An Wavelet Transform-Based Discrimination Algorithm for Electrocardiogram

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***Abstract*—Serious arrhythmic events in most of patients suffering from sudden cardiac arrest are Ventricular Fibrillation (VF) and Ventricular Tachycardia (VT). For these serious arrhythmic events, the timely employment of an electrical defibrillator may lead to successful results. From this viewpoint, widespread deployment of Automated External Defibrillators (AEDs) has been suggested and the most important component in AEDs is accurate and quick detection of these events by means of an appropriate algorithm. However quick and accurate detection of ventricular arrhythmia is not easy. In this paper, we analyze ECG data by using Gabor Wavelet Transform (GWT) and on the basis of the analysis results, we propose a new detection algorithm. Finally, we evaluate the proposed detection algorithm.**

I. Introduction

Sudden cardiac arrest is very important public health problem and is caused by Ventricular Tachycardia (VT) and Ventricular Fibrillation (VF). Especially, VF is the serious arrhythmic event in most of patients suffering from sudden cardiac arrest. Despite improvements in emergency systems, about 30,000 people die from sudden cardiac arrest annually in Japan and 275,000 in Europe[1]. For improving survival rate, it is well known that the chain of survival defined as early access, early cardiopulmonary resuscitation (CPR), early defibrillation, and early advanced care is important. In particular, early defibrillation is a key role to survive the patient suffering from sudden cardiac arrest[2, 3] and the timely and widespread deployment of Automated External Defibrillators (AEDs) has been recommended by the American Heart Association (AHA)[4]. From this viewpoint, AEDs are installed in train stations, airports and so on.

AEDs analyze the electrocardiogram (ECG) and recognize whether an electrical shock should be applied or not, i.e. the performance of detection algorithms in AEDs is of great importance. In other words, quick and reliable detection performance for analysis algorithms is required. Thus it is very important to improve the performance of detection algorithms and a wide variety of algorithms have been studied, such as VF-filter algorithm[5], correlation waveform analysis[6], fuzzy inference based discrimination algorithm[7], spectral analysis[9], Hilbert Transform based method[8], and so on. In the work of Oya et al.[15, 16], although good detection performance for ventricular arrhythmia can be achieved, Pulseless Electrical Activity (PEA) has not been considered. Namely accurate, quick and reliable detection of ventricular arrhythmia and/or PEA is not easy, and thus many researchers are now tackling the development of ECG detection algorithms.

In this paper, on the basis of the existing result[17], we propose a new detection algorithm for the ECG based on wavelet transform. The proposed algorithm consists of two parts. Firstly, the proposed algorithm recognizes Sinus Rhythm (SR) which is Nonshockable ECG, and next Shockable ECGs (VF and VT) are detected. The performance of the proposed algorithm is evaluated by using the receiver operating characteristic (ROC) curve. The result in this paper is very useful because the proposed algorithm can achieve good performance and quick detection comparing with the existing results[16, 17].

Notations: For a vector x_p $(p = 1, \cdots, \mathcal{M})$ with an appropriate dimension, the mean vector of x is denoted by $\overline{x}$, i.e. $\overline{x}$ means $\overline{x} \stackrel{\triangle}{=} \dfrac{1}{\mathcal{M}} \displaystyle\sum_{p=1}^{\mathcal{M}} x_p$. Besides, for a matrix $\mathcal{X}$ which has an appropriate dimension, $\mathcal{X}^{-1}$ and $\mathcal{X}^T$ represent its inverse and its transpose, respectively and $f^\sharp(t)$ means a complex conjugate of the function $f(t)$. The symbols "$\stackrel{\triangle}{=}$" and "$\star$" mean equality by definition and symmetric blocks in the matrix representation, respectively.

II. Analysis of ECG via Wavelet Transform

In order to develope a detection algorithm, we have to collect various ECG data. It is well known that there are some database such as Boston's Beth Israel Hospital and MIT arrhythmia database (MIT-BIH database)[11], American Heart Association database (AHA database)[12], Creighton University Ventricular Tachyarrhythmia database (CU database)[13] and so on, and in this study we use AHA database and MIT-BIH database. In addition we are collecting various ECG data by using the ECG data collection system which is running at trauma and critical care center of Kyorin University Hospital. The ECG data collection system can record not only ECG data but also video image and voice data, i.e. we can verify the relation between the ECG data and disposal to a patient. In this section firstly we show Gabor Wavelet Transform (GWT) and derived quality parameters for some ECG data. In the

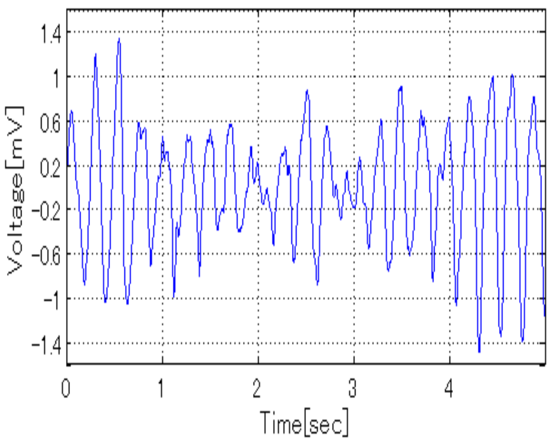

Fig. 1. An example of VF signals

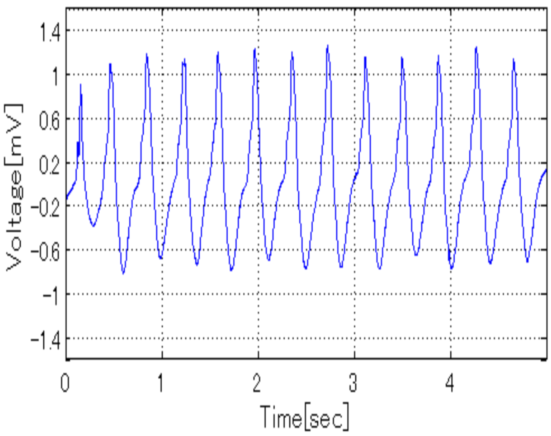

Fig. 2. An example of VT signals

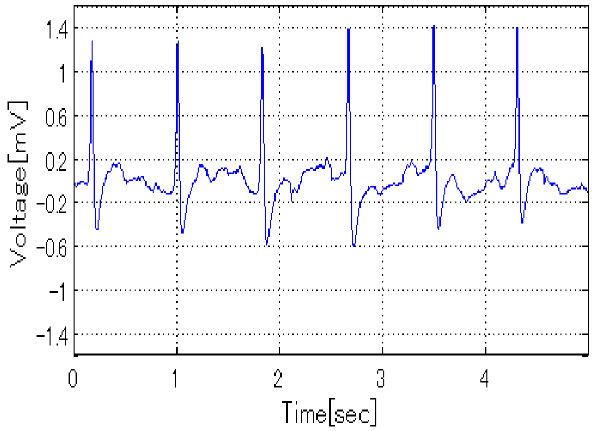

Fig. 3. An example of SR signals

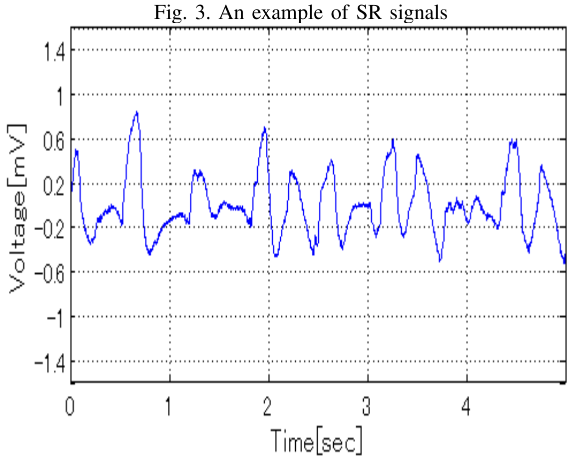

Fig. 4. An example of PEA signals

next section, we show our detection algorithm based on these quality parameters.

A. ECG signals and Gabor Wavelet Transform (GWT)

It is well known that there are the following 5 types of ECG signals.

i) Ventricular Fibrillation (VF) : Shockable
ii) Ventricular Tachycardia (VT) : Shockable
iii) Sinus Rhythm (SR) : Nonshockable
iv) Pulseless Electrical Activity (PEA) : Nonshockable
v) Asystole (Asys) : Nonshokable

Figures 1 – 4 show VF, VT, SR and PEA, respectively, and in this paper, we have focused these four types of ECG signals except for Asys, because Asys can easily be deteceted. Additionally on the basis of the present AED system, we introduce the following analysis conditions for the ECG data.

- Data length is 5.0 [sec].
- The amplitude is larger than 0.1[mv].
- The frequency band width considered here is $[1.0, 10.0]$ [Hz].

Besides, the sampling frequency for the ECG data is 1.0[kHz] (the ECG data correction system) or 360[Hz] (AHA database and MIT-BIH database).

In this paper, we adopt Gabor Wavelet Transform (GWT)[17] so as to analyze ECG signals. The continuos wavelet transform is defined as

$$\mathcal{W}_\psi f(b,a) \triangleq \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) {\psi_{a,b}}^\sharp (t) dt \tag{1}$$

where the function $\psi_{a,b}(t)$ is derived by $\psi_{a,b}(t) = \psi\left(\frac{t-b}{a}\right)$. The function $\psi(t)$ is reffered to as "the mother wavelet" and in this paper, we adopt Gabor wavelet

$$\psi(t) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{t^2}{2\sigma^2}} e^{j\omega_0 t}. \tag{2}$$

Now we show some analysis results. Figures 5 – 8 show the analysis results for VF, VT, SR and PEA, respectively. Note that these ECG signals can be obtained by applying a low-pass filter with a cut-offfrequency of 0.5[Hz].

VF and VT are shokable ECG signals and the characteristics of VF appear in the range between 3.0[Hz] and 6.0[Hz], and we see from Figure 5 that the peak frequency which has maximum power varies randomly. On the other hand, the ECG

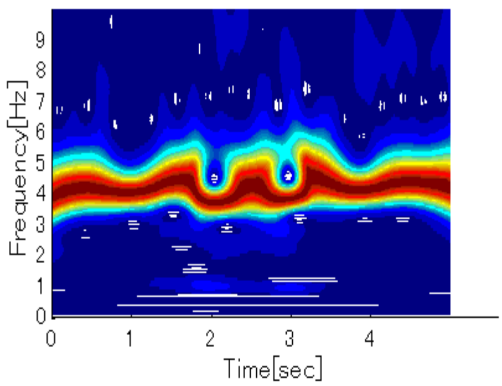

Fig. 5. Scalogram of VF in Figure 1

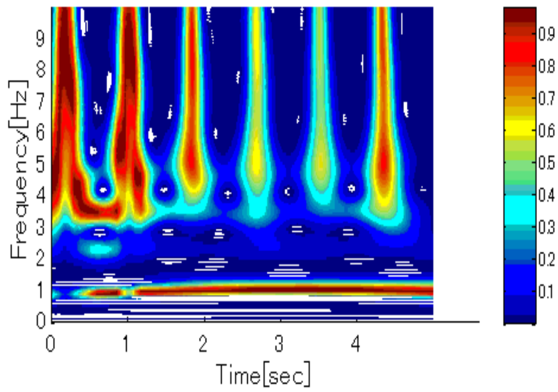

Fig. 7. Scalogram of SR in Figure 3

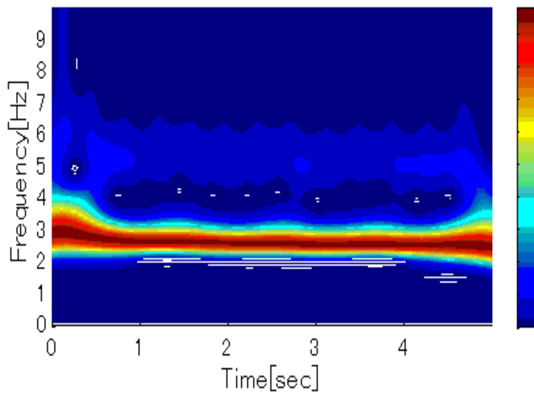

Fig. 6. Scalogram of VT in Figure 2

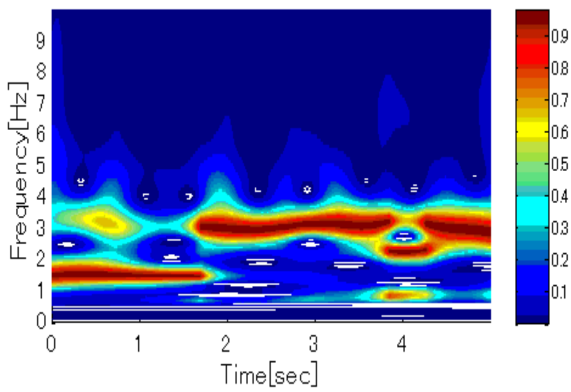

Fig. 8. Scalogram of PEA in Figure 4

for VT is periodic and its peak frequency is nearly constant. For SR, one can see from Figure 7 that a striped pattern in scalogram can be verified. In addition, we find that a part of PEA signals has a similar property to SR, i.e. there exists a signal like QRS pattern.

B. The Quality Parameters

In order to develope a discrimination algorithm for ECG signals, on the basis of the existitng results[15, 16, 17] we adopt the following quality parameters.

i) $\mathcal{NSI}$ (Normalized Spectrum Index)[15, 16]
The parameter $\mathcal{NSI}(k)$ is defined as

$$\mathcal{NSI}(k) \triangleq \frac{\sum_j \mathcal{Y}_{(k,j)} f_j}{\sum_j \mathcal{Y}_{(k,j)}} \tag{3}$$

where j $(j = 10, \cdots, 100)$ and k $(k = 1, \cdots, \mathcal{N})$ means the sample number for the frequency sample (j) in scalogram and the time one (k), respectively. Note that $\mathcal{N}$ is the number of the time sample, i.e. $\mathcal{N} = 5000$ in this paper. Additionally, $\mathcal{Y}(k, j)$ and f_j denote the normalized power in the scalogram obtained by $\mathcal{W}_\psi f(b, a)$ and the frequency for the j-th frequency element at the time sample k in scalogram, respectively. Note that $\mathcal{Y}(k, j)$ can be computed as

$$\mathcal{Y}_{(k,j)} = \frac{\mathcal{E}_{(k,j)}}{\max_j(\mathcal{E}_{(k,j)})} \tag{4}$$

where $\mathcal{E}_{(k,j)}$ denotes the scalogram of the obtained ECG signal. Figures 9 – 12 show $\mathcal{NSI}(k)$ for VF, VT, SR and PEA, respectively.

ii) Variance for $\mathcal{NSI}$[17]
In this paper, we introduce the parameter σ^2 for $\mathcal{NSI}$ defined as

$$\sigma^2 \triangleq \frac{1}{\mathcal{N}} \sum_{k=1}^{\mathcal{N}} (\mathcal{NSI}(k) - \mu^*)^2 \tag{5}$$

where the parameter μ^* is a median of $\mathcal{NSI}$ given by

$$\mu^* = \frac{\max_k \{\mathcal{NSI}(k)\} - \min_k \{\mathcal{NSI}(k)\}}{2} + \min_k \{\mathcal{NSI}(k)\} \tag{6}$$

and the parameter σ^2 can be used to detect SR.

iii) Slope for the peak frequencies in scalogram
We calculate the sum of slope for peak frequencies in the

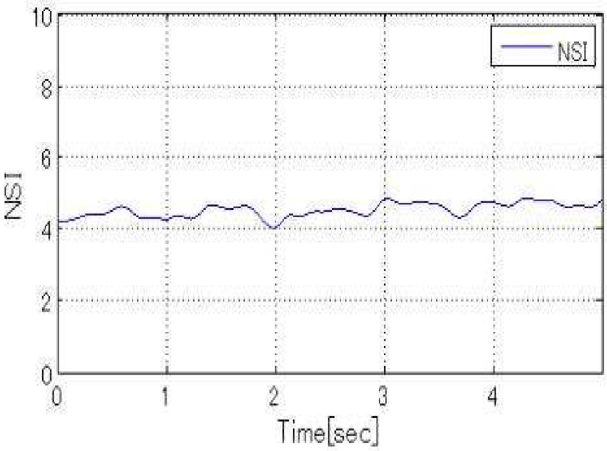

Fig. 9. $\mathcal{NSI}(k)$ of VF in Figure 5

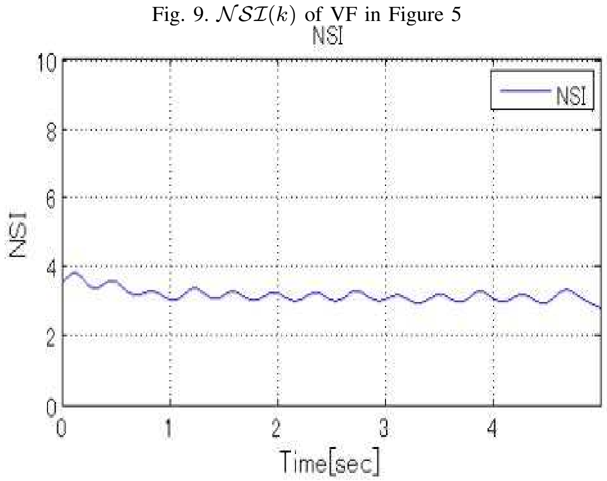

Fig. 10. $\mathcal{NSI}(k)$ of VT in Figure 6

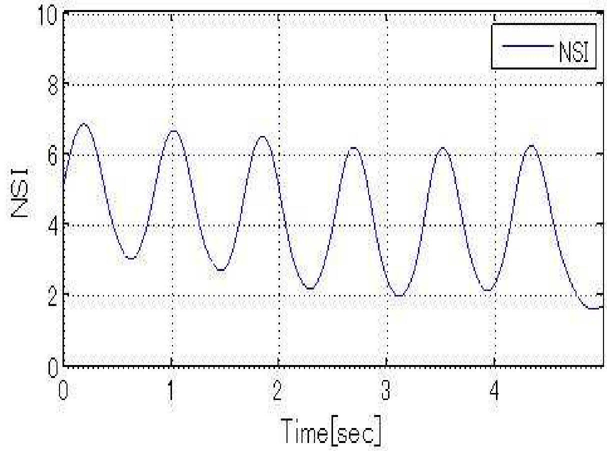

Fig. 11. $\mathcal{NSI}(k)$ of SR in Figure 7

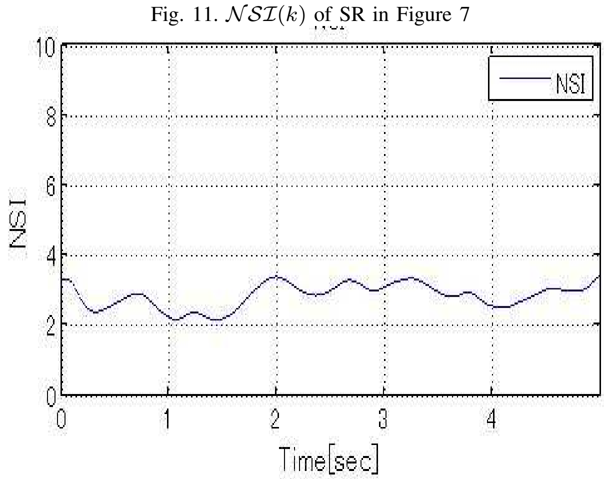

Fig. 12. $\mathcal{NSI}(k)$ of PEA in Figure 8

scalogram. The slope parameter proposed in this paper is defined as

$$\mathcal{Y}_{\text{slope}} = \frac{1}{\mathcal{N}-1} \sum_{k=1}^{\mathcal{N}-1} |\mathcal{Y}_{\text{peak}}(k+1) - \mathcal{Y}_{\text{peak}}(k)| \quad (7)$$

where $\mathcal{Y}_{\text{peak}}(k)$ is the peak frequency which has maximum energy at the time sample k in the scalogram.

iv) VF-Filter[5]
In VF filter algorithm, the following parameters $\mathcal{T}$ and $\mathcal{L}$ are calculated.

$$\mathcal{T} = \frac{2\pi \sum_{k=1}^{\mathcal{N}} |\mathcal{ECG}(k)|}{\sum_{k=1}^{\mathcal{N}} |\mathcal{ECG}(k+1) - \mathcal{ECG}(k)|} \quad (8)$$

$$\mathcal{L} = \frac{\sum_{k=1}^{\mathcal{N}} |\mathcal{ECG}(k) + \mathcal{ECG}(k - \mathcal{T}/2)|}{\sum_{k=1}^{\mathcal{N}} (|\mathcal{ECG}(k)| + |\mathcal{ECG}(k - \mathcal{T}/2)|)} \quad (9)$$

where $\mathcal{T}$ is an average period and $\mathcal{L}$ means VF filter leakage. Besides, $\mathcal{ECG}(k)$ in (8) and (9) denotes the original ECG signal.

v) Energy Ratio
By using power spectrum via Fourier transform, we calculate the following energy ratio $\mathcal{H}$.

$$\mathcal{H} = \frac{\mathcal{P}_{[2-10]}}{\mathcal{P}_{[1-10]}} \quad (10)$$

where $\mathcal{P}_{[\alpha-\beta]}$ means the total energy for the frequency ingredient between α [Hz] and β [Hz]. This quality parameters distinguish whether the ECG signal is Non-shockable (SR) or not.

III. A Discrimination Algorithm and Results

By using the above quality parameters, we develop a new discrimination algorithm for venricular arrhythmia. In this paper, we adopt Mahalanobis Distance[17] in order to detect shockable ECG signals. Mahalanobis distance in this paper can be calculated by using above quality parameters.

A. *Mahalanobis Distance*

By using various ECG signals included in AHA database, MIT-BIH database and so on, we construct a discrimination algorithm. In this paper, we adopt Mahalanobis distance so as to distinguish various ECG signals.

Firstly in order to show the role of Mahalanobis distance for the proposed algorithm, let us introduce the following two groups $\mathcal{G}_1$ and $\mathcal{G}_2$.

$$\begin{array}{l}\mathcal{G}_1 : y_1^{(1)}, y_2^{(1)}, \cdots, y_{n_1}^{(1)}, \\ \mathcal{G}_2 : y_1^{(2)}, y_2^{(2)}, \cdots, y_{n_2}^{(2)}\end{array} \tag{11}$$

where $y_p^{(m)}$ $(p = 1, \cdots, n_m,\ m = 1, 2)$ represents a quality parameter vector for each group, i.e. $y_p^{(m)} = (y_{p_1}^{(m)}, y_{p_2}^{(m)}, \cdots, y_{p_{n_m}}^{(m)})^T$. Note that n_m is the number of the quality parameters. Then Mahalanobis distance for the group $\mathcal{G}_m$ $(m = 1, 2)$ is defined as

$$\begin{array}{l}\mathcal{D}_1^2 \stackrel{\triangle}{=} (y - \overline{y}_1)^T \mathcal{S}_1^{-1} (y - \overline{y}_1) \\ \mathcal{D}_2^2 \stackrel{\triangle}{=} (y - \overline{y}_2)^T \mathcal{S}_2^{-1} (y - \overline{y}_2).\end{array} \tag{12}$$

In (12), $\overline{y}_m$ and $\mathcal{S}_m$ represent a sample mean vector and a covariance matrix for the group $\mathcal{G}_m$ which is characterized some quality parameters, respectively and these parameters are defined as

$$\begin{array}{l}\mathcal{G}_1 : \left\{\begin{array}{l}\overline{y}_1 = \dfrac{1}{n_1}\displaystyle\sum_{i=1}^{n_1} y_i^{(1)} \\ \mathcal{S}_1 = \dfrac{1}{n_1 - 1}\displaystyle\sum_{i=1}^{n_1} (y_i^{(1)} - \overline{y}_1)(y_i^{(1)} - \overline{y}_1)^T\end{array}\right. \\ \mathcal{G}_2 : \left\{\begin{array}{l}\overline{y}_2 = \dfrac{1}{n_2}\displaystyle\sum_{i=1}^{n_2} y_i^{(2)} \\ \mathcal{S}_2 = \dfrac{1}{n_2 - 1}\displaystyle\sum_{i=1}^{n_2} (y_i^{(2)} - \overline{y}_2)(y_i^{(2)} - \overline{y}_2)^T\end{array}\right.\end{array} \tag{13}$$

Additionally the symbol y in (12) is a parameter vector calculated by using an ECG signal to be distinguished, and if $\mathcal{D}_\mathcal{U}^2 < \mathcal{D}_\mathcal{V}^2$ then the ECG signal belongs to the group $\mathcal{G}_\mathcal{U}$ $(\mathcal{U}, \mathcal{V} = 1 \text{ or } 2,\ \mathcal{U} \neq \mathcal{V})$.

B. The Proposed Discrimination Algorithm

The proposed discrimination algorithm in this paper consists of two steps as follows.

i) First step (Detection of SR)
In this step, two groups $\mathcal{G}_1$ and $\mathcal{G}_2$ mean SR and the other ECG signals, i.e. the group $\mathcal{G}_1$ means SR and the group $\mathcal{G}_2$ is characterized by the quality parameters for the other ECG signals.The quality parameter vectors in this step are given by $\overline{y}_1 \stackrel{\triangle}{=} \overline{y}_{\mathcal{G}_1} = \left(\ \overline{\sigma^2{}_{\mathcal{G}_1}}\ \ \overline{\mathcal{Y}_{\text{slope}}^{(\mathcal{G}_1)}}\ \right)^T$ and $\overline{y}_2 = \overline{y}_{\mathcal{G}_2} = \left(\ \overline{\sigma^2{}_{\mathcal{G}_2}}\ \ \overline{\mathcal{Y}_{\text{slope}}^{(\mathcal{G}_2)}}\ \right)^T$, respectively. Note that for the group $\mathcal{G}_m$, $\overline{\sigma^2{}_{\mathcal{G}_m}}$ and $\overline{\mathcal{Y}_{\text{slope}}^{(\mathcal{G}_m)}}$ denote mean values for the quality parameters σ^2 and $\mathcal{Y}_{\text{slope}}$, respectively. From the analysis results, the sample mean vectors and their covariance matrices for these parameter vectors are given as

$$\begin{array}{l}\overline{y}_1 = \begin{pmatrix} 1.5778 \\ 0.3615 \end{pmatrix},\ \overline{y}_2 = \begin{pmatrix} 0.1730 \\ 2.6316 \end{pmatrix}, \\ \mathcal{S}_1 = \begin{pmatrix} 0.0141 & 0.0003 \\ \star & 0.0156 \end{pmatrix}, \\ \mathcal{S}_2 = \begin{pmatrix} 0.0165 & 0.0237 \\ \star & 0.8115 \end{pmatrix}.\end{array} \tag{14}$$

ii) Final step (Detection of VF and VT)
Two groups $\mathcal{G}_1$ and $\mathcal{G}_2$ in this final step mean Shockable (VF, VT) and Nonshockable (PEA), respectively. In this final step, the quality parameter vector y_m consists of $\mathcal{L}$ in (9), $\mathcal{Y}_{\text{slope}}$ in (7) and $\mathcal{H}$ in (10). For this quality parameter vector, the sample vectors and the covariance matrices for groups $\mathcal{G}_1$ and $\mathcal{G}_2$ can be calculated as

$$\begin{array}{l}\overline{y}_1 = \begin{pmatrix} 0.5793 \\ 3.5910 \\ 98.1244 \end{pmatrix},\ \overline{y}_2 = \begin{pmatrix} 0.7738 \\ 0.4426 \\ 46.2004 \end{pmatrix}, \\ \mathcal{S}_1 = \begin{pmatrix} 0.0133 & 0.0138 & -0.1035 \\ \star & 0.1786 & -0.1787 \\ \star & \star & 2.0649 \end{pmatrix}, \\ \mathcal{S}_2 = \begin{pmatrix} 0.0009 & 0.0000 & 0.0293 \\ \star & 0.0459 & 1.4120 \\ \star & \star & 147.4730 \end{pmatrix}.\end{array} \tag{15}$$

Namely, the proposed algorithm composed of the following two steps.

Step 1) Recognize whether the obtained ECG signal is "Nonshockable" signal (SR) or not ?.
Step 2) Detection of "Shockable" signal (VF or VT).

Consequently, in this paper, we develope the following discrimination algorithm.

DISCRIMINATION ALGORITHM

1⋆) By applying GWT to ECG, we obtain its scalogram.
2⋆) Calculate $\mathcal{NSI}(k)$.
3⋆) Derive the quality parameters σ^2 in (5) and $\mathcal{Y}_{\text{slope}}$ in (7).
4⋆) Based on two quality parameters σ^2 and $\mathcal{Y}_{\text{slope}}$, calculate Mahalanobis distance ${\mathcal{D}_k}^2$ $(k = 1, 2)$.
5⋆) If ${\mathcal{D}_1}^2 < {\mathcal{D}_2}^2$, go to (8⋆). Otherwise (6⋆). **(Step 1)**
6⋆) Derive $\mathcal{L}$ in (9), $\mathcal{Y}_{\text{slope}}$ in (7), and $\mathcal{H}$ in (10).
7⋆) If ${\mathcal{D}_1}^2 < {\mathcal{D}_2}^2$, go to (9⋆). Otherwise (10⋆). **(Step 2)**
8⋆) The ECG is "Nonshockable" signal (SR) ! %
9⋆) The ECG is "Shockable" signal (VF or VT).
10⋆) The ECG is "Nonshockable" signal (PEA) ! %

IV. Performance of the Proposed Algorithm

In the previous section, based on the result of characteristic analysis we have proposed the detection algorithm for ECG. In this section, we adopt Receiver Operating Characteristic

TABLE I
AUC

	(A)	(B)
Proposed algorithm	1.00	0.87
Previous algorithm[17]	1.00	0.81

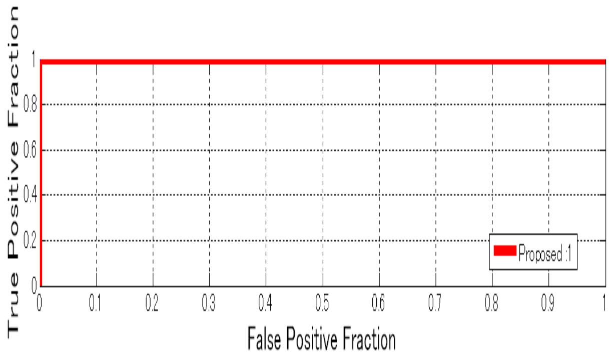

Fig. 13. Nonshockable (SR) and other ECG

(ROC) curve to evaluate the performance of the proposed discrimination algorithm, i.e. we evaluate the performance of proposed algorithm by using ROC curve.

A. *AUC (Area Under the Curve) and Performance Analysis*

In order to perform the proposed algorithm, AUC (Area Under Curve) which can be calculated by using ROC curve plays an important role. AUC takes the value between 0.0 and 1.0 and if AUC equals to 1.0, then the detection performance is optimal[14]!¶In this paper, the proposed algorithm has been applied to 2,000 ECG signals (SR!′929!$VF!′682!$VT!′26!$ PEA!′363), and we compare the performance of the proposed algorithm with one of our previous work[17].

TABLE I shows the AUC for the proposed algorithm and our previous one[17], respectively. Note that (A) and (B) in TABLE I mean "Step 1)" in the proposed algorithm and "Step 2)", respectively. Besides, Figures 13 and 14 are ROC curves for "Step 1)" in the proposed algorithm and "Step 2)", respectively. Note that the vertical axis and the horizontal one in Figures 13 and14 denote True Positive Fraction (Specificity) and False Positive Fraction (Sensitivity), respectively. From Figure 13, we see that the value of AUC equals to 1.0, i.e. SR is detected completely. Besides one can see from Figure 14 that the value of AUC is 0.87. Namely, we find that the proposed algorithm achieves good discrimination performance comparing with our previous one[17].Therefore the proposed algorithm is useful and meaningful.

V. Conclusions and Future Works

This paper has dealt with the discrimination problem for ECG signals and firstly we have run the characteristic analysis for ECG signals. Next, we have developed the discrimination algorithm based on analysis results. Besides, we have evaluated the performance of the proposed discrimination algorithm by using AUC.

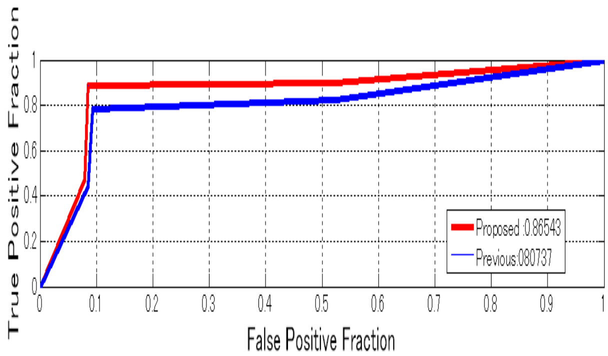

Fig. 14. Shockable (VF or VT) and Nonshockable (PEA)

In this paper, some quality parameters for some ECG signals such as VF, VT, SR and PEA have been derived and by using Mahalanobis distance, the proposed discrimination algorithm recognizes whether the obtained ECG signal is "Shockable" or not. As a result, the proposed algorithm shows good discrimination performance comparing with our previous one. However, there are more complex ECG signals which are difficult to distinguish and the performance of the proposed algorithm has to be improved. Therefore our future research subjects are customization and extension of the proposed algorithm to some cases such as nonsustained ventricular tachycardia (NSVT), the case that patient's sinus rhythm was resumed and so on.

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