



A New Recognition System Based on Gabor Wavelet Transform for Shockable Electrocardiograms

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Authors' contributions

This work was carried out in collaboration among all authors. TO and HO designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. SA, KN, HM and YH managed the analyses of the study and the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

This paper presents a new recognition system for shockable arrhythmias for patients suffering from sudden cardiac arrest. In order to develop the recognition system, lots of electrocardiogram (ECGs) have been analyzed by using gabor wavelet transform (GWT). Although, there is a huge number of spectrum feature parameters, recognition performance for all combinations for spectrum feature parameters are evaluated, and on the basis of the evaluation results, useful and effective spectrum features for ECGs are extracted. As a result, the proposed recognition system based on the selected effective spectrum feature parameters can achieved good performance comparing with the existing results.

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1 INTRODUCTION

Sudden cardiac arrest is the abrupt loss of heart function, breathing and consciousness, and it is the leading cause of sudden death. It is well known that Ventricular Fibrillation (VF) is the serious arrhythmic event for patients suffering from sudden cardiac arrest, and Ventricular Tachycardia (VT) can be associated with an increased risk of sudden death, i.e. these arrhythmias are very serious and dangerous events. For patients suffering from sudden cardiac arrest, “the chain of survival” consisting of “early access”, “early cardiopulmonary resuscitation (CPR)”, “early defibrillation”, and “early advanced care” plays a key role for improvement of survival rate. Moreover, American Heart Association (AHA) recommends continuous chest compression during cardiopulmonary resuscitation (CPR) [1], and survival rates from witnessed VF sudden cardiac arrest decrease 7% to 10% if no CPR is provided¹. Additionally, the timely use of an electrical defibrillator (i.e. Automated External Defibrillators (AEDs)) may also lead to successful results for such patients², and thus AHA has recommended the timely and widespread deployment of AEDs [1, 2].

Now, AEDs evaluate the ECG of the patient and make judgement decision whether an electrical shock should be applied or not. Namely, the most important function in AEDs is the accurate and prompt recognition performance for Shockable ECGs. In order to achieve more higher performance, a wide variety of recognition systems has been proposed such as VF-filter [3], Hilbert Transform based method [4], correlation waveform analysis [5], fuzzy inference based discrimination algorithm [6] and so on. Moreover, a BP Neural Network-based approach for detection of Shockable ECGs

has also been presented [7]. On the other hand, there are the existing results for wavelet transform-based detection systems (e.g. [8, 9, 10, 11]). In our existing result [10], firstly some spectrum feature parameters based on are extracted, and next detection systems based on such spectrum feature parameters based on gabor wavelet transform (GWT) are presented. In addition, the detailed analysis result of our recognition system has also been presented [11, 12]. In these results [11, 12], the detection performance has been evaluated by using the average value for AUC (Area Under the Curve), and our results achieve more higher recognition performance comparing with the other systems (e.g. [3]–[7]). Furthermore, one can see that either systems proposed in our results [10, 11, 12] can detect “Sinus Rhythm (SR)” perfectly. However, there are still an important problem which should be solved as soon as possible. That is exact evaluation of the detection performance for Shockable and Non-Shockable ECGs. In other words, the detection performance for all combinations for spectrum feature parameters has not verified. Additionally, recognition systems in our results [10, 11, 12] consist of three classifiers (SR, Shockable (VF/VT) and Non-Shockable (PEA)), and those have same input parameters, and thus it may be able to reduce computational amounts in our results.

In this paper, we firstly show the evaluation result for effective spectrum feature parameters, and next a new recognition system for shockable ECGs are proposed. Namely, the recognition performance for all combinations³ for spectrum feature parameters which are selected in our results (e.g. [10, 11]) is evaluated. Next, the new recognition system based on the evaluation result for spectrum feature parameters is developed. Additionally, spectrum feature parameters for detection of “SR” have been discussed. It is

¹When bystander CardioPulmonary Resuscitation (CPR) is provided, the decrease in survival rates is more gradual and averages 3% to 4% per minute [13, 2].

²Note that VF and VT are referred to as “Shockable” ECGs.

³The total number of combinations for spectrum feature parameters is more than 2.7×10^7 .

obvious that the proposed recognition system can achieve more higher performance, and it is a natural extension of our results [10, 11]. Therefore, one can easily see that the result developed in this paper is very significant and efficient. This paper is organized as follows. In Section 2, “Shockable” and “Non-Shockable” ECGs are shown, and spectrum

feature parameters for ECGs are presented in 3. Moreover, performance evaluation results for all combinations for spectrum feature parameters are presented in Section 4. Furthermore, discussions for feature parameters associated with detection of “SR” are given. Finally, the new detection system is developed.

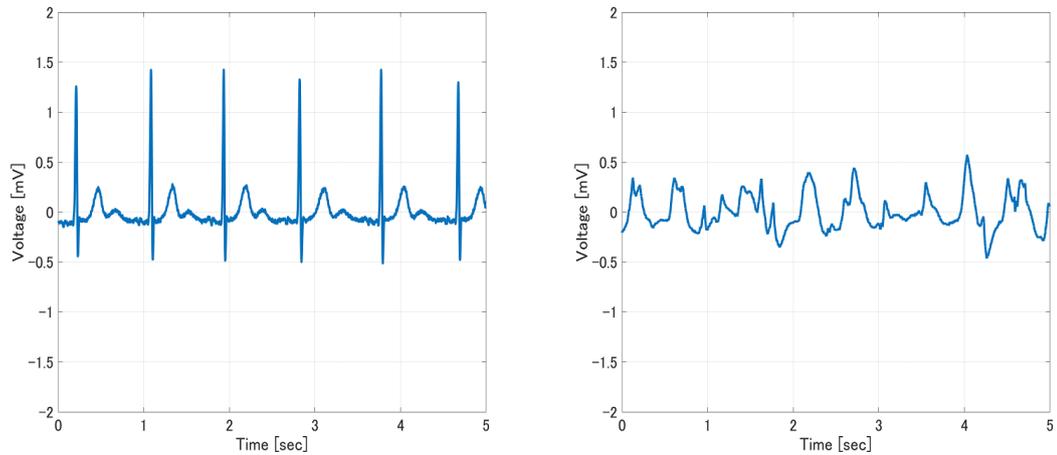


Fig. 1. An Example of Non-Schokable ECGs (SR : Left, PEA : Right)

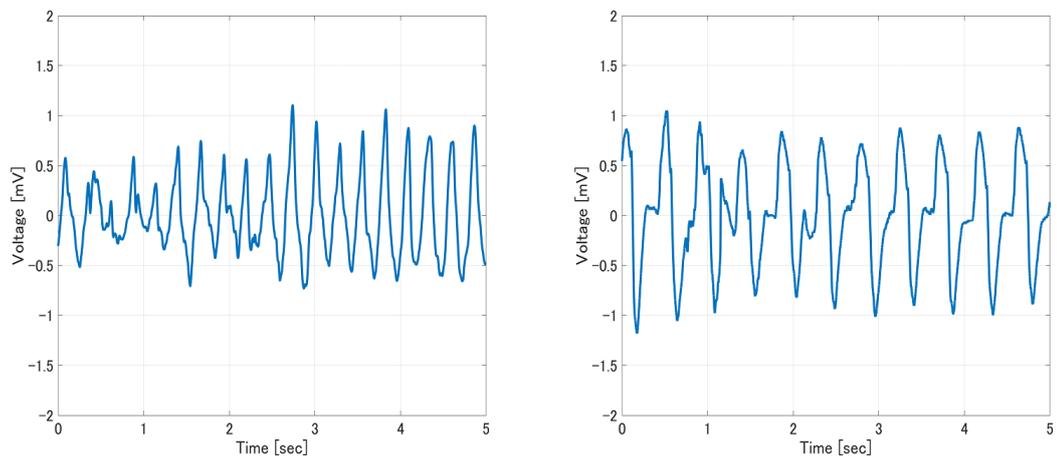


Fig. 2. An Example of Schokable ECGs (VF : Left, VT : Right)

2 SHOCKABLE AND NON-SHOCKABLE ECGS

In this section, firstly Shockable and Non-Shockable ECGs are presented, and their scalograms based on GWT are shown.

As shown in the our previous results [11, 12], one can see that there are the following 5 classes for ECGs;

- | | | |
|--|---|--------------|
| (i) VentricularFibrillation (VF) | } | Shockable |
| (ii) VentricularTachycardia (VT) | | |
| (iii) SinusRhythm (SR) | } | Nonshockable |
| (iv) PulselessElectricalActivity (PEA) | | |
| (v) Asystole (Asys) | | |

Note that “Asys” is also referred to as “a flat line”, i.e. it can easily be identified. Thus we consider “SR”, “VF”, “VT” and “PEA”. In addition, Shockable ECGs (VF and VT) and PEA are particularly investigated, provided that SR can perfectly be detected by the existing results [9, 10]. Furthermore in addition to some database such as AHA [14], MIT-BIH [15] and CU [16], ECG data corrected by “ECG data correction system” which is running at trauma and critical care center of Kyorin University Hospital (see [9] for details) are analyzed⁴.

Now, we show an example for ECGs for SR, PEA, VF and VT, respectively (see Figs 1. and 2.). In Fig. 1, “Left (resp. Right)” is “SR (resp. PEA)”, and “Left (resp. Right)” in Fig. 2. represents “VF (resp. VT)”. Furthermore, in order to analyze ECGs, GWT is adopted, and scalograms for ECGs in Figs 1. and 2. are shown in Fig. 3. and 4., respectively. Additionally, on the basis of scalograms, Normalize Spectrum Index (NSI) and Scale Distribution Width (SDW) [9, 10] can be derived, and spectrum feature parameters for ECGs are extracted by using indexes such as NSI, SDW and so on.

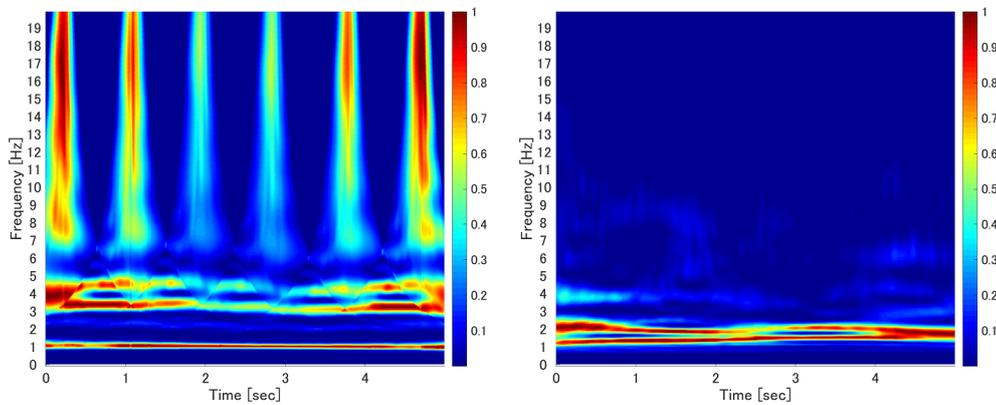


Fig. 3. Scalogram of Shockable ECGs in Fig. 1. (SR : Left, PEA : Right)

⁴Note that same conditions for analysis as those in the existing results [9, 10] are adopted.

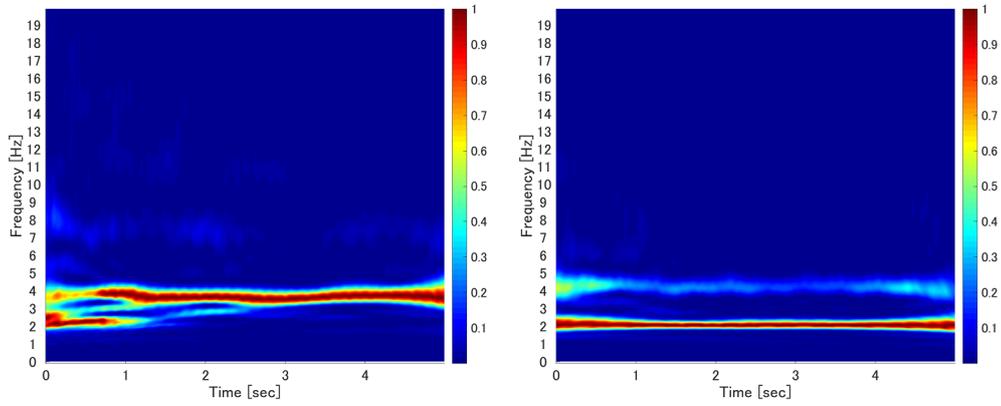


Fig. 4. Scalogram of Schokable ECGs in Fig. 2. (VF : Left, VT : Right)

Table 1. Extracted Spectrum Feature Parameters [12]

No.	Spectrum Feature parameter	Parameter name
1	Mean of NSI	\overline{NSI}
2	Variance of NSI	\mathcal{V}_{NSI}
3	Standard Variation of NSI	SD_{NSI}
4	Accumulation for Slope of NSI	\mathcal{A}_{NSI}
5	Skewness of NSI	SQ_{NSI}
6	Kurtosis of NSI	\mathcal{K}_{NSI}
7	Mode of NSI	\mathcal{M}_{NSI}
8	Accumulation for Slope of NSI's Histogram	\mathcal{A}_{NSI}^h
9	Mean of SDW	\overline{SDW}
10	Variance of SDW	\mathcal{V}_{SDW}
11	Standard Variation of SDW	SD_{SDW}
12	Accumulation for Slope of SDW	\mathcal{A}_{SDW}
13	Skewness of SDW	SQ_{SDW}
14	Kurtosis of SDW	\mathcal{K}_{SDW}
15	Mode of SDW	\mathcal{M}_{SDW}
16	Energy ratio [9]	$\mathcal{H}_{0,1}$
17	Difference of NSI and peak frequency [10]	\mathcal{E}^P
18	Weight of frequency [10]	\mathcal{S}^P
19	Total Power of Scalogram [10]	\mathcal{P}_{NNS}

Table 2. Spectrum Feature Parameters for Recognition of “SR”

No.	Spectrum Feature Parameters					AUC (Minimum Value)	
						SR vs VF	SR vs PEA
2	\mathcal{V}_{NSI}	\mathcal{P}_{NNS}	–	–	–	1.0	1.0
3	SD_{NSI}	\mathcal{P}_{NNS}	–	–	–	1.0	1.0
4	\mathcal{A}_{NSI}	\mathcal{P}_{NNS}	–	–	–	1.0	1.0
6	$\overline{\text{NSI}}$	\mathcal{V}_{NSI}	\mathcal{P}_{NNS}	–	–	1.0	1.0
7	$\overline{\text{NSI}}$	SD_{NSI}	\mathcal{P}_{NNS}	–	–	1.0	1.0
8	$\overline{\text{NSI}}$	\mathcal{A}_{NSI}	\mathcal{P}_{NNS}	–	–	1.0	1.0
10	$\overline{\text{NSI}}$	\mathcal{M}_{NSI}	\mathcal{P}_{NNS}	–	–	1.0	1.0
12	$\overline{\text{NSI}}$	$\overline{\text{SDW}}$	\mathcal{P}_{NNS}	–	–	1.0	1.0
⋮							
76	\mathcal{E}^{P}	\mathcal{S}^{P}	\mathcal{P}_{NNS}	–	–	1.0	1.0
⋮							
1162	\mathcal{V}_{NSI}	\mathcal{A}_{NSI}	\mathcal{M}_{NSI}	SD_{SDW}	\mathcal{P}_{NNS}	1.0	1.0
⋮							

3 SPECTRUM FEATURE PARAMETERS BASED ON GWT

In this section, we show spectrum feature parameters which have shown in the existing results [9, 10, 11].

In the existing results [9, 10, 11], 38 spectrum feature parameters have been suggested. one can easily see that the total number of combinations for 38 spectrum feature parameters presented in the existing results [9, 10, 11] is more than 2.7×10^7 . Moreover, for these spectrum feature parameters, combinations that covariance matrices for Maharanobis distance become singular (i.e. Maharanobis distance cannot be calculated in this case) have been discussed in our previous work [12]. Thus, the spectrum feature parameters corresponding to combinations such that Mahalanobis distance cannot be calculated are excluded. Furthermore, spectrum feature parameters based on original ECGs are sensitive/fragile. As a result, 19 spectrum feature parameters based on GWT in Table 1. have been extracted [12]. Although

we have verified the recognition performance for “all of combinations (=11,628)” for 5 spectrum feature parameters [12], the best combination for spectrum feature parameters have not been still shown. In this paper, we evaluate the best combination for spectrum feature parameters and the evaluation result will be shown in the next section.

4 EVALUATION OF SPECTRUM FEATURE PARAMETERS AND THE PROPOSED NEW DETECTION SYSTEM

This section gives our main results, i.e. evaluation results for all combinations for spectrum feature parameters and a new detection system based on the evaluation result is proposed. In order to verify the recognition performance corresponding to various combinations for spectrum feature parameters, we adopt \mathcal{K} -fold cross-validation ($\mathcal{K} = 4$) [11, 17]

Table 3. Spectrum Feature Parameters (The Top 10 : Case A)

Ranking	Spectrum Feature Parameters						
	\mathcal{V}_{NSI}	SD_{NSI}	\mathcal{A}_{NSI}	\mathcal{M}_{NSI}	SD_{SDW}	\mathcal{P}_{NNS}	–
1	$\overline{\text{NSI}}$	\mathcal{V}_{NSI}	SD_{NSI}	\mathcal{A}_{NSI}	\mathcal{P}_{NNS}	–	–
2	$\overline{\text{SDW}}$	SD_{SDW}	\mathcal{P}_{NNS}	–	–	–	–
3	\mathcal{V}_{NSI}	SD_{NSI}	\mathcal{A}_{NSI}	\mathcal{S}^{P}	\mathcal{P}_{NNS}	–	–
4	$\overline{\text{SDW}}$	SD_{SDW}	\mathcal{M}_{SDW}	\mathcal{P}_{NNS}	–	–	–
5	$\overline{\text{NSI}}$	\mathcal{V}_{NSI}	SD_{NSI}	\mathcal{A}_{NSI}	SD_{SDW}	\mathcal{P}_{NNS}	–
6	\mathcal{V}_{NSI}	SD_{NSI}	\mathcal{A}_{NSI}	SD_{SDW}	\mathcal{S}^{P}	\mathcal{P}_{NNS}	–
7	$\overline{\text{NSI}}$	SD_{NSI}	\mathcal{A}_{NSI}	\mathcal{M}_{NSI}	\mathcal{P}_{NNS}	–	–
8	$\overline{\text{NSI}}$	SD_{NSI}	\mathcal{A}_{NSI}	\mathcal{M}_{NSI}	SD_{SDW}	\mathcal{P}_{NNS}	–
9	$\overline{\text{NSI}}$	SD_{NSI}	\mathcal{A}_{NSI}	\mathcal{M}_{NSI}	$\mathcal{A}_{\text{NSI}}^{\text{h}}$	SD_{SDW}	\mathcal{P}_{NNS}
10	$\overline{\text{NSI}}$	SD_{NSI}	\mathcal{A}_{NSI}	\mathcal{M}_{NSI}	$\mathcal{A}_{\text{NSI}}^{\text{h}}$	SD_{SDW}	\mathcal{P}_{NNS}

Table 4. Average and Minimum Values of AUC (The Top 10 : Case A)

Ranking	$\overline{\text{AUC}} \times 10^{-1}$	$\underline{\text{AUC}} \times 10^{-1}$	$\sigma \times 10^{-4}$
1	<u>9.6778</u>	9.0575	1.4295
2	<u>9.6748</u>	9.0841	1.3758
3	<u>9.6735</u>	9.3207	1.4593
4	<u>9.6732</u>	9.1371	1.3316
5	<u>9.6731</u>	9.9609	1.3175
6	<u>9.6702</u>	9.0371	1.4226
7	<u>9.6700</u>	9.0983	1.3649
8	<u>9.6674</u>	9.1269	1.3944
9	<u>9.6647</u>	9.1310	1.3995
10	<u>9.6633</u>	9.0779	1.3254

4.1 Evaluation Results for Spectrum Feature Parameters

In our work [11], “3” feature parameters have been adopted, and we have shown the recognition performance based on 3 feature parameters. Moreover, recognition performance based on “3”, “5” and “19” feature parameters have been discussed in the existing result [12]. However, the best combination for spectrum feature parameters have not been still evaluated. Therefore, all of combinations for feature parameters in Table 1. are verified. For the purpose of evaluation of recognition performance, \mathcal{K} -fold cross-validation ($\mathcal{K} = 4$) is adopted, and training data is randomly separated into a train and evaluation partition. Since we have 1,132 ($=\mathcal{N}_{\text{total}}$) signals (PEA (Non-shockable) : 224 ($=\mathcal{N}_{\text{total}}^{\text{PEA}}$), SR (Non-shockable) : 552 ($=\mathcal{N}_{\text{total}}^{\text{SR}}$), Shockable (VF and VT) : 356 ($=\mathcal{N}_{\text{total}}^{\text{DC}}$)). If \mathcal{T} signals in $\mathcal{N}_{\text{total}}$ ones are used for training, then the left out $\mathcal{N}_{\text{total}} - \mathcal{T}$ signals are utilized for testing. In addition, training and testing are repeated 50 times.

Table 5. Spectrum Feature Parameters (The Top 10 : Case B)

Ranking	Spectrum Feature Parameters				
1	\overline{SDW}	SD_{SDW}	\mathcal{P}_{NNS}	–	–
2	\overline{SDW}	SD_{SDW}	\mathcal{M}_{SDW}	\mathcal{P}_{NNS}	–
3	\overline{SDW}	SD_{SDW}	\mathcal{M}_{SDW}	\mathcal{S}^P	\mathcal{P}_{NNS}
4	\overline{SDW}	SD_{SDW}	\mathcal{K}_{SDW}	\mathcal{M}_{SDW}	\mathcal{P}_{NNS}
5	\overline{SDW}	SD_{SDW}	\mathcal{M}_{SDW}	\mathcal{E}^P	\mathcal{P}_{NNS}
6	\mathcal{M}_{NSI}	\mathcal{A}_{NSI}^h	\mathcal{E}^P	\mathcal{P}_{NNS}	–
7	\mathcal{M}_{NSI}	\mathcal{A}_{NSI}^h	\mathcal{K}_{SDW}	\mathcal{E}^P	\mathcal{P}_{NNS}
8	\overline{SDW}	SD_{SDW}	\mathcal{K}_{SDW}	\mathcal{P}_{NNS}	–
9	\mathcal{A}_{NSI}^h	\overline{SDW}	SD_{SDW}	\mathcal{E}^P	\mathcal{P}_{NNS}
10	\mathcal{M}_{NSI}	\mathcal{A}_{NSI}^h	SD_{SDW}	\mathcal{E}^P	\mathcal{P}_{NNS}

Table 6. Minimum and Average Values of AUC (The Top 10 : Case B)

Ranking	$\underline{AUC} \times 10^{-1}$	$\overline{AUC} \times 10^{-1}$	$\sigma \times 10^{-4}$
1	<u>9.3207</u>	9.6735	1.4593
2	<u>9.3175</u>	9.6731	1.5813
3	<u>9.3146</u>	9.6444	1.6396
4	<u>9.3064</u>	9.6606	1.6830
5	<u>9.3023</u>	9.6394	1.7527
6	<u>9.3023</u>	9.6210	1.7255
7	<u>9.3003</u>	9.5981	1.8046
8	<u>9.2983</u>	9.6490	1.5495
9	<u>9.2954</u>	9.6143	1.8574
10	<u>9.2901</u>	9.6307	1.6238

Firstly, we discuss combinations for feature parameters corresponding to recognition of “SR”. In the existing results [9, 10, 11], it has been shown that the recognition performance for “SR” is perfect, i.e. 100%. In this section, we show more detailed analysis results for detection of “SR”. There are lots of combinations for spectrum feature parameters for detection of “SR”, and a part of those is shown in Table 2.. Namely, by adopting combinations for the feature parameters in Table 2., “SR” is perfectly-recognized. In Table 2., “No.” means index for combinations, and “–” means “None”. Additionally, spectrum feature parameters in No. 76 and No. 1162 have also been shown in our results [11, 12]. On the other hand, for the complete detection of “SR”, there are some combinations consisting of 2 or 3 feature parameters (see Table 2.). This fact shows that the computational amount for the recognition of “SR” can be reduced. In the following, efficient spectrum feature parameters for detection of “Shockable ECGs (VF/VT)” and “Non-Shockable (PEA)” are evaluated, and on the basis of the evaluation results, the spectrum feature parameters for recognition of “SR” are also determined.

Now the evaluation results for “Shockable ECGs (VF/VT)” and “Non-Shockable (PEA)” are shown in Tables 3. and 4.. In this paper, we show the following two cases for the top 10 combinations for

spectrum feature parameters;

- Case A : Descending order in the average value of AUC,
- Case B : Descending order in the minimum value of AUC,

Moreover, recognition performance for “Shockable (VF/VT)” and “Non-Shockable (PEA)” are evaluated by the average value and the minimum one for AUC, and thus $\overline{\text{AUC}}$, $\underline{\text{AUC}}$ and σ in Tables 4. and 6. mean the minimum value, the average one and the variance for AUC. Tables 3. and 4. (resp. Tables 5. and 6.) represent the results for Case A (resp. Case B), i.e. Tables 5. and 6. show the evaluation result in the worst case. Note that “–” in Tables 3. and 5. means “None”.

From Tables 3. and 5., the number of spectrum feature parameters for “Case B” is less than one “Case A”. Moreover, one can see from Tables 4. and 6. that although $\overline{\text{AUC}}$ (average value) and σ (variance) in “Case A” nearly equal to ones in “Case B”, $\underline{\text{AUC}}$ (minimum value) in “Case A” is not good comparing with in “Case B”. This results show that the recognition performance for “Shockable (VF/VT)” and “Non-Shockable (PEA)” in “Case A” is 9.0371×10^{-1} or more and it can be achieved by using at least 5 spectrum feature parameters, while the recognition performance in “Case B” is 9.2901×10^{-1} or more. Additionally, we find that the difference between $\overline{\text{AUC}}$ and $\underline{\text{AUC}}$ in “Case A” is more larger than “Case B”, and the third combination (Ranking 3) for spectrum feature parameters in “Case A” is same as the best one (Ranking 1) in “Case B”.

Table 7. Comparison between the existing results and the proposed detection system

	Proposed	[9]	[18]	[12]
$\overline{\text{AUC}} \times 10^{-1}$	9.6735	8.700	9.2600	9.6530

Table 7. shows the results of the comparison between the existing results and the proposed detection system. Note that since the performance evaluation for the existing results [9], [18] and [12] have been discussed the mean value of AUC, we compare the mean values of AUC for the proposed detection system and the existing results. In [9], discrimination algorithm based on Mahalanobis distance with 3 feature parameters (VF-Filter Leakage [3], \mathcal{A}_{NSI} and $\mathcal{H}_{0,1}$). [18] have also adopted 3 feature parameters (Average of amplitude for ECG signals, \mathcal{A}_{NSI} and S^p) and presented a Neural Network-based detection system. Moreover, in the work of [12], 5 feature parameters (\mathcal{V}_{NSI} , \mathcal{A}_{NSI} , \mathcal{M}_{NSI} , SD_{SDW} and \mathcal{P}_{NNS}) have been utilized for recognition. From Table 7, we find that the proposed detection system can achieve good recognition performance both of minimum and average values for AUC.

4.2 The Proposed Recognition System for Shockable ECGs

As mentioned in 4.1, one can see from Tables 3, 6. that the following important points for the evaluation results;

- The recognition performance for “Shockable (VF/VT)” and “Non-Shockable (PEA)” in “Case A” is 9.0371×10^{-1} or more, and one in “Case B” is 9.2901×10^{-1} or more.
- The difference between $\overline{\text{AUC}}$ and $\underline{\text{AUC}}$ in “Case A” is large comparing with “Case B”.
- The third combination (Ranking 3) for spectrum feature parameters in “Case A” is same as the top one (Ranking 1) in “Case B”.

On the basis of these important points, we adopt the following spectrum feature parameters for recognition of “Shockable (VF/VT)” and “Non-Shockable (PEA)”;

- \overline{SDW} , SD_{SDW} , \mathcal{P}_{NNS} ,

and then the recognition performance for “Shockable (VF/VT)” and “Non-Shockable (PEA)” is at least 9.3207×10^{-1} or more.

Next we consider spectrum feature parameters for detection of “SR”. From Table 2., “SR” can perfectly be detected by at least 2 spectrum feature parameters. Although it is desirable that the spectrum feature parameters for detection of “SR” are included in \overline{SDW} , SD_{SDW} , \mathcal{P}_{NNS} , that is not satisfied. However, we see that spectrum feature parameters \overline{SDW} and \mathcal{P}_{NNS} in “No.12” in Table 2. are also included in the best combination (Ranking 1) in Table 5.. Therefore, in order to discriminate “SR”, “Shockable ECGs (VF/VT)” and “Non-Shockable (PEA)”, the 4 spectrum feature parameters \overline{NSI} , \overline{SDW} , SD_{SDW} and \mathcal{P}_{NNS} are required. Namely, by using the spectrum feature parameters \overline{NSI} , \overline{SDW} , SD_{SDW} and \mathcal{P}_{NNS} , the guaranteed recognition performance for “Shockable ECGs (VF/VT)” and “Non-Shockable (PEA)” is at least 9.3207×10^{-1} or more.

From the above discussion, we develop a new recognition system for Shockable ECGs, and the procedure of the proposed recognition system is as follows;

The Procedure of The Proposed Recognition System

- (i). Derive the scalogram based on GWT for ECGs.
- (ii). Compute the spectrum feature parameters

- \overline{NSI} , \overline{SDW} , SD_{SDW} and \mathcal{P}_{NNS} ,

and construct two vectors $y_{SR} \triangleq (\overline{NSI}, \overline{SDW}, \mathcal{P}_{NNS})$ and $y_{DC} \triangleq (\overline{SDW}, SD_{SDW}, \mathcal{P}_{NNS})$.

- (iii). Compute the following 3 Mahalanobis distances;

$$\begin{aligned} \mathcal{D}_{SR}^2 &\triangleq (y_{SR} - \bar{y}_{SR})^T \Sigma_{SR}^{-1} (y_{SR} - \bar{y}_{SR}), \\ \mathcal{D}_{DC}^2 &\triangleq (y_{DC} - \bar{y}_{DC})^T \Sigma_{DC}^{-1} (y_{DC} - \bar{y}_{DC}), \\ \mathcal{D}_{PEA}^2 &\triangleq (y_{DC} - \bar{y}_{PEA})^T \Sigma_{PEA}^{-1} (y_{DC} - \bar{y}_{PEA}). \end{aligned} \quad (4.1)$$

where $\Sigma_{SR} \in \mathbb{R}^{3 \times 3}$, $\Sigma_{DC} \in \mathbb{R}^{3 \times 3}$ and $\Sigma_{PEA} \in \mathbb{R}^{3 \times 3}$ are covariance matrices and \bar{y}_{SR} , \bar{y}_{DC} and \bar{y}_{PEA} are mean values for spectrum feature parameter vectors corresponding to $y_{SR} \triangleq (\overline{NSI}, \overline{SDW}, \mathcal{P}_{NNS})$ and $y_{DC} \triangleq (\overline{SDW}, SD_{SDW}, \mathcal{P}_{NNS})$.

- (iv). Discrimination of the victim' ECG :

- If $\mathcal{D}_{SR}^2 < \mathcal{D}_{DC}^2$ and $\mathcal{D}_{SR}^2 < \mathcal{D}_{DC}^2$, then the victim's ECG is “Nonshockable” (SR).
- If $\mathcal{D}_{DC}^2 < \mathcal{D}_{SR}^2$ and $\mathcal{D}_{DC}^2 < \mathcal{D}_{PEA}^2$, then the victim's ECG is “Shockable (VF/VT)”.
- If $\mathcal{D}_{PEA}^2 < \mathcal{D}_{SR}^2$ and $\mathcal{D}_{PEA}^2 < \mathcal{D}_{DC}^2$, then the victim's ECG is “Nonshockable (PEA)”.

5 CONCLUSIONS

In this paper, we have proposed a new recognition system for shockable ECGs for patients suffering from sudden cardiac arrest. In order to develop the proposed system, recognition performance in “all of combinations” for spectrum feature parameters has been evaluated. The evaluation of recognition performance has been done by using both the average value and the minimum one for AUC, and the variance for AUC has also been shown. Furthermore, efficient feature parameters for

recognition of “Sinus Rhythm (SR)” have been discussed. Although the recognition systems in our previous results [10, 11, 12] consist of three classifiers (SR, Shockable (VF/VT) and Non-Shockable (PEA)) which have same inputs, the classifier for “SR” in the new recognition system has different inputs from classifiers for Shockable (VF/VT) and Non-Shockable (PEA). Consequently, the proposed recognition system can achieve good performance and quick recognition comparing with our result [10, 11, 12]. Namely, one can easily see that the result developed in this paper is a natural extension of

our previous results [10, 11, 12] and the proposed system is very efficient and significant.

On the other hand, both the recognition system in this paper and our previous results [10, 11, 12] have slightly possibility for classifying "PEA" into "Shockable". Since the electrical defibrillation should not be applied to the patient whose ECG is PEA, such result should be avoided. Therefore, we will improve our recognition system so as to avoid such result, i.e. improvement for achievement of more higher sensitivity for recognition of PEA will be tackled. Additionally, our future research subject is extension of the proposed system to some cases such as the case that patient's sinus rhythm was resumed, nonsustained ventricular tachycardia (NSVT), and so on.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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