Early Prediction of Ventricular Tachyarrhythmias Based on Heart Rate Variability Analysis

Hyojeong Lee[1], Myeongsook Seo[1, 2], Segyeong Joo[1, 3]

[1]University of Ulsan College of Medicine, Seoul, Korea
[2]Department of Internal Medicine and
[3]Department of Biomedical Engineering, Asan Medical Center, Seoul, Korea

Abstract

Ventricular tachyarrhythmias (VTAs) are fatal events and it is obvious that early prediction of VTAs could help in reducing mortality rate due to sudden cardiac death (SCD).

Heart rate variability (HRV) reflects all symptoms associated with autonomic nervous system (ANS) as well as heart disease. Thus, HRV has frequently been used in various studies.

We collected 220 recordings (VTAs - ventricular tachycardia (VT) and ventricular fibrillation(VF): 110, Control data: 110) from 81 adult patients in Intensive care unit (ICU), Asan Medical Centar (AMC) and proposed three classifiers for prediction of VTAs events using eleven HRV parameters.

Our group already developed a predictor for VTAs using ventricular arrhythmias dataset in Physionet before 10 seconds ahead of the events. In this study, we tried to predict VTAs earlier than an hour using parameters from HRV analysis and artificial neural network (ANN) models.

The ANN model for prediction of VTAs showed a significantly high accuracy as 86.11% (189/220) and Area under the curve (AUC) of receiver operating characteristic (ROC) was 0.88.

1. Introduction

Sudden cardiac death (SCD) or sudden cardiac arrest is usually from cardiac causes, heralded by abrupt loss of consciousness within one hour of the onset of acute symptoms. Cause of this SCD is very varies, it is as follows; acute myocardial infarction, angina pectoris, dilated cardiomyopathy, hypertrophic cardiomyopathy, aortic disease, valvular heart disease, QT prolongation, Brugada syndrome and etc. [1-4]. But ventricular tachyarrhythmias (VTAs) occupies the largest percentage of cause of SCD.

The time between adjacent two R peaks is named RR interval or NN interval in a continuous electrocardiograms (ECGs). Heart rate variability (HRV) is the variation between sequences of this RR intervals. HRV analysis is usually achieved in different parameters in time, frequency domain and nonlinear analysis. If detecting the R peaks in ECGs is difficulty in noise environment, you can analyse photoplethysmography (PPG), instead of ECGs.

A former number of papers have been described for predicting VTAs. In such papers, there are various predictors of VTAs including HRV such as signal averaged ECGs, HRV, Holter monitoring, T wave alternans, syncope, left ventricular systolic dysfunction, QT dispersion, electro-physiologic testing, QRS duration and etc. [5-8]. However, accuracy of them was rather low or samples used in the experiment was very fewer. It seems difficult to apply in real life.

Meanwhile, our group already developed a predictor for VTAs using VT and VF dataset in physionet before 10 seconds ahead of the events [5]. The results showed 73.3% sensitivity, 73.8% specificity, and 75.6% accuracy.

The main purpose of this study was to better predict the VTAs earlier by collecting data of a real patients in beds. Furthermore we should be able to take flexible expediency about occurrence of VTA events. In addition, mortality caused by SCD will be significantly decreased.

2. Methods

2.1. Recordings

To collect ECGs from patients, we developed a system for retrieving ECGs in real-time from 15 patient monitors (IntelliVue, Philips, USA) in an intensive care unit (ICU) at Asan medical center (AMC) after obtaining approval from institutional reviewer board (IRB). ECGs obtained from patients with implantable cardioverter defibrillator (ICD) and pacemaker were excluded and every ECGs of VTA events were reviewed by an experienced physician. RR intervals of 5 minutes before an hour from every VTA events were collected and for the control dataset, RR intervals of 5 minutes from the same patient were extracted

when there was no events for at least one day after the collection period.

The VTA events divided into ventricular tachycardia (VT) and ventricular fibrillation (VF). The collected events were total 110 (71 VT and 39 VF events) from 81 adult patients. Therefore, total recordings used in this study contain 110 VTAs recordings and 110 control recordings (total: 220).

2.2. Data preprocessing

We detected R peaks using R-peaks detection algorithm to analyze HRV from ECGs and RR intervals were calculated (Figure 1) [9]. Several ectopic beats were removed to reduce error before extracting parameters. A method based on the integrated pulse frequency modulation model was utilized to eliminate the ectopic beats in the database. Then, time domain, frequency domain parameters and poincaré nonlinear parameters were extracted in 5 minutes window before an hour from VTA occurrence. Above all, parameters in frequency domain were extracted by detrending RR interval using high-pass filter and FFT filter after resampling and cubic spline interpolation. After the signal was filtered, it was applied to a peak detection algorithm and extracted RR intervals.

Power spectral density (PSD) of the data was calculated in several frequency bands. The process was conducted using MATLAB (The MathWorks Inc., Natick, USA).

2.3. Parameter extraction

The number of parameters used in the experiment is total eleven. It is as in the following.

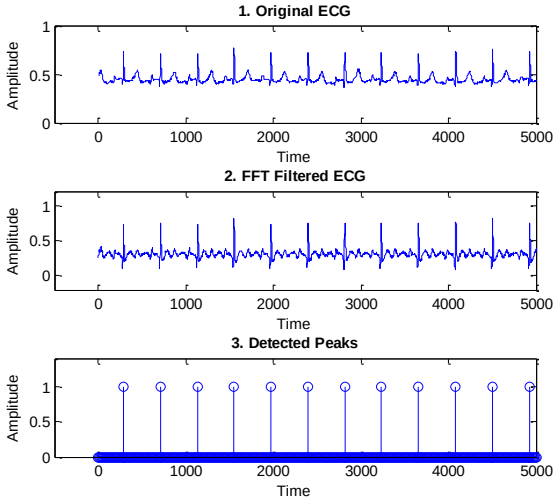

Figure 1. Pre-processing of dataset in 5 minutes window. (1) Original ECG, (2) FFT filtered ECG, (3) Final detected peaks

Mean NN (Mean of NN intervals), SDNN (Standard deviation of NN intervals), RMSSD (Square root of the mean squared differences of successive NN intervals), pNN50 (Proportion of interval differences of successive NN intervals greater than 50 ms) in time domain. VLF (Power in very low frequency range (0-0.04Hz)), LF (Power in low frequency range (0.04-0. 15Hz)), HF (Power in high frequency range (0.15-0.4Hz)), LF/HF (Ratio of LF over HF) in frequency domain. SD1 (Standard deviation 1 of the successive intervals), SD2 (Standard deviation 2 of the successive intervals), SD1/SD2 (Ratio of SD1 over SD2) in poincaré nonlinear analysis.

Below table shows an average, standard deviation of parameters used in the experiment and a p-value (Table 1).

Table 1. Statistical differences of parameter

	Control dataset		VTA(VT+VF) dataset		
parameter	AVG	SD	AVG	SD	p-value
Mean NN	0.6949	0.1623	0.7007	0.1755	0.316
SDNN	0.0562	0.0415	0.0613	0.0395	0.068
RMSSD	0.0615	0.0519	0.0658	0.0491	0.158
pNN50	0.1822	0.2001	0.1893	0.1855	0.299
VLF	3.09E-05	5.39E-05	3.66E-05	7.22E-05	0.196
LF	0.0006	0.0011	0.0007	0.0011	0.312
HF	0.0013	0.0018	0.0013	0.0018	0.314
LF/HF	0.5226	0.6369	0.5538	0.5430	0.297
SD1	0.0356	0.0287	0.0385	0.0278	0.127
SD2	0.0751	0.0555	0.0819	0.0530	0.066
SD1/SD2	0.4549	0.1705	0.4767	0.1658	0.052

AVG = average; SD = standard deviation.

3. Results

3.1. Artificial neural network (ANN)

Artificial neural network (ANNs) are a mathematical model that tries to simulate the structure and functionalities of biological neural networks. ANNs are usually presented as systems of interconnected neurons which send messages to each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning.

ANN used in this study is total three models (for prediction of VT, VF, VTA (VT and VF)). Also, the models are formed in three layers, called the input layer, hidden layer, and output layer. The input layer has 11 neurons, and The 11 HRV parameters were used as input neurons. The output layer was composed of only one neuron to return a value between -1 and 1. The number of each hidden neurons of ANN model was 33, 5, and 25 in VT, VF and VTA (VT+VF) (Figure 2).

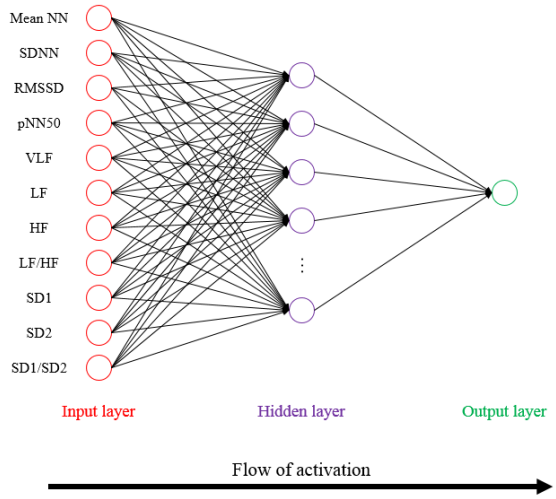

Figure 2. Architecture of artificial neural network and three layers with full interconnection.

3.2. Performance

Three classifiers with ANN were developed to predict VT, VF and VTA (VT+VF). Randomly selected 2/3 of data were used in training ANNs and the remaining 1/3 of data were used for performance evaluation of the trained ANNs. The performance of the predictors are shown in the Table 2 and Figure 3.

Table 2. VTAs classification outcomes

	Se.(%)	Sp.(%)	Acc.(%)	PPV(%)	NPV(%)
VTA	86.11	86.11	86.11	86.11	86.11
VT	73.91	73.91	73.91	73.91	73.91
VF	76.92	69.23	73.08	71.43	75.00

Se. = sensitivity; Sp. = specificity; Acc. = accuracy; PPV = positive predictive value; NPV = negative predictive value.

The ANN showed an each accuracy of 73.08% (57/78) in VF, 73.91% (104/142) in VT and 86.11% (189/220) in VTA (VT+VF). Area under the curve (AUC) of receiver operating characteristic (ROC) for predictor for VT, VF and VTA are 0.74, 0.74 and 0.88, respectively.

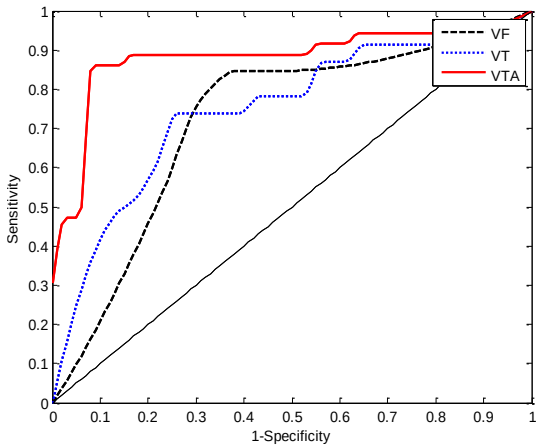

Figure 3. ROC curves for predictors for VT, VF and VTA (VT+VF). Solid line = VTA (VT+VF) prediction, dotted line = VT prediction, dashed line = VF prediction

4. Discussion

We demonstrates that HRV prior to VTA occurrence is able to predict VTA events. As seen in above results, it seems a significantly high predictive value despite recording before 1-hour from VTA occurrence. Prediction outcome of VTA and VT was respectively equal to 86.11% and 73.91% on every items. On the other hand, prediction outcome of VF each was different. Sensitivity was slightly higher, but specificity was lower than other values.

This VTA prediction technology will help a flexible emergency treatment when VTA occurs. However, the number of data used in the experiment is relatively small (total 220 recordings). So this results may be insufficient in a statistical point. In addition, if this data is broken or lost in the data delivery process, it may adversely affect the results.

Although there are several limitations, the result is quite encouraging and these predictors can be adopted in many healthcare devices with a little more improvement. Further mortality caused by SCD would reduce. With more number of data, it will show a better result and be able to apply to healthcare system of ICD. We are not currently satisfied, it will be more research.

5. Conclusion

In this paper, three ANN classifiers were trained and tested with the parameters of HRV analysis extracted within 5 minute-window prior to 1 hour before VTA events. Also, each ANN model was trained with 2/3 of dataset and tested with the remaining dataset, which was set aside during training process. Our group continuously collects patient data with the proposed system and this could help in developing better classifier for VTAs. In addition, development of the method to predict VTAs will facilitate to adopt the algorithms in various, wearable and portable medical device.

Acknowledgements

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2014R1A1A2053862).

References

[1] M. Borjesson, A. Pelliccia. Incidence and aetiology of sudden cardiac death in young athletes: An international perspective. British Journal of Sports Medicine 2009:43:644-8.
[2] D. Corrado, G. Basso C Fau - Rizzoli, M. Rizzoli G Fau - Schiavon, G. Schiavon M Fau - Thiene, G. Thiene. Does sports activity enhance the risk of sudden death in adolescents and young adults?. Journal of the American College of Cardiology 2003:42:1959-63.
[3] E. G. Ellsworth, M. J. Ackerman. The changing face of sudden cardiac death in the young. Heart Rhythm 2005:2:1283-5.
[4] D. P. Zipes, H. J. J. Wellens. Sudden Cardiac Death. Circulation 1998:98:2334-51.
[5] S. Joo, K. J. Choi, S. J. Huh. Prediction of spontaneous ventricular tachyarrhythmia by an artificial neural network using parameters gleaned from short-term heart rate variability. Expert Systems with Applications 2012:39:3862-6.
[6] R. E. Lane, M. R. Cowie, A. W. C. Chow. Prediction and prevention of sudden cardiac death in heart failure. Heart 2005:91:674-80.
[7] J. P. Piccini, M. Zhang, K. Pieper, S. D. Solomon, S. M. Al-Khatib, F. Van De Werf. Predictors of sudden cardiac death change with time after myocardial infarction: Results from the VALIANT trial. European Heart Journal 2010:31:211-21.
[8] L. G. Tereshchenko, B. J. Fetics, P. P. Domitrovich, B. D. Lindsay, R. D. Berger. Prediction of ventricular tachyarrhythmias by intracardiac repolarization variability analysis. Circulation: Arrhythmia and Electrophysiology 2009:2:276-84.
[9] S. Chernenko. ECG processing: R-peaks detection. Available: http://www.librow.com/cases/case-2

Address for correspondence:

Segyeong Joo
Dept. BME, AMC, University of Ulsan, Seoul, Korea
sgjoo@amc.seoul.kr