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Contactless heart rate variability measurement by IR and 3D depth sensors with respiratory sinus arrhythmia

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Abstract

Heart rate variability (HRV) is known to be correlated with emotional arousal, cognitive depletion, and health status. Despite the accurate HRV detection by various body-attached sensors, a contactless method is desirable for the HCI purposes. In this research, we propose a non-invasive contactless HRV measurement by Microsoft Kinect 2 sensor with Respiratory Sinus Arrhythmia (RSA) correction. The Infrared and RGB cameras are used to measure the heart rate signal, and its 3D Depth sensor is employed to capture the human respiratory signal to correct the initially calculated HRV with RSA. The correlation analysis among the calculated HRVs by different methods and devices showed a significant improvement in reliable HRV measurements. This study enlightens the researchers and developers to choose a proper method for HRV calculations based on their required accuracy and application.

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1. Introduction

Heart rate variability (HRV) is defined as the physiological phenomenon of variation in the time difference between sequential heartbeats. HRV analysis has been widely used in many medical and psychological fields. Nowadays, the

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growing popularity of healthcare and fitness tracking devices has also stimulated the use of HRV analysis in other research areas, such as human-computer interaction (HCI) and affective computing (AC). For instance, as HRV is correlated with the user's arousal and ego depletion state [1], intelligent systems can consider HRV to deliver better matching adaptive content to the users.

Measuring HRV is possible through many different devices, which vary from very complex body-attached multi-sensor devices (e.g. ECG) to single-sensor devices (e.g. PPG, Smart watches, IR sensors). Even though complex devices, i.e ECG, can measure HRV accurately, they are more utilized by professionals in a medical context, and not by applications for average users. Moreover, almost all known HRV devices require being attached to the subject's body, which is not desirable in advanced HCI applications. Therefore, there is a lack of a proper contactless method to monitor heart rate with a high usability and a reliable performance, which is practical for individuals in HCI and AC areas. Although a reliable contactless method would be a desirable solution, its precision is still in question.

Among the practically applicable contactless methods, Microsoft has introduced the feature of heart rate measurement in the Microsoft Kinect 2 sensor [2]. MS Kinect 2 uses the infrared sensor to capture the temperature fluctuations over the face skin to estimate the subject's heart rate. However, to the best of our knowledge, there is no empirical study to show the accuracy of the heart rate measurement by MS Kinect 2, especially at a level that is sufficient to measure HRV.

HRVs are not stable in a course of time, and they fluctuate due to various reasons. Respiratory Sinus Arrhythmia (RSA) is one of the reasons. RSA is the HRV fluctuations caused by inspiration and expiration of the respiratory system. Therefore, the next HRV fluctuation can be estimated by monitoring the subject's respiratory signal. The contribution of this research is to enhance the contactless HR and HRV measurements by considering the subject's RSA.

In an experimental study with users, we investigated the reliability of the Microsoft Kinect 2 sensor as a non-invasive contactless heart rate measurement method. We further considered RSA to enhance the accuracy of the HR and HRV measurements by MS Kinect 2. We calculated RSA by extracting the subject's respiratory signal using a 3D Depth sensor [3]. To assess the reliability of the proposed method, this research compares the HRV correlations extracted from HR belt, PPG sensors, smartphone RGB camera, and IR sensor (MS Kinect 2). The proposed method (Kinect2-RSA for short) has shown an improvement over the original method of the MS Kinect 2 sensor.

In this experiment, only healthy subjects were selected for HRV monitoring. However, the proposed method may not work as accurately as it has been reported in this paper on unhealthy subjects, especially those with Sinus Arrhythmia problem.

Contactless HRV measurement is an important step into the future developments of intelligent and emotion-aware interfaces. The results of the study conducted can inform researchers and developers to choose a proper method for HRV measurement based on their required accuracy and application.

The rest of the paper is organized as follows. In the next chapter, the importance of HRV analysis and its application in HCI is discussed. In addition, different heart rate (HR) devices, which are being used in this research, are introduced. Then the research methodology and the experiment setup are elaborated, and at the end, the results of correlation of the proposed method and the other devices are discussed.

2. Background

2.1. What is HRV?

Heart Rate Variability (HRV) is the time difference between two sequential heartbeats. HRV has different names such as "*R-R Variability*", "*R-R Interval*", "*Cycle Length Variability*", and "*Beat-to-Beat Interval*". The character R is derived from the *R* peak in QRS complex of the ECG signal. In an ECG signal, HRV is measured by the intervals of two consecutive *R* peaks. There is an increasing amount of research in HRV and its correlation with the health and psychological states.

2.2. Physiological HRV Fluctuations

Although the affective, health and cognitive states of the user cause HRV fluctuations, there are other physiological phenomena which causes HRV fluctuations. There are two primary types of physiological HRV fluctuations: 1) Low-frequency oscillations, and 2) Respiratory sinus arrhythmia (RSA).

1) Low-frequency oscillations: This heart rate variation is associated with Mayer waves (Traube–Hering–Mayer waves) of blood pressure and is usually at a frequency of 0.1 Hz or a 10-second period [4].

2) Respiratory arrhythmia (or Respiratory sinus arrhythmia - RSA): This heart rate variation is associated with respiration and is in synchrony with the respiratory rate across a range of frequencies [5,6]. It is a vagally mediated modulation of heart rate such that it increases during inspiration and decreases during expiration due to the connection of the heart and lungs via the pulmonary artery. According to Kollai and Mizsei [7], the variation in a healthy adult in resting mode is about 108±12ms. RSA can also be used as a supplementary source for estimating and improving the calculation of HRVs. This process is elaborated in this paper in Section 3.1.3.

A normal resting heart rate is between 60 and 80 beats per minute and the resting respiratory rate is about between 12 and 20 breaths per minute. Both respiratory and heart rate increase by exercise with the ratio of 4 heartbeats over 1 breath. The ratio between the heart rate and respiratory rate is mostly maintained, but it varies from one person to another based on the health, age and fitness [8]. The healthy ratio can be between 3 (60 BeatsPM / 20 BreathsPM) and 8 (100 BeatsPM / 12 BreathsPM).

However, the nature of the relation between the heart and lungs is more sophisticated. Heart rate is initially controlled by hormones and nerves, which are not related to the lung functionality. Also, fast breathing changes the oxygen level and the pH of the blood.

2.3. Psychological HRV Fluctuations

HRV is controlled by the human autonomic nervous system, which consists of two elements: 1) Parasympathetic nervous system (PNS); 2) Sympathetic nervous system (SNS). PNS is responsible when the arousal level is low and the person is engaged with restful activities such as resting, eating, and digesting. PNS also decreases the heart rate and increases HRV. On the other hand, SNS is active when the person is involved in high arousal states such as stress. In addition, SNS increases the heart rate and decreases HRV. High frequency (HF) activity (0.15 to 0.40 Hz), especially, has been linked to PNS activity. Activity in this range is associated with the respiratory sinus arrhythmia (RSA). Less is known about the physiological inputs of the low frequency (LF) activity (0.04 to 0.15 Hz). Though previously thought to reflect SNS activity, it is now widely accepted that it reflects a mixture of both the SNS and PNS [9]. Psychological research in affective states has shown that HRV is related to the emotional arousal [1]. Lower arousal states cause higher HRVs, and a high HRV is correlated with a better health condition.

HRV biofeedback has been studied in different medical and psychological conditions such as anxiety disorder, cardiovascular conditions, chronic pain, anger, asthma, chronic fatigue, etc. A sudden drop in HRV is a sign of overtraining and fatigue, and the person needs time and rest to recover.

Cognitive research has also shown that cognitive depletion (ego depletion) is directly correlated with HRV. Segertrom [10] showed in an experiment that cognitive depletion would cause lower HRVs, and it is also an index for the self-control power. Therefore, considering the ego depletion state of the users in adaptive user interfaces can significantly improve the user’s experience and the system’s usability during the customizations and personalization processes [11].

2.4. Heart Rate Devices

In this section, we describe different heart rate measuring devices, which are suitable for HRV monitoring. Later, the result of the proposed method is compared against these devices to show its reliability and performance.

2.4.1. Heart Rate Chest Strap – HR Belt (Electrocardiography)

A heart rate monitor chest strap (Heart rate chest strap - belt) senses the electrical signals of the heart. When the heart beats, a small electrical signal is sent through the heart muscles causing a heartbeat. The heart rate monitor chest strap can detect this electrical signal through the skin. This belt needs to be in contact with the skin. There are electrodes on the belt, capturing the electrical signal [12]. Heart rate belts usually record the R-R intervals with a fine resolution of 1ms. In this research, the Polar H7 chest strap with Bluetooth interface was used to measure R-R intervals.

2.4.2. Photoplethysmography (PPG) Based Devices

PPG is an optical method to detect the arterial pressure waves. A PPG sensor consists of two main components: 1) An optical emitter (for example an LED); and 2) an optical detector (for example a photodiode). When the optical emitter transmits light into the skin, this light is partially reflected by blood. Due to the pulsatile flow of the blood (arterial pressure waves), the intensity of the reflected light changes synchronously to the pressure waves. The distance between successive waves depends on the heart rate. Therefore, the heart rate can be measured by PPG. In this paper, in addition to the PPG sensors, we have also used a smartphone camera, which is working based on Photoplethysmography (PPG).

- *Smartphone Camera*

A simple smartphone camera, which is equipped with a flash, can act as a PPG sensor. The camera acts as the optical detector and the flash as an optical emitter. Hereby, the arterial pressure wave can be measured, and by analyzing the pressure waves, the heart rate data can be extracted. When we put our finger on a smart phone's flash, the light would be reflected back to the camera. Through the optical characteristics of blood, the highest intensity can be detected at the wavelength of the red light. If the finger is also placed over the camera lens and the flash at the same time, the camera sensor shows a red screen.

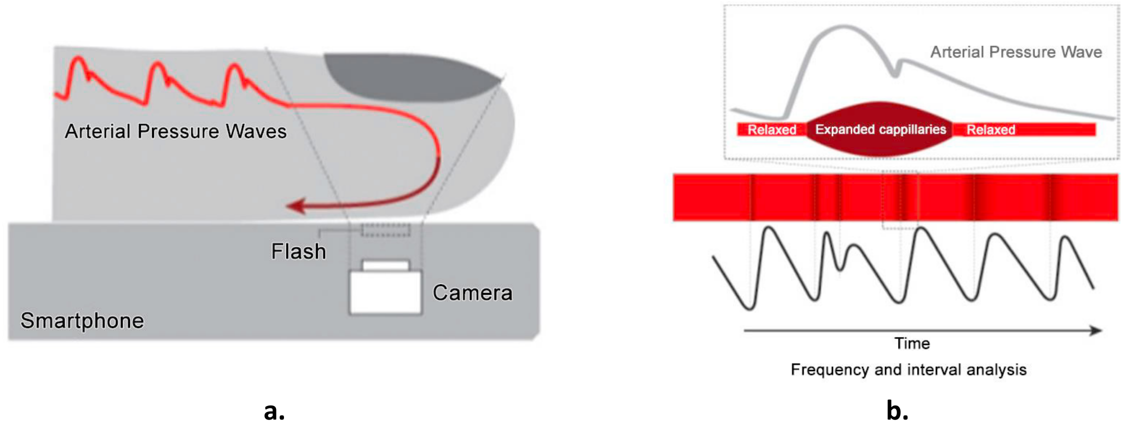


Fig. 1. a) Index finger placement over the flash and camera lens of a smartphone; b) Frequency and Interval analysis of the Arterial Pressure Wave

Even with the bare eyes, it can be seen that the intensity of the red color shown on the monitor is changing periodically. On an Arterial Pressure Wave, the expanded capillaries would increase the intensity of the red color. The interval analysis over these fluctuations would generate the R-R intervals of the heart rate.

2.4.3. Microsoft Kinect 2 Heart Rate

When a person's heart pumps blood, the volume of blood is pushed through the cardiovascular system. As the blood pumps through the body, particularly the face, more light is absorbed and less brightness, an RGB camera sensor picks up. In addition, when the blood pumps through the face, the temperature over the surface of the skin would increase, and an infrared (IR) sensor is sensible to these minor heat changes. These changes in brightness and heat values are very tiny and can be extracted using mathematical methods. The changes in brightness and heat are periodic and it generates a signal. If the signal is matched with a blood pulse, the heart rate can be calculated [2].

In order to match the change in brightness to a blood pulse, we used Independent Component Analysis (ICA) concept. This concept is the basis for finding hidden signals within a set of mixed signals. If there are two people talking in a crowded room, and there are microphones placed at various locations around the room, ICA algorithms can take a mixed sample of signals, and calculate an estimated separation of components. If the separated components are matched to the original signal of a person speaking, the target person has been found in the crowded room [2].

The ICA concept is also known as blind source separation, and here we have used the JADE algorithm in R, to provide the separation matrix of components for the R, G, B, and IR mixture of data. Then the separated components have their signals extracted using a Fast Fourier Transform to find a matching frequency range of a heart rate.

This method is applicable on Microsoft Kinect 2 sensor, and it can provide a non-invasive contactless solution, which is well suited for HCI and gaming purposes in terms of practicality and usability. Furthermore, we have enhanced the accuracy of the currently available methodology by considering the RSA correction.

3. Methodology

To evaluate and optimize the usability of HRV measurement devices for HCI and AC purposes, an experiment was conducted on five male participants (Mean age = 31; SD = 1.26) in a neutral emotional state and a healthy condition. The heart rate and respiratory of each subject were monitored using MS Kinect 2 sensor (IR 3D Depth, RGB Camera & IR Camera) with Kinect2-RSA method in parallel with an Electrocardiography (HR Belt), two PPG sensors, and a smartphone's RGB camera with flash. These devices recorded the heart rate and respiration data for a minimum of 60 seconds simultaneously. Later, the correlation values of the resulting HRVs were analyzed against electrocardiography data to evaluate the performance of each method and to compare them against the proposed method in this research.

3.1. Microsoft Kinect 2 sensor (IR Camera. RGB Camera, IR 3D Depth Camera)

3.1.1. Microsoft Kinect 2 heart rate

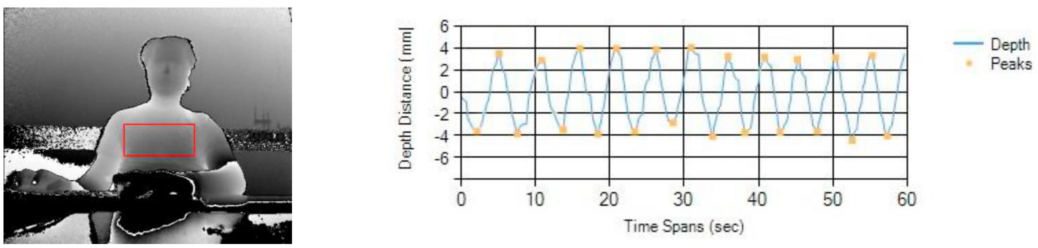
Microsoft Kinect 2 sensor is used in this experiment because it is equipped with a Full HD RGB camera plus an infrared (IR) sensor. The IR sensor can sense very small heat changes on the face surface. MS Kinect 2 sensor was set up to monitor the participant's face and record the RGB-IR channel data. For high performance in a realistic setting, the MS Kinect 2 sensor was placed within a one-meter distance from the subjects. The RGB-IR channels should be firstly mixed, then the JADE algorithm separates the components [2]. Then they will be transformed into a frequency domain to find the signal with heart rate frequency-like. R-R intervals can be measured from a frequency domain heart rate signal by computing the time difference between the beats of the R nodes.

3.1.2. Microsoft Kinect 2 respiration

Besides the heart rate extraction, we tried to capture respiration signals to contribute to measuring a more reliable and accurate heart rate variation based on RSA. To extract the respiration signal from an IR Depth sensor, we need to understand how the human respiratory system works.

When a subject is inhaling, the rib cage moves upwards and outwards, and the air is drawn into the lungs. In this case, the chest is getting closer to the 3D sensor, and when exhaling the reverse procedure occurs and the chest would go downwards and backward, and it is getting further from the sensor. Thus, the local minimum in the signal is the inspiration trough and the local maximum is the expiration peak in the resulted respiratory signal from a 3D depth sensor [3,13].

Microsoft Kinect 2 is equipped with an IR beamer and it uses the time-of-flight (ToF) technique to calculate the distance of the objects in front of the sensor. These depth values are measured in units of millimeters between the sensor and the objects [3].



a. **b.**

Fig. 2. a) Depth image of MS Kinect 2 with ROI of the chest; b) Sample extracted respiratory signal

MS Kinect 2 can sense the depth of the object within the maximum 8 meters of distance, however up to 4 meters is recommended by the manufacturer. In this experiment, the human subjects are set still in front of the sensor within a distance of one meter. Then Region of Interest (ROI) of the user's chest is selected to be monitored by MS Kinect 2 sensor. Fig. 2.a shows the output depth image of MS Kinect 2 with chest ROI selected. The mean values of the depth changes inside the selected ROI in a time-series domain represent the respiratory signal of the subject. The upper-body tiny movement would generate some noise into recorded data; therefore, we applied Kalman filter and a cut-off filter with a threshold of 20 *mm* on the extracted signal to eliminate the possible generated noise by the upper-body movements. The application to monitor the respiratory signal is developed in C#.NET 4.5 by Microsoft Visual Studio 2015 under Windows 10. Fig. 2.b shows a sample of extracted respiratory signal.

3.1.3. Microsoft Kinect 2 HR correction with Respiratory Sinus Arrhythmia (RSA)

As discussed earlier, HRV is associated with respiration [5,6]. HRV is increased during expiration and decreased during inspiration. By having an accurate heart rate signal from a healthy subject, the respiratory signal can be measured, and on the other hand, the next R-R Interval can be estimated by analyzing the respiratory signal. Therefore, in this study, we extracted the respiratory signal and the heart rate signal by Microsoft Kinect 2 to measure RSA. Respiratory signal features (inspirations and expirations) are calculated to estimate the next possible R-R Interval fluctuation based on RSA. When the first derivative of the respiratory signal (*rsf(): Respiratory function*) changes the sign (or is equal to zero), the respiration state is being changed. The second derivative of the signal says if the change is to the inspiration or expiration state. At this moment of the respiratory state change, RSA is being expected, so the next RR value would be estimated by applying the RSA variation. Then the actual measured heart rate would be compared with the estimated RR to calculate the possible error value, and the average of these two values would be considered as the next HRV (RR_{i+1}). Also, the calculated error would be replaced with the initial RSA variation (Var). The initial RSA variation is set to 108ms [7], but it is changing toward the individualized value over few respiratory cycles. This process is shown in Algorithm 1.

Algorithm 1. Pseudocode of heart rate correction with RSA

```
Var ← 108ms                                  //Initializing the variation value
function HRCorrection (RR_i)
if sgn(rsf'(i)) != sgn(rsf'(i-1)) then       //A respiration change is happening
        if rsf''(i) > 0 then                 //2nd derivative of respiratory signal at point "i" > 0 = Inspiration
                \widehat{RR}_{i+1} ← RR_i - Var
        else                                 //2nd derivative of respiratory signal at point "i" < 0 = Expiration
                \widehat{RR}_{i+1} ← RR_i + Var
        end if
        RR_{i+1} ← Performing HRV calculations
        RR_{i+1} ← Average(\widehat{RR}_{i+1}, RR_{i+1})
        Err ← \widehat{RR}_{i+1} – RR_{i+1}
        Var ← Var – Err
end if
return (RR_{i+1})
end function
```

3.2. Smartphone Camera

In this study, we used HTC One M8 to capture the videos of the Arterial Pressure Waves from the index finger of the left hand in Full HD 1920x1080 pixels at 30fps. The frame rate of 30fps can record the signal with the resolution of 33.33ms. However, this resolution can be improved up to 16.66ms and even 8.33ms by choosing the higher frame rates of 60fps and 120fps accordingly.

To analyze the captured videos, we used MATLAB to extract the arterial pressure wave signal. Firstly, each frame of the video is extracted, and the mean values of the Red (R) channel were calculated. The generated time series of the mean R channel is the signal of Arterial Pressure Wave.

The HRVs were detected from the signals in MATLAB. In the case of the camera, the resulted signal is inverted; because the inverted signal corresponds to the description of the arterial pressure waves (if more blood is in the tissue less light is reflected). Then, the signal is band-passed filtered by a wavelet approach to eliminate low frequency and high-frequency components, which could lead to wrong interpretations. Afterward, the peaks of the waves were detected by using MATLAB peak detection algorithm. Time differences between these peaks are the R-R intervals.

3.3. Analog PPG Sensors

The PPG sensors consist of a green LED, a photodiode with a peak sensitivity in the green wavelength and an analog active band-pass filter. The signal was converted by a microcontroller with an ADC resolution of 10 bits and a sample rate of 1 kHz. We used MATLAB to detect R-R intervals. Inverting the signal is not needed because the sensor's analog circuit had already inverted the signal.

Due to some outliers in the detected R-R intervals, we tried to improve the data by the least squares interpolation algorithm. For every R-R interval *n* (except the first 10) in the sample, the standard deviation of 10 previous R-R intervals was calculated and multiplied by a factor (1.5), and it was compared to the next R-R interval. If the difference between the interval *n* and the interval *n+1* is higher than the resulted value, R-R interval *n+1* is discarded and a new R-R interval is calculated through a spline interpolation (Eq. 1).

$$\forall RR_n \in RR \,|\, \left(RR_{n+1} - RR_n\right) \geq \left(SD_{i=1}^{10} RR_{n-1} \times 1.5\right) \rightarrow RR_{n+1} \notin RR \tag{1}$$

4. Evaluation and Results

Firstly, we compared the R-R interval sequence by calculating the cross-correlation in Matlab. Then, we compared the mean R-R intervals and four different HRV parameters. The mean R-R intervals (MEAN RR), the root mean square of successive differences (RMSSD), the standard deviation of R-R intervals (SDNN), the power in the low-frequency band (LF) and the power in the high-frequency band (HF) were calculated by the software Kubios HRV [14]. To compare these parameters, we calculated Lin's concordance correlation coefficients as a recommended measure of agreement between the same parameters measured with different devices [15].

Table 1 shows mean values of HR (Mean RR), RMSSD, SDNN from the time-domain signals, as well as LF and HF values over all subjects. HR belt captures accurate HRVs that is why we assess the other devices against it. In Table 1, we observed that PPG and RGB Camera have got more similar results to HR belt. It is not surprising that Kinect did not perform as well as the rest of the devices, as it is the only contactless device available for HRV measurement in this research. However, its accuracy has been improved by our suggested method of using RSA. Table 2 shows the Pearson correlation coefficient mean values and the maximum correlation of all devices against HR belt (chest strap).

Table 1. HRV analysis on various devices

	MEAN RR	RMSSD	SDNN	LF	HF
CAMERA	880.725	91.7	84.925	4133	2003.75
CAMER_INV	880.1	115.125	95.075	3109.75	3185.75
HR-BELT	884.68	58.94	74.64	3613.6	1718.2
PPG1	863	76.28	81.08	2550	1608.4
PPG1_INT	874.625	101.575	112.1	6881.25	1629.5
KINECT2	892	107.61	118.5	7025.52	1583.5
KINECT2-RSA	889	95.3	112.7	6991	1674.2

Table 2. R-R interval correlations against chest strap (HR belt)

	Camera	Camera_Inv	PPG1	PPG1_Int	PPG2	PPG2_Int	Kinect2	Kinect2-RSA
Mean Values	0.63	0.572	0.410	0.495	0.451	0.508	0.539	0.571
Max Values	0.918	0.699	0.673	0.779	0.673	0.798	0.664	0.681

5. Discussion

Table 3 shows the concordance (compared to chest strap data) of various parameters of the signals. These concordance values would represent the strength of agreement of each signal. According to our research hypotheses, MS Kinect 2 has a reliable precision in HRV measurement, and our proposed method of Kinect2-RSA outperformed Kinect 2 in all different tests.

The concordances of various parameters represented in Table 3 is evaluated using McBrides Scale [16]. This scale represents the strength level of agreement for each parameter.

It is concluded that they all can perform mean RR detection either perfect or substantial. However, they have very slightly lower accuracy than professional commercial devices like HR belt (chest strap) or ECG, yet they benefit the user by being readily and widely available and more convenient. Meanwhile, researchers can take the advantage of the special contactless feature of the Kinect, knowing the results are reliable and almost as good as the other devices.

Table 3. Concordance of various parameters (compared to Chest Strap) with McBrides scale agreements

	Camera	Camera_Inv	PPG1	PPG1_Int	PPG2	PPG2_Int	Kinect2	Kinect2-RSA
Mean RR	0.983†	0.964†	0.978†	0.993*	0.99*	0.992*	0.950†	0.969†
RMSSD	0.18	0.458	0.15	0.86	0.511	0.854	0.432	0.481
LF	0.953†	0.895	-0.02	0.719	0.677	0.737	0.714	0.852
HF	0.59	0.23	0	0.702	0.34	0.704	0.317	0.617

McBrides scale agreements: * > *0.99: Almost perfect;* † *0.95 - 0.99: Substantial*

6. Conclusion & Future Work

A reliable non-invasive contactless HRV measurement is an important step into the future developments of the intelligent and emotional-aware interfaces, and it is highly preferable in many intelligent and emotional-aware systems as it increases the user's satisfaction and provides higher usability to the host system. This study investigated the precision of HRV measurement by MS Kinect 2 with and without RSA correction against various heart rate devices. According to the reported results, the HR belt and PPG showed a very good correlation with each other. Even though the MS Kinect 2 sensor with RSA correction showed approximately 20% less correlation against HR belt, it outperformed Kinect 2 (without RSA correction) in all tests. In addition, because of the usability and contactless feature of the MS Kinect 2 sensor, it is still recommended to be used in the applications with less required precision. Despite the difficulty in HR belt installation, HR belt showed the best data resolution of one millisecond in R-R intervals among the studied devices.

In the next step, we will employ this method for detecting the user's affective state while interacting with an emotional-aware adaptive system. It is expected that the contactless HR monitoring integrated into an intelligent affective computing would increase the user's satisfaction as well as the system's usability.

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