Inhalation and Exhalation Detection for Sleep and Awake Activities Using Non-Contact Ultra-Wideband (UWB) Radar Signal

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Abstract. Respiratory is one of the vital signs used to monitor the progression of the illness that are important for clinical and health care fields. From home rehabilitation to intensive care monitoring, the rate of respiration must be constantly monitored as it offers a proactive approach for early detection of patient deterioration that can be used to trigger therapeutic procedures alarms. The use of invasive procedures based on contact transducers is typically necessary to measure the quantity. Nevertheless, these procedures might be troublesome due to the inconvenience and sensitivity of physical contact. Therefore, non-contact human breathing monitoring as a non-invasive procedure is important in long term intensive-care and home healthcare applications. In this paper, respiratory signals from two type of resting activities had been acquired and proposed a Deep Neural Network (DNN) model that can classify the respiratory signal into inhalation and exhalation signal. Several pre-processing techniques has been done onto the signal before it is implemented into the proposed model. The average recognition rate of the respiratory signal using the proposed method was 84.1% when the subject was sleeping and 83.8% when awake.

1. Introduction

Health care monitoring has emerged in the past few years as a primary area of concern. The application focused on vital signs measurements of health parameters, such as heart rate, human breathing rate and blood pressure. Wearable devices are a popular phenomenon in this area due to their portability. However, these devices pose many challenges. For example, patients’ daily activities will be intruded since they have to wear the device all the time including during sleep, and sometimes have to be recharged as well. Those factors make wearable devices inconvenient to use.

Currently, the use of non-contact method for measuring vital signs has gained popularity due to the flexibility and non-invasive procedure [1]. The research community is currently focused on the
use of non-contact technique for the detection of breathing rate, such as magnetic induction sensing methods [2], radio-wave monitoring method [3][4] and image-based monitoring methods [4][5].

With advances in wireless sensing, non-contact devices have become possible to localize human and determine vital signs. From previous works[6]–[13], it had been proven that RF signal can be used as device free human localization and activity identification. The algorithm developed were able to localize and detect up to 3 persons, simultaneously in a closed environment setting without requiring them to carry additional devices.

Depending on the type of sensing technique, the devices can be broadly classified into two categories. Active device employs dedicated transmitters, uses high bandwidth, and often requires complex arrays of antennas along with them. Passive tools, on the other hand, are covert, require low bandwidth and use networks such as WiFi and cellular signals to track targets.

Ossberger et al. [14] explained how ultra-wideband radar pulses could be used to detect respiratory motion. The work claimed that the pulsation of a human chest due to respiratory movement could be detected with great accuracy by using sub-nanosecond. The device also able to penetrate through walls allowing for respiration detection up to 5m distance as well as behind walls penetration. However, the system employed separate transmitter and receiver antennas which is nonportable. Some researches [15][16] also expanded the use of the radars to track heart rate along with breathing rate [17][18], vital signs or movements [19]. All these systems have common drawbacks that needed the subject to stay static while the experiments are being conducted. Other than using UWB radars, Ravichandran et al. [20] used WiFi signals in natural home environment to estimate respiration rate in a closed space.

Alshaer et al. [21] used polysomnogram (PSG) which is a contact device to assess snoring. The work quantified the relationship between snoring and sleep apnea using an algorithm. Snoring, which is one of the indicators of sleep disorder, produced the wheezing sound caused by the flow of air through a narrowed airway that resulted in the vibration of the tissue. It is assumed that the inhalations and exhalations [22] related to the snoring events can be used to detect sleep apnea.

In this research, we proposed to investigate and characterized the RF signal into inhalation and exhalation signal in order to detect and monitor breathing activity which is an important parameter to indicate the healthiness of the human. Human breathing requires constant movements of inhalation and exhalation, and can be used to study the physiological condition, stress levels or even emotions such as fear and relief of the subject.

This paper is organized as follows: Section II presents research activities carried out included the device used, subject, data collection and processing part. Section III describes the results and its analysis. Lastly the conclusion had been made in Section IV as well as the future works.

2. Materials and Methods

2.1. Subjects
The subject participated in this experiment was a male aged 54 and weighed 98 kilograms. The subject is a snorer. The data is collected multiple times that involved subject’s different resting activities such as sleeping and watching TV.

2.2. UWB Radar System
To monitor the breathing, a typical ultra-wideband (UWB) radar system on chip (SoC) named XeThru X4M200 was used. This UWB radar as shown in Figure 1 is a system built by Novelda originally from Oslo, Norway. The SoC highlights the transmitter that consented with guidelines for unlicensed operation that satisfy the emission levels issued by authorities of Federal Communication Commission (FCC) as well as Malaysian Communications and Multimedia Commission (MCMC) [23]. The radio frequency (RF) directly tested using the technique of swept threshold as well as RF interference rejection.
XeThru device relies on monitoring the body’s intermittent breathing and chest movements while a person is at rest. By using the pulse doppler theory, which is the basis of XeThru respiration tracking, this periodic motion is observed from a distance in sliding time windows. At each range bin, a frequency spectrum is measured, and a pulse doppler matrix is generated, where a static object can be removed, while the small movements measured from the subjects. This allows the XeThru sensor to accurately find the number of respirations per minute (RPM) of a breathing person.

The bandwidth of the transmitter used in this study was 1.4 GHz while central frequency ($f_c$) of the sensor was 7.29 GHz. The receiver sampled the signal reflected and can cover up to 9.9 m. The detection distance range used in this study was set at 1.22 m distance. The SoC was a controller which communicate with the radar sensor via universal serial bus (USB) cable and received raw radar in real-time. The average of the output power in dBm/MHz was lower than -44 dBm. Hence, it complies in terms of average transmitted power with FCC and MCMC [23].

2.3. Data Collection
For adults aged more than 12 years, the respiratory rate is ranged at 12 respirations per minute to 20 respirations per minute [24] as shown in Table I. For the subject chosen, the measurement of the data during sleep and watching TV carried out as in Figure 2(a) and Figure 2(b) respectively.

![Figure 1](image1.png)

**Figure 1** Ultra-wideband radar, XeThru X4M200

![Figure 2](image2.png)

(a) (b)

Figure 2 (a) Experimental setup when subject is sleep. (b) Experimental setup when subject is watching TV.
Table- I: Respiratory rate classification in adult patients [24]

| Respiratory Rate                      | Range (rpm) |
|---------------------------------------|-------------|
| Eupnoea (normal relaxed breathing)    | 12 – 20 rpm |
| Normal range >65 years                | 12 – 25 rpm |
| Normal range >80 years                | 10 – 20 rpm |
| Bradypnoea (slow respiratory rate)   | <12 rpm     |
| Tachypnoea                            | >20 rpm     |

2.4. UWB Radar Principles

The echo signals received by the receiver were two-dimensional data, where M by N, which M is the fast sampling number that shows the distance of detection while N is the slow sampling number that shows the time of detection.

As UWB radar systems reach the target, the reflection of the transmitted pulse takes place due to the high body reflectivity. The respiratory motion caused the chest occasionally extended and contracted, which resulted the distance $d(t)$ to regularly change around the antenna, $d_0$. $d(t)$ are formulated as below [25]:

$$d(t) = d_0 + m_r \sin(2\pi f_r t)$$

(1)

where $m_r$ is the respiratory amplitudes, while $f_r$ is the frequencies of respiration, and $t$ is detection time.

At the point when various channels exist, the representation of the received signal is as follows [25]:

$$r(t, \tau) = \sum A_i p(\tau - \tau_i) + A_T p(\tau - \tau_c(t))$$

(2)

where $p(t)$ is a standardized received pulse, $A_i$ is the multi-path component amplitude, and the corresponding delays are $\tau$, while $A_T$ is the pulse amplitude reflected by the movement of the chest. For $r-\tau_c$ represents the distance of the subject chest with sensor.

The UWB radar sensor can detect the distance itself, depending on the time of arrival. Due to high precision measurement of respiratory data, the use of maximum energy had been chosen. The topic could be placed after the previously described process by computing the energy alongside the distance step, at which the signal could be acquired.

2.5. Algorithm Construction

By using Python, a deep neural network model was used to classify the inhalation and exhalation pattern. Four parameters were considered during algorithm construction to gain better performance.

First parameter is splitting the dataset into train and test datasets. The train and test datasets were split with the ratio of 0.7 and 0.3 respectively by using sklearn Python package.

Second parameter is the hidden layers of the neural network that used sequential model in Keras python package, which is a linear stack of layers. Three dense layers were applied and densely connected due to the receiving input of each neuron in previous layer. The layers layout is shown in Figure 3 below.
Third parameter is the activation functions. There were two type of functions had been implemented. The first applied function was Rectified Linear Unit (ReLU). This function activates all the neurons at the same time. If the output of the linear transformation is less than zero, the neurons will be deactivated [26]. This activation function can be applied onto the signal since the recorded UWB radar signal started at initial time of $t_0=0s$. ReLU function had been applied on the first and second hidden layers of the model. Next activation function applied was Softmax function. It is a combination of multiple sigmoids which can be used for multi-class classification problems [27]. The function returns the probability for a data-point that belong to each individual class. Hence, Softmax function generally works better. In order to classify the data in this study, this function had been applied on the third layer of the model.

Last parameter to be implemented in the model is the optimizer. The optimizer used was adaptive moment estimation (Adam) which is an adaptive learning rate optimization algorithm. Adam is designed specifically to train deep neural networks that computing individual learning rate for each weight of the network [28].

3. Results and Discussion
The average respiratory rates and the average respiratory pattern amplitude recorded according to the activities are shown in Table II.

| Activities       | Average Respiratory Rate (rpm) | Average Respiratory Pattern Amplitude |
|------------------|--------------------------------|---------------------------------------|
|                  |                                | Inhale  | Exhale    |
| Sleeping         | 12 rpm                         | 3.0     | -3.0      |
| Watching TV      | 16 rpm                         | 2.0     | -1.5      |

The respiratory pattern also recorded along the experiment. The inhalation and exhalation patterns were read using the movement of the subject’s chest. For each respiratory signal, there is rising and falling pattern. These rising patterns can be described as inhalation mechanical distance taken place over a period time, while falling patterns showed exhalation mechanical distance taken place over time as showed in Figure 4. Both signal datasets obtained were replotted into line graphs as shown in Figure 5(a) and (b). The non-uniform radar signals are showed that there are several signals that differ from other signals due to the subject movements, such as hand movement, head movement and others.
As shown in Figure 2(a) and Figure 2(b), a subject was put at rest while the UWB radar positioned perpendicularly from the subject. The non-uniform radar signals are shown in Figure 5(a) and (b), in which there are several signals that differ from other signals due to the subject movements, such as hand movement, head movement and others.

**Figure 4** Respiratory rate and respiratory pattern [29]

**Figure 5** (a) Respiratory pattern when sleeping and (b) watching TV.

**Figure 6** Bits representation of the signal data.
The amplitude of the raw collected dataset was shifted up to ensure all the signals becoming positive in order to serve as input for activation function [30].

Next, the data is transformed into binaries that represented by bits for the robustness against the mismatch of the domain between training and testing of the neural network [31] as shown in Figure 6.

Finally, the binaries were classified into two features which are inhalation that represented the rising signal, as well as exhalation, indicated by the falling signal.

The two datasets of sleeping and watching TV which contained 10,000 data respectively were trained with 100 number of epochs of each dataset. The datasets consisted two classes of data which are exhalation data that labelled with 0, and inhalation data labelled with 1. The obtained average accuracy rate and loss rate in this study is shown in Figure 7. The sleeping dataset shows better accuracy performance of 84.1%, which is slightly higher as compared to watching TV dataset which is 83.8%. The comparison differs in 0.3%. While for loss rates, it is rated 15.9% for sleeping dataset which is slightly lower than watching TV dataset with loss rate of 16.2%. The loss rate differs in 0.3%, same as accuracy rate. Accuracy rate represents the average performance of each epoch while the validated accuracy validates the average number of simulation performance. Loss rate measures the error rate of the model performance.

4. Conclusion
We conducted experiments on subject matter to test the viability and accuracy of non-contact vital sign monitoring via UWB radar sensors. We measured the subject’s respiratory pattern using a radar sensor while he was resting, and the experimental results demonstrated the performance of the method purposed. The experimental results showed that the approach could satisfy the needs of human respiratory monitoring. Our study shows that the DNN model produced better accuracy rate in inhalation and exhalation detection when the subject was sleeping instead of watching TV. The accuracy rate differs 0.3%.

Due to the advantages of the UWB radar signal, identification of inhalation and exhalation part for other patients with severe sleep disorder symptoms may be explored in the future. In addition, the realization of the vital sign detection of moving targets through a radar sensor will also be one of the new further area of study. As to increase the algorithm performance, adding hidden layers, changing activation functions either in the hidden layers or output layer, also increasing neuron numbers can be applied.

Acknowledgement
This research is fully supported by Fundamental Research Grant Scheme (FRGS) by Ministry of Higher Education Malaysia (FRGS/1/2018/SKK06/UNIMAP/02/1). The authors also would like to thank the
subject of this experiment for his willing and consent to carry out the experiment. Also, many thanks to University of Yamanashi for providing short course of deep learning.

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