A. Participants

Eighty five healthy subjects (N_T=85, Age Range: 12-80 yr) out of which thirty seven were females (N_F=37, Age Range: 17-65 yr) and forty eight were males (N_M=48, Age Range: 12-80 yr) participated in the study. No subjects had any history of respiratory or cardiovascular disease. The local ethics committee approved the study and written informed consent was obtained before enrolling participants in the study.

B. Data Collection

Oscillometric BP signals were collected using a digital BP wrist monitor (Biosign Technologies Inc., Toronto, ON) at a sampling rate of 100 Hz. Five signals each were collected from 84 subjects and four signals were collected from 1 subject, resulting in a total of 424 digital BP signals (Duration Range: 30.83-94.80 s, Duration Median: 54.70 s). BP measurement standards recommend classic auscultatory brachial BP method to provide comparison terms for the validation of other techniques [9]. However, occlusion of brachial arteries by upper arm sphygmomanometers precludes simultaneous brachial and wrist measurements. Therefore, to validate the digital BP wrist monitor measurements, for every subject, after each of the 5 digital oscillometric acquisitions, two nurses recorded separately, but simultaneously, systolic BP (SP_1 and SP_2) and diastolic BP (DP_1 and DP_2) values using a classic upper arm sphygmomanometer provided with means for simultaneous readings. This resulted in 5 pairs of systolic BP $\{SP_{1,k}, SP_{2,k}, \mid k=1,..,5\}$ and diastolic BP $\{DP_{1,k}, DP_{2,k}, \mid k=1,..,5\}$ values per subject – 5 measured by nurse 1 $\{SP_{1,k}, DP_{1,k}, \mid k=1,..,5\}$ and 5 by nurse 2 $\{SP_{2k}, DP_{2k}, \mid k=1,..,5\}$.

Thus, each of the 5 classic BP measurements taken by nurse 1 and nurse 2 $\{(SP_{1,k}, SP_{2,k}), (DP_{1,k}, DP_{2,k}), | k=1,..,5\}$ corresponded with a delay of about one and a half minute with the five oscillometric signals recorded by the digital BP monitor per subject. This delay between consecutive arm and wrist measurements should be as short as possible to minimize the natural BP variation in time, but also should be long enough to let the system settle down after occluding arteries during measurements. The 1.5 minute delay between measurements is a compromise that aims to minimize the method errors [9].

C. Data Analysis

For each oscillometric BP signal, pulse peaks were identified using a band-pass filtering and local maxima detection technique. Data was visually inspected and manually corrected for any peaks falsely identified or missed by the peak detection algorithm. Corresponding pulse-to-pulse interval time series were derived based on peaks identified.

To aggregate classic BP measurements, average of 2 systolic (and 2 diastolic) values recorded by nurse 1 and nurse 2 was computed, resulting in 5 systolic and diastolic BP measurements per subject. This was followed by computing the average of 5 systolic and 5 diastolic values per subject. This resulted in 1 systolic and 1 diastolic value per subject for all 85 subjects. For all 85 subjects, mean arterial pressure [10] was computed as MAP = diastolic + 1/3*(systolic-diastolic), resulting in 1 MAP value per subject.

Each peak-to-peak interval time series was analyzed separately. Area under the curve (AUC) of the maximal overlap discrete wavelet transform (MODWT) spectral density curve was computed to characterize wavelet variability [11]. Mean, SD, RMSSD, FFT, and sampEn metrics were also computed for all peak-to-peak interval time series. Each variability metric per subject per signal was correlated with corresponding subject age and MAP using a linear regression analysis. An analysis was performed for both sexes together and separately. A correlation and p-value was calculated for each least square fit to the linear regression at a 95 % confidence level.

III. Results

Fig. 1 shows the peak detection on an oscillometric BP signal (top panel), the corresponding pulse-to-pulse interval time series (bottom panel), and its MODWT spectral density curve (right panel).

Table 1 shows results of the regression analysis between various variability metrics for each of the five recordings and age. Regressions are studied separately for the entire population, females, and males. The wavelet analysis (MODWT) shows the highest, most significant, and consistent negative correlations with age across all 5 recordings for the entire population considered together (N_T=85) and separately (N_F=37, N_M=48) on the basis of sex. The SD technique is the next best in performance but fails for one recording (# 5) for the entire population (N_T=85), and three recordings (# 2, 3, 5) for males (N_M=48). Other techniques namely fast Fourier transform (FFT), FFT high frequency (HF), FFT low frequency (LF), FFT LF/HF, and sampEn are still worse in performance. Mean and RMSSD metrics showed no correlations with age and are not reported in Table 1. We also note that sampEn sometimes does not return a variability number for a particular subject/recording hence the number of points (N) on which regression is performed reduces. Lastly, Table 1 shows that pulse wave variability is more strongly correlated with age for females than males. Fig. 2 shows the correlation (r=-39%, p=0.0002) between MODWT PRV metric and age for recording 1 for the entire population (N_T=85).

A table (not included) similar to Table 1 was produced to study correlations between PRV and MAP. Again, the MODWT was the best in performance showing significant negative correlations with MAP for all 5 recordings for the entire population (N_T=85) and for females (N_F=37). The best correlation (r=-60%, p=0.00002) between PRV and MAP was achieved by the MODWT metric for recording 2 (Fig. 3) for females (N_F=37). None of the PRV metrics (including MODWT) showed any correlations with MAP for males (N_M=48).

IV. Discussion

The main contribution of our paper is the use of the proposed wavelet PRV analysis metric and others (SD, FFT, sampEn, etc.) to analyze extremely short BP waveforms (< 95 s) collected during routine BP measurements. To the best of our knowledge, no attempts have been made till date to characterize variability, an important biomarker of health and illness, from oscillometric waveform signals collected primarily for the purpose of estimating systolic, diastolic, and MAP in a conventional digital BP monitor.

The proposed wavelet PRV metric clearly shows superiority in analyzing short oscillometric BP signals. First, it achieves the best correlations with age and MAP as compared to other techniques. Second, the values of the correlations achieved by the wavelet metric are close and comparable to correlation values achieved by techniques such as SD and FFT on much longer ECG signals (> 180 s) as shown by other researchers [2], [3] – please see Table 2 and Table 3. This is a very significant and promising result indeed. We conclude that it is feasible to conveniently incorporate a variability analysis module inside a digital BP monitor to enhance its analysis capabilities, functionality, and accuracy.

We attribute the success of the wavelet analysis to the fact that it is a recursive filtering technique which characterizes a signal in both time and frequency domain simultaneously. This renders the wavelet analysis as a robust tool for assessing signals that are noisy, non-stationary, and non-periodic. We used the Daubechies family LA8 wavelet filter for performing the wavelet analysis. LA8 is an eight-tap least asymmetric wavelet filter. We employed the MODWT wavelet filtering scheme, which is a stationary or redundant wavelet transform. In the MODWT, the signal is never subsampled and instead the filters are upsampled at each level of decomposition, making the MODWT a shift-invariant transform. We chose the LA8 filter as it has shown to give stable results in different analysis scenarios. Moreover, it has also been shown that when using the shift-invariant MODWT filtering scheme, the choice of the

analyzing wavelet has minimal effects on the outcome of the analysis [11].

The fact that the analyzed signals were extremely short seems to be the main reason for a comparatively diminished performance of other techniques, which assume stationarity (sampEn), and periodicity (FFT). Interestingly and perhaps rightly so, SD, which in principle does not require a signal to be stationary or periodic, achieved the next best performance after the wavelet analysis. In general, we found better PRV-age and PRV-MAP correlations for females than males. No correlation was found between PRV and MAP for males. Further analysis of oscillometric BP waveforms of varying durations and frequencies promises to offer interesting insights into signal dynamics and physiologic implications.

The main challenge we faced was due to a noise of about 5% in all our signals. Since the signal durations were extremely short, one or two artifactual or missing beats per signal affected the variability analysis to some extent. We had to eyeball all our data and manually correct artifactual or missing beats before carrying out the variability analysis. We are currently working on filtering and cleaning algorithms for removing noise from oscillometric BP waveforms. We believe that a certain amount of preprocessing of the oscillometric BP waveforms before variability analysis would go a long way in doing away with the need to manually clean the data. Nonetheless, the current results with manual cleaning are promising and we hope to fully automate this process as we develop more sophisticated data cleaning and preprocessing algorithms.

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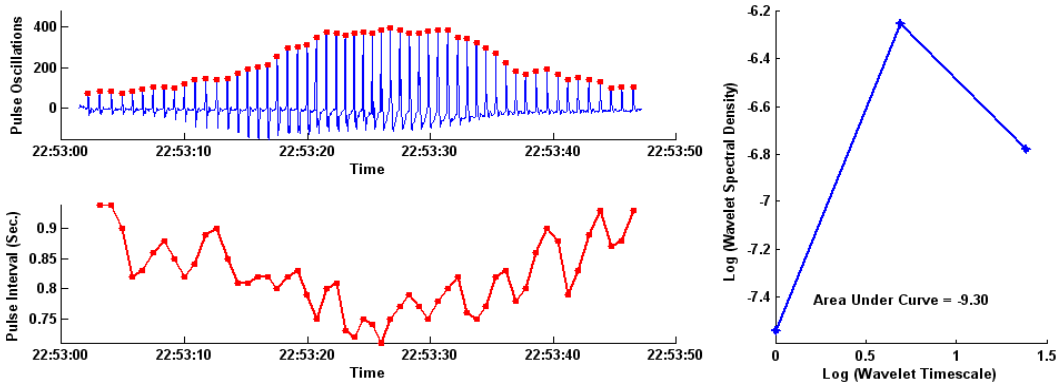

Figure 1. Computation of the wavelet spectral density PRV metric

TABLE I. CORRELATION BETWEEN VARIOUS PULSE RATE VARIABILITY (PRV) METRICS AND AGE FOR MALES AND FEMALES CONSIDERED TOGETHER AND SEPARATELY

Sex	PRV Metric	Recording 1 & Age			Recording 2 & Age			Recording 3 & Age			Recording 4 & Age			Recording 5 & Age		
		N	*R*	*P*	*N*	*R*	*P*	*N*	*R*	*P*	*N*	*R*	*P*	*N*	*R*	*P*
All (N_T=85)	***MODWT***	85	-39%	0.000203	85	-39%	0.000184	85	-38%	0.000313	85	-38%	0.000325	84	-33%	0.002179
	SD	85	-36%	0.000005	85	-33%	0.002347	85	-17%	0.000024	85	-32%	0.000371	84	-18%	0.076495
	FFT HF	85	-22%	0.107643	85	-23%	0.529186	85	-10%	0.062128	85	-19%	0.132966	84	-19%	0.263102
	FFT LF	85	-9%	0.295701	85	-7%	0.451939	85	-6%	0.509544	85	-9%	0.307855	84	-7%	0.824657
	FFT LF/HF	85	6%	0.408142	85	7%	0.708557	85	12%	0.069933	85	6%	0.221481	84	10%	0.154922
	SampEn	60	-21%	0.103416	72	-24%	0.043960	63	-27%	0.005572	70	-27%	0.004420	67	-19%	0.055257
Females (N_F=37)	***MODWT***	37	-57%	0.000200	37	-56%	0.000295	37	-50%	0.001586	37	-47%	0.003415	37	-44%	0.006610
	SD	37	-56%	0.000296	37	-54%	0.000597	37	-6%	0.003355	37	-37%	0.013503	37	-21%	0.031368
	FFT HF	37	-16%	0.296669	37	-18%	0.349151	37	-2%	0.121749	37	-19%	0.265065	37	-21%	0.157261
	FFT LF	37	-6%	0.887299	37	-7%	0.931184	37	-8%	0.887328	37	-10%	0.708159	37	-7%	0.890454
	FFT LF/HF	37	0%	0.834548	37	-2%	0.928092	37	3%	0.853751	37	3%	0.867846	37	8%	0.348439
	SampEn	26	-19%	0.349662	31	-19%	0.315845	25	-18%	0.391782	27	-10%	0.012837	30	-31%	0.027249
Males (N_M=48)	***MODWT***	48	-30%	0.039931	48	-30%	0.040217	48	-34%	0.018151	48	-36%	0.011409	47	-31%	0.031175
	SD	48	-26%	0.002304	48	-24%	0.828357	48	-28%	0.096311	48	-29%	0.001414	47	-17%	0.214248
	FFT HF	48	-26%	0.128535	48	-25%	0.956607	48	-20%	0.444388	48	-19%	0.308767	47	-17%	0.857744
	FFT LF	48	-15%	0.298055	48	-12%	0.595059	48	-10%	0.612267	48	-12%	0.607546	47	-10%	0.999613
	FFT LF/HF	48	8%	0.472402	48	8%	0.583288	48	15%	0.297588	48	3%	0.908801	47	9%	0.426646
	SampEn	34	-21%	0.242371	41	-31%	0.045099	38	-31%	0.055209	43	-33%	0.031876	37	-13%	0.428793

N: Number of Subjects, R: Correlation, P: p-value

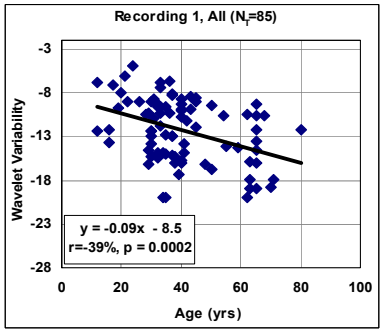

Figure 2. Regression between wavelet spectral density PRV metric and age for males and females (N_T=85)

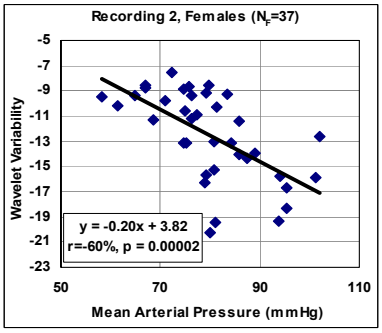

Figure 3. Regression between wavelet spectral density PRV metric and mean arterial pressure (MAP) for females (N_F=37)

TABLE II. HRV AND BP CORRELATION: COMPARISON OF OUR PROPOSED WAVELET PRV ANALYSIS METRIC WITH OTHER PUBLISHED WORK

HRV and BP Correlation Comparison								
Author	**Sample Size (N)**	**Signal Analyzed**	**Signal Duration**	**HRV Metric**	**BP Monitor**	**BP Measurement**	**HRV-BP Correlation**	**P**
Mussalo et al. [2]	91	ECG	512 s	FFT LF	Classic Sphygmomanometer	Diastolic	-30%	< 0.01
Ahmad et al.	85	Oscillometric BP Waveforms	30.83 s to 94.80 s	MODWT Spectral Density	Classic Sphygmomanometer	MAP	-35% (Recording 2)	< 0.002

N: Number of Subjects, P: p-value

TABLE III. HRV AND AGE CORRELATION: COMPARISON OF OUR PROPOSED WAVELET PRV ANALYSIS METRIC WITH OTHER PUBLISHED WORK

HRV and Age Correlation Comparison						
Author	**Sample Size (N)**	**Signal Analyzed**	**Signal Duration**	**HRV Metric**	**HRV-Age Correlation**	**P**
Choi et al. [3]	135	ECG	180 s	FFT HF	-42%	< 0.01
Choi et al. [3]	135	ECG	180 s	FFT LF	-31%	< 0.01
Choi et al. [3]	135	ECG	180 s	FFT LF/HF	-15%	0.09
Ahmad et al.	85	Oscillometric BP Waveforms	30.83 s to 94.80 s	MODWT Spectral Density	-39% (Recording 2)	< 0.0002

N: Number of Subjects, P: p-value