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공학석사 학위논문

Unconstrained Apnea and Asthma Symptom Detection Using Ultra Wide Band Radar

UWB 레이더를 이용한 무구속적 무호흡 및 천식 증상 검출

2017년 2월

서울대학교 대학원

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고 명 준

Abstract

Unconstrained Apnea and Asthma Symptom Detection Using Ultra Wide Band Radar

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Respiration and coughing are evident vital signs to check one's condition are sound. Long-term respiration monitoring is needed to find out if the person is in good health condition. Long-term respiration monitoring can be cumbersome when devices are constraining subject's body. Measuring respirational signal with the unconstrained method is good for patients or babies or elders who have a lower level of enduring cumbersomeness.

The purpose of the study is to prove the feasibility of Ultra Wide Band (UWB) radar for detecting abnormal respiration. UWB Radar uses 3.1 to 10.6 GHz frequency range and transmit pulse with very short

duration. Impulse radiation is 50 degrees from Vivaldi antenna. Its small size and low power consumption make UWB radar application for home or inside a vehicle. Apnea and coughing data was classified from normal breathing data with classifier such as Support Vector Machine (SVM), Decision Tree (DT) and Random Forest (RF) with statistic and frequency domain features.

For apnea detection, reference device data showed the best result with RF classifier with 100% mean sensitivity, 70% mean precision, 0.82 F measure and UWB radar data showed the best result with RF classifier with 100% mean sensitivity, 70% mean precision, 0.82 F measure.

For coughing detection, reference device data showed the best result with RF classifier with 100% mean sensitivity, 71% mean precision, 0.83 F measure while UWB radar data showed the best result with RF classifier with 100% mean sensitivity, 83% mean precision, 0.91 F-measure.

Detecting apnea and coughing while a person is moving or in different posture should be studied in future studies. This study expects more application of UWB radar in long-term vital sign monitoring.

Keyword: Ultra wide band radar, Respiration, Apnea, Cough, Asthma, Unconstrained
Student Number: 2015-21207

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List of Abbreviations

UWB Ultra Wide Band

OSA Obstructive Sleep Apnea

SAR Specific Absorption Rate

SVM Support Vector Machine

DT Decision Tree

RF Random Forest

Chapter 1. Introduction

1.1 Background

Recent years, obesity has been an issue around the world. Being overweight and obesity makes tissue wall of pipes fatter which makes narrower windpipe. Narrow windpipe makes hard to keep open especially when a person is lying on the bed. The elasticity of that wall also decreases as people ages. This narrow wall of windpipe can block air flow and cause apnea during sleep. This is called obstructive sleep apnea [1]. It is a serious disorder which stops breathing repeatedly for more than 10 seconds. This can result in lower oxygen in the blood and can wake up a person repeatedly during sleep time. It will decrease the quality of sleep and can trigger the release of stress hormones [2]. These can cause increased chance of heart attack, stroke and having high blood pressure. Untreated sleep apnea can also result in risk for obesity and diabetes. People with obstructive sleep may not aware of their sleep quality and feel they slept well through the night.

Asthma is increasing allergic disease recently, it is caused by the genetic and environmental factors [3]. About 26 million people in the US are suffering asthma, many of them are not aware that they have it when the symptoms are not severe. The common symptoms of asthma are

coughing and shortness of breath. Worse asthma can be noticed with more frequent of symptoms. Asthma can be deadly when left untreated. These two conditions can be monitored in-house if there is a simple device or system that can detect abnormal respiration signal.

1.1.1 Breathing

Breathing is a movement which makes air moving in and out of lungs. Air brings in fresh oxygen and takes out carbon dioxide. This two gas exchange is important to survive. When people inhale, thoracic cavity becomes larger and get smaller when exhaled. Breathing makes changes in thoracic cavity volume. Respiratory rates vary with age. Six-months-old babies breathe 25-40 breaths per minute, Adults breathe 12-18 breaths per minute, Elderly over 65 years old breathe 12-28 breaths per minute. [4, 5]

1.1.2 Apnea

Apnea is the absence of breathing [6]. There is no movement of thoracic cavity change. Continuous apnea can cause low oxygen level in blood which can cause damage to the body [7]. Apnea can happen voluntarily, chemically, and during sleep. There are three types of sleep apnea. Obstructive Sleep Apnea (OSA), Central Sleep Apnea (CSA) and the combination of two kinds. Most common sleep apnea is OSA [8, 9, 10]. The causes of OSA are enlarged tonsil, obesity, allergies and family history. People who suffer from OSA often doesn't aware of they have it. The cause of CSA is from a lack of breathing effort. Sleep apnea can cause heart attack, stroke, diabetes, heart failure etc, if not taken care of. OSA occurs the mostly from age group 30 to 64 years old [13]. Multi-criteria are considered when diagnosing OSA. Mild OSA patient has 5 to 14.9 apneic events per hour, the severe patient has more than 30 apneic events per hour. Apnea will have to occur more than 30 times during 7-hour sleep to diagnose patients OSA. OSA patients hold events of minimum 10 seconds of apnea between breaths with a neurological arousal [8, 11, 12].

1.1.3 Coughing

Coughing is a quick movement or reflex to clear the airway from irritants or particles. A cough is done with three steps. First, inhalation, second, forced exhalation with pressure built within glottis. Third, high pressure quickly released from glottis. Coughing makes a unique sound and it can be voluntary or involuntary. Coughing is natural protective procedure [14].

1.1.4 Asthma

Asthma is a common lung disease characterized by variable symptoms. Symptoms are wheezing, coughing, chest tightness and short of breath. These symptoms depend on the person and may get worse at night or activity. Asthma is caused by genetic and environmental factors. Environmental factors are air pollutions or allergens. Asthma is incurable. Symptoms can be prevented by avoiding allergens and irritants.

1.2 Existing Methods

There are several methods to measure respiration. The simplest way is impedance pneumography which is strain gauge type of sensor that wraps around the chest. This sensor will expand when people inhale, shrink when exhale. The current that goes through this sensor will change as the resistance in the sensor changes in the expansion and shrinkage. It is a very basic form of sensor that can be low cost but bothersome.

Capnography uses the principle that CO_2 gas absorbs infrared ray. Infrared ray passes across the gas chamber to the sensor, CO_2 gas will fill the chamber from exhaling then infrared ray will attenuate by CO_2 gas. This could be the most accurate way of measuring respiration but it is bulky and cumbersome for patients or people.

Another simple and intuitive method for checking respiration from patient or people is by looking at their chest or shoulder movement. It can be done without any equipment but watching them with bare eye is tiresome and is possible for short-term only.

Constrained method using the microphone for detecting cough has been studied previously [15]. These studies analyzed sound data record from a microphone attached to the subject's body. This method shows sensitivity rate ranging from 80% to 98%. Limitation of this method is that sound can be easily interrupted by environment noise and

it is bothersome for subjects. However, UWB radar utilizes small vibration or movement of the body so that it's nearly impervious to sound noise or weather condition such as rain, fog etc. For this reason, UWB radar is used in a subway station where immediate detection is needed if a person falls into the railway by accident [16].

Previously, continuous microwave Doppler radar was used to measure respiration and heartbeat in the 1970s [17]. Doppler radar had to set with big equipment and antennas which were not practical for use inside of home or vehicle. Many studies on Doppler radar sensing respiration, coughing, talking, heart beat were found [18, 19, 20, 21]. One study showed comparison result with reference device. Correlation between reference device and their Doppler radar was ranging from 0.80 to 0.92 [22]. The main difference between Doppler radar and UWB radar is how the pulse is emitted. Doppler radar emits continuous wave with a certain frequency. However, UWB radar emits pulse within very short of time with a wide range of frequency, hence the name Ultra wideband radar became.

1.3 Ultra Wide Band Radar

Ultra Wide Band radar used in this study is consist of one body and two antennas. It utilizes a wide range of frequency as its name represent. Typical Ultra Wide Band Radar uses 3.1 to 10.6 GHz frequency range and transmits pulse with very short duration. The one used in this study consumes less than 120mW and operates between -40°C and 85°C. Figure 1 illustrates Vivaldi type antenna sized 50 mm by 50 mm by 2 mm. Figure 4 shows sample pulse used in impulse radar. Figure 5 shows the impulse radiation graph at 8.2 GHz from the antenna. Figure 2 shows a range of usable frequency of the Antenna. Figure 3 is the gain in the frequency range. UWB radar has precision in position sensing in sub-mm. Its range can be from 1m to 1km. The pulse radiation angle of UWB radar used in this study is 25 degrees from the antenna on each side which makes a total of 50 degrees.

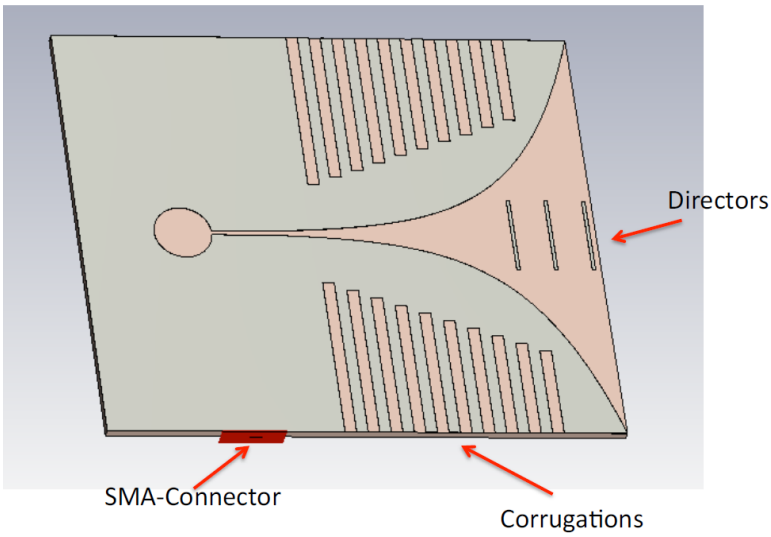

Figure 1. Vivaldi antenna (figure from RFbeam Microwave GmbH, *Simulation Report*, BISworks Vivaldi-Antenna, St.Gallen, Aprill 17th 2016)

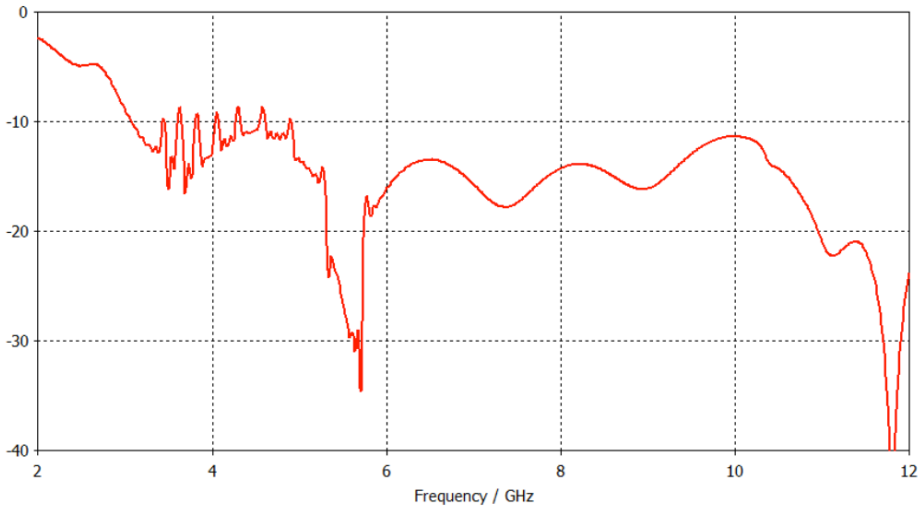

Figure 2. Range of usable frequency of the antenna (figure from RFbeam Microwave GmbH, *Simulation Report*, BISworks Vivaldi-Antenna, St.Gallen, Aprill 17th 2016)

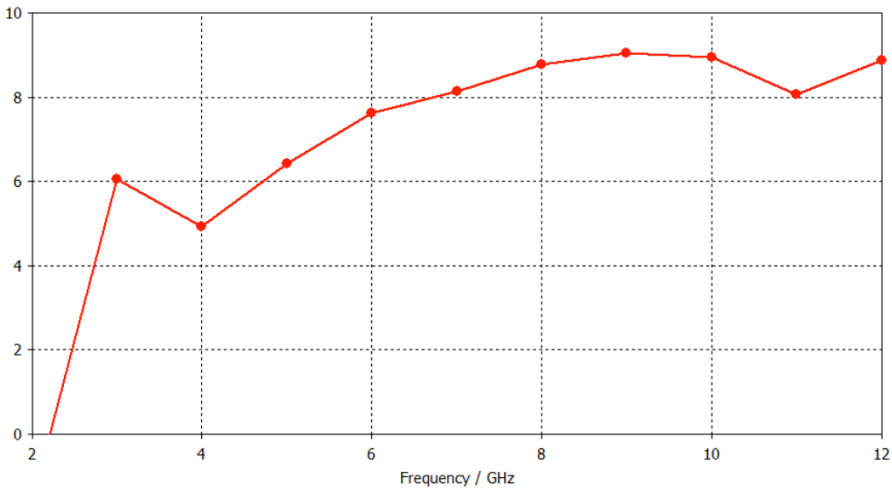

Figure 3. Range of gain in frequency range (figure from RFbeam Microwave GmbH, *Simulation Report*, BISworks Vivaldi-Antenna, St.Gallen, Aprill 17th 2016)

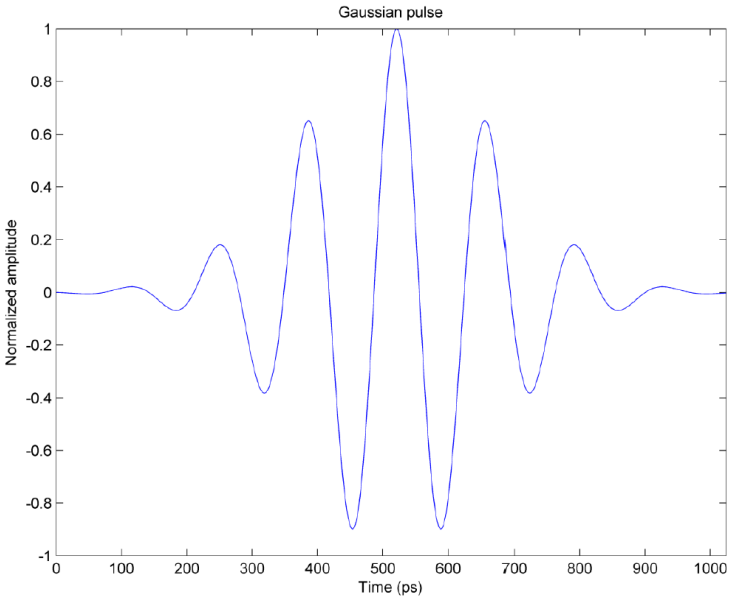

Figure 4. Sample pulse used in impulse radar technology (figure from Novelda, *Nanoscale impulse radar* by Nikolaj Andersen and Tor Sverre (Bassen) Lande)

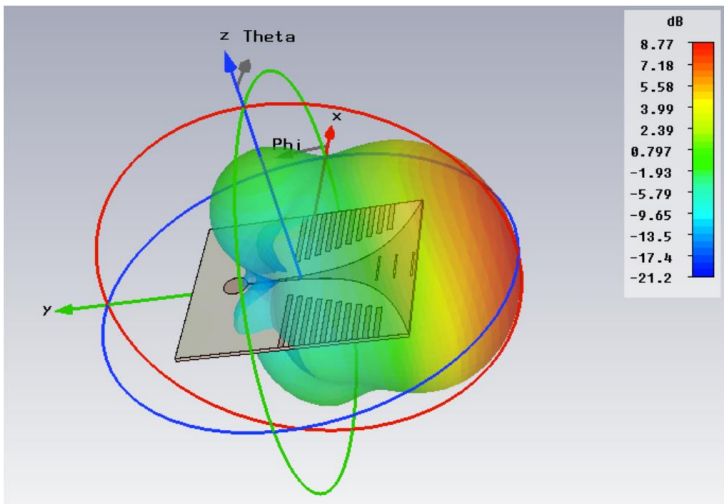

Figure 5. Impulse radiation graph at 8.2 GHz from the antenna (figure from RFbeam Microwave GmbH, *Simulation Report*, BISworks Vivaldi-Antenna, St.Gallen, Aprill 17th 2016)

Electromagnetic waves from UWB radar has been tested for specific absorption rate (SAR) by KOSTEC (South Korea). It showed 0.000153 W/kg for contact test while Galaxy S6 showed 0.599 W/Kg and iPhone 6 0.814 W/Kg. UWB radar generates less electromagnetic power than cellular phones. The International standard for SAR is less than 2 W/kg. A number of electromagnetic waves human will be receiving is less than amount when it's contacted because UWB radar is used from a long distance.

UWB radar comes in various sizes from model to model. Figure 6 is the actual photo of UWB radar used in this study. Low power consumption makes it possible of using radar in automobile vehicle or home use. A typical use of UWB radar is for communication because it can transmit high-volume data with a high-density pulse with short duration [23]. It is also immune to interference with rain, fog, clutter, aerosols and etc [16].

Figure 7 shows the simplified impulse radar principle. The UWB radar sends out impulse signal from the antenna and when the reflected waves are received by the antenna, single microcomputer chip inside the radar module calculates the difference and figure out the distance and movement [23].

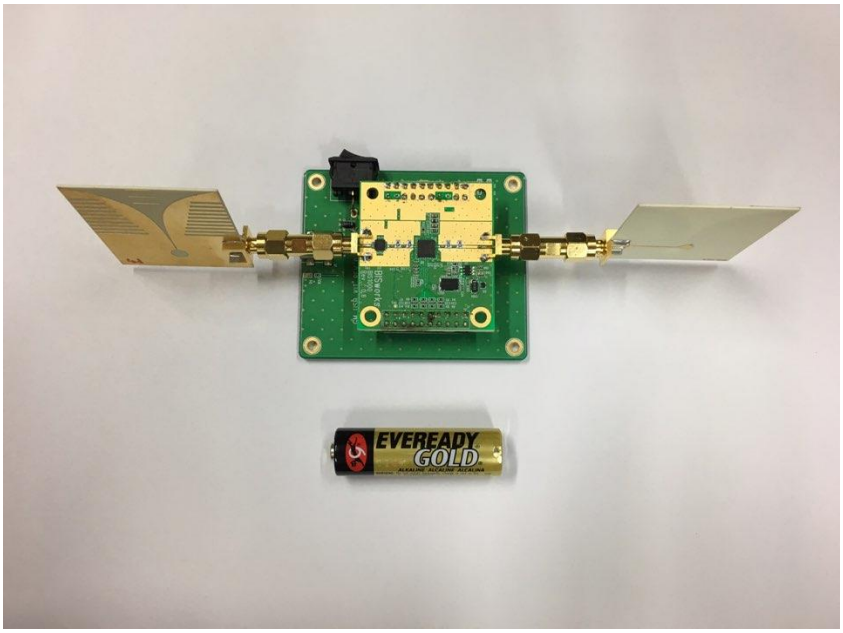

Figure 6. Photo of AA sized battery and UWB radar used in the study (BIS works, South Korea)

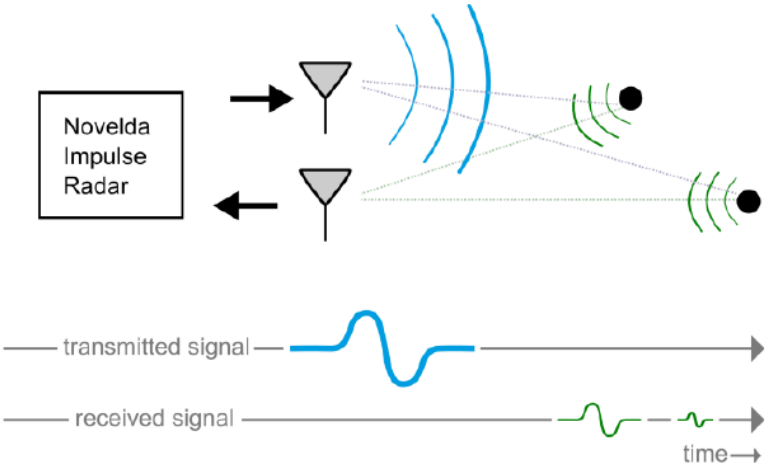

Figure 7. Principle of impulse radar (figure from Novelda, *Nanoscale impulse radar* by Nikolaj Andersen and Tor Sverre (Bassen) Lande)

1.4 Classifiers

Three classifiers of Support Vector Machine, Decision Tree, and Random Forest were chosen because they were introduced earlier, proved to show the good result when classifying data in practical application such as this study case [24].

1.4.1 Support Vector Machine

Support Vector Machine was first suggested by Russian scientist Vladimir Vapnik in late 1970 but didn't get much of attention. In the 1990s, it proved its generalization ability in practical applications such as recognizing handwritten numbers. Figure 8 can help explain how support vector machine works. Triangles and squares are two different kinds of data. Drawing line between clusters of each type of data means classifying them [24].

Line number 1 and 5 obviously drew a line that contains error. Line number 2, 3 and 4 all contain no error so they seem to like all good classifiers. In fact, those lines are not same if it was considered to classify unknown added data in the future. This idea is called a generalization. Line 2 and 4 might have an error because they are so close to a cluster of each data that if new data occur near their cluster, it is more likely to classify new data wrong. Line 3 however, have a good margin from each cluster so it is less likely to make an error of classifying data. In other words, line 3 has more ability in generalization and better in terms of classifiers [24].

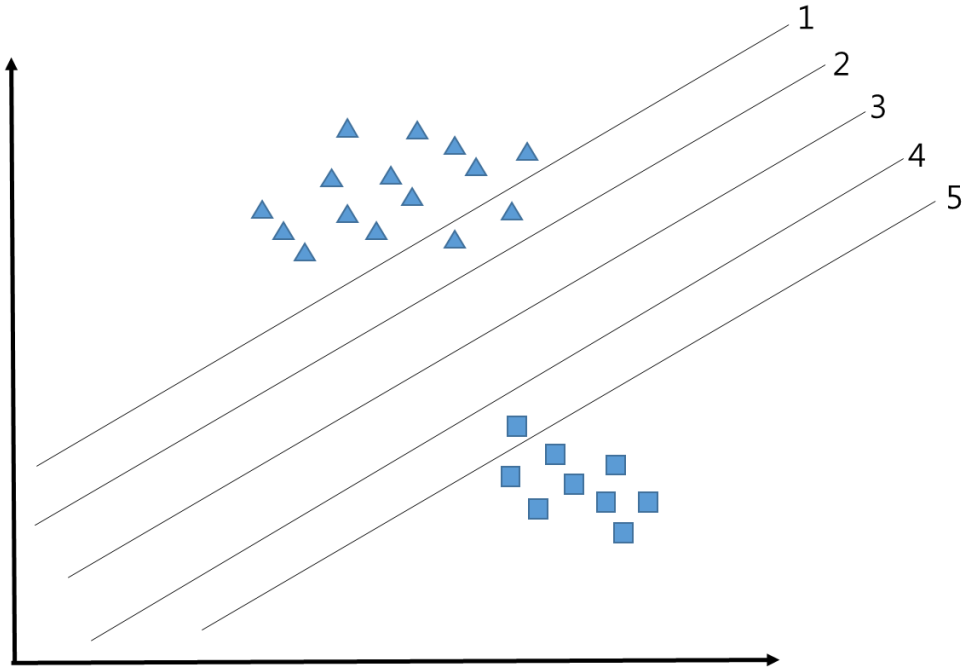

Figure 8. Simple example of how Support Vector Machine works

1.4.2 Decision Tree

Decision Tree classifier uses a predictive model with a decision tree. Decision Tree is consist of node and edge. Figure 9 shows a simple example of how decision tree can pick one fruit from another by asking questions. Questions are the most often the key factor in the decision tree. In this case, it's shape and color. So it is important to know the features that can differentiate each dataset. Key characteristics of the decision tree are that you can see how trees made a decision and showed the result [24].

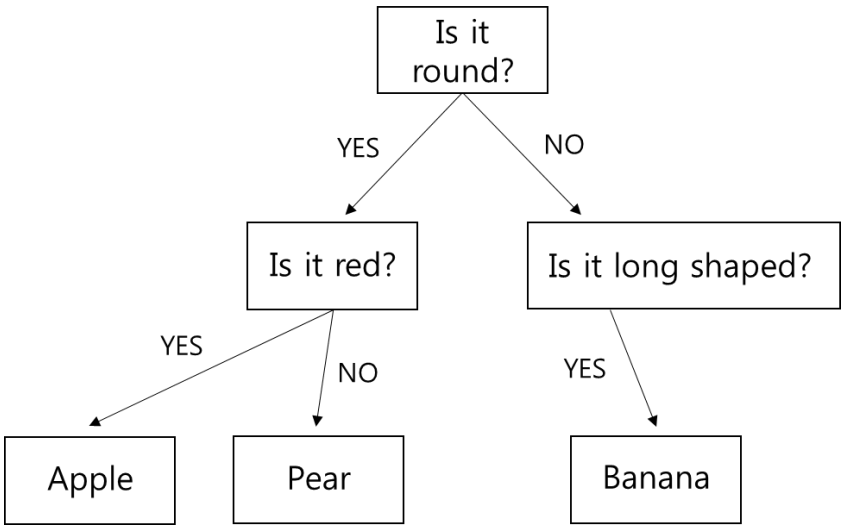

Figure 9. Simple example of how decision tree works

1.4.3 Random Forest

Random Forest or Random Decision Forests utilize multiple decision trees to reduce error. A single decision tree will get random dataset so it will become a random tree, many of this kind of random trees will form a random forest. Random forest is used on two major points. One is that most of the trees will show the correct prediction of class and the other is that each tree will make mistakes in different places. After each tree shows the result, the poll will be drawn to pick which result is more frequent and decide that result is true [24].

1.5 Purpose

This study is to prove the feasibility of UWB radar for detecting apnea and coughing signal. Two experiment was designed in order to differentiate apnea and coughing from the normal respirational signal. All data were measured in the closed experiment room and processed later with lab computer environment.

Chapter 2. Methods

2.1 Ultra Wide Band Radar Measurement

In this particular experiment, UWB radar (BIS works, South Korea) with a bandwidth of 7.4 GHz – 9.0 GHz with Vivaldi-Antenna was used. The radar was placed 1.9m away from the bed on the ceiling with 50 Hz sampling rate while subjects lay in hard bed. Antenna edge was aimed directly at anticardium of each subject.

2.2 Experimental Protocol

Fourteen subjects participated in the apnea experiment. Eleven subjects participated in the coughing experiment. The experiment was done in hard bed in a closed indoor room. Figure 10 shows the how radar and reference device has been set up. The radar was placed 1.9meter away from the subjects' bed. MP150 (Biopac systems, Inc. USA) with respiratory effort transducer (TSD201) with amplifier (TEL 100M) were used as a reference device.

Subjects' clothes were not controlled but all wore their own t-shirt on upper body but different trousers for the bottom. Subjects wore respiratory effort transducer sensor where their last ribs are.

Table 1 shows experiment protocol for apnea. The whole experiment took 5 minutes. After the experiment begun, all subjects breathed normally for 30 seconds and forced themselves to hold their breath for about 10 to 15 seconds as one set. This set was repeated 5 times continuously.

Table 2 shows experiment protocol for coughing. Coughing experiment was conducted after resting from apnea experiment. The whole experiment took 2 minutes and 30 seconds. Subjects breathed normally for 15 seconds and simulated coughing for about 5 to 10

seconds as one set. This set was also repeated 5 times continuously.

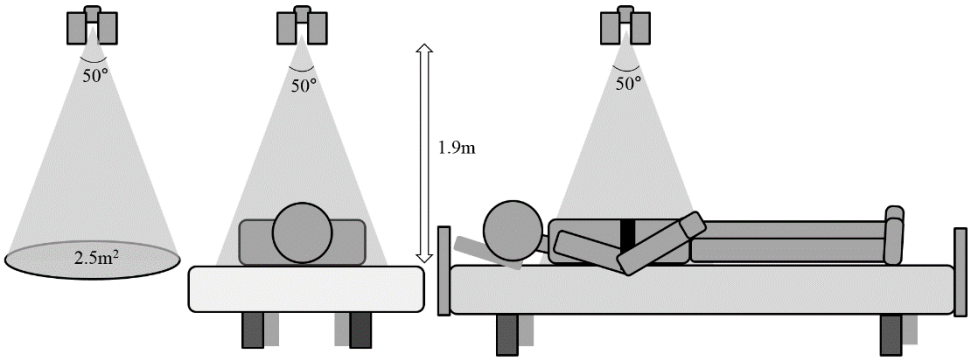

Figure 10. UWB radar pulse coverage (LEFT), section view (MIDDLE) and side view (RIGHT) of experiment setup.

Table 1. Experiment protocol for classifying normal breathing and apnea

Duration(s)	30	30	30	30	30	30	30	30	30	30
Respiration	NB	A	NB	A	NB	A	NB	A	NB	A

NB: Normal Breathing A: Apnea

Table 2. Experiment protocol for classifying normal breathing and coughing

Duration(s)	15	15	15	15	15	15	15	15	15	15
Respiration	NB	C	NB	C	NB	C	NB	C	NB	C

NB: Normal Breathing C: Coughing

2.3 Validation of Respiration Detection

Normal breathing detection was validated before the main experiment. The distance between each peak of respiration wave signal from reference and UWB radar were compared to check the validity of UWB radar measuring the respirational signal. Table 3 Shows correlation of respiration from reference and UWB radar. Mean correlation showed 0.89.

Table 3. Correlation of respiration signal from reference device and UWB radar

Subjects	Correlation
1	0.9262
2	0.8446
3	0.8634
4	0.9097
5	0.8734
6	0.9438
7	0.8308
8	0.9466
9	0.9056
10	0.9335
11	0.94
12	0.9114
13	0.8177
14	0.8766
Mean	0.8945

2.4 Design of Classification

Normal breath and apnea data were classified with the algorithm steps shown in Table 4. Apnea datasets have 70 events of apnea and 70 events of normal breathing. Coughing datasets have 55 events of coughing and 55 events of normal breathing. All of the feature candidates for classifying apnea from normal breathing are listed in Table 5-1 and Table 5-2. Decision tree map was drawn to check which features are useful to distinguish each class. Final features used for classifying apnea from normal breathing are listed in Table 6 and Table 7. Final features used for classifying coughing from normal breathing are listed in Table 8 and Table 9. All of these features were also used simultaneously through each classifier. Apnea and Coughing datasets were divided into 1:9 ratio randomly for training and validation. Classifiers used in this study are Support Vector Machine (SVM), Decision Tree (DT) and Random Forest (RF) and each classification result is from 10-fold cross-validation. All data acquisition was done with a desktop computer with Window 7(64 bit) and processed with MATLAB R2016a.

Table 4. Algorithm steps for classifying normal breathing from apnea / coughing data

1. Start
2. Data achieve from UWB Radar and Reference device
3. Datasets labeled each as “Normal” and “Apnea” / “Coughing”
4. Features collected from each data
5. Training and Test data sets picked randomly
6. Classification using SVM, DT and RF
7. Result from 10-fold cross validation
8. End

2.4.1 Feature Extracting

Reference data for apnea were from processing raw data with 5th order Butterworth filters, 0.1Hz high pass filtered and then 15 Hz low pass filtered. Radar data for apnea were from processing raw data with a 5th order Butterworth filters, 0.01Hz high pass filtered and then 10 Hz low pass filtered. Statistic features were collected after filtering. Frequency-domain features were made with Fast Fourier transform from the filtered data.

Figure 11 shows the example data set of normal breathing and apnea data. Subjects simulated apnea starting at about 14 seconds and ending at about 25 seconds. The amplitude of the apnea range is attenuated because there is no movement of chest or cavity when subjects hold their breath. After 25 seconds, subjects start to breathe again so the signal comes back to normal sinusoidal graph with respiration.

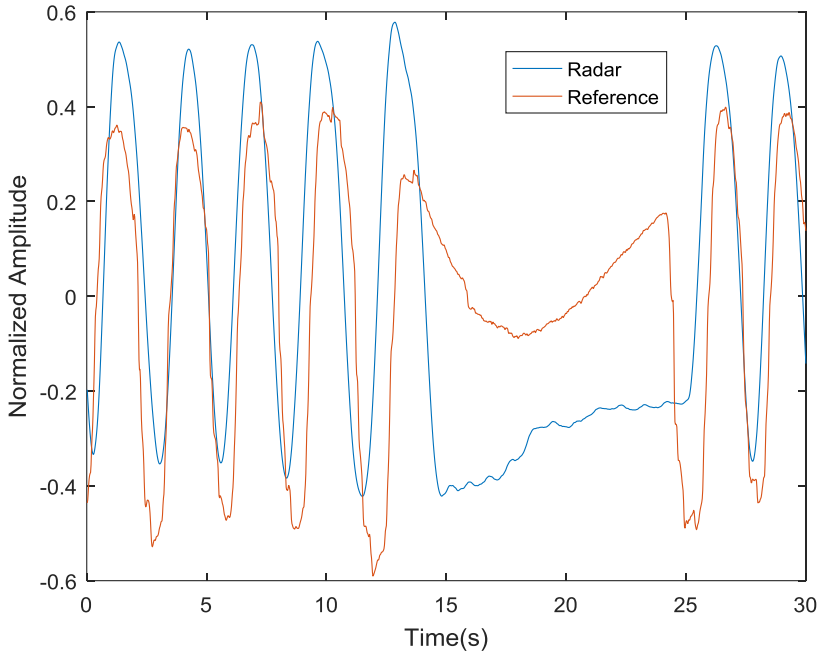

Figure 11. Example of apnea data (14s~25s) and normal breathing data in time domain

Figure 12 shows the frequency information of normal breathing and apnea from reference device. Max peak of normal breathing data is higher than apnea in this case. Figure 13 shows the frequency information of normal breathing and apnea from UWB radar. Max peak of normal breathing data is also higher than apnea data.

Figure 14 explains how features “Relative Sum of frequency” and “Relative Peak of Power” were made. Most frequency power is in the frequency zone between 0 Hz to 1 Hz. There are some of the frequency power beyond 1 Hz. I divided 0 Hz to 1 Hz zone into five bands with an increment of 0.2 Hz, 1 Hz to 2 Hz zone into two bands and 2 Hz to 5 Hz as one band. These bands will be eight relative frequency features shown in Table 5-2.

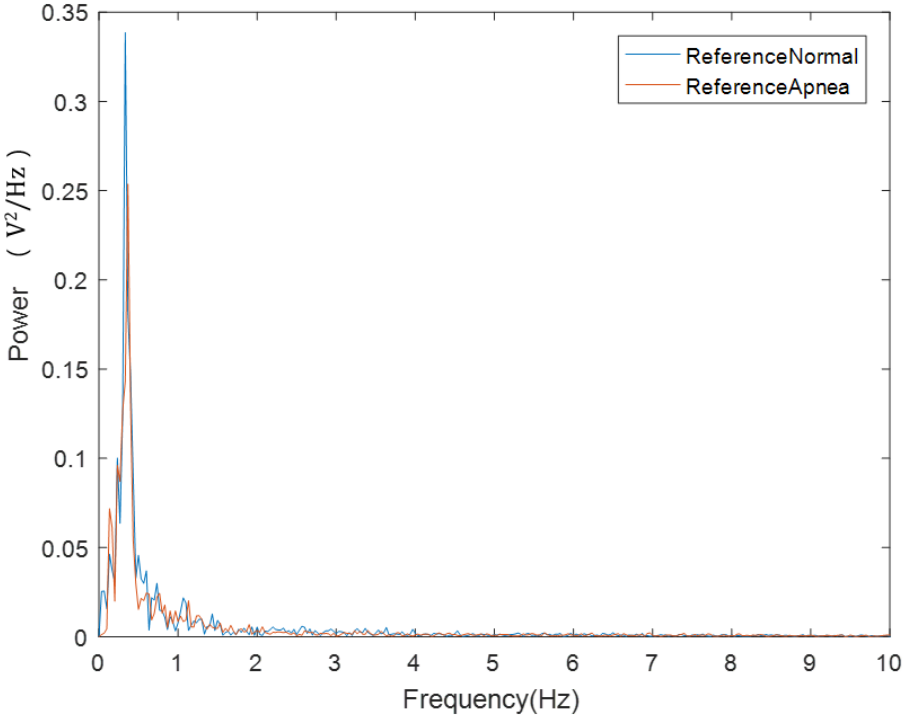

Figure 12. Example of frequency in normal breathing data and apnea data from reference device

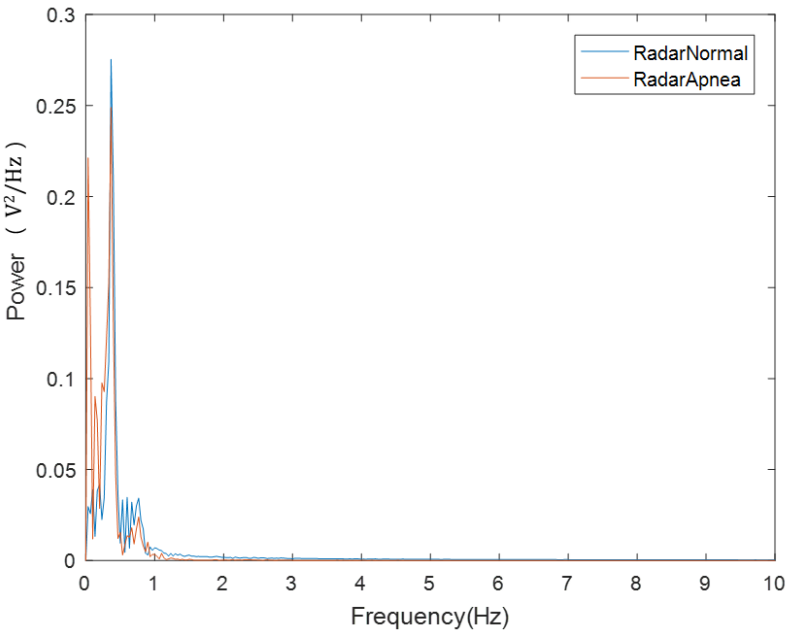

Figure 13. Example of frequency in normal breathing data and apnea data from UWB radar device

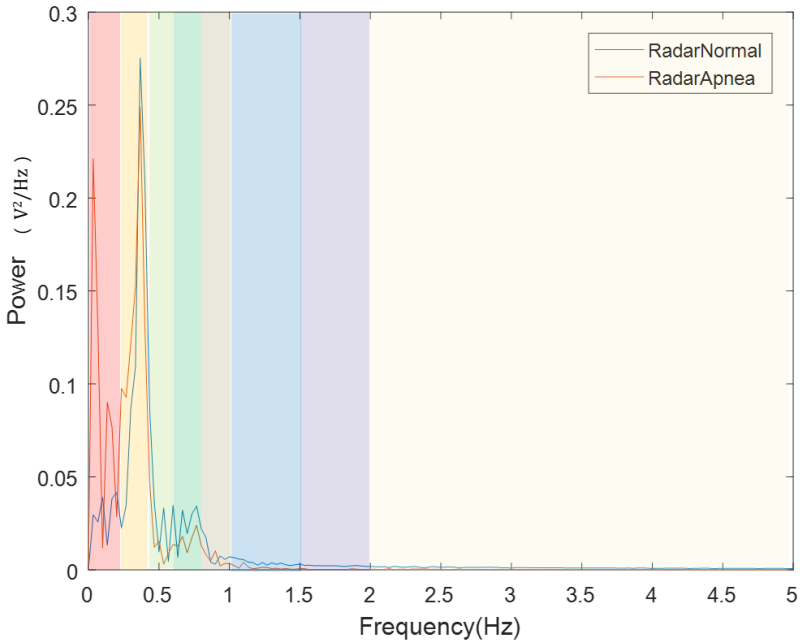

Figure 14. Frequency division of apnea data from UWB radar for frequency feature extraction

Table 5-1, 5-2 shows all of the candidate feature available from MATLAB 2016a toolbox. “Relative Sum of frequency” and “Relative Peak of Power” were designed to make new relative frequency features. After running through all of the features with Decision Treemap, final features were determined.

Statistic Feature	Definition	Frequency Feature	Definition
Mean	Mean of Amplitude	Max Power	Find the Biggest Power in all frequency
Standard Deviation	Standard Deviation of Amplitude	Max frequency	Find the Frequency that has biggest power
Variance	Variance of Amplitude	Sum of Frequency	Summation of all power of frequency
Harmonic Mean		Mean of Frequency	Mean of all frequency
Mean excluding outliers	Mean Excluding the highest and the lowest data	Relative Sum of Power in each band	$\frac{Sum\ of\ Power\ in\ \text{one}\ Band}{Sum\ of\ Power\ in\ Whole\ Band}$
Mean absolute deviation		Relative Peak Power in each band	$\frac{Peak\ of\ Power\ in\ \text{one}\ Band}{Sum\ of\ Power\ in\ Whole\ Band}$

Table 5-1. All of candidate features used for classifying normal breathing data and apnea data

Table 5-2. All of candidate features used for classifying normal breathing data and apnea data in frequency domain

Features
Relative Sum of Power in 0 Hz ~ 0.2 Hz
Relative Sum of Power in 0.2 Hz ~ 0.4 Hz
Relative Sum of Power in 0.4 Hz ~ 0.6 Hz
Relative Sum of Power in 0.6 Hz ~ 0.8 Hz
Relative Sum of Power in 0.8 Hz ~ 1.0 Hz
Relative Sum of Power in 1.0 Hz ~ 1.5 Hz
Relative Sum of Power in 1.5 Hz ~ 2.0 Hz
Relative Sum of Power in 2 Hz ~ 5 Hz
Relative Peak of Power in 0 Hz ~ 0.2 Hz
Relative Peak of Power in 0.2 Hz ~ 0.4 Hz
Relative Peak of Power in 0.4 Hz ~ 0.6 Hz
Relative Peak of Power in 0.6 Hz ~ 0.8 Hz
Relative Peak of Power in 0.8 Hz ~ 1.0 Hz
Relative Peak of Power in 1.0 Hz ~ 1.5 Hz
Relative Peak of Power in 1.5 Hz ~ 2.0 Hz
Relative Peak of Power in 2 Hz ~ 5 Hz

Decision Treemap in Figure 15 Shows the most effective features for reference device data and Table 6 shows the final chosen features for reference device data for classifying apnea data.

Decision Treemap in Figure 16 Shows the most effective features for UWB device data and Table 7 shows the final chosen features for UWB radar for classifying apnea data.

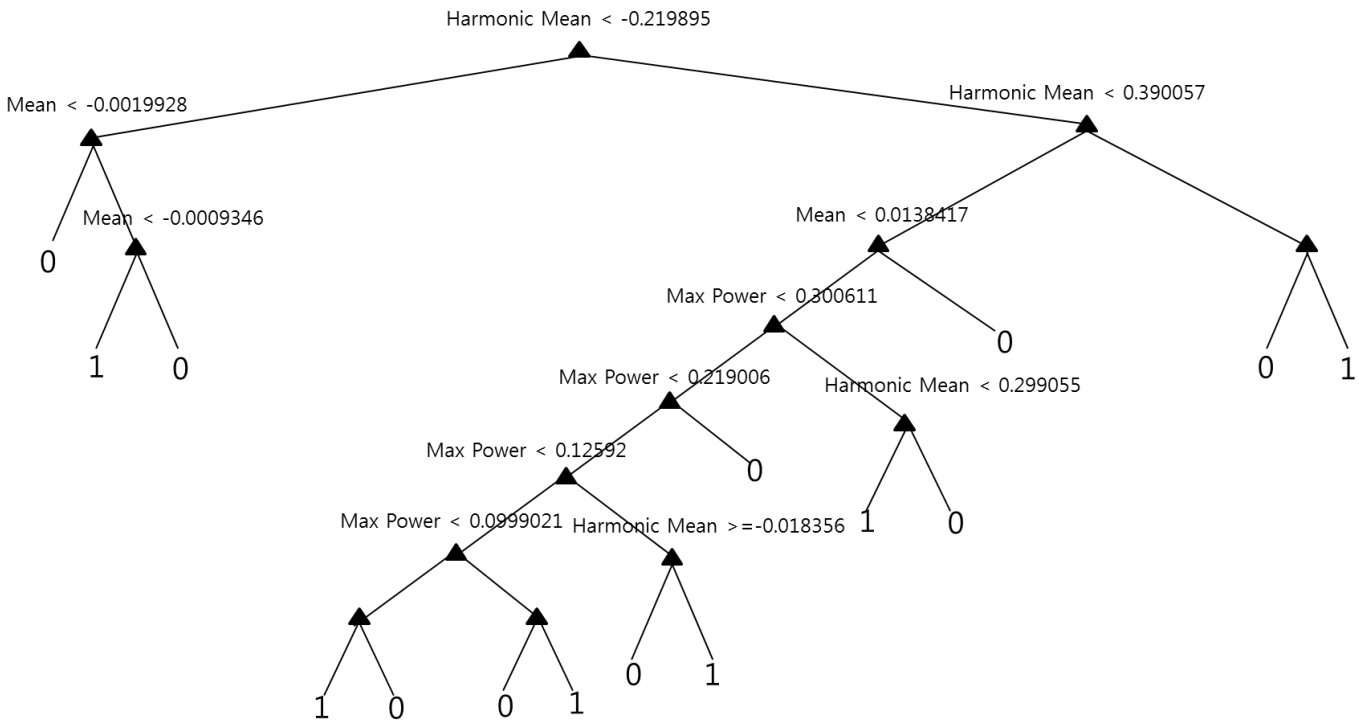

Figure 15. Decision tree map using selected features for classifying apnea data from normal breathing data from reference device

Table 6. Chosen Features for classifying normal breathing data from apnea data from reference device

Feature Class	Features
Time Domain Features	Mean Mean excluding outliers Harmonic Mean
Frequency Domain Features	Max Power Max Frequency Sum of Frequency

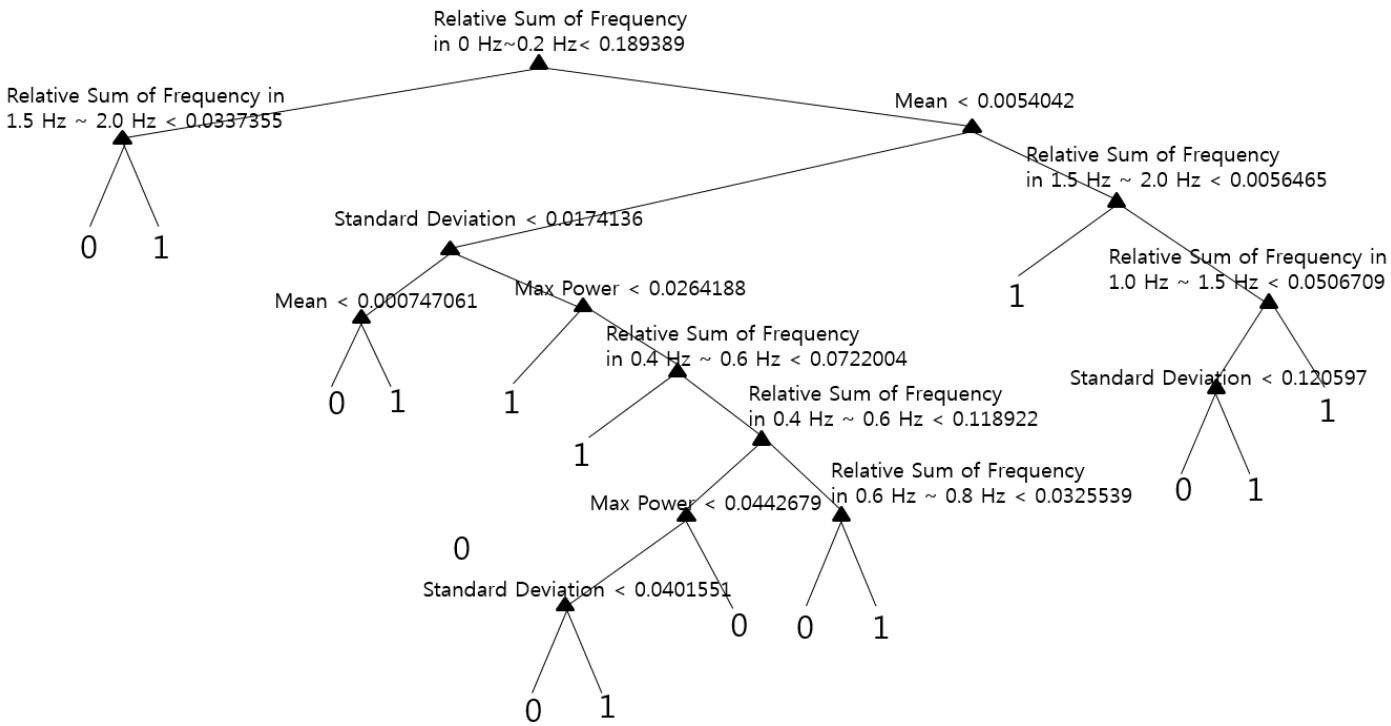

Figure 16. Decision tree map using all of features for classifying apnea data from normal breathing data from UWB radar

Table 7. Chosen features for classifying normal breathing data and apnea data from UWB radar

Feature Class	Features
Time Domain Features	Mean
	Standard Deviation
Frequency Domain Features	Max Amplitude
	Max Frequency
	Relative Sum of Power in 0 Hz ~ 0.2 Hz
	Relative Sum of Power in 0.2 Hz ~ 0.4 Hz
	Relative Sum of Power in 0.4 Hz ~ 0.6 Hz
	Relative Sum of Power in 0.6 Hz ~ 0.8 Hz
	Relative Sum of Power in 0.8 Hz ~ 1.0 Hz
	Relative Sum of Power in 1.0 Hz ~ 1.5 Hz
	Relative Sum of Power in 1.5 Hz ~ 2.0 Hz
	Relative Sum of Power in 2 Hz ~ 5 Hz
	Relative Peak of Power in 0 Hz ~ 0.2 Hz
	Relative Peak of Power in 0.2 Hz ~ 0.4 Hz
	Relative Peak of Power in 0.4 Hz ~ 0.6 Hz
	Relative Peak of Power in 0.6 Hz ~ 0.8 Hz
	Relative Peak of Power in 0.8 Hz ~ 1.0 Hz
	Relative Peak of Power in 1.0 Hz ~ 1.5 Hz
	Relative Peak of Power in 1.5 Hz ~ 2.0 Hz
	Relative Peak of Power in 2 Hz ~ 5 Hz

Figure 17 shows the example data set of normal breathing data and coughing data. Subjects simulated coughing at about 19 seconds and ended at 25 seconds. Amplitude fluctuates during coughing. After 25 seconds, subjects start to breathe normally again so the signal comes back to the normal sinusoidal graph.

Coughing data were from processing raw data with a 5th order Butterworth filters, 0.1Hz high pass filtered and 10 Hz low pass filtered for reference device data, 0.01 Hz high pass filtered and 10 Hz low pass filtered for UWB radar data.

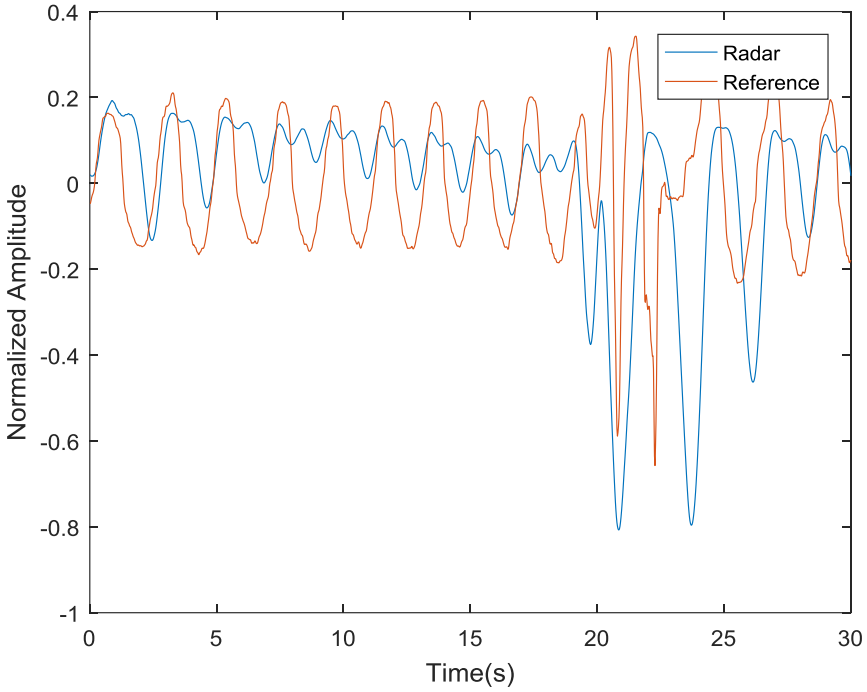

Figure 17. Example of coughing data (19s~25s) and normal breathing data in time domain

Figure 18 shows the frequency distribution of normal breathing data and coughing data from reference device. Max peak of normal breathing is dominant than coughing. Figure 19 shows frequency distribution of normal breathing data and coughing data from UWB radar. Much of power is concentrated in the range of 0 Hz to 2 Hz. Coughing data has a higher power in most frequencies than normal breathing in both devices.

Figure 20 shows how the frequency is divided in each band to achieve “Relative Sum of frequency” and “Relative Peak of Power”. 0 Hz to 1 Hz frequency range has been divided into 5 bands because its range contains much power relative to other range. 1 Hz to 2 Hz range was divided into two bands and 2 Hz to 5 Hz range as one band. After using all of the candidate features, decision treemap was drawn to pick the final features for the classifier.

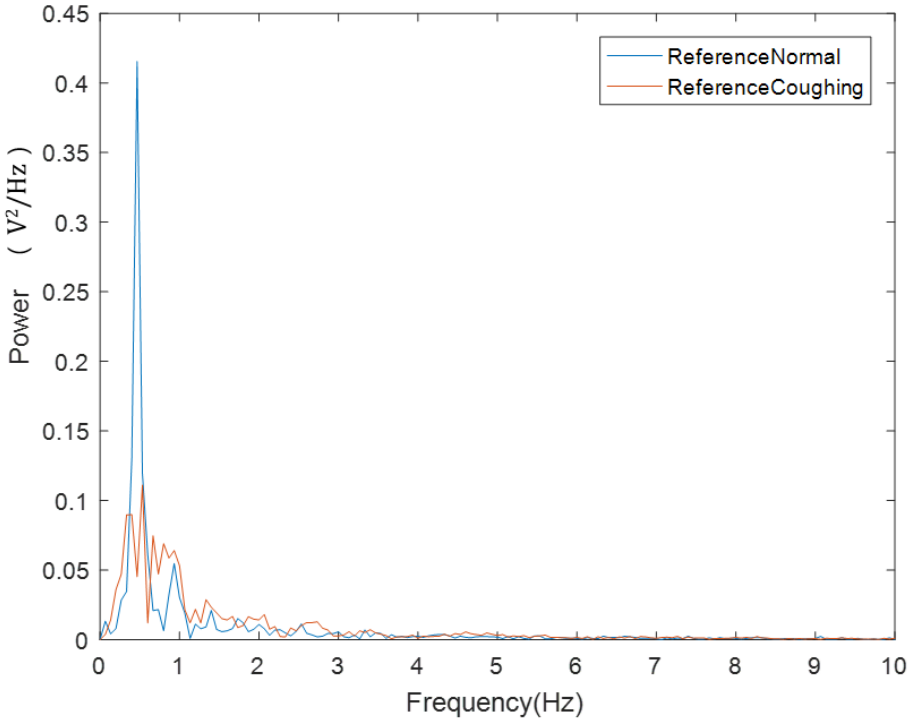

Figure 18. Example of frequency in normal breathing data and coughing data from reference device

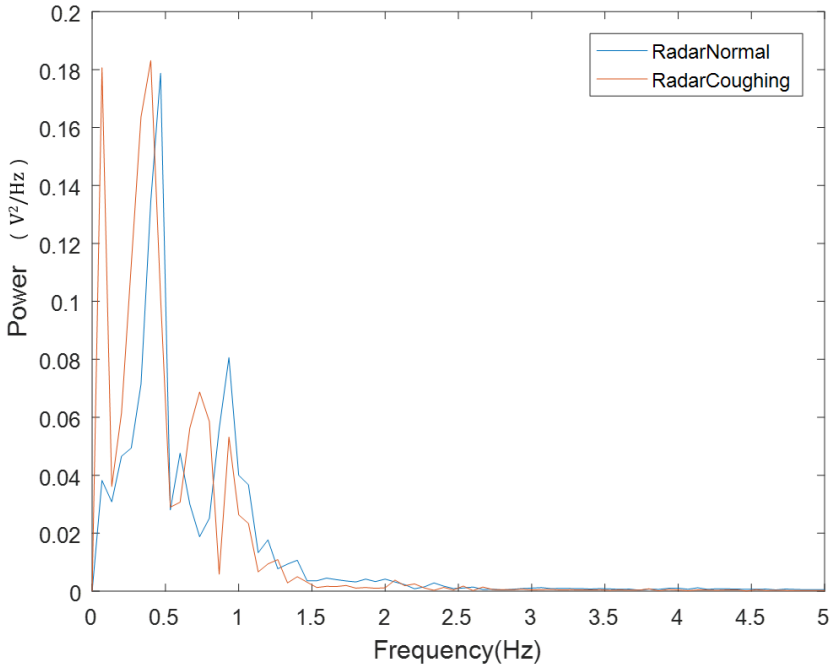

Figure 19. Example of frequency in normal breathing data and coughing data from UWB radar device

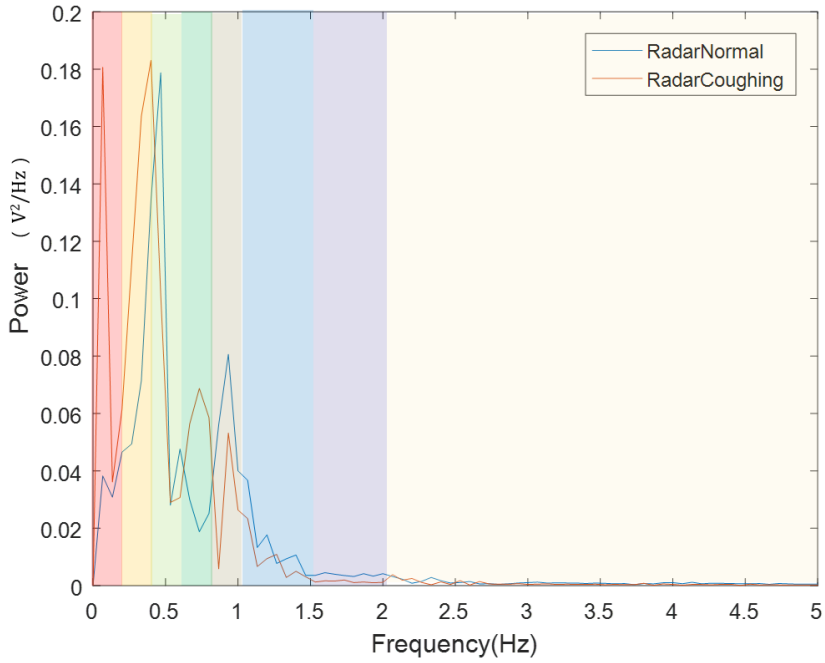

Figure 20. Frequency division of coughing data from UWB radar for frequency feature extraction

Figure 21 shows the decision tree map for classifying the coughing data from normal breathing data with reference device. Based on decision treemap, features were finally picked for classification. Table 8 shows the final features used with reference device for classifying coughing data.

Figure 22 shows the decision tree map for classifying the coughing data from normal breathing data with UWB radar. Based on decision treemap, features were finally picked for classification. Table 9 shows the final features used with UWB radar for classifying coughing data.

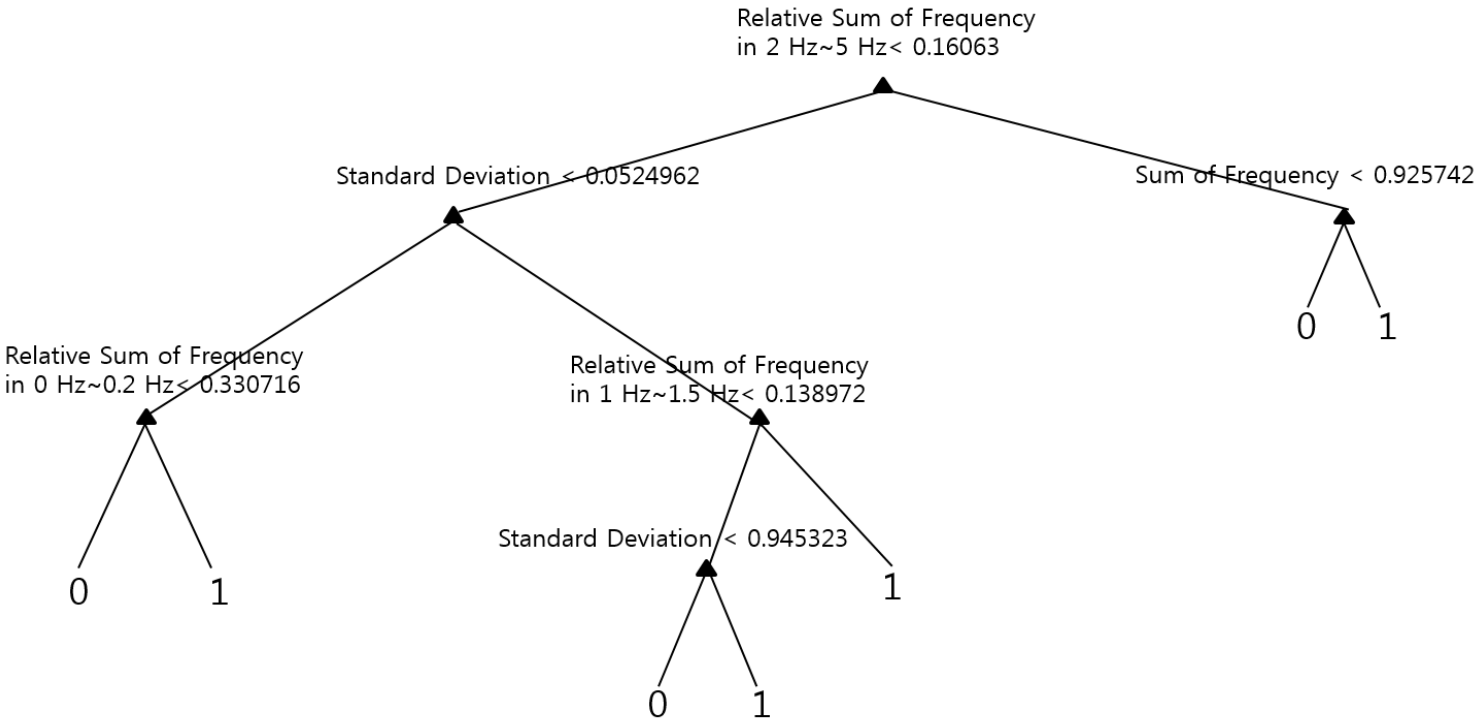

Figure 21. Decision tree map using all of features for classifying coughing data from normal breathing data from reference device

Table 8. Chosen features for classifying normal breathing data and coughing data from reference device

Feature Class	Features
Time Domain Features	Standard Deviation
Frequency Domain Features	Sum of Frequency
	Relative Sum of Power in 0 Hz ~ 0.2 Hz among 0 Hz ~5 Hz
	Relative Sum of Power in 1.0 Hz ~ 1.5 Hz among 0 Hz ~5 Hz
	Relative Sum of Power in 2 Hz ~ 5 Hz among 0 Hz ~5 Hz

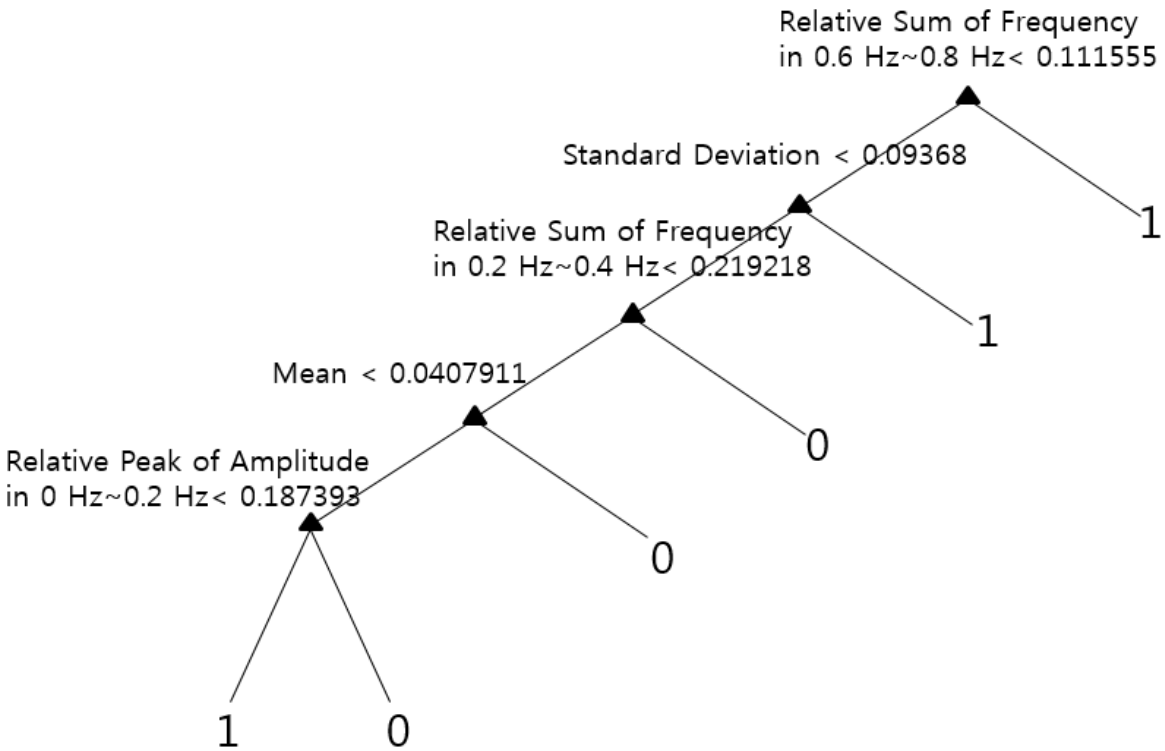

Figure 22. Decision tree map using all of features for classifying coughing data from normal breathing data from UWB radar

Table 9. Chosen features for classifying normal breathing data and coughing data from UWB radar

Feature Class	Features
Time Domain Features	Mean Standard Deviation
Frequency Domain Features	Relative Sum of Power in 0.2 Hz ~ 0.4 Hz among 0 Hz ~5 Hz Relative Sum of Power in 0.6 Hz ~ 0.8 Hz among 0 Hz ~5 Hz Relative Peak of Power in 0 Hz ~ 0.2 Hz among 0 Hz ~5 Hz

Chapter 3. Results

3.1 Feature Evaluation

Features used in this classifiers were chosen after looking into decision tree map using all of features in Figure 15, Figure 16, Figure 21 and Figure 22. Table 6, Table 7, Table 8, and Table 9 show which features are used in classifiers.

3.2 Classification Result

Classification result is written in precision and sensitivity and F measure. Precision means a number of correctly chosen results from all chosen results. Sensitivity means a number of correctly chosen results from all correct results. F measure combines precision and sensitivity into one measure. It is harmonic mean of precision and recall. Table 10 and equation below explains the meaning and how sensitivity, precision and F measure were calculated.

Table 10. Confusion matrix

		Predicted Condition	
		Predicted Condition Positive	Predicted Condition Negative
True Condition	Condition Positive	True Positive	False Negative
	Condition Negative	False Positive	True Negative

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$\text{Sensitivity} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$\text{F-measure} = 2 * \frac{Precision * Sensitivity}{Precision + Sensitivity}$$

Equation for Precision, Sensitivity, and F-measure

The result of classification for apnea is shown in Table 11. Classifier RF shows the best result in both devices. Radar has 100% sensitivity, 70% precision, 0.82 F measure. Reference device also has 100% sensitivity, 70% precision, 0.82 F measure.

The result of classification for coughing is shown in Table 12. Classifier RF shows the best result in both devices. Radar has 100% sensitivity, 83% precision, 0.91 F measure. Reference device has 100% sensitivity, 71% precision, 0.83 F measure.

Measuring apnea with UWB radar is as good as reference device. Although it is a contactless method, it shows the good result of measuring breathing signal and apnea signal. For detecting coughing, UWB radar shows a better result than reference device.

The reference device is a strain gauge type of respirational sensor that wraps around the rib cage. It is very simple and easy method to detect respiration. When coughing, thoracic cavity or chest doesn't create much of movement that could show distinct cough signal characteristic from the reference data. UWB radar can cover 2.5m^2 area in this experiment set up which is about 89cm radius circle. UWB radar aims at subject's anticardium, so it can cover the area from the face and neck to the chest area of the subjects which can contain more signal than just cavity or chest. Head and mouth will also move in order to cough.

This makes the bigger movement other than chest or cavity movement which will make the amplitude of signal changes quite drastically. This factor may have contributed better result in distinguishing coughing data from normal breathing data using UWB radar.

Table 11. Classification result of classifying apnea data from normal breathing data

Classifier	UWB RADAR			Reference		
	Mean Precision	Mean Sensitivity	F measure	Mean Precision	Mean Sensitivity	F measure
SVM	54%	66%	0.59	75%	23%	0.35
DT	57%	53%	0.55	60%	64%	0.62
RF	70%	100%	0.82	70%	100%	0.82

Table 12. Classification result of classifying coughing data from normal breathing data

Classifier	UWB RADAR			Reference		
	Mean Precision	Mean Sensitivity	F measure	Mean Precision	Mean Sensitivity	F measure
SVM	82%	72%	0.77	82%	91%	0.86
DT	84%	82%	0.83	83%	83%	0.83
RF	83%	100%	0.91	71%	100%	0.83

3.3 Discussion

The aim of the study was to validate the feasibility of UWB radar to monitor abnormal respirational signals such as apnea and coughing. Using UWB radar's ability to detect small movement with the unconstrained method will make a wide application for monitoring those signals. There have been studies using Doppler radar to measure respirational signal previously but the device size and detection result made impractical for wide applications.

At this development of stage, it is hard to measure respirational signal while the subject is moving. UWB radar has sub-mm of accuracy so even very small body movement will be taken hugely in radar raw signal. It is important to stand or sit very still while measuring UWB radar to get clean signal without too much of noise.

This study is based on a situation when a person or patient is lying in the bed. Measuring different posture while in bed need to be done in further studies. This study gathered data with experiment set up indoor. Measuring data outside field also needs to be tested. Data gathered from radar and reference were processed in the computer separately in this study. A system which can monitor real time and alerting the alarm when a person is not breathing or coughing would be more useful in real life application.

Chapter 4. Conclusion

We conducted this study in order to find out the feasibility of UWB radar differentiating abnormal respiration signals from normal breathing signals. We set up UWB radar perpendicular to the chest of fourteen subjects for apnea experiment and eleven subjects for coughing experiment and built an algorithm which can differentiate abnormal respiration signal from normal breathing signal. UWB radar can monitor a wider area of body movement and has great sensitivity to measure very small movement compare to the reference device. This may have made possible for UWB radar to detect cough signal better than the reference device. Using UWB radar can be beneficial to patients, elders or babies who needs long-term vital sign monitoring. The small sized, low energy consumption characteristics of UWB radar and the unconstrained way of measuring respiration signal will make wide applications in smart homes, vehicles, and hospitals etc.

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국문 초록

UWB 레이더를 이용한 무구속적 무호흡 및 천식 증상 검출

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호흡과 기침은 사람의 상태의 판단에 명백한 지표이다. 한 사람의 건강을 체크 하기 위해서는 장기간 호흡 관찰이 필요하다.

이러한 장기간 호흡 관찰을 하기 위한 장비가 신체를 제한 한다면 매우 번거로울 것이다. 이 연구에서 무호흡, 기침 같은 비정상적 호흡을 감지하기 위해 UWB 레이더를 사용하여 분류기를 통해서 데이터를 분류하는 알고리즘을 작성하였다. 레퍼런스 장비와 레이더에서 취득한 데이터는 Support Vector Machine, Decision Tree, Random Forest 와 같은 분류기를 사용 하였다. 분류 하기 위해 필요한 각 신호의 특성은 통계적 특성과 주파수영역대 특성을 이용하였다.

무호흡 신호 분류에서 레퍼런스 장비와 UWB 레이더 모두 Random Forest 분류기에서 가장 좋은 성능을 보였다. 레퍼런스 장비에서 100% mean sensitivity, 70% mean precision, 0.82 F measure을 보였고, UWB 레이더에서도 Random Forest 분류기로 이와 같은 수준의 100% mean sensitivity, 70% mean precision, 0.82 F measure 를 보였다.

기침 신호 분류에서도 Random Forest분류기가 가장 좋은 성능을 보였다. 레퍼런스 장비의 분류 결과는 100% mean sensitivity, 71% mean precision, 0.83 F measure를 보였고, UWB 레이더에서는 100% mean sensitivity, 83% mean precision, 0.91 F measure 을 보였다.

추후 연구에서, 사람이 움직이고 있는 상황 혹은 다른 형태의 자세에서 호흡과 기침을 감지하는 추후 연구가 더 필요하다고 생각한다. 본 연구가 장기간 생체신호를 무구속적으로 관찰하는데 많이 적용되기를 기대한다.

주요어: UWB 레이더, 호흡, 무호흡, 기침, 천식, 무구속적
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