KinRes: Depth Sensor Noise Reduction in Contactless Respiratory Monitoring

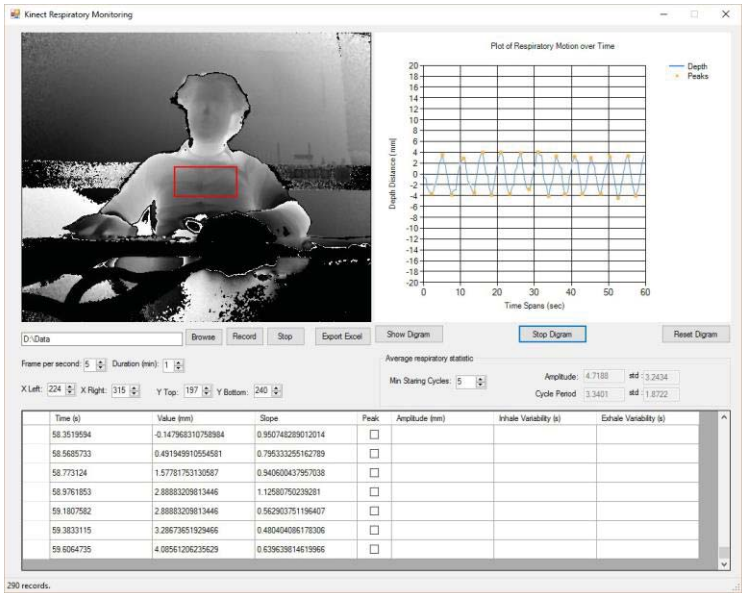

Figure 1: KinRes screenshot with IR 3D Depth image from Microsoft Kinect 2 sensor (left) and the extracted respiratory signal (right).

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Abstract
This paper proposes a novel reliable solution, named KinRes, to extract contactless respiratory signal via an IR-3D Depth sensor (Microsoft Kinect 2) on human subjects interacting with a computer. The depth sensor is very sensitive to the minor changes so that the body movements impose noise in the depth values. Previous studies on contactless respiratory concentrated solely on the still laid subjects on a surface to minimize the possible artifacts. To overcome these limitations, we low-pass filter the extracted signal. Then, a greedy self-correction algorithm is developed to correct the false detected peaks & troughs. The processed signal is validated with a simultaneous signal from a respiratory belt. This framework improved the accuracy of the signal by 24% for the subjects in a normal sitting position.

Author Keywords
Microsoft Kinect; Signal Processing; Greedy Algorithm

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I.4.3. Image Processing and Computer Vision: Enhancement

Introduction
The human respiratory signal is one of the biological features which is the interest of the researchers in

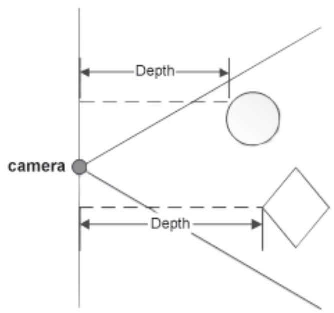

Figure 2: Depth values of the objects within the distance of max 4 meters – Source: *"Kinect Sensor: Microsoft Robotics, 2012"*

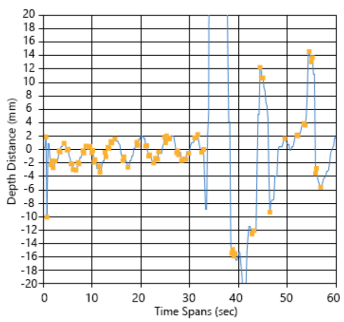

Figure 3: Moving backward and forward interference in respiration monitoring with incorrectly detected peaks and troughs

many areas from medicine [8], rehabilitation [3; 7] and psychology [1] to the computer and cognitive science [2]. Respiratory monitoring devices usually require being attached to the human body in order to acquire the respiration signal, which limits its applications. To overcome this constraint, the contactless respiration monitoring has been suggested with versatile applications. In contactless respiration tracking, a depth sensor is commonly used [4]. Microsoft Kinect 2 is one of the available devices, which is equipped with an IR 3D Depth sensor. As shown in Figure 2, it can measure the object's depth accurately [5].

To extract the respiration signal from a 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 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 respiratory signal from the depth sensor.

Depth sensors are sensitive to the noises, which are generated by: 1) the subject's movements (Figure 3); 2) data acquisition in a high-frequency sampling rate; and 3) sensor limitations and errors (Figure 5.a). A high quality noise-free signal is essential to measure the respiratory characteristics.

This paper proposes a novel real-time solution, called KinRes [1] (presented in Figure 1), to minimize the error and to maximize the accuracy of the respiratory signal extracted from Microsoft Kinect 2 on a normal sitting user interacting with a computer. To the best of our knowledge, we are the first to study the subjects' respiratory signal with normal body movements. KinRes employs signal filters and a smart self-correction method. This system is developed by C#.NET in Microsoft Visual Studio 2015.

1 KinRes source code is publicly available on GitHub.

Respiratory Signal Characteristics

The respiratory signal in a time domain is the sequential values of the depth changes of the subject's chest in millimeters. This signal has four main characteristics:

1. *Peak-to-Peak Amplitude* is the depth difference of the two subsequent local maximum (peak) and local minimum (trough), which is in the unit of length.
2. *Inspiration (Inhale) Variability* is the time difference between two subsequent inspiration troughs.
3. *Expiration (Exhale) Variability* is the time difference between two subsequent expiration peaks.
4. *Breaths per Minute (BPM)* is equal to the number of troughs or peaks in one minute.

Methodology

The chest region of interest (ROI) detection is the primary step in signal extraction. This is usually the only area which is being monitored in respiratory tracking systems [4; 9]. Figure 4 illustrates how KinRes operates and is explained as follows.

Noise Filtering

First, the raw signal extracted from the chest ROI is filtered to eliminate high-frequency noise and the native sensor errors by Simple Moving Average (SMA) and Kalman filters (Figure 5.b). After that, the user's movement would be detected by assigning a moving threshold to differentiate the chest breathing movement from the body movements. The extracted

"***Peaks and Troughs*** of the respiratory signal are the key elements of the signal characteristics. Peak-Trough Variability (PTV) is proposed as a new self-correction parameter to identify incorrectly measured peaks & troughs."

"**KinRes** can measure the respiratory characteristics precisely by employing a smart greedy algorithm for self-correction, and decreasing the signal artifacts, noise and errors."

PT ϵ *[peaks/troughs collection]*
for *every* PT_n *in PT* ***do***
  if $PTV(PT_n, TT_{n-1}) <= 300$ *ms* ***then***
    if $f''(PT_n) < 0$ ***then***
      Remove $\rightarrow min(PT_n, PT_{n-1}) \epsilon PT$
    end if
    if $f''(PT_n) > 0$ ***then***
      Remove $\rightarrow max(PT_n, PT_{n-1}) \epsilon PT$
    end if
  end if
end for

Algorithm 1: Abnormal Peak/Trough detection and correction (Self-Correction)

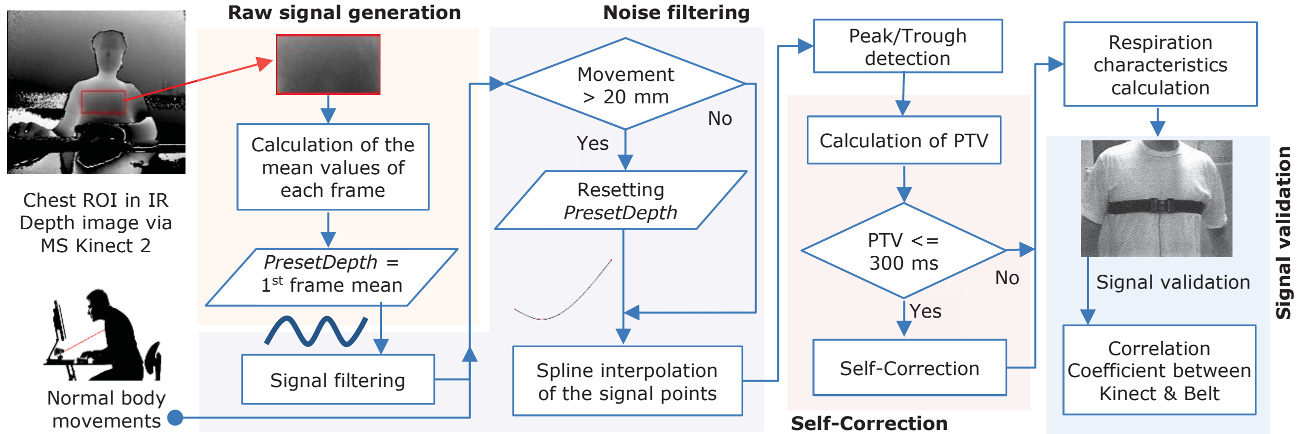

Figure 4: KinRes Methodology: Respiratory signal extraction from an IR Depth sensor (Microsoft Kinect 2)

sampling data are connected with a spline interpolation to generate a smoother signal. When the signal is filtered and interpolated, the peaks and troughs of the signal are calculated to measure the respiratory characteristics.

Self-Correction: Greedy Algorithm

Because of the possible remaining artifacts in the signal, all measured peaks, troughs, amplitudes, and variabilities may be affected. For this purpose, Peak-Trough Variability (PTV) is proposed. PTV is the time difference between two sequential detected peak and trough. Based on the average of all normal PTVs, those out of a threshold band (e.g. 300ms) indicate the incorrectly calculated peak or trough. In the case of abnormal PTV, if the second derivative of the signal was negative, the higher value is accepted as the local maximum, otherwise, in the concave up signal, the lower value is the local minimum (Algorithm 1).

Signal Validation & Results Analysis

In order to evaluate the KinRes signal quality (Figure 6), 24 signals from 12 male subjects (Mean age = 27.58; SD = 2.84) were captured. The process has been performed simultaneously from KinRes (Kinect 2 distance: 1 meter) and the Sleep Sense® respiratory belt in a 32 Hz sampling rate for a minimum length of one minute. Then, their correlations were computed. All the signals were acquired in a normal sitting position; however, each participant was recorded in two modes, one with no significant body movements, and the other mode with normal body movements while interacting with a PC.

The best achieved correlation coefficient of KinRes with the Kalman filter on interacting/moving subjects was 0.8637. In overall, the mean correlation coefficient value of 0.9094 of Kalman filter in both modes outperformed SMA (refer to Table 1). Utilized filters improved the accuracy of the system by more than 24% in active mode, compared to the raw depth signal.

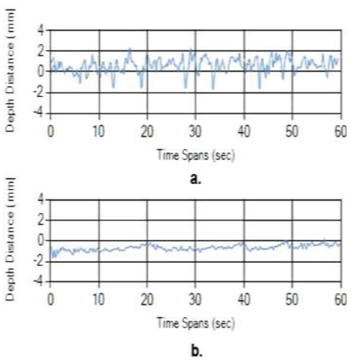

Figure 5: Captured noise from a static object within 60 seconds in the distance of 2 meters from Kinect 2 – a) Raw signal without filtering; b) Filtered signal.

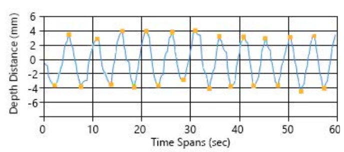

Figure 6: Respiratory signal after noise reduction with correctly detected peaks/troughs

	Static	Active
NO-FILTER	0.8724	0.6195
SMA	**0.9565**	0.8411
KALMAN	0.9551	**0.8637**

Table 1: Correlation Coefficient results of two modes of signals (static/still; active/normal) from KinRes against respiratory belt

Despite the higher average correlation of the Kalman filter, it takes few seconds for Kalman to adjust itself with the fluctuations ratio, and the correlation of the signal is lower than SMA at the beginning. However, unlike SMA, it does not require any predefined and fixed frame size.

The result of this study is identical from many aspects in comparison to the prior works. These results are obtained from a normal sitting user behind a desk with normal movements; however, the best-reported results are on the subjects who were laid on a surface similar to the radiotherapy situations [4; 6; 9]. For instance, Xia et al. reported a mean correlation coefficient of 0.969 in a fixed laid position with a translation surface placed on the chest to minimize the noise [9], while this is not a practical position in HCI and pervasive health applications.

Conclusion

This paper has proposed a real-time contactless respiratory tracker, KinRes, which is able to compute and analyze the respiratory characteristics precisely by employing a smart greedy algorithm for self-correction and decreasing the signal artifacts and errors.

KinRes was tested on the subjects sitting behind a desk and interacting with a PC; however, the previous studies were done on subjects who were laying down with minimal movements (static). A commercial respiratory belt validated the recorded normalized signals from KinRes, and the correlation results were identically high.

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