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Comparison of Heart Rate Variability Signal Features Derived from Electrocardiography and Photoplethysmography in Healthy Individuals

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Abstract – **The heart rate variability (HRV) signal is indicative of autonomic regulation of the heart rate (HR). It could be used as a noninvasive marker in monitoring the physiological state of an individual. Currently, the primary method of deriving the HRV signal is to acquire the electrocardiogram (ECG) signal, apply appropriate QRS detection algorithms to locate the R wave and its peak, find the RR intervals, and perform suitable interpolation and re-sampling to produce a uniformly sampled tachogram. This process could sometimes result in errors in the HRV signal due to drift, electromagnetic and biologic interference, and the complex morphology of the ECG signal. The photoplethysmographic (PPG) signal has the potential to eliminate the problems with the ECG signal to derive the HRV signal.**

To investigate this point, a PDA-based system was developed to simultaneously record ECG and PPG signals to facilitate accurately controlled sampling and recording durations. Two healthy young volunteers participated in this pilot study to evaluate the applicability of our approach. To improve data quality, ECG and PPG recordings were acquired three times/subject. A comparison between different features of the HRV signals derived from both methods was performed to test the validity of using PPG signals in HRV analysis.

We used autoregressive (AR) modeling, Poincare′ plots, cross correlation, standard deviation, arithmetic mean, skewness, kurtosis, and approximate entropy (ApEn) to derive and compare different measures from both ECG and PPG signals. This study demonstrated that our PDA-based system was a convenient and reliable means for acquisition of PPG-derived and ECG-derived HRV signals. The excellent agreement between different measures of HRV signals acquired from both methods provides potential support for the idea of using PPGs instead of ECGs in HRV signal derivation and analysis in ambulatory cardiac monitoring of healthy individuals.

I. INTRODUCTION

Currently, the primary method of deriving the HRV signal is to acquire the electrocardiogram (ECG) signal [1], apply appropriate QRS detection algorithms to locate the R wave and its peak [2], find the RR intervals, and perform suitable interpolation and re-sampling to produce a uniformly sampled tachogram. The RR tachogram allows us to perform time-domain, frequency-domain and nonlinear dynamics analyses to extract useful features to investigate the autonomic control of the heart rate in a quantitative fashion [3]. ECG signals are acquired by placing Ag/AgCl electrodes on clearly defined anatomical positions. One lead (channel) of ECG recording requires three electrodes to produce the signal thus requiring three wires to be connected to the subject.

Fluctuations in the ECG signal baseline, drift, powerline noise, motion artifacts due to electrode movement and electromyographic (EMG) interference due to muscular activity frequently contaminate the ECG signal [4]. In addition, morphological variations in the ECG waveform and the high degree of heterogeneity in the QRS complexes make it difficult to distinguish them from tall peaked P and T waves.

Photoplethysmography (PPG) is performed by assembling an infrared emitter and detector inside a probe placed on the forefinger or earlobe. The infrared light is emitted through the blood vessels in the finger or earlobe and reflected off the bone or tissue [5]. The amount of light reflected back to the detector is determined by the amount of blood flowing to the tissue at any given time and converted into a voltage. A high volume of blood results in a high voltage and a low volume results in a low voltage. The change in blood volume is directly related to the amount of blood pumped into the aortic valve during ventricular depolarization. A blood pressure signal is derived from the effect that the changing blood volume has on the reflected infrared light. The probe keeps a constant pressure on the forefinger or earlobe. The finger or earlobe is not part of any electric circuit because the emitter and detector communicate through light rather than current flow in ECG circuits. The PPG signal requires only one wire. This reduces the number of wires from three in ECG to one in PPG, which is very desirable in ambulatory situations.

PPG has some advantages over ECG and can be used for some applications in cardiac monitoring. In order to effectively compare the two signals, a custom-designed PDA-based recording system was developed to record these signals simultaneously and then transfer them to a desktop computer for further analysis. This paper explores the potential application of PPG signal in determining HRV and how it relates to ECG-derived HRV in healthy individuals.

II. MATERIALS AND METHODS

A. PDA-Based Data Acquisition

Both electrocardiography and photoplethysmography produce waveforms that peak due to the ventricular depolarization phase of the cardiac cycle. This common characteristic forms the basis for comparison of ECG-derived HRV and PPG-derived HRV signals. A PDA-based system (Fig. 1) was built around custom-designed ECG and PPG

circuitry and the LabVIEW programming environment was used to provide a user friendly graphical interface for data collection [6]. This was to ensure that the ECG and PPG data were recorded with exact starting time and recording duration. The system was set to record data for 5 minutes with a sampling rate of 196 samples per second. This sampling rate provides an acceptable signal-to-noise ratio [7] while maintaining a low memory usage on the PDA. With availability of more memory on PDAs, it is envisioned to use a minimum sampling rate of 500 Hz as recommended in [7] to minimize errors in R peak detection for HRV derivation.

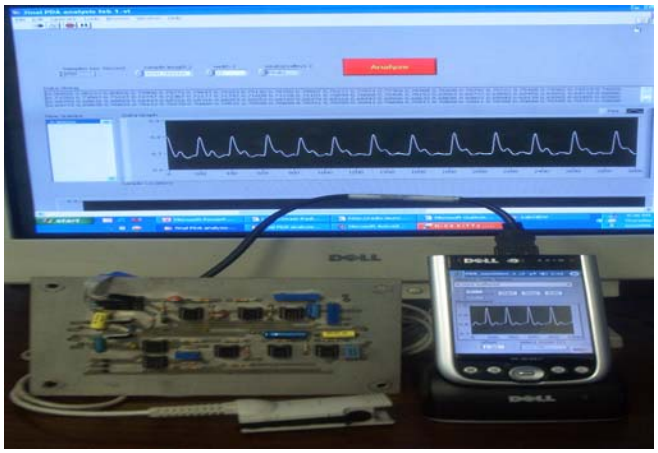


Fig. 1. A PDA-based ECG and PPG acquisition system.

ECG and PPG data from two healthy subjects (no history of cardiac abnormalities problems), 1 male and 1 female, with ages 24 and 25 is collected and used in this pilot investigation. The data were recorded for 5 minutes with both signals saved to the PDA's internal memory. The recording process was repeated two more times in sequence on the same day to collect repeated data from each volunteer in a relaxed condition. The recordings were designated PPGn and ECGn, where n = 0, 1, 2. The data stored in the PDA were transferred to a desktop computer for further processing and analysis.

B. Derivation of the HRV signal

Each PPG and ECG data set acquired by the system was fed into a custom-designed HRV program developed in LabVIEW to derive the HRV signal. The derivation method incorporated a peak detection algorithm that found the time of occurrence for every QRS complex in the ECG signal and the Dicrotic notch in the PPG signal. The durations between successive peak locations were calculated to produce a time series of RR and DD intervals (HRV signal). These values were saved in a file for further analysis. The algorithm was applied to each PPG and ECG signal.

C. Poincare' Plots and Some Time-domain Measures

Time domain analysis closely followed the techniques described by the Task Force guidelines [8]. *Poincare'* plots for the two signals, RR or DD intervals were derived. These plots are useful visualization tools to show the consistency of the entire HRV signal. Good quality HRV signals produce a *Poincare'* plot with all data points clustered together. Corrupted HRV signals will result in a *Poincare'* plot with scattered data points [9].

Histograms to determine the duration of the RR and DD intervals were then obtained. These values provided the total number of detected beats and quantified the changes in the heart rate. Numerical calculations of max RR (DD), min RR (DD), RR (DD) standard deviation, and RR (DD) mean were then performed.

D. Frequency-Domain Parameters

Spectral analysis was carried out on both signals by using the FFT, AR and Lomb periodogram methods. All methods provided very similar spectral densities. According to [8], for short term data (5 minutes in duration), the HF (0.15 - 0.4 Hz) and LF (0.04 - 0.15 Hz) components of the HRV signal are useful. The HF and LF powers were normalized by dividing by the total power. A high value for the normalized HF indicates dominance in parasympathetic activity and a high value in LF may indicate dominance in sympathetic activity [10]. The normalized HF and LF were also used to determine the LF/HF ratio, which is indicative of sympatho-vagal balance. Power spectral analysis was performed using auto regressive (AR) estimation methods [11]. The AR method results in smoother graphical representations [12] of the spectrum.

E. Comparing HRV Data Sets

1. Statistical Measures

Comparisons were made between some statistical measures of the HRV data sets derived from both ECG and PPG signals to validate our approach. Firstly, we needed to show that the PDA-based system was reliable in acquiring and storing the data. Secondly, we needed to demonstrate that similar HRV data could be derived from PPG and ECG signals. Cross correlation was used to determine the relation between the HRV data sets derived from both methods. The data sets were numerically related through the correlation coefficient calculated by using:

$$R = \frac{m\sum x_m y_m - \sum x_m \sum y_m}{\sqrt{\left[m\sum x_m{}^2 - \left(\sum x_m\right)^2\right] * \left[m\sum y_m{}^2 - \left(\sum y_m\right)^2\right]}} \quad (1)$$

where **m** equals the number of intervals, **x** represents the RR intervals, and **y** represents the DD intervals. A correlation coefficient close to 1 indicates direct relation, whereas values close to -1 indicate inverse relation, while values close to 0 indicate little or no relation.

Comparisons between the distribution probabilities were made by determining the variance. Matching data sets have similar probability distributions [13]. The shapes of the probability distributions were compared using the Kurtosis coefficient. This coefficient was calculated by using:

$$Kurtosis(X) = \frac{E\left[\left(X-\mu\right)^4\right]}{\sigma^4} \quad (2)$$

where **X** represents the HRV data set, μ is the mean value, and σ represents the standard deviation. This is an indication of how much the values peak around the mean of the data set. A kurtosis greater than 3 indicates a leptokurtic data set and a value less than 3 indicates a platykurtic data set [14].

The amount of asymmetry in a data set probability distribution can be estimated by the skewness value determined by:

$$Skew(X) = \frac{E\left[\left(X-\mu\right)^3\right]}{\sigma^3} \quad (3)$$

where **X** represents the HRV data set, μ is the mean value, and σ represents the standard deviation. A positive skewness indicates that most of the data are located to the left of the mean and a negative value shows that most of the data are on the right side of the mean [15].

Lastly, Approximate Entropy (ApEn) of each data set was computed to quantify the unpredictability of fluctuations in the HRV time series. A small ApEn indicates a predictable signal and a large ApEn indicates very little predictability [16]. ApEn was found based on ApEn (m, r, N) in a custom-written LabVIEW program. For HRV applications we used 2 for **m** and 0.2*Standard Deviation for **r** [17]. **N** is the length of the data set.

2. PPG- and ECG- derived HRV Signals

PPG (ECG) data were recorded three times from each volunteer in a relaxed state. To check the reliability of the PDA-based recording system, the final outputs of the HRV analysis were carefully checked for each data type. For instance, all three PPG-derived HRV signals showed matching power spectrums and similar distribution of DD intervals. Similar observations were made in ECG-derived HRV signals. Repeating the experiments three times and obtaining similar results demonstrated the consistency of the PDA-based data acquisition system for both signals.

3. Comparison of PPGn- HRV to ECGn- HRV

To verify the validity of the PDA-based data acquisition system, similar methods were used to show that ECG-derived HRVs are closely comparable to PPG-derived HRVs in their time-domain, frequency-domain and nonlinear dynamic properties. Close agreement between HRV data from PPG and corresponding ECG records helped us to conclude that PPG could serve as an alternative and possibly a better method for HRV data acquisition in physiological monitoring.

III. RESULTS AND DISCUSSION

The HRV analysis results from two subjects are presented. Subject 1 is a 24-year old male. The HF and LF peaks in Fig. 2a are clearly distinguishable. The repeated tests showed similar results. The probability distribution of the HRV data from subject 1 showed a kurtosis above 3, classifying it as leptokurtic. Accompanied by a negative skewness near zero, it is observed that the probability distribution is clustered to the right of the mean and peaks about the mean. Repeated ECG measurements produced similar results. The similarity in the repeated tests is observed in Table 1b, where the correlation coefficients between each of the ECG HRVs are very close to 1, indicating almost perfect match between the repeated tests. This can be observed in Figures 2a and 2b where the power spectra of each of the repeated signals overlap closely. These results are indicative of excellent measurement repeatability for the system. Time, statistical, and frequency domain values in Table 1a show that the PPG method is a reliable means in derivation of the HRV signal. The HRV features derived from the PPG method are very similar to those derived from the ECG method. This similarity can be clearly viewed in detail in Table 1c where the correlation coefficients are used to compare PPG HRV with corresponding ECG HRV. The coefficients deviate only 1% from 1, hence indicating that the HRV data acquired from both methods are practically perfect matches. Figures 2c-2e show the similarities in power spectra of both HRVs. In Fig. 3, the same similarities could be easily visualized by in Poincare′ plots. The Poincare′ plots of average PPG HRV and the average ECG HRV indicate that the heart rate intervals cluster together in a common region. This also shows that the peak detection algorithm was accurate in detecting every peak in the ECG and PPG signals. These results show that that in subject 1, the PPG signal provided equivalent HRV data as derived from the ECG data.

The HRV analysis for subject 2, a 25 year old female, resulted in a power spectra different from subject 1. Both HF and LF peaks are clearly distinguishable, however the HF peak is closer to the LF peak in this subject. The probability distributions (Table 2a) are similar for both subjects. This is concentrated to the right of the mean and highly peaked about the mean (leptokurtic). Approximate entropy indicates that subject 2's HRV is more predictable than subject 1's HRV. Figs. 4a and 4b show the repeatability of the system by displaying the common characteristics in the HRV power spectra derived from both signals. Table 2b shows that all three HRV signals derived from the ECG method provide similar results. This similarity is obvious with a 5% maximum difference away from a correlation coefficient of 1. The numerical and graphical results clearly demonstrate that the PDA-based system is reliable and produces repeatable and consistent results. Also, the similarity of PPG-derived HRV with ECG-derived HRV (seen in Table 2c) is apparent with a correlation coefficient only 1% away from 1. The Poincare′ plots in Fig. 5 clearly demonstrate the matching of HRV signals derived from both PPG and ECG signals.

The different methods used in this pilot study proved very helpful in showing how closely the time-domain, frequency-domain, and nonlinear dynamics measures of the HRV data match when comparisons are made between PPG with PPG, ECG with ECG, and PPG with ECG records.

As heart rate is always changing the PPG or ECG signals recorded in one 5-minute time frame would not match the PPG or ECG signals recorded at another 5-minute time frame. However, the statistical and spectral properties of these signals should be very similar as they reflect the same underlying process in the same physiological system. The time-domain recordings of the PPG vs PPG and ECG vs ECG data comparisons were generally similar in character but did not match perfectly because the autonomic nervous system is continuously modulated by different physiological stimuli that affect the HRV signal.

IV. CONCLUSIONS

The HRV data sets derived from ECG and PPG signals for each of the two volunteer subjects were closely matched. This demonstrated that the PDA-based system was reliable in recording the same information for the same state of relaxation and health in each subject.

The tachograms and power spectra of the HRV data sets associated with each pair of corresponding PPG and ECG signals resulted in correlation coefficients very close to 1. Statistical measures demonstrated that the majority of the HRV data points collected from both PPG and ECG signals were located to the right side of the mean and mainly characterized as leptokurtic. This demonstrated that the PPG signal could be as dependable as the popular ECG in the derivation of the HRV signal.

Advantages of the PPG method over the ECG method (in addition to ease of data acquisition), may provide justification that PPG signals are not only a useful supplement but also potentially a practical replacement for ECG-derived HRV signals in ambulatory cardiac monitoring in healthy individuals and athletes. This point requires further investigation in a larger number of healthy subjects. This pilot study demonstrated that our custom-developed PDA-based system is a useful and reliable tool in HRV studies that require ease of application to the subject. It also showed that it may be possible to acquire PPG signals instead of ECG signals when the number of electrodes and wires could interfere with long term data acquisition and complicate the monitoring of individuals without any cardiac problems. Further investigation is underway to acquire more data to validate the system on a large data set in different subject groups.

REFERENCES

[1] S. Cerutti, A. L. Goldberger, and Y. Yamamoto, "Recent Advances in Heart Rate Variability Signal Processing and Interpretation," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 1, p.p. 1-3, January 2006.

[2] A. Ruha, S. Sallinen, and S. Nissila,"A real-time microprocessor QRS detector system with a 1 ms timing accuracy for the measurement of ambulatory HRV," *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 3, p.p 159-167, March 1997.

[3] H. Nazeran, Y. Pamula, and K. Behbehani,"*Heart Rate Variability: Sleep Disordered Breathing*", in "Encyclopedia of Biomedical Engineering" Metin Akay (Ed.), Wiley and Sons, New York, USA, 2006.

[4] J. Webster, *Medical Instrumentation: Application and Design*. John Wiley & Sons, pp. 245-247, 1998.

[5] P. Prasad, *Introduction to Biophotonics*. John Wisely & Sons, 2003.

[6] M. Bolanos, H. Nazeran, I. Gonzales, R. Parra, and C. Martinez, "A PDA-Based Electrocardiogram/Blood Pressure Telemonitor for Telemedicine", Proceedings of the 26th Annual International Conference of the IEEE EMBS, San Francisco, CA, USA, p.p 2169-2172, September 2004.

[7] M. Merri, D.C. Farden, J.G. Mottley, and E .L. Titlebaum, "Sampling frequency of the electrocardiogram for spectral analysis of the heart rate variability," *IEEE Transactions on Biomedical Engineering,* vol. 37, no. 1, p.p.99-106, January 1990.

[8] The Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, "Heart Rate Variability: Standards of Measurement, physiological interpretation, and clinical use," European Heart Journal, vol 17, p.p. 354-381, 1991.

[9] M. Brennam, M. Palaniswami, and P. Kamen, "Do existing measures of Poincaré plot geometry reflect nonlinear features of Heart Rate Variability?," *IEEE Transactions on Biomedical Engineering*, vol.48, no.11, p.p. 1342-1347, Nov.2001.

[10] "Importance of HRV in assessing physiological change," http://www.withyourvoice.com/About%20HRV.htm Accessed April 5, 2006.

[11] M. Arnold, X.H.R. Milner, H. Witte, R. Bauer, and C. Braun, "Adaptive AR modeling of nonstationary time series by mean of Kalman filtering," *IEEE Transactions on Biomedical Engineering*, vol. 45, no. 5, p.p. 553-562, May 1998.

[12] L.T. Mainardi, A.M. Bianchi, G. Baselli, and S. Cerutti, "Pole-Tracking Algorithms for the Extraction of Time-Variant Heart Rate Variability Spectral Parameters," *IEEE Transactions on Biomedical Engineering*, vol. 42, no. 3, p.p. 250-259, March 1995.

[13] R. Merletti, A. Gulisashvili, and L.R. Lo Conte, "Estimation of Shape Characteristics of Surface Muscle Signal Spectra from Time Domain Data," *IEEE Transactions on Biomedical Engineering*, vol. 42, no. 8, p.p. 769-776, August 1995.

[14] L.T. DeCarlo, "On the Meaning and Use of Kurtosis," Psychological Methods, vol. 2, no. 3, 1997.

[15] M.L. Harper, "Biostatistics for the Clinician," Pharmacotherapy Self-Assessment Program, 4th edition.

[16] G B Moody, "Approximate Entropy (ApEn)," Physio Toolkit, www.physionet.org/physiotools/ApEn/ Accessed April 5, 2006.

[17] S. Chatlapalli, H. Nazeran, V. Melarkod, R. Krishnam, E. Estrada, Y. Pamula, and S. Cabrera "Accurate Derivation of Heart Rate Variability Signal for Detection of Sleep Disordered Breathing in Children," Proceedings of the 26th Annual International Conference of the IEEE EMBS, San Francisco, CA, USA, September 2004.

TABLE I
HRV SIGNAL FEATURES IN A MALE SUBJECT.

Subject	**Sex**	**Age**			
1	Male	24			
		ECG HRV 0	**ECG HRV 1**	**ECG HRV 2**	**Avg.**
TIME	**Min RR (s)**	0.81	0.82	0.76	**0.80**
	Max RR (s)	1.22	1.16	1.17	**1.18**
	Mean RR (s)	1.06	1.01	1.00	**1.02**
	Mode RR (s)	1.08	1.02	1.00	**1.03**
	Stand Dev (s)	0.061	0.057	0.070	**0.063**
STAT	**Variance**	0.00	0.00	0.00	**0.00**
	Skewness	-0.32	-0.41	-0.52	**-0.42**
	Kurtosis	3.45	2.94	3.21	**3.20**
	ApEn	0.052	0.055	0.040	**0.049**
FREQ	**Total Pwr (s^2/Hz)**	1.08	1.03	1.10	**1.07**
	HF Power (n.u.)	0.44	0.41	0.41	**0.42**
	LF Power	0.62	0.64	0.64	**0.63**

	(n.u.)				
	LF/HF	1.41	1.56	1.56	**1.51**
		PPG HRV 0	**PPG HRV 1**	**PPG HRV 2**	**Avg.**
TIME	**Min DD (s)**	0.82	0.82	0.76	**0.80**
	Max DD (s)	1.22	1.17	1.17	**1.19**
	Mean DD (s)	1.06	1.01	1.00	**1.02**
	Mode DD (s)	1.08	1.02	1.00	**1.03**
	Stand Dev (s)	0.062	0.058	0.071	**0.064**
STAT	**Variance**	0.00	0.00	0.01	**0.00**
	Skewness	-0.30	-0.39	-0.50	**-0.40**
	Kurtosis	3.32	2.93	3.18	**3.14**
	ApEn	0.053	0.055	0.040	**0.049**
FREQ	**Total Pwr (s^2/Hz)**	1.13	1.05	1.07	**1.08**
	HF Power (n.u.)	0.44	0.39	0.42	**1.25**
	LF Power (n.u.)	0.61	0.64	0.64	**0.63**
	LF/HF	1.38	1.64	1.52	**1.51**

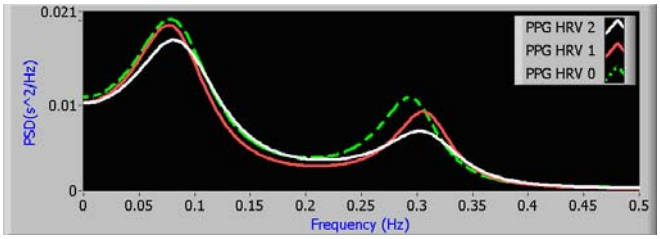
(a)

		Total Power	**HF**	**LF**
ECG	**HRV 0 vs HRV 1**	0.95	0.94	0.94
	HRV 1 vs HRV 2	0.98	0.92	0.97
	HRV 2 vs HRV 0	0.95	0.90	0.99
PPG	**HRV 0 vs HRV 1**	0.96	1.00	0.91
	HRV 1 vs HRV 2	0.95	0.94	0.94
	HRV 2 vs HRV 0	0.93	0.90	0.96

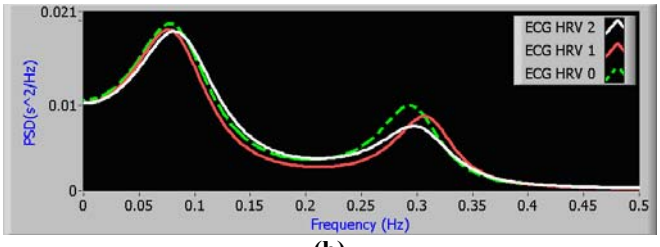
(b)

	Tachogram	**Total Power**	**HF**	**LF**
PPG HRV 0 vs ECG HRV 0	0.99	0.99	0.99	0.99
PPG HRV 1 vs ECG HRV 1	0.99	0.99	0.99	0.99
PPG HRV 2 vs ECG HRV 2	0.99	0.99	0.99	0.99

(c)



(a)



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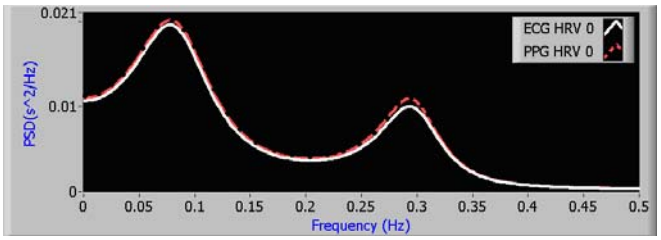

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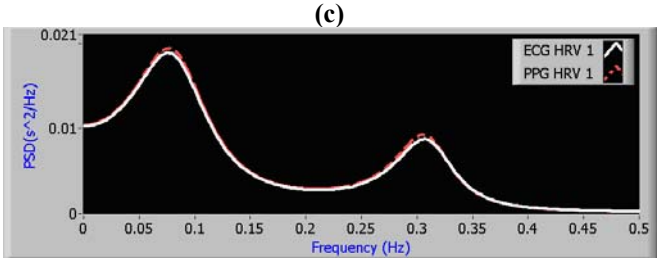

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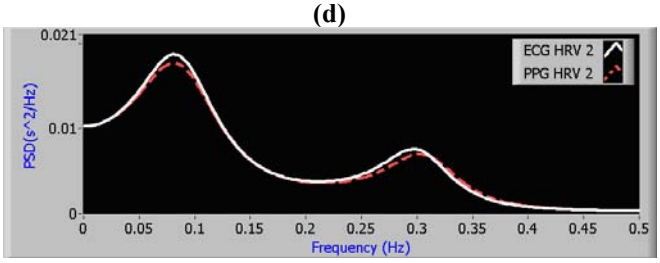
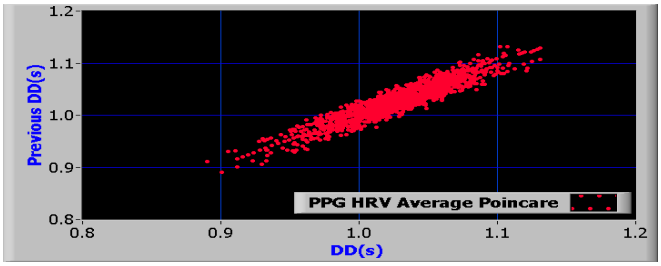
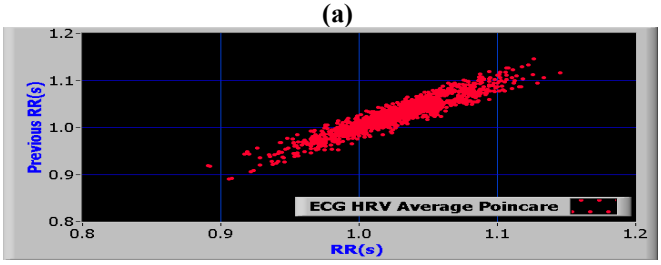


(e)

Fig. 2. Comparison of HRV power spectra in subject 1 (male).



(a)



(b)

Fig. 3. Comparison of Poincare′ plots in subject 1: a) Poincare′ plot of average PPG HRVs, b) Poincare′ plot of average ECG HRVs.

TABLE II
HRV SIGNAL FEATURES IN A FEMALE SUBJECT.

Subject	**Sex**	**Age**			
2	Female	25			
		ECG HRV 0	**ECG HRV 1**	**ECG HRV 2**	**Avg**
TIME	**Min RR (s)**	0.82	0.73	0.78	**0.78**
	Max RR (s)	1.22	1.20	1.23	**1.22**
	Mean RR (s)	1.06	1.03	1.02	**1.04**
	Mode RR (s)	1.11	1.07	1.04	**1.07**
	Stand Dev(s)	0.07	0.07	0.07	**0.07**

STAT	Variance	0.01	0.01	0.01	**0.01**
	Skewness	-0.96	-1.52	-0.73	**1.07**
	Kurtosis	3.93	5.88	4.42	**4.74**
	ApEn	0.03	0.02	0.02	**0.02**
FREQ	Total Pwr (s^2/Hz)	2.01	1.97	1.27	**1.75**
	HF Power (n.u.)	0.52	0.41	0.49	**0.47**
	LF Power (n.u.)	0.53	0.63	0.59	**0.58**
	LF/HF	1.01	1.54	1.20	**1.25**
		PPG HRV 0	**PPG HRV 1**	**PPG HRV 2**	**Avg**
TIME	Min DD (s)	0.83	0.72	0.71	**0.75**
	Max DD (s)	1.22	1.19	1.23	**1.21**
	Mean DD (s)	1.06	1.03	1.02	**1.04**
	Mode DD (s)	1.10	1.06	1.03	**1.06**
	Stand Dev (s)	0.07	0.08	0.07	**0.07**
STAT	Variance	0.01	0.01	0.01	**0.01**
	Skewness	-0.91	-1.46	-0.75	**-1.04**
	Kurtosis	3.73	5.59	4.80	**4.71**
	ApEn	0.03	0.02	0.03	**0.03**
FREQ	Total Pwr (s^2/Hz)	2.14	2.13	1.49	**1.92**
	HF Power (n.u.)	0.55	0.45	0.55	**0.52**
	LF Power (n.u.)	0.51	0.61	0.54	**0.55**
	LF/HF	0.93	1.35	0.98	**1.09**

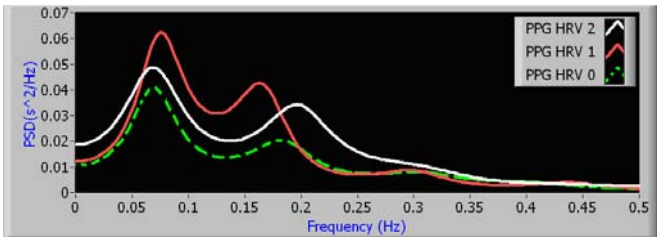
(a)

		Total Power	**HF**	**LF**
ECG	**HRV 0 vs HRV 1**	0.99	0.99	0.99
	HRV 1 vs HRV 2	0.98	0.97	0.98
	HRV 2 vs HRV 0	0.99	1.00	0.98
PPG	**HRV 0 vs HRV 1**	0.99	0.98	0.99
	HRV 1 vs HRV 2	0.97	0.95	0.99
	HRV 2 vs HRV 0	0.98	1.00	0.98

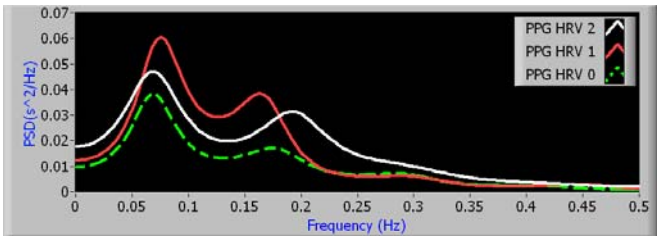
(b)

	Tachogram	**Total Power**	**HF**	**LF**
PPG HRV 0 vs ECG HRV 0	0.99	0.99	0.99	0.99
PPG HRV 1 vs ECG HRV 1	0.99	0.99	0.99	0.99
PPG HRV 2 vs ECG HRV 2	0.99	1.00	1.00	1.00

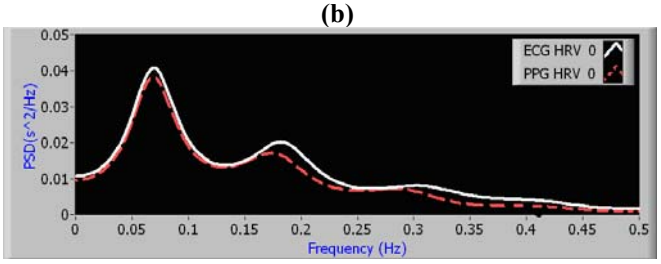
(c)



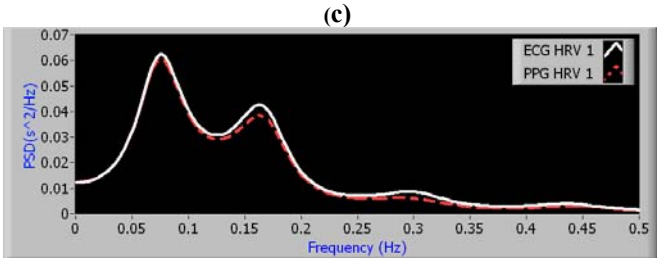
(a)



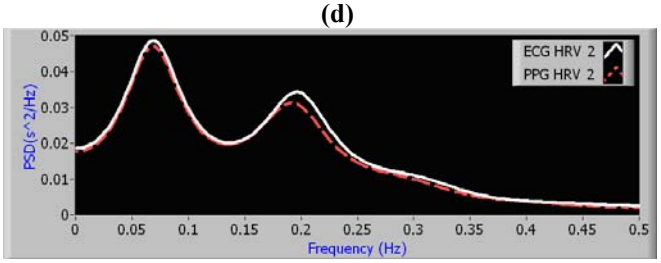
(b)



(c)

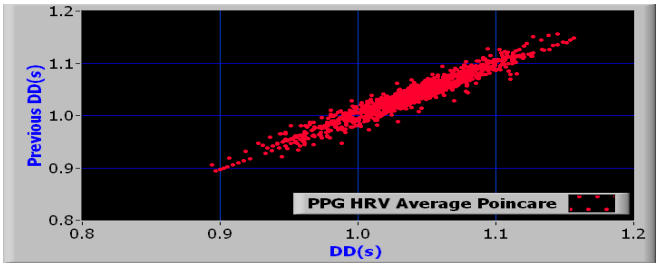


(d)

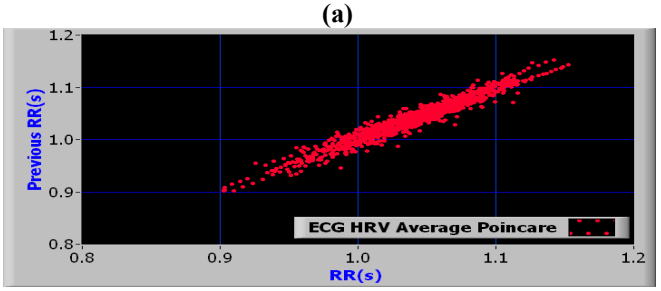


(e)

Fig. 4. Comparison of HRV power spectra in subject 2 (female).



(a)



(b)

Fig. 5. Comparison of Poincare′ plots in subject 2: a) Poincare′ plot of average PPG HRVs, b) Poincare′ plot of average ECG HRVs.