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Predicting Successful Defibrillation in Ventricular Fibrillation using Wave Analysis and Neuro-fuzzy

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Abstract

The purpose of this study was to predict successful defibrillation in ventricular fibrillation using parameters extracted by wave analysis method and neuro-fuzzy. Total 15 dogs were tested for predicting successful defibrillation. Feature parameters were extracted for return of spontaneous circulation (ROSC) and non-ROSC by wave analysis method, and these parameters are an irregularity factor, spectral moments, mean power of level-crossing spectrum, and mean of alpha-significant value. Additionally, two parameters by analyzing method of frequency were extracted into a mean of power spectrum and a mean frequency. Then extracted parameters were analyzed in which parameters result to have high performance of discriminating ROSC and non-ROSC by a statistical method of t-test. The average of sensitivity and specificity were 62.5% and 75.0%, respectively. The average of positive predictive factor and negative predictive factor were 61.2% and 75.8%, respectively.

Key words : ventricular fibrillation, defibrillation, adaptive neuro-fuzzy inference system, cardiopulmonary resuscitation

I. INTRODUCTION

Ventricular Fibrillation of a heart causes arrhythmia complicating acute myocardial infarction since chaotic and abnormal electrical activities leads to the loss of coordinated myocardial contraction [1].

The recovery to normal activation of a heart gets hard as time of ventricular fibrillation increased more since return of spontaneous circulation(ROSC) has an inverse proportional relation with the time elapsed [2]. Treating methods for removing ventricular fibrillation were introduced to defibrillation, cardiopulmonary resuscitation(CPR), and drug administration [3]. These treating methods result to increase blood-flow in the body and to help a heart to be recovered from abnormal status. Even though the defibrillation is ultimate treating method to recover a heart into the natural circulating status, this method can be caused to damage heart muscles by repeating defibrillations. Therefore, the predicting result of defibrillation helps to prevent repeated and unnecessary defibrillations and to analyze the effectiveness of a treatment by cardiopulmonary resuscitation [4].

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The most accurate prediction fators of successful defibrillation are the coronary perfusion pressure and the myocardial blood flow [5]. However, it is not available to use these for emergency situations in hospital because these factors could be measured by invasive methods using catheter into the heart [6]. For this reason, many analytical methods using electrocardiogram(ECG) were proposed for predicting defibrillation about success or not [7].

This paper described predicting successful defibrillation in ventricular fibrillation using parameters extracted by wave analysis and neuro-fuzzy method. Using wave analysis method, characteristics of not only amplitude but also distribution of amplitude was analyzed. Added to this, power spectrum analysis which is one of existing analysis methods was used for extracting features. The results which were ROSC or no-ROSC after defibrillation were trained for neuro-fuzzy inference system and tested for evaluating performance of predicting defibrillation.

II. METHODS

A. Animal Experiment

Total 15 dogs which have weight of 21 ~ 30kg were used for animal experiment. They were performed an operations under a general anesthesia using ketamine sulfate and pentothal by an intramuscular injection and an intravenous injection, respectively. In this study, ventricular fibrillation of dog's heart was artificially induced from an apparatus which has 60 Volts and 30mA with 60Hz, the protocol of animal experiment is shown in Table 1.

Table 1. Protocol of animal experiment

Period	Time(min.)	Operation	Drug
	0:00~3:30	Inducing ventricular fibrillation	
A	3:30~4:00	No operation with ventricular fibrillation	
B	4:00~4:30	CPR and first drug administration	epinephrine 1mg
C	5:30~6:00	CPR	
D	7:00~7:30	CPR and second drug administration	epinephrine 1mg
E	8:30~9:00	CPR	
	10:00	Defibrillation	

Total five periods from A to E were divided after three and half minutes from inducing ventricular fibrillation. The drug administration was operated about 1 mg of epinephrine when these were four minutes and seven minutes after ventricular fibrillation. In the period from B to E, standard CPR was operated by an automatic mechanical resuscitator(Thumper, Michigan Instruments, USA). The chest compression was 80 per minute, and the ratio of compression over relaxation was 50 to 50. Finally, after 10 minutes, a defibrillator(Lifepak, Medtronic, USA) was operated and examined that dogs were survival or dead.

During the experiment, ECG data was acquired by MacLab (ADinstruments, USA) with sampling rates of 400 samples per second and a resolution of 16 bits. Among 15 dogs, six dogs were survival and the others were dead.

B. Wave Analysis and Extraction of Characteristic Features

Wave analysis was proposed by WAFO(wave analysis for fatigue and oceanography) group in Lund University, Sweden [8]. This is composed with some mathematical and statistical tools for analyzing random signal and random loads. Especially, wave analysis considers a random signal as a composition of troughs and crests with various levels. Since an amplitude of a wave is defined the difference between global maximum and global minimum, small signals with low level of trough-to-crest amplitude which have no an effective activation of a heart can be removed from an ECG signal of ventricular fibrillation.

Before the extraction of features, the moving average filter with 500ms was used for removing baseline wondering, and 10^{th} order FIR band-pass filter with a pass band of 5 to 30 Hz was used for removing the moving artifact by a CPR operation and the noise of high frequency.

Among many parameters which were proposed in this analysis, five features were used for features. Theses are irregularity, level-crossing spectrum, spectral moment m_2, spectral moment m_4, and alpha-significant value. Additionally, two power spectrum parameters — mean power and mean frequency — were used for frequency-based features, and each feature was described as follows.

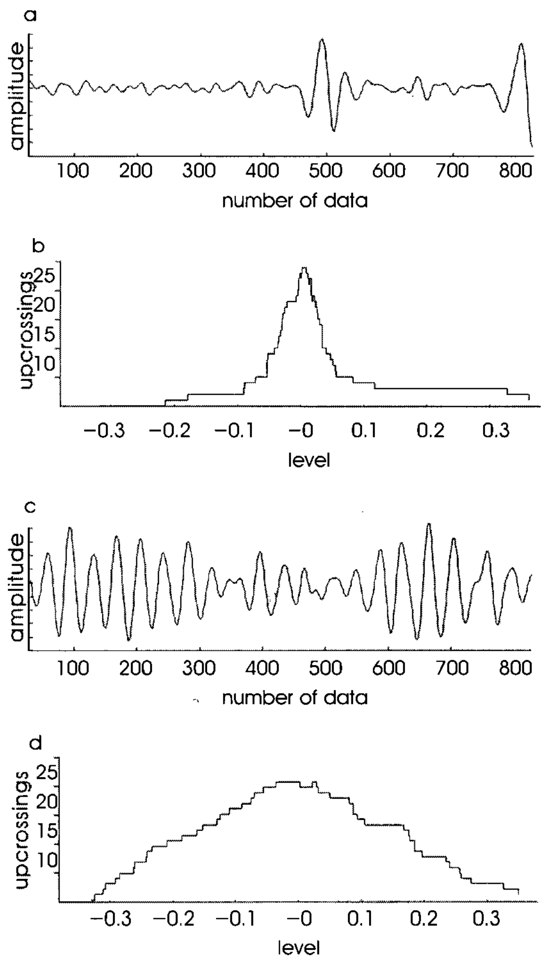

Fig. 1. Ventricular fibrillation signals and the level-crossing spectrum compared with ROSC and no-ROSC (a) ECG signal of ROSC (b) Level-crossing spectrum of ROSC (c) ECG signal of no-ROSC ECG (d) Level-crossing spectrum of no-ROSC

Irregularity(IR) means the irregular characteristics of a random signal. It is derived from the level-crossing spectrum which is a kind of a histogram. The level-crossing spectrum illustrates the number of upcrossing with each signal level. In Fig. 1, ECG signal of no-ROSC shows monotonous pattern, the other hand ECG signal of ROSC shows some irregular pattern. Irregularity is calculated from a mean up-crossing level$_{f0}$ divided by sum of the number of local maxima and local minima as the following:

$$IR=\frac{f_0}{N_{local\ maxima}+N_{local\ minima}} \tag{1}$$

Mean power of level-crossing spectrum(MPLC) is given by:

$$MPLC=\frac{1}{L}\sum_{i=1}^{L}S(i) \tag{2}$$

where $S(i)$ is values of upcrossing and L is data length of the level-crossing spectrum. In Fig. 1, in the case of a ventricular fibrillation signal of no-ROSC, the level-crossing spectrum shows relatively high mean value of spectrum in compared with low mean value of ROSC spectrum which is wide spread.

The i-th order spectral moment of power spectrum in frequency domain is given by:

$$m_i=\int_0^{\infty}\omega^i s(\omega)d\omega \tag{3}$$

where $s(\omega)$ is power spectrum of a random signal. The variance of power spectrum is approximated into zero-th order spectral moment as the following:

$$\sigma^2=\Delta\omega\sum s(\omega_i)\approx\int_0^{\infty}s(\omega)d\overline{\omega}=m_0 \tag{4}$$

Therefore spectral moment m_2(SM2) and m_4(SM4) means the first and second derivative of variance.

One of the severity factor for a random signal is defined by the significant wave characteristic which is composed with significant amplitude and significant crest. Among these, given that significant crest is a mean value of one-third of a crest height, alpha-significant value which is derived from sum of the sequence of crests M_i^{tc} can be defined as:

$$M_\alpha^{tc}=\frac{1}{\alpha n}\sum_{i=(1-\alpha)n}^{n}M_i^{tc},\ 0<\alpha\leq 1 \tag{5}$$

Hence, mean of alpha-significant value(MRS) is the average of alpha-significant values where an alpha is from 0 to 1.

Two further features are mean power(MP) and mean frequency(MF) of a power spectrum, and these are given by:

$$MP=\frac{1}{L}\sum_{i=1}^{L}P(i) \tag{6}$$

$$MF=\frac{\sum_{i=1}^{L}f(i)P(i)}{\sum_{i=1}^{L}P(i)} \tag{7}$$

where $P(i)$ and $f(i)$ are power of spectrum and frequency, respectively [9].

From these seven parameters, characteristic features were derived with each period, and then statistical analysis was processed by t-test for estimating which features shows low p-value as a high performance in classification.

C. Adaptive Neuro-fuzzy Inference System

The neuro-fuzzy algorithm adopted in this study was the adaptive neuro-fuzzy inference system(ANFIS), one of the neuro-fuzzy algorithms, which combined fuzzy with neural network [10].

First of all, assume that the fuzzy inference system is the basic system with two inputs and one output. Two input features were selected by t-test between ROSC and no-ROSC with each period, and the output shows a prediction value of defibrillation. For the first order Sugeno fuzzy model, typical rule sets which have two fuzzy if-then rules can be expressed as the following [11]:

$$\begin{aligned}&Rule\ 1: if\ x\ is\ A_1\ \text{and}\ y\ is\ B_1\\ &\qquad then\ f_1=p_1x+q_1y+r_1\\ &Rule\ 2: if\ x\ is\ A_2\ \text{and}\ y\ is\ B_2\\ &\qquad then\ f_2=p_2x+q_2y+r_2\end{aligned} \tag{8}$$

where p_i, q_i and r_i(i=1 or 2)are coefficients of the first order Sugeno fuzzy model to be learned by neural network. This inference structure of the Sugeno model and its equivalent ANFIS structure are represented in Fig. 2.

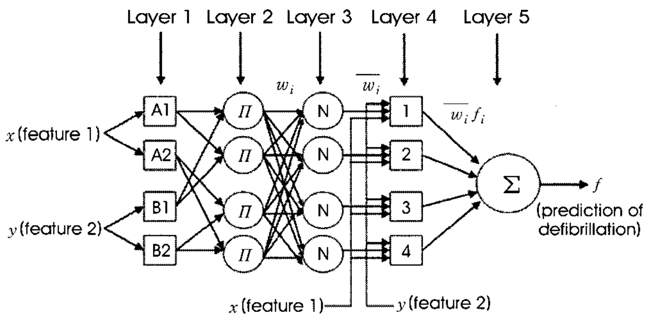

Fig. 2. First-order Sugeno fuzzy model of 2-input type and equivalent ANFIS structure with Sugeno fuzzy model

Layer 1 : Each output of A_i and B_i in layer one is shown in the following output nodes :

$$O_{1,i}=u_{a_i}(x), \quad for\ i=1,\ 2\ or \qquad (9)$$
$$O_{1,i}=u_{B_{i-2}}(x), \quad for\ i=3,\ 4$$

In the expressions above, x (or y) is the input for the node. A_i (or B_{i-2}) and $u_{A_i}(x)$(or $u_{B_{i-2}}$) means the fuzzy set of each nodes and fuzzy membership function of each nodes, respectively.

Layer 2: This layer generates connection stiffness. Input signals from the node are multiplied. For example, the relationship is expressed in the following equation :

$$O_{2,i}=w_i=u_{A_i}(x)\times u_{B_1}(y), \quad i=1,\ 2 \qquad (10)$$

Operators such as T-norm, which performs fuzzy *AND* operation, are used as the function of this node.

Layer 3: This is the layer of stage to normalize connection stiffness. The ratio of summation of all the connection stiffness of the rules to the connection stiffness of the *i*-th node is calculated as the following.

$$O_{3,i}=\overline{w_i}=\frac{w_i}{w_1+w_2}, \quad i=1,\ 2 \qquad (11)$$

Layer 4: This layer calculates results of the rule based on the final part of the inference rule.

$$O_{5,i}=all\ output=\sum_i \overline{w_i}f_1=\frac{\sum_i \overline{w_i}f_1}{w_i} \qquad (12)$$

Layer 5: This layer adds all the inputs, which were obtained from, layer 4.

$$O_{4,i}=\overline{w_1}f_1=\overline{w_1}(p_i x+q_1 y+r_1) \qquad (13)$$

The half length of each period was used for training data, and then, the other period of data was used for testing data.

Ⅲ. RESULTS

The results for the features with each period and analysis results by *t*-test are shown in Table 2 and Fig. 3. In the feature of irregularity(IR), a period B resulted in the smallest *p*-value, and it means that ROSC has more irregular than no-ROSC in period B. Therefore the irregularity is the best feature to differentiate between ROSC and no-ROSC in period

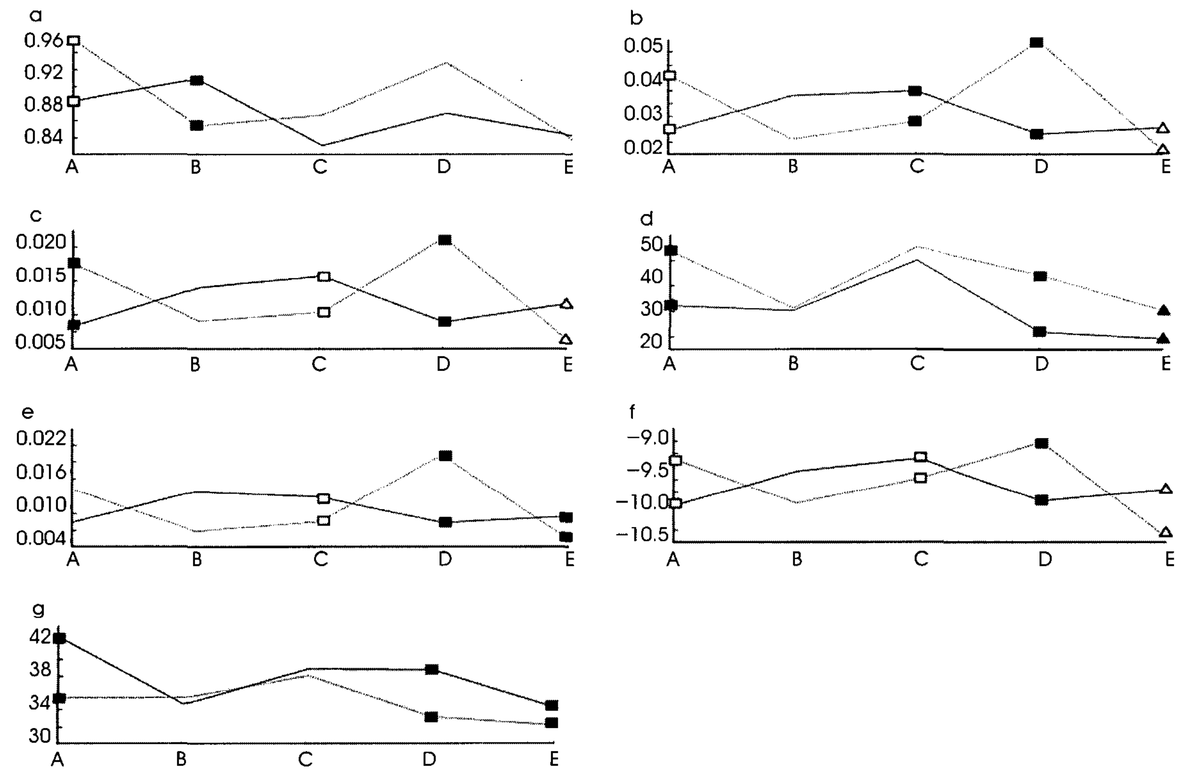

Fig. 3. Average of characteristic features compared with ROSC(——) and no-ROSC(········) with each period
(a) Irregularity (b) Spectral moment m_2 (c) Spectral moment m_4 (d) Mean power of level-crossing spectrum (e) Mean alpha-significant value (f) Mean power of spectrum, dB (g) Mean frequency, Hz
□ : *p<0.05*, ■ : *p<0.01*, △ : *p<0.001*, ▲ : *p<0.0001*

B. In the feature of spectral moment m_2(SM2)and m_4(SM4), most period except for period B showed a discrimination performance of p<0.05 between ROSC and no-ROSC.

Table 2. p-values of features with each period

	A	B	C	D	E
IR	0.0500*	0.0034**	0.5804	0.1252	0.8291
SM2	0.0169*	0.1193	0.0035**	0.0050**	0.0010***
SM4	0.0067**	0.1988	0.0184*	0.0023**	0.0003***
MPLC	0.0048**	0.8058	0.4399	0.0079**	0.0001****
MRS	0.0651	0.1018	0.0185*	0.0047**	0.0025**
MP	0.0224*	0.2843	0.0127*	0.0037**	0.0003***
MF	0.0012**	0.3683	0.7613	0.0088**	0.0050**

*p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

The mean power of level-crossing spectrum(MPLC) showed the trend that the case of ROSC was greater than no-ROSC over all periods. Especially in a period E, the feature of MPLC showed the best discrimination performance in all over the features and the periods. The mean alpha-significant value(MRS) and mean power of spectrum(MP) resulted in having a reliable performance of p<0.05 in the latter three period from C to E.

In order to select two input features which were used for the neuro-fuzzy inference system, p-values were sorted in small order as shown in Table 3. On the whole, a period E shows the best discrimination performance by the features of MPLC and SM2 in compared with other periods. The period A and D had the similar discrimination performance about p-value of 0.003. The period C showed relatively low performance even though p-value was smaller than 0.01, but it is reliable criteria to discriminate ROSC and no-ROSC because of p<0.05.

Table 3. Selected features and averages of the smallest two p-values with each period

	A	B	C	D	E
Input 1	MF**	IR**	SM2**	SM4**	MPLC****
Input 2	MPLC**	MRS	MP*	MP**	SM2***
Average	0.0032	0.0543	0.0081	0.0030	0.0002

*p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

However, a period B was not available to discriminate between two signals using two features of IR and MRS because of p>0.05. Given that only one feature of IR was used, it possible to be reasonable factor. But since just one input feature does not compose a neuro-fuzzy inference system, a period B was excluded to estimate a prediction of defibrillation.

By using these selected two features with each period, the process of training data was performed. Total 10 times of epoch were trained, then an epoch to have the smallest error was finally selected to the inference system of predicting successful defibrillation.

The results for predicting defibrillation from animal experiments of 15 dogs are shown in Table 4 and Table 5.

Table 4. Prediction results of true positive(TP), false positive(FP), false negative (FN), and true negative(TN)

Period	TP	FP	FN	TN
A	5	2	1	7
C	2	3	4	6
D	4	2	2	7
E	4	2	2	7

Table 5. Performance of predicting defibrillation with each period

Period	Sensitivity	Specificity	Positive predictive factor	Negative predictive factor
A	83.3%	77.8%	71.4%	87.5%
C	33.3%	66.7%	40.0%	60.0%
D	66.7%	77.8%	66.7%	77.8%
E	66.7%	77.8%	66.7%	77.8%

As results, the maximum sensitivity and specificity were 83.3% in period A and 77.8% in all period except for B. The best prediction performance was shown in a period A, on the contrary, a period C showed relatively low performance.

The average of sensitivity and specificity were 62.5% and 75.0%, respectively. The average of positive predictive factor and negative predictive factor were 61.2% and 75.8%, respectively. On the whole, specificity and negative predictive factor were greater than sensitivity and positive predictive factor.

IV. DISCUSSION AND CONCLUSION

The purpose of this study was to predict successful defibrillation in ventricular fibrillation using parameters extracted by wave analysis method and neuro-fuzzy. Total 15 dogs were tested for predicting successful defibrillation. The FIR bandpass filter of 5~30Hz was used for removing CPR and noise from ECG signals. Then feature parameters were extracted for ROSC and non-ROSC by wave analysis method, and these parameters are an irregularity factor, spectral moments, mean power of level-crossing spectrum, and mean of alpha-significant value. Additionally, two parameters by analyzing method of frequency were extracted into a mean of power spectrum and a mean frequency. Then extracted parameters were analyzed in which parameters result to have high performance of discriminating ROSC and non-ROSC by a statistical method of t-test.

The characteristic features with the best discrimination performance each period from A to E were mean frequency, irregularity, spectral moment m_2, spectral moment m_4, and mean power of level-crossing spectrum, respectively. But a period B resulted in the worst discrimination performance. Since the first drug ministration and CPR were operated, the discrimination performance of the period B between ROSC and no-ROSC would be worse rather than other periods. On the contrary, since defibrillations were operated by defibrillator and ventricular fibrillation signals were changed into normal or abnormal ECG in the period E, it seems to be possible to discriminate ROSC and no-ROSC apparently.

Consequently, the performance of prediction resulted in that unsuccessful cases had further good performance than successful cases. The cause of this result is that no-ROSC cases were many more than ROSC cases. But since no-ROSC cases happen more frequently in experiment cases of animal or practical cases, it seems to be reliable to use the predictive factor of successful defibrillation on the basis of unsuccessful results rather than successful results.

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