Master's Thesis of Engineering

Automatic Cardiopulmonary Resuscitation Quality Estimation from Photoplethysmography Signal using Convolution Neural Network

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Abstract

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Cardiopulmonary resuscitation (CPR) is a first aid procedure to preserve the function of the body with chest compression and artificial respiration. The CPR guideline recommends compressing the chest to a depth of 5cm between 100 – 120 times per minute. However, it is not appropriate to perform CPR in accordance with the guideline to all patients because of their different physical characteristics. In the United States, about 600,000 patients with cardiac arrest occur each year and the survival rate of cardiac arrest patients outside the hospital is about 10%, which is considerably lower than survival rate of patients in hospital. According to the American

Heart Association(AHA), the quality and coping speed of CPR have a significant impact on the survival rate of patients with cardiac arrest.

A study to monitor the patient's condition during CPR and detecting the return of spontaneous circulation (ROSC) are progressing actively for monitoring the quality of CPR. End-tidal carbon dioxide (ETCO2), trans-thoracic impedance (TTI), arterial blood pressure, and other bio-signals have been used in the research, which suggest many possibilities of monitoring CPR. These signals, however are invasive or time consuming. Among the various bio-signals, the photoplethysmography (PPG) used in this study is noninvasive and has the advantage of reflecting information in real time.

The goal of this study is to estimate the quality of CPR using convolution neural network of PPG signal. The PPG and ETCO2 used in this study were obtained from preclinical experiments using 15 pigs. Cardiac arrest was induced in each pig, and both data were acquired for 290seconds during CPR in cardiopulmonary induction pigs. The PPG data was divided into 5 seconds and stored again. Each of the stored data was converted into images by applying spectrogram transformation and wavelet transformation. The data stored as an image contains the ETCO2 value corresponding to the same time interval. The quality of CPR was divided into two classes. The criteria of the two classes was based on ETCO2 values which were obtained during CPR of survived pigs and non-survived pigs. All image data were divided into two classes based on the criteria.

The obtained data in this study were trained using the 'VGG' based neural network. The training set of data were 90% of total data and test set of data were 10% of total data. The classification accuracy is 84.09% when the image is applied with the spectrogram transformation of the PPG signal and classification accuracy is 88.37% when the wavelet transformation is used. The result of this study that training of the transformed image from the PPG signal using the convolution neural network is effective in CPR quality estimation.

Keyword : Cardiopulmonary resuscitation, Photoplethysmography, Convolution neural network, Wavelet, Spectrogram, End-tidal carbon dioxide,
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List of Abbreviations

PPG	Photoplethysmography
ETCO2	End Tidal Carbon Dioxide
CPR	Cardiopulmonary Resuscitation
IHCA	In the Hospital Cardiac Arrest
OHCA	Out of Hospital Cardiac Arrest
ROSC	Return of Spontaneous Circulation
TTI	Trans Thoracic Impedance
NIRS	Near Infrared Spectroscopy
ABP	Arterial Blood Pressure
CO	Cardiac Output

Chapter 1. Introduction

1.1 Background

1.1.1 Cardiopulmonary Resuscitation

Cardiopulmonary Resuscitation (CPR) is first aid treatment to provide oxygen to the human body a person who is in cardiac arrest. CPR is a repetitive process of chest compression and artificial ventilation. The CPR guideline specifies that the rescuer compresses the chest of the subject by about depth of at least 5 cm, a rate of at least 100 times per minutes and infuse exhaling air into subject's mouse [1, 2]. The main purpose of CPR is to supply the oxygenated blood to the heart and brain to sustain the metabolism of body. Rapid and substantial improvement in oxygen delivery is required to decrease the morbidity and mortality of ischemic organ injury. High quality of CPR is the best way to achieve a successful return of spontaneous circulation (ROSC), and help patients survive cardiac arrests [1]. Long-term CPR increases the fatigue of operator and reduces CPR quality. Recently automatic mechanical CPR devices developed to overcome these problem [3]. Reliability is an essential part of Mechanical CPR devices and it requires techniques to monitor CPR quality for better performance.

1.1.2 Photoplethysmography

Photoplethysmography (PPG) is a widely used and studied biological signal measurement method. PPG provides volumetric information through changes in the blood volume of organ. The changes in volume caused by the pressure pulse are detected by illuminating the skin with the light from light emitting diode (LED) and then measuring the amount of light transmitted or reflected to photodiode. PPG signal has the information about cardiac cycle and respiration cycle which is shown in Figure 1. The systolic and diastolic cycle is appears as a peak. The respiration cycle changes the waveform at regular interval which is caused by varying of intrapleural pressure. The PPG signal obtained from the device varies from subject to subject and changes depending on the surrounding environment such as temperature and contact pressure. The pulse oximetry is typical example of containing PPG signal which illuminates the skin and measures changes in light absorption [4]. PPG is currently used for monitoring heart rate, cardiac cycle and respiration. [5] .

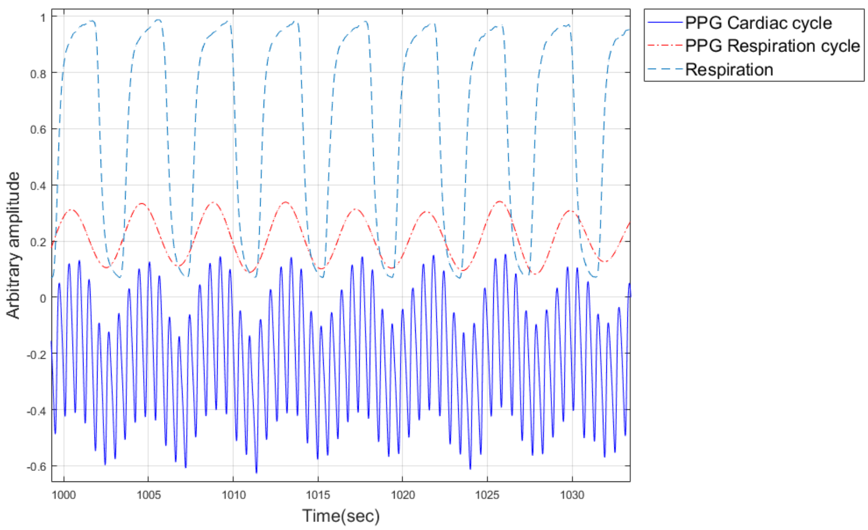

Figure 1. Cardiac cycle and respiration cycle in Photoplethysmography(PPG) signal

Extract respiration cycle from PPG signal and match with real time respiration cycle.

1.1.3 End-tidal carbon dioxide

Capnography is the monitoring of the concentration of partial pressure of carbon dioxide in the respiratory gases. It is presented as a graph of time and expiratory concentration of carbon dioxide which is measured in millimeters of mercury. End-tidal carbon dioxide (ETCO2) refers the partial pressure of carbon dioxide at the end of an exhaled breath. Carbon dioxide is produced by the metabolism of the body and is transported to the lungs by the blood flow (Figure 2). Therefore, the measured ETCO2 is closely related to metabolism of cell and blood flow in the body [6].

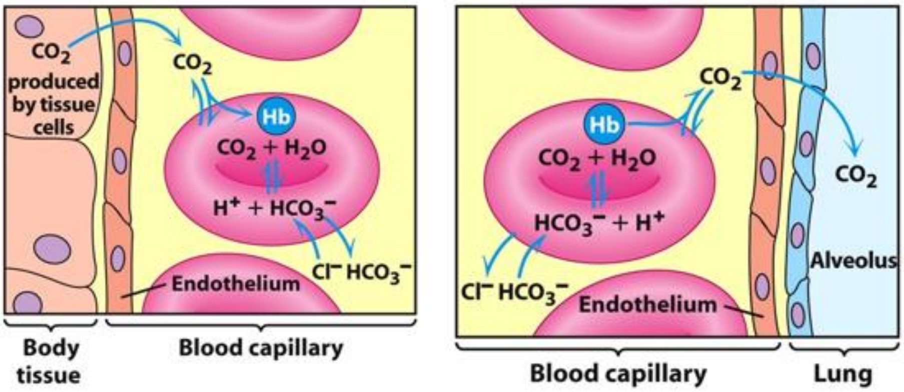

Figure 2. CO2 delivery metabolism

The blood carries the carbon dioxide gas emitted from the tissue and delivers it to the lung [7].

1.2 Research needs

CPR guideline is recommended to compress the inter-nipple line of the chest about 5-6cm depth, 100-120 times per minute [1, 2]. However, it is not desirable to follow the guidelines uniformly because each patient has different physical characteristics. Therefore, it is necessary to monitor the condition of the cardiac arrest patient in actual CPR situation and perform CPR according to feedback [1]. It is Patient specific CPR and it can provide higher chance of ROSC.

According to American Heart Association (AHA) statistics (Table.2), approximately 600,000 patients with cardiac arrest occur each year in the United State [8]. Patients with cardiac arrest are divide into two groups according to their arrest site. One is in hospital cardiac arrest (IHCA) group and the other is out of hospital cardiac arrest (OHCA) group. The biggest difference between two places is the CPR quality that the patient receives.

As shown in the Table.1, The incidence of OHCA is about 1.5 times greater than the incidence of IHCA. IHCA has a survival rate of 10% in the last 5 years and OHCA has a survival rate of about 23% [8]. The statistic result show that the place has a great influence on the survival rate in the cardiac arrest situation. The difference in statistical survival rates at two sites is due to the quality of CPR. From the statistical results, we can observe that the environment with high CPR quality, i.e. CPR feedback monitoring, has a survival rate twice as high.

Monitoring the patient condition and providing adequate CPR is a great help in increasing the survival rate of all CA patient. Through this study, we estimate CPR quality not only in IHCA situation but also in poor OHCA situation using PPG signal that can be easily using recently.

Table 1. Survival rate of cardiac arrest in the United States during the last five years.

	Out of Hospital	In the Hospital
2016	Survivor rate: 12%	Survivor rate: 24.8%
2015	Survivor rate: 10.6%	Survivor rate: 25.5%
2014	Survivor rate: 10.4%	Survivor rate: 22.7%
2013	Survivor rate: 9.5%	Survivor rate: 23.9%
2012	Survivor rate: 11.4%	Survivor rate: 23.1%

The survival rate of cardiac arrest are different between two sites [8].

Table 2. Incidence of cardiac arrest in the United States during 2012 and 2013.

	Out of Hospital	In the Hospital
2013	359,400	209,000
2012	382,800	209,000

Total incidence of cardiac arrest is nearly 600,000 case among the year. Cardiac arrest is occur about one in 500 people in US [8].

1.3 Related research

1.3.1 Invasive monitoring

At constant cycle respiration, ETCO2 reflects the degree of circulation and the degree of aerobic respiration in the body. Studies showing high ETCO2 values after the actual ROSC have also been conducted in the past. These studies were identified through preclinical experiment and clinical trials. Related studies also suggest that ETCO2 is decreasing during cardiac arrest situation, and there is a linear relationship between cardiac output and ETCO2 during CPR [9, 10]. According to previous study, ETCO2 is an objective CPR monitoring signal, but it has some disadvantage. In order to measure ETCO2 airway must be secured, which requires expertise and can take a considerable amount of time. The need of secured airway can be difficult to monitor in OHCA situation.

Arterial blood pressure (ABP) can be an objective indicator of CPR quality [11, 12]. The occurrence of blood pressure in a cardiac arrest situation proves the flow of the blood. It has been proven that CPR is effective when the blood pressure is maintained at a constant target value during CPR. Systolic blood. In order to monitor the actual arterial blood pressure, however, a catheter must be inserted.

Rapid and substantial improvement in oxygen deliver is required to decrease the morbidity and mortality of ischemic organ injury. Continuous central venous oxygen saturation measurement can obtain quantitative results [13]. The measurement need a central venous cannulation which is inserted patient body. It can be useful for IHCA, however in the situation of OHCA it is difficult to measure the venous oxygen saturation.

1.3.2 Noninvasive monitoring

The primary aim of CPR is an adequate supply of oxygen to the tissues. A pulse oximeter both measures hemoglobin oxygen saturation and arterial pulse, It would appear ideal for monitoring the equality of CPR [14-16]. Motion, ambient light, hypo-perfusion can affect the reliability of pulse oximetry [17]. Pulse oximetry may show a wide range of bias and decreased accuracy and precision in a model of low perfusion cardiopulmonary collapse and during CPR [18]. It is challenging technique however the accuracy of oxygen saturation is not reliable.

Trans-thoracic impedance (TTI) has been studied for decades as a noninvasive technique for estimating stroke volume and cardiac output. It has been suggested to equip automated external defibrillators with the ability to measure the transthoracic impedance through defibrillator pads [19-21]. However TTI is strongly influenced by compressions [21].

Near infrared spectroscopy (NIRS) is used for monitoring cerebral oxygenation. Cerebral oxygenation is one of the major sign that represent CPR quality. Recently, studies have been measure cerebral oxygen saturation during CPR [23]. NIRS directly reflect the cerebral oxygenation and can be feedback monitoring signal to avoid brain damage from cardiac arrest. However NIR responds slowly upon ROSC [22, 24].

Table 3. Advantage and disadvantage of CPR monitoring method.

	Advantage	Disadvantage
ETCO2	Objective indicator of tissue metabolism	Invasive Secured airway
ABP	Objective indicator of blood flow	Invasive Need of Catheter
Venous oxygen saturation	Objective indicator of blood oxygen saturation	Invasive Need of Cannulation
Pulse oximeter	Noninvasive Simple device	Low accuracy Sensitive to Temperature and ambient light
TTI	Noninvasive	Artifacts of compression
NIRS	Noninvasive	Slow response

The advantages and disadvantages of six representative CPR monitoring schemes are briefly summarized. Arterial blood pressure (ABP), Trans-thoracic impedance (TTI), and Near infrared spectroscopy(NIRS) are abbreviations for the CPR monitoring method described in section 1.3.

1.4 Research objective

Studies about CPR quality monitoring Using PPG have been conducted in various way. Research to detect spontaneous pulse of ROSC using only PPG signal during CPR was conducted in 2013 [25]. The aim of the study is to detect the ROSC during CPR. The PPG wave form allows for the detection of spontaneous pulse during ventilation pauses, and frequency analysis of the PPG waveform allows for the detection of a spontaneous pulse and the determination of the pulse rate (PR) [25]. The frequency of chest compression and ROSC pulse frequency are sufficiently distinct in Spectrogram. However, in this study, there is no description of CPR quality to be ROSC.

The study of detecting the cardiac output (CO) algorithm based on PPG signal have been conducted in 2015 [22]. The presence and absence of the cardiac is determined by the PR of PPG signal. This study also aims to detect the signal of ROSC. TTI signal used for determination of compression characteristics. However two different type of signals are used in this study.

The study of the potential of the potential to represent chest compression based on PPG signal which is extracted from pulse oximeter is conducted in 2015 [26]. The study used area under curve (AUC) and amplitude of PPG signal. The study compared the correlation with ETCO2 using AUC and amplitude to show potential that PPG signal can represent the ETCO. AUC can be meaningful information about chest compression. The correlation with AUC and ETCO2 is about 0.65 and correlation with amplitude of PPG and ETCO2 is about 0.5. The result show that PPG signal from pulse oximeter has the potential to show chest compression quality. However the result of correlation is low and it can’t estimate the current CPR quality.

Previous studies have shown that PPG contains various information in CPR, and manty studies have been carried out to apply PPG practically. However motion artifact, ambient light, temperature, contact force and other factors are reflected in the PPG during CPR and PPG is sensitive to these environmental factors. Analysis of the correlation between PPG with ABP and ETCO2 by simply calculating AUC or amplitude through a complex PPG signal is difficult to obtain usable result.

Because of complexity of PPG signal, in this study, PPG signals are trained using convolution neural network and classified into two classes. The PPG signal is obtained through pre-clinical pig experiment, and for training, the signal is converted to an image through frequency transformation. The criteria of 2 class is based in ETCO2 during CPR and we aim to classify ETCO2 values using trained signal. Through this study we are investigating the potential of monitoring CPR quality with using CNN of PPG transformed image.

Chapter 2 Methods

2.1 Data acquisition

2.1.1 Experimental protocol

A feedback CPR animal study was conducted on 18 pigs with average weight of 30.65 kg range 27-37 kg (Figure 3). The pigs are divided into three groups according to the CPR method. The three groups were robot, Lucas, and manual, each of method performed on six pigs. Cardiac arrest in pigs was induced by directly stimulating the heart with 5V voltage. The pigs are followed by a 11 min cardiac arrest. CPR was then performed for 4min. Chest compression was delivered by Robot, Lucas to 12 pigs automatically and 6 pigs were delivered manual chest compression. The chest compression rate was 100 times per minute and the ventilation rate was 10 times per minute. The scheme of Experimental protocol is shown in Figure 4.

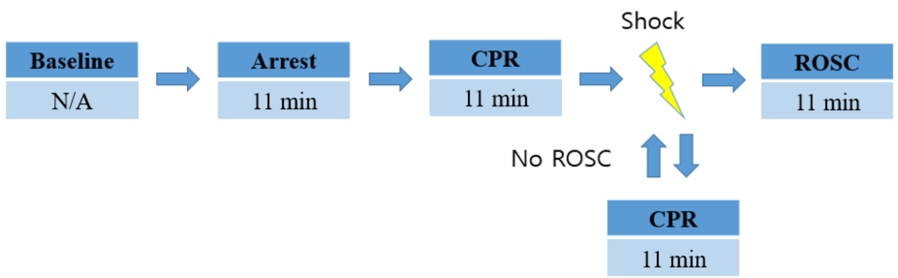

Figure 3. Scheme of experimental protocol

After 4min CPR If pigs were not ROSC, The additional 1 min CPR was performed and electrical shock was delivered to pig maximum 5times.

2.1.2 PPG data

PPG data was obtained by the attaching the sensor to the ear of pig (EP520, Laxtha Inc, Korea). The driving voltage of the sensor is 3.3V and the control voltage is 1.5V. The delay time of the sensor is 72 ms, which is not a problem in detecting heart rate pulse. The sensor is separate device from the pulse oximetry which is attached to the tail of pig and only outputs the waveform. The reason for attaching the sensor to the ear of h pig is that the blood flow to the brain is more important than the flood flow of other parts of the body. The signal output of the sensor was obtained by using the NI-DAQ (National Instruments, USA) and Labview software(Nation Instrument, USA) was used to receive the data and display the data over time. The sampling rate is 60 Hz and the data were recorded throughout the total experiment time.

(a) (b)

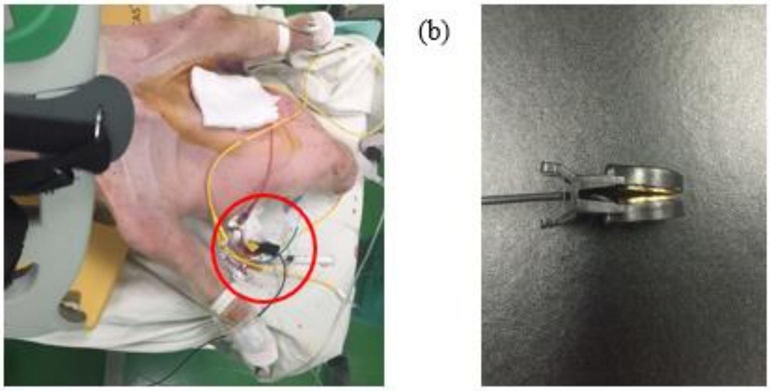

Figure 4. Attached Photoplethysmography(PPG) sensor

(a) Sensor attached to left ear of pig (b) PPG sensor (EP 520Laxtha Inc)

2.1.2 ETCO2 data

ETCO2 data was obtained by using sensor module (C300, National Medical Inc, China). The sensor module was attached to airway tube. The resolution of sensor is 0.1 mmHg range of 0 mmHg – 150 mmHg. The input voltage was 5V and delivered from laptop. The ETCO2 data was transferred to laptop using RS-232 communication method and processed by MATLAB (R2017a, Mathworks, Natick, USA). The sampling rate is 36 Hz.

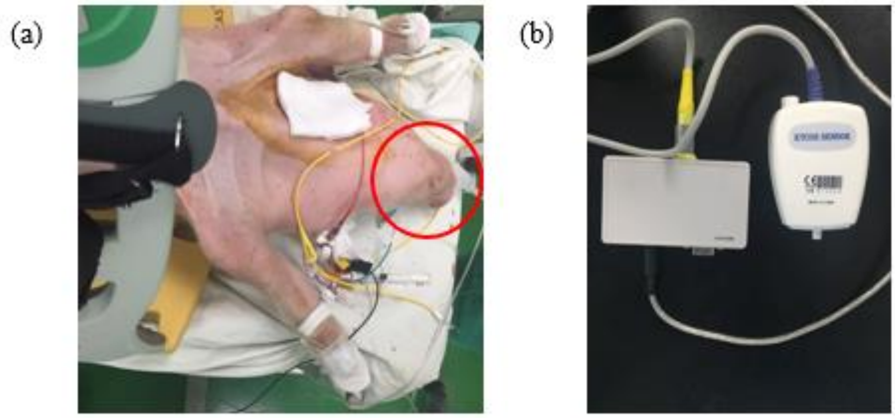

Figure 5. Attached end-tidal carbon dioxide(ETCO2) sensor module

(a) The sensor attached to secured airway tube (b) ETCO2 sensor module

2.2 Data processing

2.2.1 Data pre processing

The First step of data preprocessing is to synchronize the time axis of the ETCO2 data and PPG data. Because of difference in sampling frequency and separated data collecting method the raw data is unsynchronized between PPG and ETCO2. However, we obtained the data with time information, so the difference in sampling frequency is not a problem. The raw data obtained with the time information may differ in total length depending on the start time or end time of data acquisition, however the data at a specific time does not change (Figure 6).

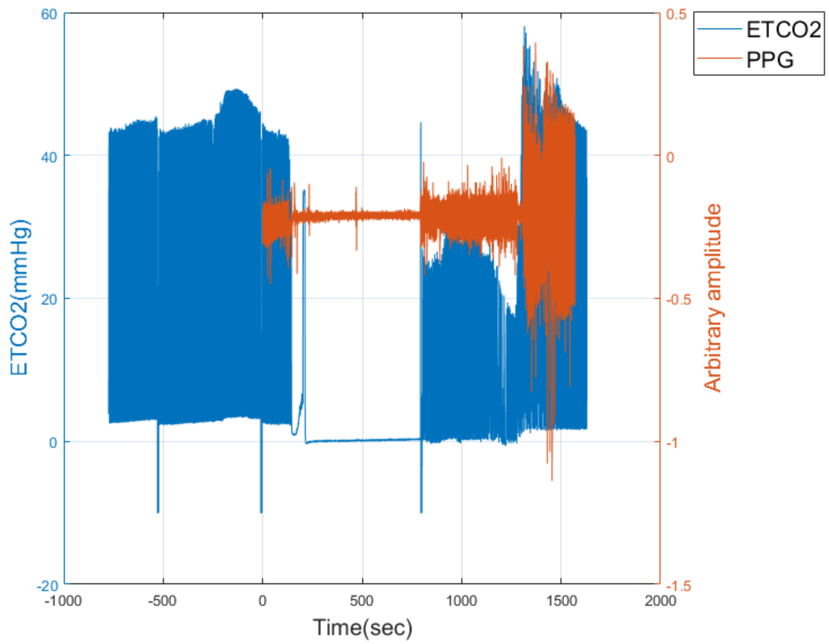

Figure 6. Total raw data of Photoplethysmography(PPG) and end-tidal carbon dioxide(ETCO2)

Only the CPR interval is extracted from the synchronized data and the moving average process is performed to smoothing the both ETCO2 and PPG data.

$$\text{Moving average} = \frac{1}{n}\sum_{i=0}^{n-1} P_{M-i} \qquad (1)$$

The period selected depends on the type of movement of interest, in this study the moving average period is 5 data sample. The time length of the data to be processed is 290 seconds, which includes interval of 50seconds before CPR. Data before the CPR contains the information about start point (Figure 7). The ETCO2 and PPG are synchronized based on the peak indicating the start of CPR. During the CPR period the pressure value of ETCO2 continuously changes based on the CPR quality. The value representing the ETCO2 is the peak value of expiration. So we detect the peak of every expiration ETCO2 data (Figure 8).

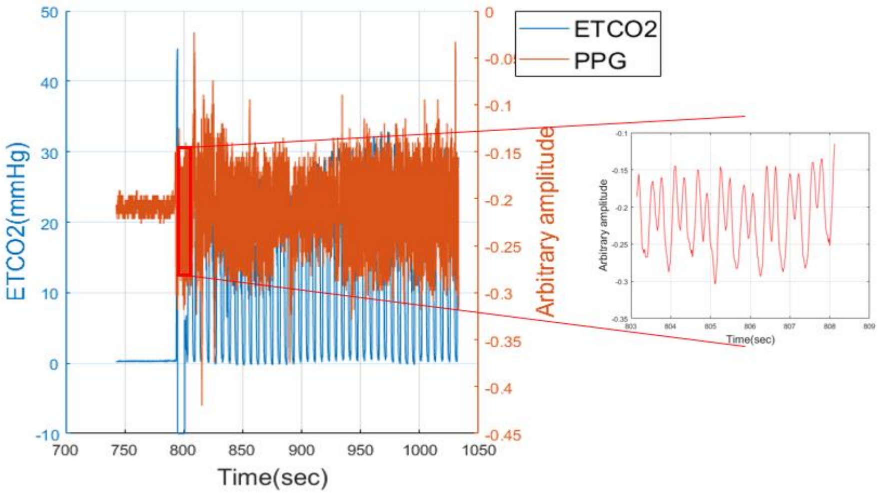

Figure 7. Synchronized time period of interest data

PPG is an acronym for Photoplethysmography. At the Beginning of the CPR, ETCO2 shows a sharp increase, which is caused by the air remaining in the lung at the time of cardiac arrest. Pressure value of the ETCO2 increases at the expiration and shows a value of zero at the time of inspiration. Periodic useless values of data appearing during inspiration should be replaced.

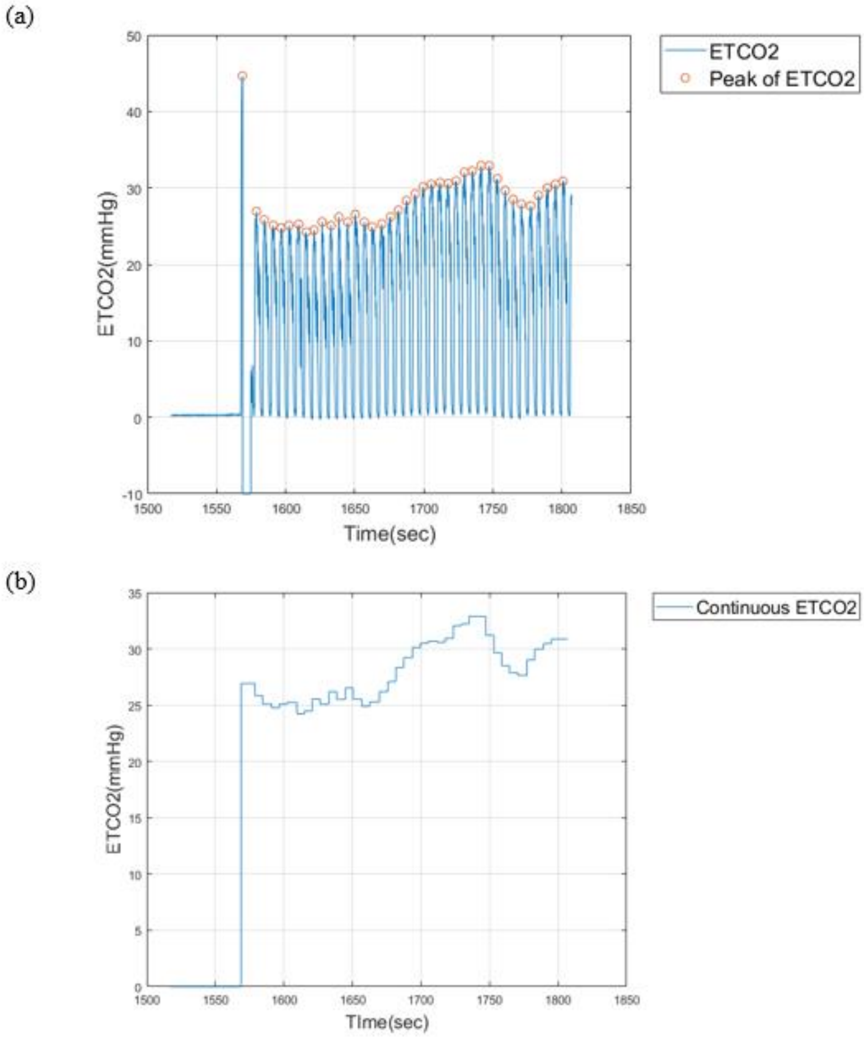

Figure 8. Continuous end-tidal carbon dioxide(ETCO2) data

(a) Peak of the ETCO2 data (b) Replacement of inspiration ETCO2 data

The inspiration data can be replaced with the expiration data that follows after as there is a time delay in the ETCO2 reflection of the specific time cardiac output caused by the blood circulation time. After replaced all the inspiration data during CPR, periodic ETCO2 data is converted into continuous data (Figure 8). The time period of one cycle respiration is 6 second, as given mechanical ventilation is 10 times per minute.

Interest PPG data is segmented by every 5 seconds to reflect one cycle of respiration. As we synchronized the data, every segmented data has matching ETCO2 value. The maximum number of segmented data is depends on CPR period length. However our interest length of data is 290 seconds, so that maximum number of segment is 58. Each of the segment data is contains various complexity data such as hear rate, motion artifact, cardiac output, and other factors which were difficult to recognize and analysis. All of preprocessing outputs are stored with Synchronized time value and ready to transform training set data.

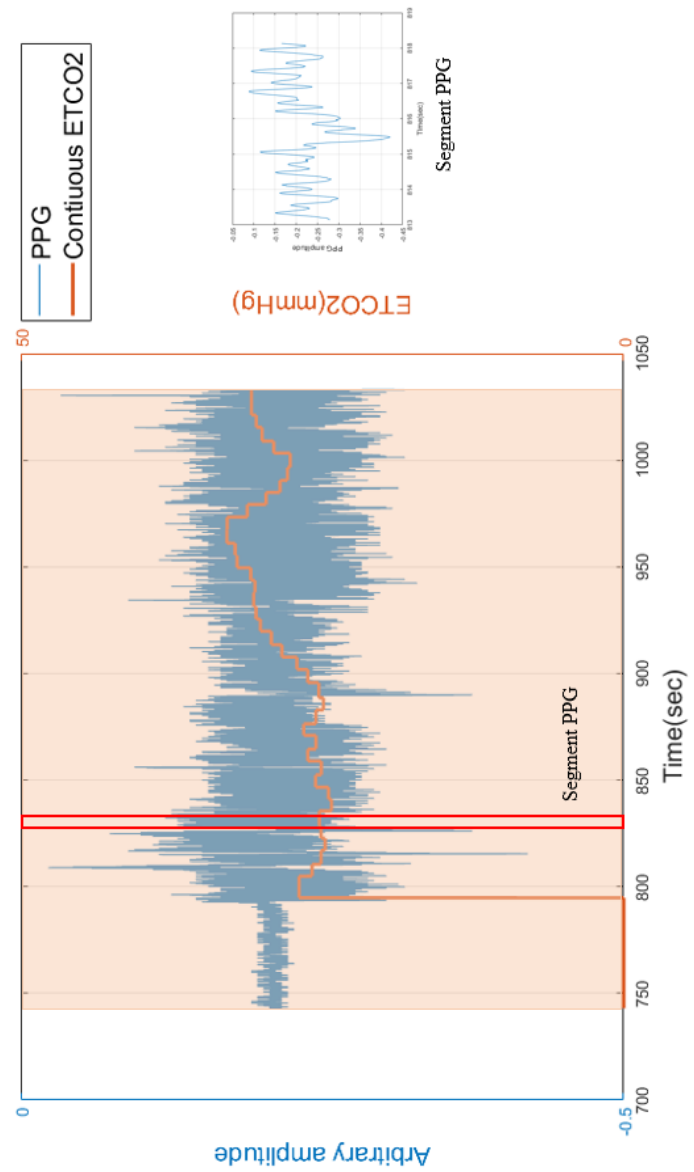

Figure 9. The segment of 5seconds data

The maximum number of segment is 58. All segments time length is 5seconds. PPG is an acronym for Photoplethysmography.

2.2.2 Spectrogram

The spectrogram is a toll in signal spectral analysis and other fields. The spectrogram can be defined as an intensity plot of Short-Time Fourier Transform (STFT) magnitude which is purposes of spectral display. STFT is a powerful tool for signal processing. It defines a particularly useful class of time –frequency distributions which specify complex amplitude versus time and frequency for any signal [27]. The common format of spectrogram is a graph with a time axis and frequency axis. A third dimension indicating the amplitude of particular frequency at particular time is represented by the intensity or color of image. The spectrogram is widely used in study of speech synthesis. The mathematical definition of the STFT is shown with length of the window and signal of PPG.

$$X_m(\omega) = \sum_{n=-\infty}^{\infty} x(n)w(n-mR)e^{-jwn} = DTFT_{\omega}(x \cdot SHIFT_{mR}(w)) \quad (1)$$

$$x(n) = PPG\ signal\ at\ time\ n \quad (2)$$

$$w(n) = length\ M\ window\ function\ (Blackman) \quad (3)$$

$$X_m(\omega) = DTFT\ of\ windowd\ data\ centered\ about\ time\ mR \quad (4)$$

$$R = hop\ size, between\ successive\ DTFTs \quad (5)$$

$$\sum_{m=-\infty}^{\infty} w(n-mR) = 1 \quad (6)$$

Where $x(n)$ is the PPG data which was segmented with 5 seconds. The Blackman window was used in PPG STFT with constant overlap. In this study two different length of window size was applied to the output segmented signals. The one is about 0.3seconds of window size and the other is about 0.6 seconds. The two window sizes correspond to the half cycle and one cycle of heart compression. After the applying every segmented PPG signal the transformed images which represent frequency axis and intensity of color are produced. The output images are stored with the Synchronized ETCO2 data.

2.2.3 Continuous wavelet transformation

Unlike Fourier transform, the continuous wavelet transform possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization. One of the popular applications of wavelet transform is image compression. The advantage of using wavelet is that it provides significant improvements in picture quality at higher compression ratios over conventional techniques. Wavelet transform has the ability to decompose complex information and patterns into elementary forms, it is commonly used in acoustics processing and pattern recognition. Moreover, wavelet transform can be applied to various scientific area such as electrocardiogram analysis, texture analysis, filter design, and other analytic researches. The mathematic formula of continuous wavelet transformation is expressed by following integrals. The continuous wavelet transform is a convolution of the input data sequence with a set of functions generated by the mother wavelet. The $\varphi(\mathrm{t})$ is a continuous function in both time domain and the frequency domain called the mother wavelet and the over line with mother function in (1) represent operation of complex conjugate. It can be used to recover the original x(t).

The x(t) is the PPG signal which was segmented and the scale factor of α dilate or compress the signal. When scale factor is low, the signal is more detailed resulting graph.

$$X_{\omega}(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t)\varphi\left(\frac{t-b}{a}\right) dt \tag{7}$$

2.3 Convolution neural network

The Convolution Neural Network (CNN) is used for various purposes such as image recognition and speech recognition. Especially, in the field of image recognition, most techniques using deep learning are based in CNN. CNN can express the relation with in a layer by using convolution layers instead of fully connected layer [28]. CNN consists of an input and an output layer as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolution layers, pooling layers, fully connected layers and normalization layer. So far neural networks have used fully connected neural network. However the problem with the fully connected layer is that the shape of data is ignored. The image is a three dimensional shape and the shape contains spatial information. However the Fully connected layer ignores these spatial features and treats all input data as equivalent neurons, so that information contained in the shape can not be reflected. On the other hand, the CNN layer maintains shape of the data. When an image is input as three dimensional data, it is transmitted as three-dimensional data to the next layer. The computation of convolution is the same as the corresponding filter operation in image processing. The convolution operation moves the window of the filter at regular intervals and applies it to the input data. The sum of all product operations is stored in the output location. In a fully connected neural network, there is a weight, and in CNN, the parameter of the filter corresponds to the weight in connected neural network.

Before performing a convolution operation, the data can be filled in the surrounding with a specific value, which called padding. The interval between filter movements is called Stride.

In this Study, we used 'VGG' network which is a basic CNN consisting of convolution layer and pooling layer. 'VGG' is a series of convolution layer using small 3x3 filter. The input image should be 224 x 224 size of pixels. The total input data was 870 images with 224x224x3 matrix which were Spectrogram and wavelet transformation separately conducted. Therefore our image data is two type that the one is spectrogram and the other is wavelet images. We have trained 783 data from the total data and rest of 87 images are randomly selected to test the trained set.

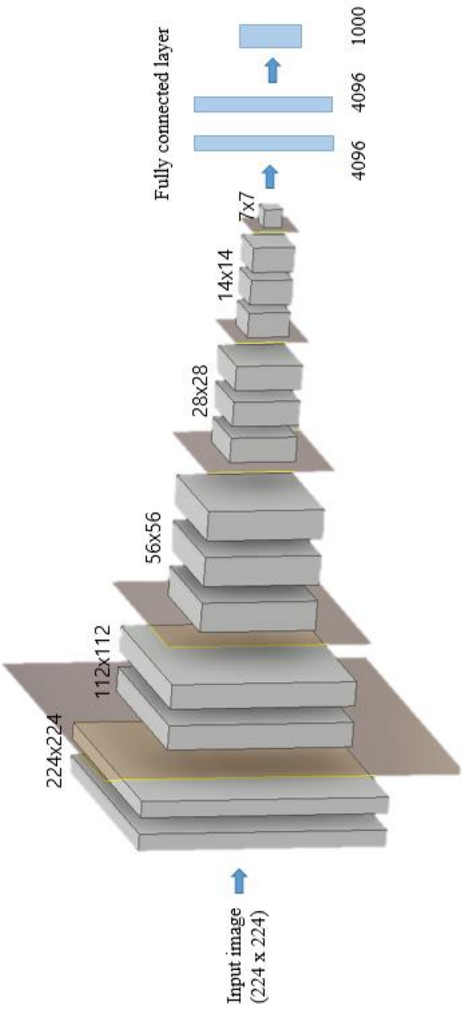

Figure 10. VGGnet with 16 layer

The network for object recognition developed and trained by Oxford's renowned Visual Geometry Group(VGG). VGG is one of the Convolution neural network which is divided into VGG16 and VGG19 depending on the depth of layer. VGG is simple and easy to configure and has been applied to various field.

2.4 Classification

The data from 15 pigs were used to establish classification criteria. Among 15 pigs, with-ROSC pigs are 9 cases and without-ROSC pigs are 6 cases. Average of ETCO2 of with-ROSC cases is higher than without-ROSC cases. The boundary of ETCO2 is 24 mmHg between with-ROSC and without-ROSC. Data is divided into two classes, the one is larger than 24 mmHg and the other is smaller than 24 mmHg. Eight pigs have an average ETCO2 greater than 24 mmHg and seven pigs have an average ETCO2 lower than 24 mmHg. In the group of above 24 mmHg the Six out of eight survived, however in the group of below 24 mmHg the four out of seven died. The survival rate and the mortality rate are 75% and 53%, respectively, based on the criteria. In this study we used the trained spectral image of the PPG signal to determine the CPR quality based on criteria which was obtained from pre-clinical experiment data. The total 870 data is divided into two class which is above 24 mmHg and below 24 mmHg. Each class of data is 595 images and 275 images. The 10% of each class data is randomly selected and separate test data from training data. Therefore the training set and test set of data are 782 images and 88 images. In this study we separate the total data based on average ETCO2 criteria and trained using 'VGG' network.

	Train images	Test images
Class 1(below 24 mmHg)	247	28
Class 2(above 24 mmHg)	535	60

Table 4. The number of train set and test set images

The Training data and Test data are not equally same number of images, however it is quite similar with total ratio of with ROSC pigs and without ROSC pigs (9:6).

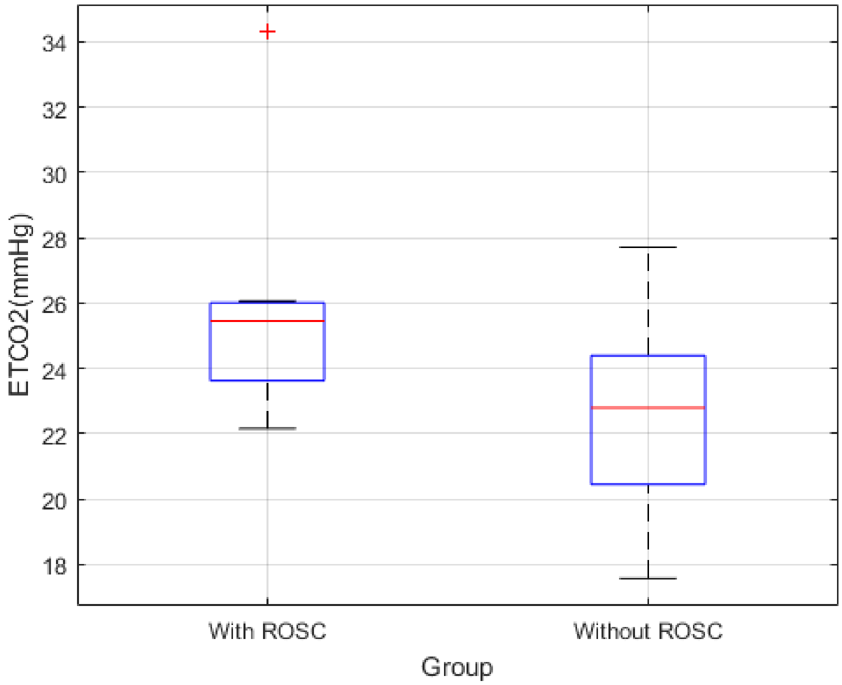

Figure 11. The boxplot of end-tidal carbon dioxide (ETCO2) of With return of spontaneous circulation (ROSC) group and Without ROSC group

The graph shows that the group of with Return of spontaneous circulation (ROSC) is in the range of 22 mmHg to 34 mmHg and the group of without ROSC is in the range of 17 mmHg to 27 mmHg. The Average of two group is almost same distance from 24 mmHg. The maximum possibility of ROSC was represented when the 24 mmHg is criteria.

	With ROSC	Without ROSC
Average ETCO2	25.52	22.49

Table 5. Average ETCO2 of with ROSC group and Without ROSC group

Total center value of the average ETCO2 of two group is 24.005 mmHg. The selected criteria is matched with center value of the average ETCO2 of two group.

	With ROSC	Without ROSC	Total
Above 24 mmHg	6(0.75)	2(0.25)	8(1)
Below 24 mmHg	3(0.43)	4(0.57)	7(1)

Table 6. The cases and survival rate based on ETCO2 criteria

When the criteria was set by 24 mmHg the survival rate and the mortality rate is significantly difference with rate of 75% and 57%. It is more meaningful then when the other criteria was selected.

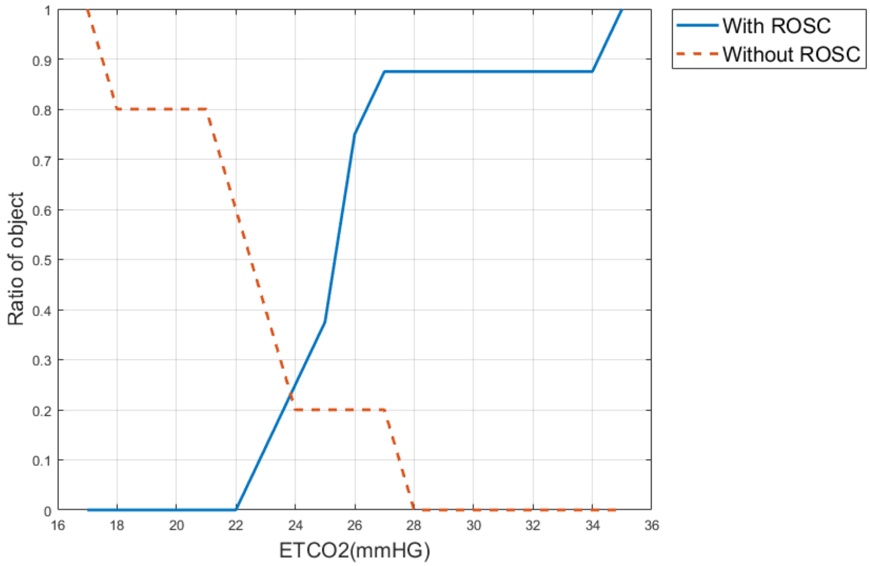

Figure 12. end-tidal carbon dioxide(ETCO2) based return of spontaneous circulation(ROSC) ratio

Return of spontaneous circulation(ROSC) represents the survival or death of an object. As ETCO2 increases, the With ROSC ratio increases. On the other hand, the ratio of Without ROSC decreases. The above figure shows that the ratio of ROSC crosses from 24 mmHg of ETCO2. The With ROSC ratio is increased by about 0.7 and the Without ROSC ratio is decreased about 0.6 around 24 mmHg of ETCO2.

The ETCO2 data in preclinical experiments show a dramatic change in survival rate from 24 mmHg. Therefore, in this study, 24 mmHg was set as the criterion of classification. We divided into PPG signal over 24 mmHg and below 24 mmHg. The learning and classification according to the above ETCO2 criteria.

Chapter 3. Results

3.1 Training image

3.1.1 Spectrogram image

The total segmented data was conducted STFT and converted to image data. Total data is 870 images with training set and test set. All of images were stored with ETCO2 data and classified in two class. The images are different each other because of their original signal has complex information. The intensity of the color means power over frequency (dB/Hz). The image size was resized to 224x224 because of the input size of VGG network is 224x224. The x-axis of image is length of segmented signal. The scale of the x-axis is seconds and total length is 5 seconds. The y –axis of image represents frequency information. Thus, the stored image in is the form of graph before it is stored, ant it also contains intensity information of the three dimensional color. It is hard to grasp the characteristics of the image corresponding to the two classes, but it can be confirmed that a compression frequency component is reflected. In case of class 1, the frequency component period does not appear for a certain time before CPR starts. As shown in Figure12, images belonging to the same class are not always the same because noise such as motion artifacts in the signal complicates the signal, and information about perfusion is not always constant. The images containing complex information are shown in spectrogram. The output spectrogram images are learned using VGG network. In order to apply the STFT to the acquired PPG signal, we have to determine the specific length of the signal, the window size and the overlapping range. The length of the signal is same as the length of the segmented signal. We applied two different window sizes to the signal, and extracted two different images from same ETCO2 counterpart. The images are different but contain the same ETCO2 value and are derived from the same PPG signal. The differences in images occur due to the window size, and each window size was about to the half cycle and one cycle of chest compression rate. As shown in the Figure.12, if the window size is too large, we can see the image is not smooth because of the distortion of the signal. This distortion affects the outcome of learning. Therefore, it is important to set the window size to an appropriate size. In the case of images of the same window size, it is difficult to distinguish the difference of each image, however images with different window sizes show a clear difference.

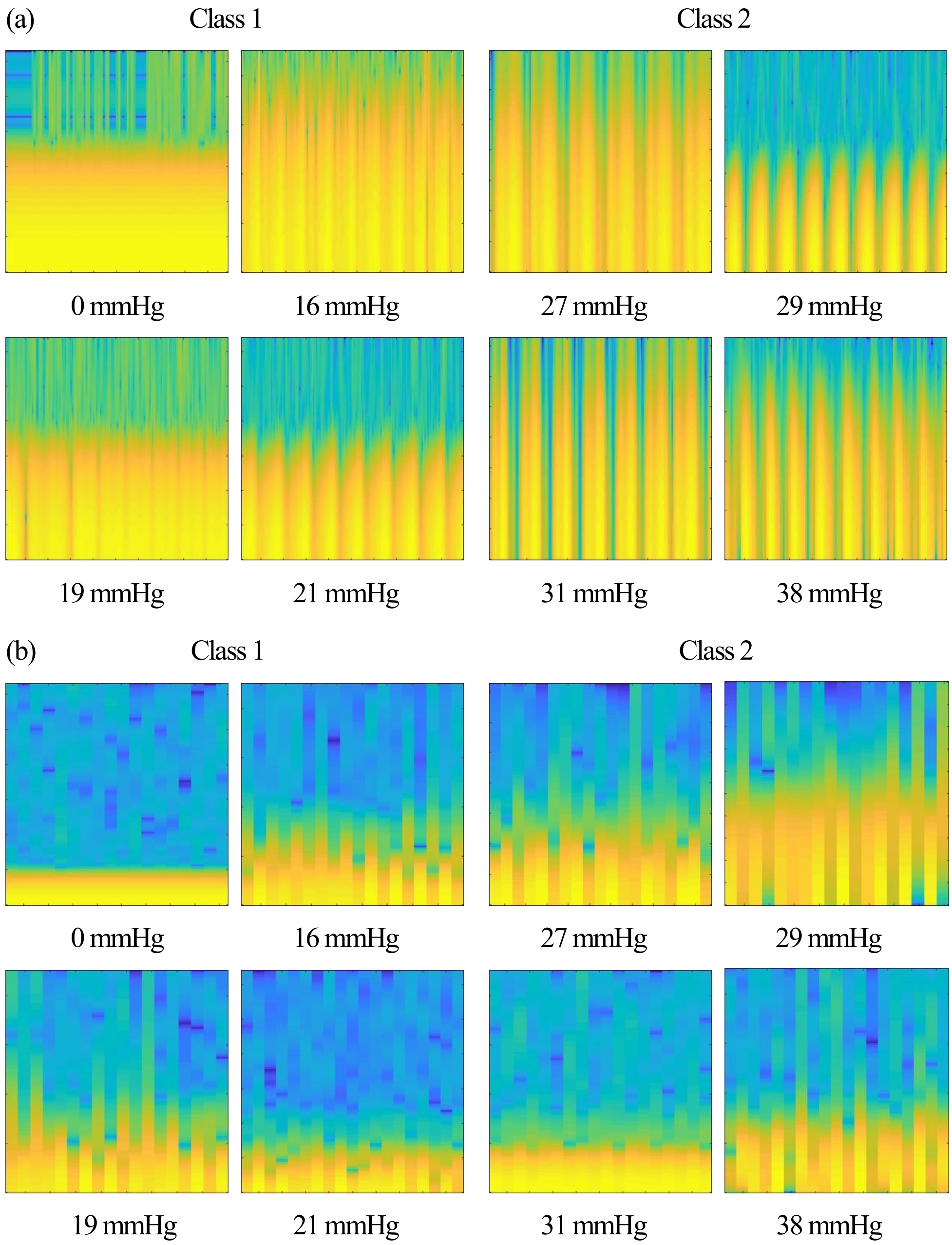

Figure 13. Spectrogram images of class 1 and class 2 with two different window size

(a) Spectrogram images with about half cycle of window size. (b) Spectrogram images with about one cycle of window size. Both (a) and (b) images are divided into each of class. Although images belong to the same class, they are not the same. The two classes were divided by 24 mmHg, and the images were stored separately according to the criteria of ETCO2. Each image was extracted at a specific time during the CPR period and stored with ETCO2 at that time.

3.1.2 Wavelet image

Wavelet images were obtained through continuous wavelet transform. Total data is 870 images with training set and test set. The cone of influence showing where edge effects become significant is also plotted. Outside of the dashed white line regions where edge effects are significant. In the image, x-axis means time and y-axis means frequency. The third axes representing coefficient value. As shown in Figure.15, it is difficult to clearly distinguish between images in the same class by the naked eye. In addition, it is difficult to find distinct differences in images between different classes. The wavelet transform does not need to set the window size unlike the spectrogram. Nonetheless, the image contains the majority of the signal's information, and the information contained may include contact forces or motion artifacts that are difficult to actually analyze. The visible highlight lines that are common to wavelet images show information about time and frequency. Although not shown in the image, a distinct line in the actual graph is between 1 and 2 value on the y-axis. This means a frequency of 1.5 Hz, which is consistent with the actual frequency of chest compressions. ETCO2 values corresponding to images can be the same but the images can not be the same, if the ETCO2 is the same value. All 870 images were divided into class 1 (595) and class 2 (275), and two classes stored 10% images as test sets separately. The images containing complex information are shown in wavelet transformation and trained by using the VGG network. The output images were not subjected to any image processing and were simply resized to a size of 224x224.

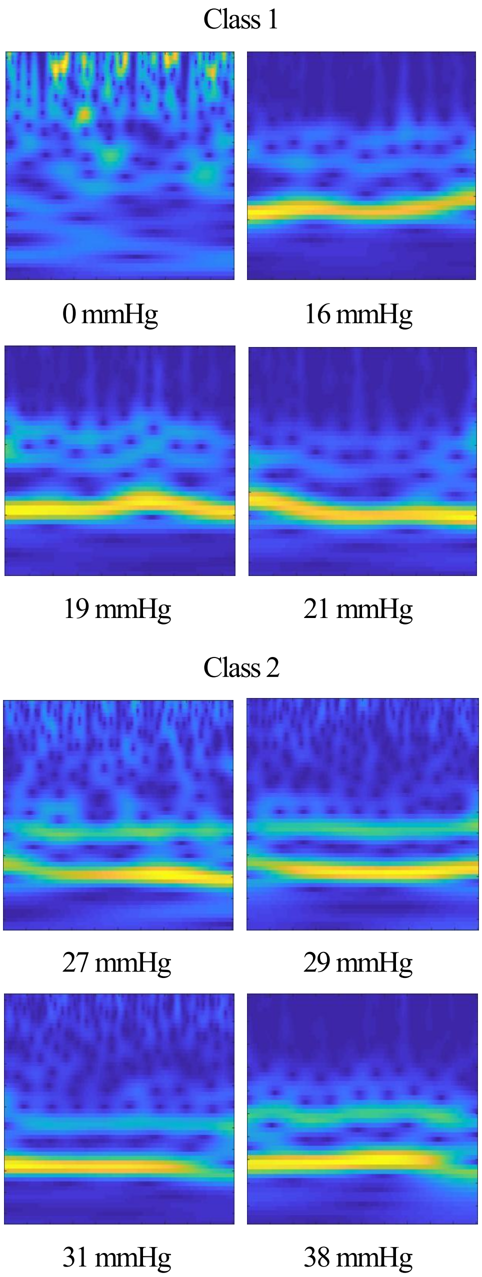

Figure 14. Wavelet images of class 1 and class 2

Wavelet images have the same spectra as the x and y axes, but the images are different. A wavelet image has a dashed line, and a dashed line indicates a boundary with a large edge effect.

However a uniform dashed line through all wavelet images are not necessary for training.

3.2 Classification accuracy

We output two types of images from the PPG signal. The types of images are the spectrograms and wavelets that were mentioned earlier. Both types of images come from the same PPG signal, but the way they output information to the image is different, as you can see from the eye. We first used the spectrogram image to train the information that the image has. Tensor flow was used for learning and VGG network was used. A total of 870 data were divided into two classes as mentioned above, and 10% of the data were stored separately from each class and used for the verification of learning. As learning progresses, the result about parameters are shown in Fingure14. The x-axis of the graph represents an epoch, which means that one epoch has trained the entire training image once. Thus, the x-axis can be seen as the progress of learning. The loss function is an indicator of the performance of the neural network and indicates how much the current neural network can not process the training data. Conversely, the negative value of the loss function indicates how well the neural network currently processes it. Therefore, the lowering of the loss function as learning progresses means that the current learning is well done. Training accuracy rises over time, which means that the neural network is learning the training data well. Test accuracy was checked once per epoch. Confirm the accuracy of the classification through the learning model of randomly selected 10% data. First, from the results of learning using the spectrogram image, the test accuracy starts from around of 60%. As the learning progresses, it gradually increase and converges to 84.09% over time. This means that the trained model is correct with 84.09% probability. As a result, the training model using the spectrogram image showed 84.09% probability of correctly classifying the two types of PPG measured at CPR. However classification accuracy of spectrogram with a large window size is 74% because of the distortion which was occurred performing the STFT. We also trained using wavelet images. We used the same VGG network and used the same image size. The results of the study using the wavelet image are shown in Figure 15. The model that trained wavelet image was confirmed to be classified with accuracy of 88.37%. Likewise, test accuracy using a wavelet images starts at around 60% and converges to 88.37% as the epoch passes. The result means that when the trained model classifies the test image, the correct answer is set to 88.37% probability.

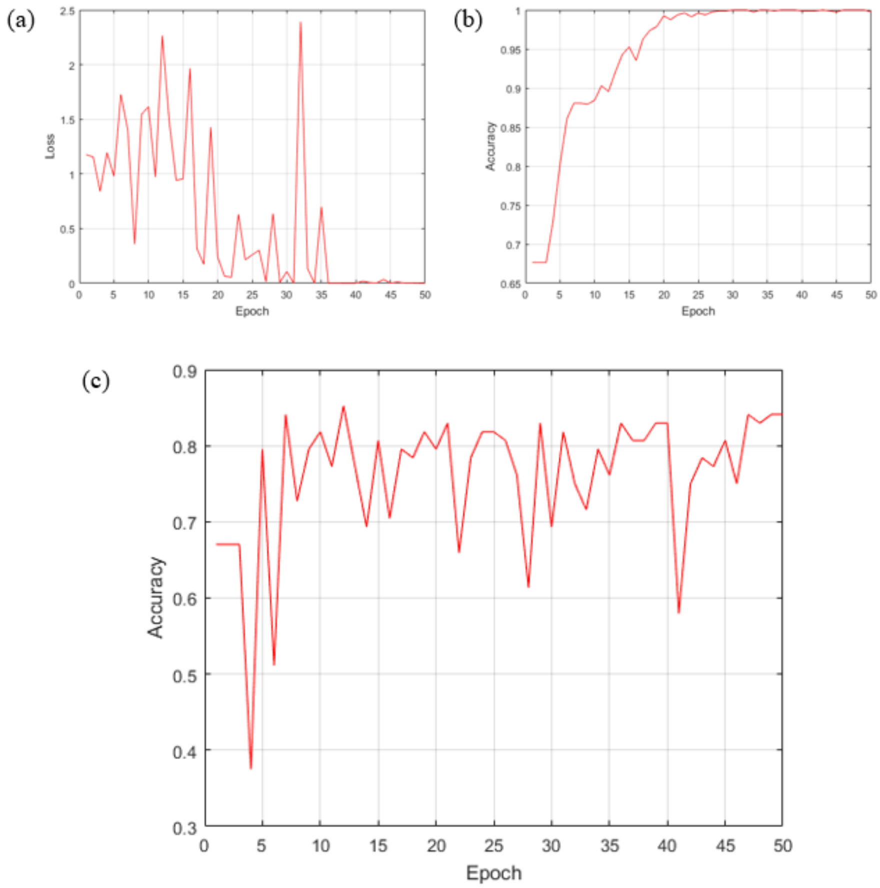

Figure 15. Training result of spectrogram images with small window.

(a) Loss function which is an Index that searches for optimal parameter. The loss function uses the mean square error and the cross entropy error. The loss function means that the training process is well going or not (b) Training accuracy rises over the time it means that neural network is learning the training data well. (c) Test accuracy is gradually increase, and the maximum accuracy is 84.09%

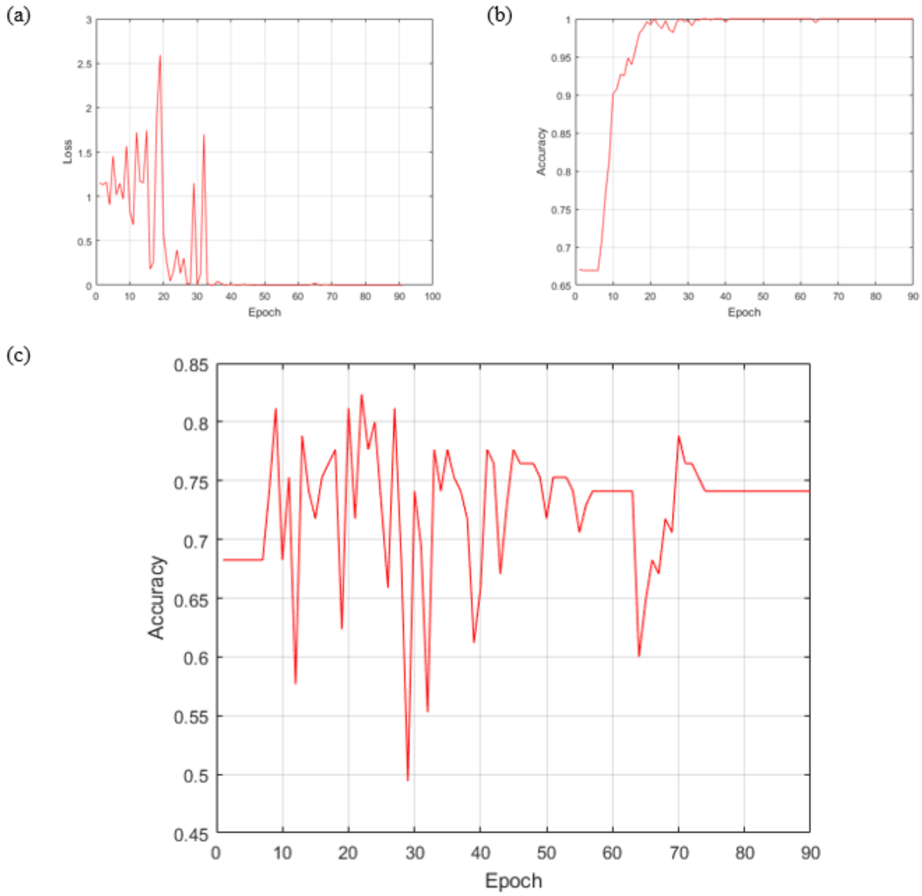

Figure 16. Training result of spectrogram images with large window.

(a) The loss function continues to decrease, and it can be confirmed that the convergence occurs when the epoch becomes 40 or more. (b) Training accuracy (c) Test accuracy begins at the around 60% and ends at 74%. This is due to insufficient information.

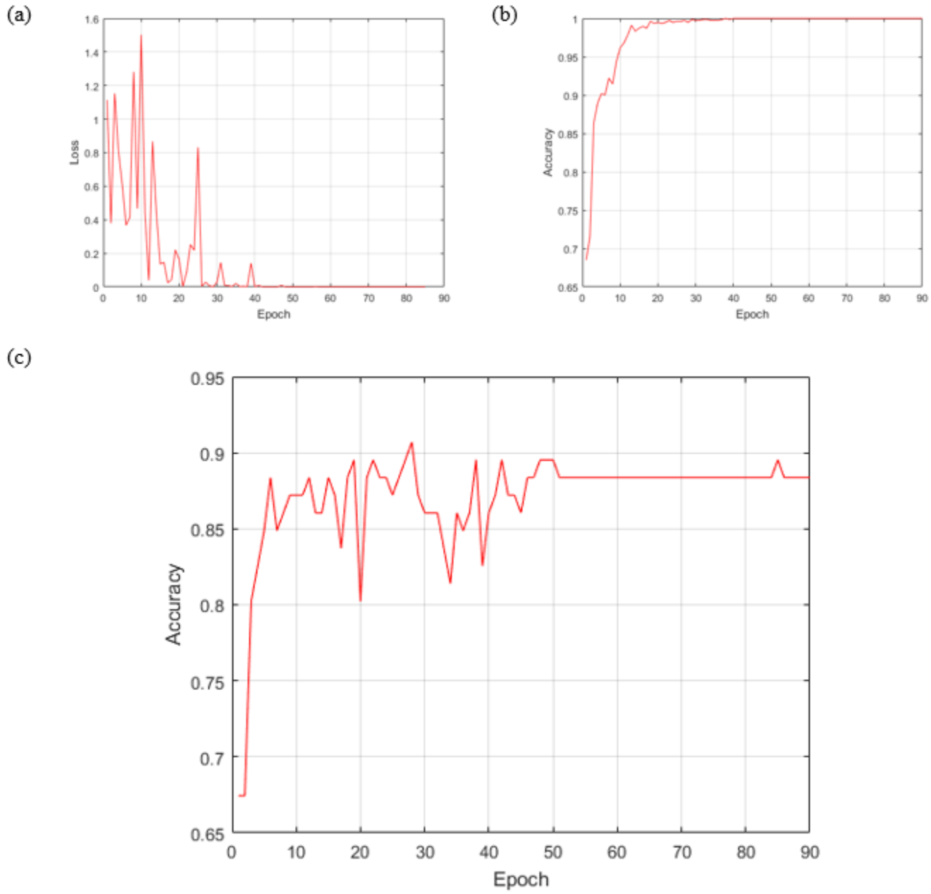

Figure 17. Training result of wavelet images.

(a) Loss function of wavelet image decrease with Epoch. (b) Training accuracy (c) Test The test accuracy starts at around 60% and gradually increases, converging at 88.37% when enough epoch has passed.

Chapter 4. Discussion

This study implements the estimation of CPR quality using PPG signal which is easy to obtain and deep learning which is a strong classification method. We overcomes the existing invasive CPR monitoring method and this study have the advantage of being cheaper and simpler than other non-invasive methods. The result of the study showed high accuracy, especially 88% in the classification using wavelet images. The study confirms the potential of the CPT quality estimation function of PPG signal, and it can be considered as a research example that presents another possibility for future research.

Despite the above significance, this study has several disadvantages. ETCO2, which is selected as the criteria for classification in this study, may show different values depending on the characteristics and status of pigs. The data has extracted from pigs in a controlled environment such as room temperature, lying on the bed, so the classification criteria can be changed depending on the type and characteristics of the objects. In this study the data was obtained from a specific CPR situation through preclinical experiments. Classification of data obtained through preclinical experiment gas limitations that are difficult to apply to people. There is also a limit to the amount of data. The environment in which data can be obtained was limited and data acquisition time was not long. So the total length of the data we got is 60 minutes, which is four minutes from 15 pigs. The number of transformed data images is 870, and it is uncertain whether it can provide sufficient information for learning. However, we saw the results increase test accuracy, and we can see that 870 images of data provided sufficient information for learning. Nevertheless, the problem still remains that the accuracy of the test starts at 60%. The cause is the imbalance of the data between the classes. For class1, training data is 247, while for class2, 535 training data is about twice the difference. There is also a difference in the number of images per class in the test image. 60% means the maximum value of accuracy that can be shown if only one class is selected as soon as learning starts. However, when compared to the survival rate of pigs in preclinical experiments, the cause of the data imbalance can be seen. In 15 preclinical trials, nine pigs survived. Thus, the survival rate of pigs is 60%, and if the surviving pigs belong to class 2, the imbalance of the data is explained. Conversely, we can see that the criterion of dividing the class is correlated with the survival rate. However, from the viewpoint of deep learning, the amount of balanced data is necessary in order not to bias the training. Therefore, it is important to acquire sufficient amount of data through more experiments.

The results of this study show that the accuracy of training the spectrogram image with small window size is 84%, the accuracy of training the spectrogram image with large window size is 74% and the accuracy of training the wavelet image is 88%. The difference in the results confirms what images have richer information. The STFT to obtain the spectrogram has the disadvantage that time information is lost when it is converted to a function of frequency because infinitely repeated sine wave is basic waveform. It is possible to know which frequency component is large, but it is not known at which position the component appears in a temporal position. In addition, when we look at two different window sizes of spectrogram classification results, the large window size in the STFR affects providing sufficient information in signals. In this study, we used two different window sizes which are the length of half period of a chest compression and one period of a chest compression. Comparing the classification accuracy of 74% and 84% of two different spectrogram images, we can see that the half period of window size has more information. However, the wavelet transform has the advantage of knowing the frequency information as well as the time information because it changes the position of the waveform along with the size of the wave. The wavelet transform analyzes the entire signal without dividing it, so there is little loss of information. We confirmed that learning using wavelet is better than learning using spectrogram through the results.

We classified the quality of CPR into two class through this study, but it is also meaningful to perform comparative analysis with indicators such as cardiac output and blood pressure in the future. We intend to extend this study a little further and to expand one more class to be classified in the future. The third class can be a PPG signals in the ROSC.

Chapter 5. Conclusion

In this study, the quality of CPR was successfully estimated using PPG spectrum images. The quality of CPR was divided into two classes. Classification criteria was determined using the ETCO2 value and the presence or absence of ROSC of pigs in preclinical experiments. PPG signals obtained from preclinical experiments were successfully synchronized with ETCO2 and were segmented at regular intervals according to the respiratory cycle. The segmented PPG signals were converted into spectrogram and wavelet images, stored by class and trained in the VGG network. Two different types of image-trained models showed 84.09% and 88.37% test accuracy, respectively. Despite training over the same network, these results can infer that the wavelet image contains more information than the spectrograph. The number of data is small because it is the signal of the specific section obtained from the preclinical experiment. Nonetheless, increasing test accuracy can infer that sufficient data amount information is reflected. Although the quality of CPR is divided into two classes, we have identified the potential of estimating CPR quality using PPG signals. For future work detecting the start of CPR and presence or absence of ROSC will be possible to judge the effectiveness of CPR.

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국문 초록

합성곱 신경망을 이용한 광용적맥파 신호 기반의 심폐소생술 품질 추정

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심폐소생술은 심정지가 발생한 환자에게 흉부 압박과 인공호흡을 통해 신체의 기능을 보존해주는 응급처치이다. 심폐소생술의 가이드 라인에는 흉부를 5cm의 깊이로 분당 100회에서 120회 사이로 압박을 하도록 권장하고 있다. 그러나 환자마다 신체적 특성이 다르므로 심폐소생술을 받는 환자에게 모두 가이드라인에 맞도록 심폐소생술을 수행하는 것은 적절하지 않다. 매년 미국에서는 약 60만명의 심정지환자가 발생하며, 병원 밖에서의 심정지환자의 생존율은 10% 내외로 병원 안에서의 심정지환자에 비해 상당히 낮은 편이다. 미국 심장 협회에 따르면 심폐소생술의 품질과 대처 속도는 심정지환자의 생존율에 큰 영향을 준다.

심폐소생술의 품질을 확인하기 위해 심폐소생술 도중 환자의 상태를 모니터링하는 연구와 환자가 다시 심장이 박동을 시작하는 것을 추정하는 연구는 활발하게 진행되어왔다. 호기 말 이산화탄소(ETCO2)량, 흉부의 임피던스, 동맥압 등과 같은 여러가지 생체신호들이 이용되었으며, 이를 통해 심폐소생술의 모니터링의 많은 가능성을 제시하고 있다. 그러나 신체에 침습적이거나, 시간이 오래 걸리는

문제점들이 있다. 여러 생체 신호들 중에서 본 연구에 사용된 광용적맥파(PPG)는 비침습적이고, 실시간으로 정보를 반영하는 장점을 갖고있다.

본 연구의 목표는 PPG 신호를 합성곱 신경망을 이용해 심폐소생술의 품질을 추정하는 것이다. 본 연구에서 사용된 PPG와 ETCO2는 15마리의 돼지를 이용한 전임상 실험을 통해 얻었다. 각각의 돼지는 심정지가 유도되며, PPG와 ETCO2 데이터는 심정지 유도된 돼지에게 심폐소생술이 수행된 290초동안 획득하였다. 얻어진 PPG 데이터는 5초의 구간으로 나누어 다시 저장하였으며, 저장된 데이터 각각을 스펙트로그램 변환과 웨이브릿 변환을 적용하여 이미지로 변환하였다. 이미지로 저장된 데이터는 같은 시간 구간에 대응되는 ETCO2 값을 포함하고 있다. 심폐소생술의 품질은 2개의 그룹으로 나누었으며, 그룹의 기준은 생존한 돼지와 생존하지 못한 돼지의 심폐소생술시 얻어진 ETCO2의 값에 근거하였고, 기준에 맞춰 모든 이미지 데이터를 두 그룹으로 나누어 분류 하였다.

본 연구에서 얻어진 이미지 데이터의 학습은 널리 알려진 'VGG' 기반의 합성곱 신경망을 사용하였다. 두개의 그룹으로 분류된 전체 데이터 중 학습에 사용된 데이터는 90%이며, 나머지 10%는 학습을 평가하기 위해 사용되었다. PPG 신호의 스펙트로그램 변환을 이용한 이미지로 학습시킨 경우 분류의 정확도 84.09%이며, 웨이브릿 변환을 이용한 이미지를 학습시킨 경우 분류 정확도는 88.37% 이다. 본 연구의 결과는 PPG 신호로부터 변환된 이미지를 추출하여 합성곱 신경망으로 학습시키는 것이 심폐소생술 품질 추정에 잠재성이 있음을 보여준다.

주요어 : 심폐소생술, 광용적맥파, 합성곱 신경망, 웨이브릿, 스펙트로그램 호기말 이산화탄소

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