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Statistical Analysis of Heart Rate and Heart Rate Variability Monitoring Through the Use of Smart Phone Cameras

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Abstract—**Video recordings of finger tips made using a smartphone camera contain a pulsatile component caused by the cardiac pulse equivalent to that present in a photoplethysmographic signal. By performing peak detection on the pulsatile signal it is possible to extract a continuous heart rate signal. We performed direct comparisons between 5-lead electrocardiogram based heart rate variability measurements and those obtained from an iPhone 4s and Motorola Droid derived pulsatile signal to determine the accuracy of heart rate variability measurements obtained from the smart phones. Monitoring was performed in the supine and tilt positions for independent iPhone 4s (2 min recordings, n=9) and Droid (5 min recordings, n=13) experiments, and the following heart rate and heart rate variability parameters were estimated: heart rate, low frequency power, high frequency power, ratio of low to high frequency power, standard deviation of the RR intervals, and root mean square of successive RR-differences. Results demonstrate that accurate heart rate variability parameters can be obtained from smart phone based measurements.**

I. INTRODUCTION

With the increasing advancement of portable technology, it is now possible to create new physiological monitoring solutions for personal use. This monitoring can be cheap, easy to use and available to anyone. Smart phones have been explored as devices in many medical applications [1, 2]. One reason smart phones can be used for such monitoring is their built-in digital camera, which can be used to collect physiological signals. Smart phones are getting more advanced with greater resolution on their cameras and higher processing power. These advances make them not only useful tools for collecting data but also for analysis.

It has recently been shown that a continuous heart rate signal can be extracted from a smart phone video camera which can then be analyzed to monitor additional vital signs including respiration rate and heart rate variability [3-5]. This idea is promising because of the ability to write an application for a smart phone to be used as a health monitor without the need for additional equipment. Given the expanding growth of smart phones, such an application would be accessible to a large portion of the population.

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The ability to obtain a signal with a cardiac pulse component from the video image comes from photoplethysmographic (PPG) imaging which uses optical information caused by color changes in the skin due to cardiac activity [3]. This idea can be applied to the camera of a smart phone. An area of the skin is illuminated with the white LED flash and color changes are recorded with the video camera to generate a red-green-blue video [3, 4]. A subset of pixels at each frame are then averaged together for a particular color band to generate a signal. Signals obtained from mobile smart phone cameras have been compared to those obtained from a pulse oximeter and shown to produce similar waveforms with cardiac pulse peaks [6]. The cardiac peaks can then be detected and used to determine the continuous HR signal.

From a continuous heart rate signal the variability can be analyzed to monitor the autonomic nervous system to determine the influence of the sympathetic and parasympathetic components [7]. This is traditionally assessed using an electrocardiogram (ECG) with sampling rates of at least 250 Hz [8]. Using a PPG signal with sampling rates of 250 Hz to derive heart rate variability information has previously been shown as an accurate alternative to ECG based monitoring [9]. Sampling rates for smart phone video cameras range from 25 – 30 Hz. Therefore, it is necessary to determine the accuracy of the smart phone based devices in terms of estimating the heart rate variability (HRV) parameters.

Here, we compare HR data collected from smart phones with that collected from an ECG to investigate the accuracy of the smart phone based measurements made with subjects in the supine and then tilt positions. We use two different smart phones in two separate experiments to compare heart rate variability parameters with custom applications to record the pulsatile signals.

II. MATERIALS AND METHODS

A. Experimental Protocol

The protocol was approved by the Institutional Review Board at Worcester Polytechnic Institute, Worcester, MA. Independent experiments were performed to assess the performance of heart rate variability statistics computed with the Apple iPhone 4s (n=9) and Motorola Droid (n=13).

Electrodes in the standard 5-lead configuration were attached to each subject to measure the ECG with an HP 78354A system. LabChart software (ADInstruments) was used to record the ECG at a 400 Hz sampling rate. Subjects placed their right index finger on either the iPhone 4s or Motorola Droid camera lens. To record the pulsatile PPG signal, a custom application was designed for each phone that averages a 50x50 pixel region in the center of the video image at each frame with sampling rates of ~30 Hz for the iPhone 4s (green band) and ~20 Hz for the Motorola Droid (red band).

Subjects were instructed to lie in the supine position on a cot. ECG and phone data were recorded for 2 min during the iPhone 4s experiments and 5 min during the Motorola Droid experiments. Subjects were then instructed to sit up in a chair in the tilt position where data were recorded for the same respective time lengths.

B. Data Analysis

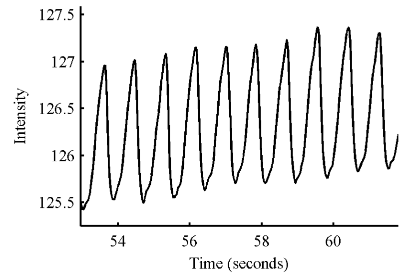
Post-recording data analysis was performed in Matlab r2011b (The Mathworks). After data collection, the LabChart and phone data for each subject were aligned in order to allow for direct comparison. Phone data was not saved with a fixed sampling rate but was recorded with a time stamp at approximately 30 Hz for the iPhone 4s and 20 Hz for the Droid. The time stamp was used to linearly interpolate the iPhone 4s data to 30 Hz and the Droid data to 20 Hz. Peak detection algorithms were used in order to determine R-wave peaks from the ECG signals and cardiac pulse peaks from the phone camera PPG signals [10]. Missed beats were manually identified and adjusted. Beat to beat intervals were determined to derive the RR-interval sequence and resampled at 4 Hz using cubic spline interpolation in order to determine the continuous HR signal.

Continuous HR signals were normalized to unit variance and then power spectra were determined using the Welch periodogram method. The low frequency power (LF) was defined as the power spectrum area from 0.04 – 0.15 Hz and the high frequency power (HF) was defined as the area from 0.15 – 0.4 Hz. Additionally, the standard deviation of the RR interval (SDNN) and the root mean square of successive difference (RMSSD) of RR intervals were determined [7].

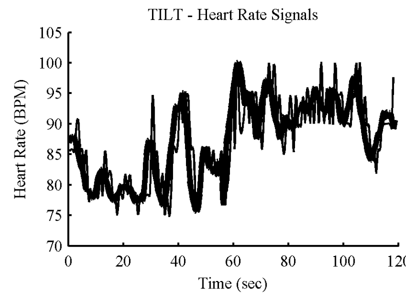
Data are displayed as mean ± standard deviation (SD). A paired t-test was used to compare between the supine and tilt positions ($p<0.05$ considered significant). Additionally, for each parameter a paired t-test was used to compare the ECG and smart phone based measurements. Parameters were compared between the ECG based measurement and phone based measurements using Bland-Altman plots to find the limits of agreement and by determining the Pearson correlation coefficients. The limits of agreement were found by taking the standard deviation across the patients of the differences in the estimated parameters between the ECG and smart phone based measurements and multiplying the result by a factor of 1.96.

III. Results

An example of green color band data from the iPhone 4s, which is similar to a PPG, is presented in Fig. 1(a). Continuous HR data derived from both an iPhone 4s and the corresponding data from the ECG is shown in Fig. 1(b). The power spectrum of the continuous HR signals acquired from the iPhone 4s and corresponding ECG are shown in Fig. 1(c).



(a)



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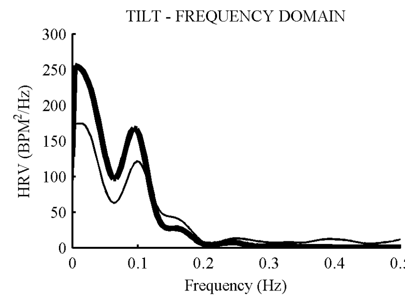


(c)

Figure. 1. (a) Example of green color data acquired from an iPhone 4s . (b) Example of HR data from an iPhone 4s (thin black) and from corresponding ECG (thick black). (c) Power spectra for the continuous HR signals shown in (b) from an iPhone 4s (thin black) and its corresponding ECG (thick Black).

The mean ± SD for the estimated parameters for all experiments are listed in Table I for the Droid experiments and Table II for the iPhone 4s experiments.

TABLE I. HEART RATE AND HEART RATE VARIABILITY PARAMETERS FOR DROID EXPERIMENTS (MEAN ± SD)

Droid		HR (BPM)	LF (unitless)	HF (unitless)
ECG	Supine	71.9±7.9	0.347±0.139	0.269±0.176
	Tilt	77.4±6.9*	0.347±0.150	0.245±0.1525
RED	Supine	71.7±7.9	0.230±0.127	0.342±0.178
	Tilt	77.1±7.3*	0.240±0.140$^{\alpha}$	0.347±0.165$^{\alpha}$
		LF/HF (unitless)	SDNN (msec)	RMSSD (msec)
ECG	Supine	2.84±4.63	0.044±0.043	0.053±0.032
	Tilt	2.13±1.6	0.035±0.027	0.052±0.028
RED	Supine	0.700±0.306	0.065±0.023$^{\alpha}$	0.061±0.025$^{\alpha}$
	Tilt	0.833±0.565$^{\alpha}$	0.073±0.026$^{\alpha}$	0.069±0.026$^{\alpha}$

*. Represents significant difference ($p<0.05$) between supine and tilt position with paired t-test

$^{\alpha}$. Represents significant difference ($p<0.05$) between ECG and RED with paired t-test

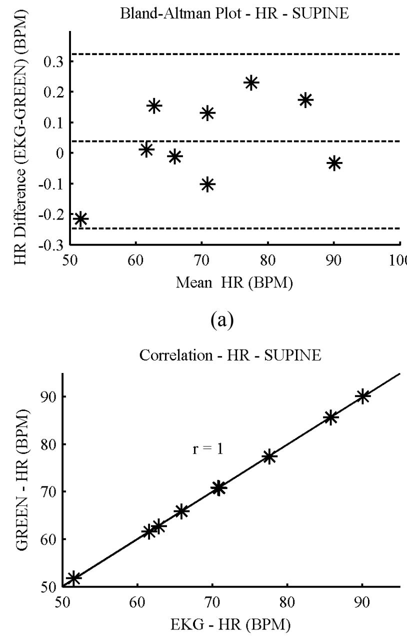
TABLE II. HEART RATE AND HEART RATE VARIABILITY PARAMETERS FOR IPHONE 4S EXPERIMENTS (MEAN ± SD)

iPhone 4s		HR (BPM)	LF (unitless)	HF (unitless)
ECG	Supine	70.8±12.2	0.266±0.164	0.349±0.183
	Tilt	75.8±12.0*	0.445±0.271	0.343±0.148
GREEN	Supine	70.7±12.1	0.200±0.113	0.417±0.189
	Tilt	75.8±11.9*	0.298±0.217$^{\alpha}$	0.432±0.135$^{\alpha}$
		LF/HF (unitless)	SDNN (msec)	RMSSD (msec)
ECG	Supine	0.834±0.427	0.030±0.014	0.038±0.012
	Tilt	1.8±1.76	0.029±0.011	0.040±0.012
GREEN	Supine	0.57±0.324	0.051±0.013$^{\alpha}$	0.050±0.013$^{\alpha}$
	Tilt	0.811±0.767$^{\alpha}$	0.053±0.018$^{\alpha}$	0.050±0.013$^{\alpha}$

*. Represents significant difference ($p<0.05$) between supine and tilt position with paired t-test

$^{\alpha}$. Represents significant difference ($p<0.05$) between ECG and GREEN with paired t-test

Bland-Altman and correlation plots were generated for the mean HR and all HRV parameters for either the iPhone 4s and ECG measurements or Droid and ECG measurements. An example Bland-Altman plot is shown in Fig. 2(a) for HR data from a tilt experiment from the iPhone 4s and its corresponding ECG, and a correlation plot is shown in Fig. 2(b) for the same. The Bland-Altman plot shows how similar the HR is between the green color band and ECG based measurements. The horizontal axis represents the mean HR for each subject while the vertical axis represents the HR difference between the green band from the iPhone 4s and the ECG recording.



(b)

Figure. 2. (a) An example Bland-Altman plot with a mean difference of 0.04 that shows the limit of agreement of 0.29 (dashed lines are mean difference ± the limit of agreement) between the continuous HR of a smart phone and its corresponding ECG signal. (b) Example of a correlation plot of the continuous HR monitored from a smart phone (y-axis) and ECG (x-axis) with the regression line and a Pearson correlation coefficient of 1.

The limits of agreement and the Pearson correlation coefficient were found for each parameter. Table III shows all of these results for the Droid phone and Table IV shows the results for the iPhone 4s.

TABLE III. LIMITS OF AGREEMENT (LA) AND PEARSON CORRELATION COEFFICIENT (R) BETWEEN DROID AND ECG BASED MEASUREMENTS

Droid		HR (BPM)	LF (unitless)	HF (unitless)	LF/HF (unitless)	SDNN (msec)	RMSSD (msec)
Supine	LA	3.2	0.64	0.56	6.9	0.046	0.02
	R	0.98	0.96	0.94	-0.15	0.92	0.97
Tilt	LA	1.4	0.59	0.41	2.7	0.039	0.024
	R	1	0.97	0.94	0.47	0.72	0.9

TABLE IV. LIMITS OF AGREEMENT (LA) AND PEARSON CORRELATION COEFFICIENTS (R) BETWEEN IPHONE 4S AND ECG BASED MEASUREMENTS

iPhone 4s		HR (BPM)	LF (unitless)	HF (unitless)	LF/HF (unitless)	SDNN (msec)	RMSSD (msec)
Supine	LA	0.29	0.18	0.21	0.53	0.01	0.009
	R	1	0.84	0.84	0.78	0.92	0.94
Tilt	LA	0.29	0.2	0.18	2.1	0.021	0.01
	R	1	0.93	0.8	0.94	0.83	0.93

IV. DISCUSSION

It has been found that by using a smart phone camera and monitoring the changes in color over time, it is possible to identify cardiac relevant information similar to that of a PPG. By identifying the cardiac pulse peaks in the PPG signal, we can obtain RR intervals and then HRV information over multiple parameters. Through comparison of the camera results to the ECG results there is evidence that demonstrates accurate HR and HRV parameters can be estimated from a smart phone.

We looked at three statistical measures which support the accuracy of the HR and HRV analysis obtained from the smart phones. For each measurement, a paired t-test was performed between the supine and tilt positions. It was found that for the Droid and corresponding ECG recording there were significant changes between the supine and tilt positions in HR, however both recordings found no significant changes for the 5 HRV parameters. The iPhone 4s and its corresponding ECG recording both displayed significant differences between the supine and tilt positions in HR. The Droid and the iPhone 4s based parameters produced the same statistical significance between the supine and tilt positions as their corresponding ECG based parameters.

The limits of agreement between the phone based measurement and ECG based measurement for each parameter were similar between the Droid and iPhone 4s. Consistent results for each HRV parameter may be processed to achieve an accurate result. In the Droid study, the correlation coefficients ranged from 0.72 – 1 for all parameters except LF/HF which had poor correlations for the supine and tilt positions. For the iPhone 4s derived parameters, correlation coefficients ranged from 0.8 – 1. HR measurements had correlation coefficients of 1 for the supine and tilt positions using both the iPhone 4s and Droid system. This displays a linear relationship between the smart phones and ECG based HR measurements. Lower correlation coefficients achieved with the iPhone 4s relative to the Droid may be due to the fact that the recording times of the iPhone 4s experiments were only 2 min compared to 5 min recording times during the Droid experiments.

One of the current issues with this technique is the low sampling rates of the cameras found in the phone. It has been stated that HRV measurements should be done with data that has a sampling rate of at least 250Hz [8]. Using our custom applications, the Droid phone had a sampling rate of approximately 20Hz and the iPhone 4s was close to 30Hz. An additional source of error is that current phones do not have a very stable surface for someone to place their finger upon and this may cause a number of motion artifacts introducing minor variations in the recordings. We manually adjusted any missed peaks in the present study, but this approach is not applicable to real-time monitoring. Motion artifacts can be adjusted for with better methods for stabilizing finger-camera interface and motion artifact detection systems to identify bad beats.

With a smart phone, it is possible to collect data from patients and process information to produce real-time measurements. The phone itself can be programmed with peak detection and HRV algorithms that can instantly process the recorded data and display the results. These results could then be directly sent to a physician or used to notify a patient of any potential cardiac problems.

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