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Original research article

Study on Ventricular Fibrillation by Using Wavelet and Identification with SVM

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ABSTRACT

Digital signal processing and data analysis are very often used methods in biomedical engineering research. Automated external defibrillators (AEDs) are portable electronic devices that automatically diagnose the potentially life-threatening cardiac arrhythmias of ventricular fibrillation in a patient. However, the precise identification of electrocardiogram waveforms is difficult in the present AEDs. The identification of state transition in the waveforms has never been dealt with. Heart signals represent an important way to evaluate cardiovascular function and often what is desired is to quantify the level of some signal of interest against the louder backdrop of the beating of the heart itself. An example of this type of application is the quantification of cavitation in mechanical heart valve patients. The aim of this project is to propose a method for improving the identification accuracy of electrocardiogram waveforms including the state transition. This will be achieved by using the wavelet transforms and the support vector machine.

Keywords: Electrocardiogram including state transition; Sudden cardiac arrest; Support vector machine; Wavelet transform

1. Introduction

The research aims to improve the performance of an Automated External Defibrillator (AED).

The AED is used to defibrillate a coronary patient with electrical shock. Without electrical defibrillation, coronary patients will die within a few minutes. In order to save these patients, at present AEDs are distributed in public facilities. AEDs do not always provide electrical defibrillation for coronary victims. They provide electrical defibrillation only when they identify an electrocardiogram (ECG) signal as being irregular. AEDs provide electrical defibrillation only when a state of ECG waveform is ventricular fibrillation (VF) or ventricular tachycardia(VT); on the other hand, it is dangerous to provide electrical defibrillation when the state is that of Pulseless Electrical Activity (PEA) or

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normal heart rhythm called Normal Sinus Rhythm (SR). AEDs can identify 95% of VF, but the likelihood that they can identify VT is only 75%. Furthermore, it is difficult to identify the state of ECG signals when State Transition (ST) occurs.

Factually, public dissemination of publicly accessible AEDs in Japan resulted in an earlier administration of shocks by bystanders and has improved the rate of survival [1-5]. The AED effectiveness depends on the device's ability to detect lethal arrhythmias and on the operator's ability to use the device correctly [6-7], and errors associated with AED use have been identified as device dependent or operator dependent [8]. There have been a few cases in which AEDs failed to recognize VF due to the presence of pacemaker spikes or artifact [9-10]. AEDs are designed such that they have a very high specificity [11]. It was deployed by support vector machine to HRV classification [12] and fibrillation detection using DWT [13-14].

In this research, we define State Transition as ECG waveforms which change states. We aim to identify ST signals as well as SR VF VT and PEA. Specifically, we extract features from ECG signals in the time and frequency domain with Wavelet Transform and classify these with Support Vector Machine (SVM). We will make it possible to identify ST waveform and enhance the quality for identification of SR, VF and VT of AED.

2. Continuous Wavelet Transform

The Continuous Wavelet Transform (CWT) is the key technique of our proposed method. CWT is defined in (2.1).

$$W_{\psi} f\left(a,b\right) = \frac{1}{\sqrt{a}} f\left(t\right) \overline{\psi\left(\frac{t-b}{a}\right)} dt, \qquad (2.1)$$

where $a,b \in R, a>0, (t)$ is the mother wavelet, and means the complex conjugate.

The Gabor Wavelet Transform (GWT) is based on the normal distribution window function $e^{j\omega t}$ of the Fourier transform. The Gabor Wavelet is shown in (2.2).

$$\psi_{\sigma^2}, \omega_0(t) = \frac{e^{\frac{-t^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}} e^{j\omega_0 t}, \qquad (2.2)$$

where the imaginary, σ^2 is the variance of the normal distribution function, and ω_0 represents the angular frequency of the basis of the Fourier transform [rad/sec] [15]. In this research, we extract features in the time and frequency domain from ECG waveform with GWT.

3. Support Vector Machine

In our proposed method, we use the Support Vector Machine (SVM) for pattern recognition features. The SVM is a pattern recognition algorithm in two classes using the hypothesis space of linear function [16]. Features of the SVM are as follows:

3.1 Learning with margin maximization

In *s*th ECG waveform, we define *r*th characteristic as $x\left(r,s\right)$. We also define a vector obtained by arranging all of the signal characteristics as follows:

$$x(s) = \left[x(1,s),...,x(N_r,s)\right]^T, s = 1,2,...,N_s. \qquad (2.3)$$

One of the hyper planes is expressed as (2.4)

$$\omega x(s) + b_{ias} = 0, \qquad (2.4)$$

where $W = \left[w\left(1\right),...,w\left(Nr\right)\right]$ is weight vector, $b_{ias} \in R$ is bias, and $x\left(s1\right)$ is the characteristic vector of a sample point (s1). The distance between the hyper plane and $x\left(s1\right)$ is called margin and is expressed as (2.5).

$$\frac{\left|wx(s) + b_{ias}\right|}{\left\|w\right\|} \qquad (2.5)$$

In the hyper plane represented by (2.4), w and bias are constants. We use (2.6) and (2.7) as the restrictions,

$$\min(\omega x(s^{+} + \mathrm{b}_{ias})) = +1, \quad (2.6)$$

$$\min(\omega x(s^{-} + \mathrm{b}_{ias})) = -1, \quad (2.7)$$

where we define $x(s^{+})$ as a point that belongs to a class and $x(s^{-})$ as that of other class. From (2.6) and (2.7), the margin γ is expressed as (2.8).

$$\begin{aligned}\gamma &= \frac{1}{2}\frac{(wx(s^{+}))}{\|w\|} - \frac{(wx(s^{-}))}{\|w\|},\\ &= \frac{1}{2\|w\|}(wx(s^{+}) - wx(s^{-})) = \frac{1}{\|w\|} = \frac{1}{ww^{t}}.\end{aligned} \quad (2.8)$$

The optimum border maximizes γ. Therefore, the optimization is minimized by ww^{t} and given by (2.9).

$$y(s)(\omega x(s) + b_{ias}) \geq 1, \quad (2.9)$$

where $y(s) \in [-1,1]$ is a label. When $x(s)$ belongs to a class, $y(s)$ is defined as 1. When $x(s)$ belongs to another class, $y(s)$ is defined as -1. Then, if the boundary separates points exactly, $y(s)$ is $(\omega x(s) + b_{ias}) > 0$. Thus, the optimization can be solved by the method of Lagrange undetermined multiplier which is formulated as a quadratic programming problem.

3.2 Identifying the nonlinear function by kernel method

The kernel method is to find a nonlinear "curved" border. The basic idea of the kernel method is transforming the dimension of the original space to a higher dimension. When we express this transform as Φ for the combination $x(s)$ and $X(s!)$, the kernel function $K(x(s), x(s'))$ is given as (2.10).

$$K(x(s), x(s')) = \Phi(x(s))\Phi(x(s'))^{T}. \quad (2.10)$$

Eq. 2.10 shows that $K(x(s), x(s'))$ is equivalent to the distance measured in a high-dimensional space and transformed by Φ. We measure the margin from the kernel function instead of normal distance. When we get separated hyper planes based on this margin, the border will become a curved shape in the original space. When we adopt the kernel to SVM, all calculations for getting the border can be based on $K(x(s), x(s'))$ and we do not have to know the transformed space or the detail of Φ. We show the example of $K(x(s), x(s'))$ in (2.11) and (2.12).

$$K(x(s), x(s')) = ((\mathrm{x(s)}x(s'))^{T} + 1)^{p}, \quad (2.11)$$

$$K(x(s), x(s')) = \exp\left(-\frac{\|x(s), x(s')\|}{\sigma_{k}^{2}}\right), \quad (2.12)$$

where (2.11) is called the polynomial kernel and (2.12) is called the Gaussian kernel, $p \in N$ and σ_{k}^{2} is the variance of the Gaussian function. In this research, we employ a Gaussian kernel for SVM.

4. The Performance Evaluation Criteria for Identification

In this research, we use the Receiver Operating Characteristic curve [17] to evaluate the performance for identification. The sensitivity and the specificity are used in this method and we can evaluate the performance visually. In this section, we explain the sensitivity, the specificity, and the ROC curve.

4.1 The sensitivity and specificity

Sensitivity and specificity are terms often used for evaluation in the medical field, but here they are used to evaluate the performance of AEDs. Sensitivity refers to the level at which a signal is determined to be positive, whereas specificity refers to the level at which a signal is determined to be negative. In general, the sensitivity and specificity are influenced by the threshold of the discriminator. For example, the specificity of the AED is set to be high, so as to reduce the possibility of defibrillating a healthy patient.

4.2 The ROC curve

Receiver Operating Characteristic (ROC) is one of the visual evaluation methods and this shows the changes of sensitivity and specificity depend on the threshold. The horizontal line of ROC shows 1 - (*specificity*), and the vertical line shows sensitivity. The ROC curve is mainly used in the subjective evaluation of the classifier.

4.3 Area under the curve

Area Under the Curve (AUC) is the area under the ROC curve and it means the quality of the evaluation method. AUC is no fewer than 0.5, nor more than 1. When we can classify something completely, AUC becomes 1. When the classification is random, AUC become 0.5. In this research, we use AUC to evaluate the quality for identifying characteristics.

5. Target Data

Conventionally, various topics regarding ECGs have been researched. There are databases of ECG for this research as follows:

- Boston's Beth Israel Hospital and MIT arrhythmia database (MIT-BIH)
- American Heart Association database (AHA)
- Creighton University ventricular tachyarrhythmia database (CU)

In this research, we use signals of MIT-BIH and AHA, as well as data from the search and rescue center at the University of Kyorin advanced studies [18]. We use ECG signals with examples of normal Sinus Rhythm (SR), Ventricular Fibrillation (VF), Ventricular Tachycardia (VT) and Pulseless Electrical Activity (PEA) clipped from these data. The total number of clipped data is 2734. The elements correspond to 1201 normal SR, 1175 VF signals, 60 VT signals and 298 PEA signals.

The number of State Transition waveforms (ST) is small, and the state transitions are not labeled in detail. It is impossible for the discrimination using SVM learning without labeling these states. Therefore, we made artificial ST signals by piecing 2 ECG signals whose labels are known and used these artificial signals for selected identification.

5.1 Wave data example of ECG

In this section, we introduce the example of ECG signals we want to identify.

5.1.1 Normal Sinus Rhythm

Normal Sinus Rhythm (SR) is a normal ECG signal. In SR, there exist signals like Fig. 1 regularly. In one period of SR signal, a convex signal called P wave begins, transitioning into a QRS wave, which is sharper than a P wave. Then, T waves and U waves appear. The amplitude of the ECG signal is the force of myocardial movement and the horizontal line of ECG signal is the time. One of the SR signals is shown in Fig. 2. In Fig. 2, the horizontal line is time [s] and the vertical line is voltage [mV],

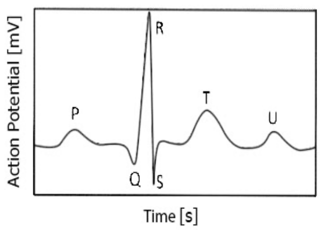

Fig. 1. View showing a frame format of SR.

Normally, the normal rhythm appears in a frequency of 1.0 to 1.7 Hz. However, there exist individual differences so that the frequency of the normal rhythm is not always in that frequency band.

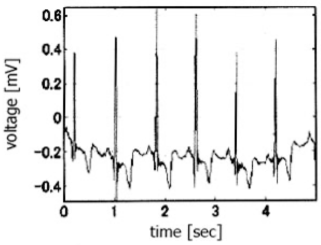

Fig. 2. An example of SR signal.

5.1.2 Ventricular Fibrillation

Ventricular Fibrillation (VF) is a serious arrhythmia. In VF, the heart quivers so that the pumping function of the heart is lost and it is impossible to send blood to the body. When this happens, the patient loses consciousness. If the state does not return to SR within a few minutes the patient dies. VF is the most dangerous arrhythmia. The abnormal excitation of the ventricle makes the amplitude and the frequency change dramatically. The electrical defibrillation is effective to save the lives of patients. One of the VF signals is shown in Fig 3. In this figure, the horizontal line is time [s] and the vertical line is voltage [mV]. As a feature of this waveform, wide QRS waves appear, as well as wide and irregular waves.

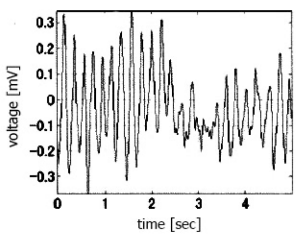

Fig. 3. An example of VF signal.

5.1.3 Ventricular Tachycardia

Ventricular Tachycardia (VT) is also a serious arrhythmia. In VT, there is abnormal stimulation of the ventricle and it causes VF or unexpected death. The electrical defibrillation is effective to save the lives of patients in this situation as well. One of the VT signals is shown in Fig 4. In Fig. 4, the horizontal line is time [s] and the vertical line is voltage [mV]. In VF, more than 3 wide QRS waves appear in a row.

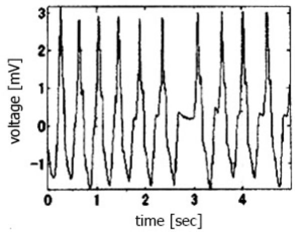

Fig. 4. An example of VT signal.

5.1.4 Pulseless Electrical Activity

Pulseless Electrical Activity (PEA) is a third kind of serious arrhythmia. In PEA, although we can see the ECG signal, no pulse can be felt and it is impossible to send blood to the body. Arrival resuscitation is effective for saving the lives of patients. Regardless of the shape of the ECG signal, if no pulse can be felt, the state of the ECG signal is PEA. So, there is a PEA whose shape of ECG signal resembles VF. One of the PEA signals is shown in Fig. 5. In Fig. 5, the horizontal line is time [s] and the vertical line is voltage [mV]. In this research, we aim to identify PEA whose ECG signal shape resembles that of VF.

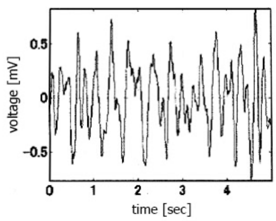

Fig. 5. An example of PEA signal.

5.1.5 State Transition wave form

In this paper, we define a State Transition signal (ST) as ECG signals that change states to resemble Fig 6. In Fig. 6, the horizontal line is time [s] and the vertical line is voltage [mV] and the state of 0-4 [sec] is SR and that of 5-10 [sec] is VF.

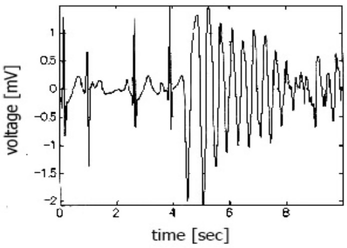

Fig. 6. An example of ST.

5.2 Problems of ECG signals

There are variations in ECG signals. For example, the state of the ECG signal is identified by physicians based on their experience and there is no rigorous standard for this identification. Therefore, it is possible that the standards of identification depend on the database of ECG signals. In other words, there are no firm characteristics of ECG signals. ECG signals are different between individuals so it is not possible to identify the state depending on the ECG signals alone. We have to develop identification methods with high robustness in order to deal with the individual differences of ECG signal.

6. Identification of ECG Waveform

To solve the problem of identifying the state of ECG signals, we use many characteristics of ECG signals. Using these parameters, a variation on each amount of characteristic will not affect the identification quality unless variations appear in the other characteristics as well. In our research, we focus on characteristics with Continuous Wavelet Transform and we propose many kinds of characteristics. We aim to perform pattern recognition more robustly using SVM.

In this chapter, we explain our proposed characteristics, how to select these characteristics, and a method to identify them.

6.1 Identification characteristics

We use characteristics which are based on Wavelet Transforms [21], band pass filters, and complexity. In addition to these, we also use basic statistics that can help to identify SR, VF, VT, PEA and ST. In this research, we obtain 165 different combinations for the characteristics. Among them, we select some characteristics to identify, according to the selection method described in the next section.

6.2 Selection for characteristics

We propose a detection algorithm for SR, VF and VT. We do not use all of the characteristics. Firstly, on the basis of the present AED system, we introduce the following analysis conditions for ECG data.

• The data length is 5.0 [sec].
•The amplitude is larger than 0.1[mv].
•The frequency band under consideration is [2.0, 10.0][Hz].

We select useful characteristics to reduce the amount of calculating, to provide a versatile system, and to develop the quality for identification. In this research, the AUC is used as an indicator of the effectiveness of the absolute value of the correlation coefficient, and also as an indicator of the independence between the characteristic values. The selection of characteristic values is choosing those indicators whose value is greater.

6.3 Method of identifying the ECG waveform:

In this research, we identify the state of ECG signals according to the following procedure:

1. Classifying ECG signals for learning and testing at random.
2. Getting characteristics that are selected from signals for learning.
3. Calculating weight vector and bias b_{ias} from characteristics obtained in Step 2 with SVM.
4. Getting selected characteristics from signals for testing.
5. Identifying the state of ECG signals with the hyper plane obtained in Step 3 and characteristics obtained in Step 4.

When implementing our application to AEDs, we calculate the hyper plane, weight vector *w,* and bias b_{ias} in advance so AEDs have to go through only steps 4 and 5. The view showing a frame format of our application is shown in Fig. 7.

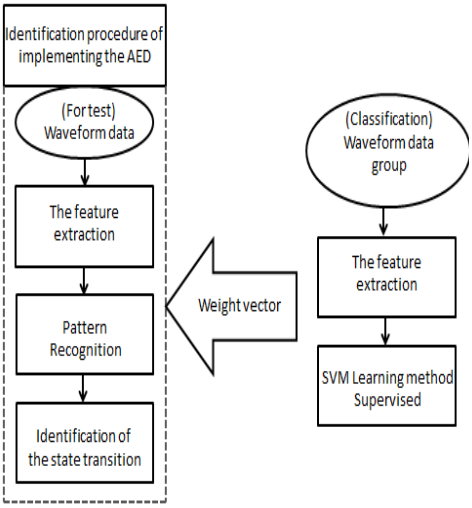

Fig. 7. Our proposed algorithm.

6.4 Results of identifying the states of EGC signal

Table 1 shows the results of identification for ECG signals. However, in identifying ST signals, we used artificial ST signals to identify and learn using SVM. According to the results of identifying SR, VF, VT and PEA in Table 1, it is possible to identify ST signals in this way.

We show the sensitivity and the specificity of the result of the identification with a hyper plane used to identify SR and PEA or VF and VT in Table 1. In order to compare the quality of our proposed method to the required performance, AEDFR2, and AEDHS4000 AEDFR2, and AEDHS4000 are made by Konmkhjke Philips N.V. [19-20], in Table 2. However, the ECG signal we used in evaluation is different from those of AEDFR2, and AEDHS4000; the quality of our proposed method is the best.

Table 1. Identification result.

Identification	AUC	Specificity	Sensitivity	Accuracy rate
SR VT and PEA	0.99	0.99	0.99	0.99
VF VT and PEA	0.99	0.95	0.94	0.95
VT, VF and PEA	0.99	0.96	0.91	0.95
SR, VF and PEA	0.99	0.96	0.91	0.95
PEA, VF and VT	0.98	0.95	0.95	0.95
SR, VF and VT	0.98	0.95	0.95	0.95
ST, VT and PEA	0.97	0.95	0.85	0.95
SR and PEA	0.99	0.96	0.94	0.95
VF and VT	0.98	0.95	0.95	0.95

Table 2. Comparison of identification result with AED.

	Specific, of SR	Specific, of VF	Specific, of VT	Specific, of PEA
Proposed Method	0.99	0.99	0.99	0.99
Required Performance	0.99	0.95	0.94	0.95
AED_{FR2}	0.99	0.96	0.91	0.95
AED_{HS4000}	0.99	0.96	0.91	0.95

7. Identification of State Transition Signal by Dividing the Signal

In the previous section, we defined an ST signal as ECG signals who change states, and we learned about ST signals along with the ECG signal SR, VF, VT and PEA that can be identified in ST. In addition, we try to identify the ST signal without the definition of ST signal. Specifically, we divide the ST signal into short signals and adopt our proposed method to each short signal. For example, in the case of ST signal like Fig. 4, if we divide the ST signal into 0-5 [sec] long signal and 5-10 [sec] long signal we can identify 0-5 [sec] long signal as SR and 5-10 [sec] long signal as VF with our proposed method.

7.1 Method of identifying the waveform state transition by dividing the waveform rapidly.

We show an example of an ST signal in Fig 8. In Fig. 8, the horizontal line is time [s] and the vertical line is voltage [mV]. In this research, we identify 10 [sec] ST signals and divide the signal into 1 [sec] signals. We adopt our method to each 1 [sec] signal.

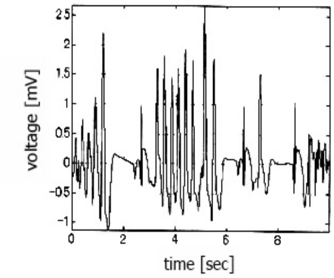

Fig. 8. A ST signal for experiment.

7.2 Identifying the waveform state transition result by dividing the wave quickly.

In Fig. 10, we show the result of identifying the ST signal shown in Fig. 8. The vertical line of Fig. 10 corresponds to the state SR, VF, VT and PEA and the horizontal line is time [s]. According to Fig. 10, we could identify parts of the signal thought to be SR, VF and VT signal in the ST signal. However, there is no detailed label of the ST signals shown in Fig 8; thus, we cannot evaluate this result objectively.

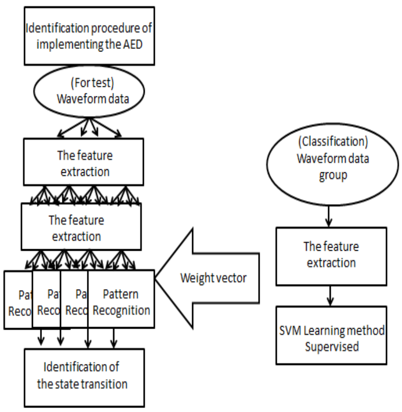

Fig. 9. Identification algorithms by dividing electrocardiogram waveforms into short Electrocardiogram waveforms.

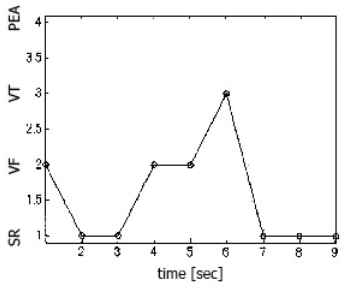

Fig. 10. Identification result of a ST signal.

8. Conclusion

In this research, we proposed characteristics based on Wavelet Transform and identification method with SVM learning. As a result, the quality of our proposed method is better than the required performance of AEDs and we could identify ECG signals that are difficult to identify, such as PEA and ST signal. Our future work is developing the quality of identification. The quality of identification for AEDs is important to save many lives so it must be developed. In the ECG signal used in the experiment, the number of some kinds of ECG signals is very small. In regards to implementation, the amount of calculation must be reduced.

References

[1] Weisfeldt ML, Everson-Stewart S, Sitlani C, Rea T, Aufderheide TP, Atkins DL, Bigham B, Brooks SC, Foerster C, Gray R, Ornato JP, Powell J, Kudenchuk PJ, Morrison LJ. Ventricular tachyarrhythmias after cardiac arrest in public versus at home. N Engl J Med. pp. 313-321,2011.

[2] Aufderheide T, Hazinski MF, Nichol G, Steffens SS, Buroker A, McCune R, Stapleton E, Nadkarni V, Potts J, Ramirez RR, Eigel B, Epstein A, Sayre M, Halperin H, Cummins RO. Community lay rescuer automated external defibrillation programs: key state legislative components and implementation strategies: a summary of a decade of experience for healthcare providers, policymakers, legislators, employers, and community leaders from the American Heart Association

Emergency Cardiovascular Care Committee, Council on Clinical Cardiology, and Office of State Advocacy. Circulation. pp. 1260-70, 2006.

[3] Hazinski MF, Idris AH, Kerber RE, Epstein A, Atkins D, Tang W, Lurie K. Lay rescuer automated external defibrillator ("public access defibrillation") programs: lessons learned from an international multicenter trial: advisory statement from the American Heart Association Emergency Cardiovascular Committee; the Council on Cardiopulmonary, Perioperative, and Critical Care; and the Council on Clinical Cardiology. Circulation. pp. 3336-40, 2005.

[4] Weisfeldt ML, Sitlani CM, Ornato JP, Rea T, Aufderheide TP, Davis D, Dreyer J, Hess EP, Jui J, Maloney J, Sopko G, Powell J, Nichol G, Morrison LJ. Survival after application of automatic external defibrillators before arrival of the emergency medical system: evaluation in the resuscitation outcomes consortium population of 21 million. J Am Coll Cardiol, pp. 1713-20, 2010.

[5] Folke F, Gislason GH, Lippert FK, Nielsen SL, Weeke P, Hansen ML, Fosbol EL, Andersen SS, Rasmussen S, Schramm TK, Kober L, Torp-Pedersen C. Differences between out-of-hospital cardiac arrest in residential and public locations and implications for public-access defibrillation. Circulation, pp. 623-30, 2010.

[6] Kitamura T, Iwami T, Kawamura T, Nagao K, Tanaka H, Hiraide A. Nationwide public-access defibrillation in Japan. N Engl J Med, pp. 994-1004, 2010.

[7] Kitamura T, Iwami T, Kawamura T, Nitta M, Nagao K, Nonogi H, Yonemoto N, Kimura T. Nationwide improvements in survival from out-of-hospital cardiac arrest in Japan. Circulation, pp. 2834-43, 2012.

[8] Callejas S, Barry A, Demertsidis E, Jorgenson D, Becker LB. Human factors impact successful lay person automated external defibrillator use during simulated cardiac arrest. Crit Care Med, 2004.

[9] Ko PC, Lin CH, Lu TC, Ma MH, Chen WJ, Lin FY. Machine and operator performance analysis of automated external defibrillator utilization. J Formos Med Assoc. 2005;

[10] Macdonald RD, Swanson JM, Mottley JL, Weinstein C. Performance and error analysis of automated external defibrillator use in the out-of-hospital setting. Ann Emerg Medpp. 262-7 2001.

[11] Yamamoto T, Takayama M, Sato N, Yodogawa K, Iwasaki YK, Kato K, Yoshida A, Yoshida R, Tanaka K, Takano T, Mizuno K. Inappropriate analyses of automated external defibrillators used during in-hospital ventricular fibrillation. Circ J, pp. 679-81, 2008.

[12] M. Ashtiyani, S. Navaei Lavasani, A. Asgharzadeh Alvarand M.R. Deevband1. Heart Rate Variability Classification using Support Vector Machine and Genetic Algorithm. J Biomed Phys Eng, vol. 4, pp. 423-34, 2018.

[13] M.Monalisa, B.Pradyut and S.Sukanta. ventricular tachycardia and fibrillation detection using dwt and decision tree classifier. Journal of Mechanics in Medicine and Biology, Vol. 19, No. 03, 2018.

[14] Czarina Isabelle M. Cruz, Jastine P. Marasigan, Anna Patricia G. Perez, Joana Erika V. Pillejera, Nikka P. Veron, Angelo R. dela C. A comparative study between DWT-ANFIS and DWT-SVM in ECG classification. IEEE Region 10 Conference (TENCON), 22-25 Nov., Singapore, 2016.

[15] Paul, S, Addison. The Illustrated Wavelet Transform Handbook. Trans. Shin, Seiichi and Kazushi, Nakano. Tokyo : Asakura Publishing Co., Ltd., 2005.

[16] Nello, Cristianini And John, Shawe-Taylor. An Introduction to Support Vec-

tor Ma¬chines and other kernel-based learning methods. Trans.Tsuyoshi Ohkita. Tokyo : kyoritsu Shuppan Co., Ltd.,2007

[17] I. Takayuki. Medical Image Engineering to understand well. 2008, Ohmsha.

[18] Y. Yamaguchi. Validation for clinical application and commercialization of early recogni-tion system for extraction waveform based on elec¬trocardiogram analysis on the way to cardiopul-monary resuscitation during. Disaster Prevention Research Institute. 2010.

[19] K. Yamaguchi. Mechanism and basic statistical analysis that you understand illustra¬tion: An Introduction to statistical data analysis Introduction. Hidekazu system, first edition. 2007.

[20] K.A. Kuroyanagi, M. Kugler, A. Iwata. feature selection method for SVM using Condent Margin (pattern recognition). Institute of Electronics, Information and Commu¬nication Engineers. 2005.

[21] H. Oya, K. Tanaka, K. Hirose, K. Nakano, and T. Okai. A wavelet transform-based detection algorithm for electrocardiogram. IEEESignal Processing. 2012.