ETD: An Extended Time Delay Algorithm for Ventricular Fibrillation Detection

Jungyoon Kim and Chao-Hsien Chu

Abstract— **Ventricular fibrillation (VF) is the most serious type of heart attack which requires quick detection and first aid to improve patients' survival rates. To be most effective in using wearable devices for VF detection, it is vital that the detection algorithms be accurate, robust, reliable and computationally efficient. Previous studies and our experiments both indicate that the time-delay (TD) algorithm has a high reliability for separating sinus rhythm (SR) from VF and is resistant to variable factors, such as window size and filtering method. However, it fails to detect some VF cases. In this paper, we propose an extended time-delay (ETD) algorithm for VF detection and conduct experiments comparing the performance of ETD against five good VF detection algorithms, including TD, using the popular Creighton University (CU) database. Our study shows that (1) TD and ETD outperform the other four algorithms considered and (2) with the same sensitivity setting, ETD improves upon TD in three other quality measures for up to 7.64% and in terms of aggregate accuracy, the ETD algorithm shows an improvement of 2.6% of the area under curve (AUC) compared to TD.**

I. INTRODUCTION

Wearable health-monitoring systems have attracted much attention due to their high potential in healthcare as cost-effective solutions for real-time healthcare monitoring, early detection of diseases, and improving treatment of various medical conditions [1]. While these systems show much promise for increasing quality of living, for practical usage, there are several challenges that need to be overcome, specifically, in areas such as reliability, multifunctionality, energy efficiency and minimizing obtrusiveness [1].

Ventricular fibrillation (VF) is one of the most serious life-threatening cardiac arrhythmia diseases. Once a patient has suffered a VF attack, accurate detection and quick first aid treatment are essential for improving the chance of survival. Weaver et al. [2] report that the survival rate of a patient, who experiences a VF attack outside the hospital, varies from 7% to 70%, depending on how quickly the patient receives first aid. Thus, solving the problem of a quick and reliable detection is an emergent research topic.

There have been many studies focused on evaluating VF detection algorithms for applying proper electrical therapy in automated external defibrillators (AEDs) [3-15]. According to previous research [4-6, 12] and our own experiments [16], the time-delay (TD) algorithm [12] has a high reliability for separating sinus rhythm (SR) from VF compared to other algorithms. It is also robust to factor impacts, such as different filtering methods and window sizes (4 and 8 seconds). However, there are weaknesses such as (1) it undercounts the density value of phase space and thus miss-judges some VF cases, (2) it cannot properly detect ECG signals with a changing baseline and (3) it operates with a fixed delay time and thus fails to detect ECG signals with variable heart rates.

In this paper, we propose an extension of the TD algorithm, called ETD, to improve the detection accuracy. We conduct experiments comparing the performance of ETD against five other detection algorithms, including TD, in terms of popular quality measures using the Creighton University (CU) database. The remainder of this paper is organized as follows. Section II reviews the logic of the TD algorithm and its weaknesses. Section III describes the proposed extended time-delay (ETD) algorithm and why it can correct the weaknesses of TD. Section IV describes the experiments and reports the evaluation results. Section V provides the discussion and conclusions of this study.

II. TIME DELAY (TD) ALGORITHM

A. The TD Algorithm

The TD algorithm uses a 40×40 square two-dimensional phase space reconstruction (PSR) diagram to analyze ECG signals for identifying a dynamic low or random behavior [12]. By plotting the signal data $X(t)$ on the x-axis against the τ time-delay data $X(t+\tau)$ on the y-axis (where $\tau = 0.5$ seconds), the plot shows the number of visited boxes.

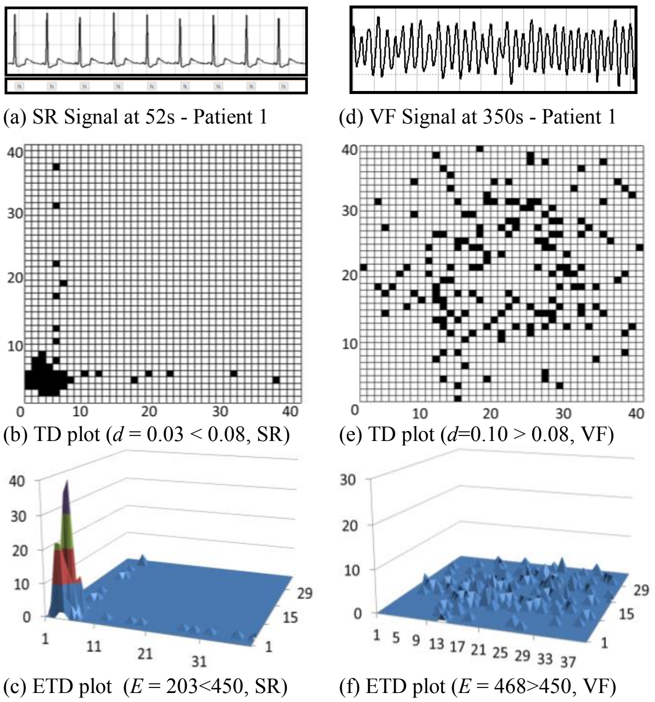
Figure 1 depicts the actual ECG signals and the patterns from time-delay plotting of TD and ETD. Figure 1(a) shows a normal ECG signal with obvious QRS complex and Figure 1(d) shows a clear case of VF attack. Since the normal ECG signal mainly consists of baseline and QRS complex, these two features will be visually shown as two lines in the phase space plot (see Figure 1(b)). In a clear VF signal case, the visited boxes over the phase space plot will appear visually as uniformly distributed boxes (see Figure 1(e)).

Unfortunately, most real-world cases are mixed with noisy data and it is difficult to judge the results visually. To objectively distinguish QRS complex from VF cases, TD counts the density of boxes visited (d) and compares it with a prescribed threshold value (d_0). If $d < d_0$, the ECG signal is considered a normal sinus rhythm (SR); otherwise, it is classified as a VF case. Using Figure 1 as an example, the threshold value of d_0 for a 4 second window segment is set as 0.08 based on an algorithm proposed for optimized threshold

JY Kim was with The Pennsylvania State University, PA 16802 USA. He is now with the *iCity* Lab of Singapore Management University, Singapore 178902 (e-mail: jykim@smu.edu.sg).

C. H Chu is with The Pennsylvania State University, PA 16802 USA. (Corresponding author: phone: +1 8148654446; fax: +1 8148656429; e-mail: chu@ist.psu.edu).

determination [16]. In Figure 1(b), d = 0.03 < 0.08, so the signal is classified as a normal SR and the signal in Figure 1(e) is recognized as VF because d = 0.10 > 0.08.



(a) SR Signal at 52s - Patient 1 (d) VF Signal at 350s - Patient 1

(b) TD plot (d = 0.03 < 0.08, SR) (e) TD plot (d=0.10 > 0.08, VF)

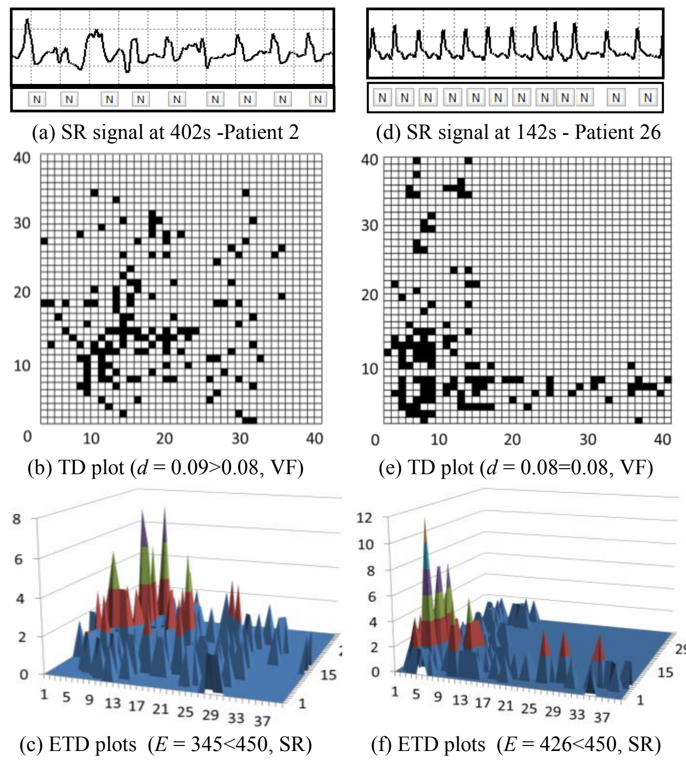
(c) ETD plot (E = 203<450, SR) (f) ETD plot (E = 468>450, VF)

Figure 1. Phase space reconstruction plots of TD and ETD (CUDB patient 1 with 4 second window size)

B. Weaknesses of TD

Although the TD algorithm performs quite well in clear SR and VF cases, there are three weaknesses that impact its overall performance:

- TD counts all overlapped visit boxes as one; thus, it may undercount the density value and misclassified some VF cases. For example, if there is no QRS complex in one window segment of ECG signal, TD may undercount the numbers of visited boxes as a small density number. This results in the signal being classified as normal, when it is in actuality abnormal.
- TD cannot properly detect signals with a changing baseline. For example, Figure 2(a) has a signal with a baseline moving up and down, which may be caused by patient movement and electrode attachment. Although the signal was annotated as a normal signal by the ECG experts, the phase space plot shows boxes distributed in a wide area (as seen in Figure 2(b)) due to the baseline drift or shift. Also, because it reduces the overlap count, which increases the d value (d = 0.09 > d_0 (= 0.08)), the TD algorithm misclassifies it as a VF case.
- TD uses a fixed delay time (τ = 0.5 seconds) to plot phase space, which may cause misclassification of changing heart rates. Although using a fixed delay time allows for minimizing the number of overlapping visited boxes for stable heart rates, the overlapped area of the plot will shift if the heart rate is changed (often in one window segment) which will cause a classification error. For example, Figure 2(d) shows the actual ECG signal, which has irregular heart rates. As can be seen in Figure 2(d), the interval of QRS complexes varies so that the number of visited boxes is increased. Figure 2(e) shows the corresponding phase space plot which looks like a weak VF case. Since in this case, d (= 0.08) is larger than typical ECG (d = 0.03), it was misclassified as a VF case, despite it being a normal SR with variable heart rate.



(a) SR signal at 402s -Patient 2 (d) SR signal at 142s - Patient 26

(b) TD plot (d = 0.09>0.08, VF) (e) TD plot (d = 0.08=0.08, VF)

(c) ETD plots (E = 345<450, SR) (f) ETD plots (E = 426<450, SR)

Figure 2. Phase space reconstruction plots of TD and ETD (CUDB patient 2 and patient 26 with 4-second window size)

III. Extended Time-delay Algorithm

Listed below are the variables used in the ETD algorithm:

- $x(t)$: Position of x-axis
- $x(t + \tau)$: Position of y-axis
- $N_{(x(t),\, x(t+\tau))}$: The number of overlapped boxes at $\{x(t), x(t + \tau)\}$ (Position of z-axis)
- β: The maximum value along the z-axis
- W: Window size
- F: Sampling frequency
- $E_{(\beta, W)}$: Total ETD value for detecting decision

We observe that a typical VF signal produces a s*ine* curve type of ECG, which fills the 2D phase space area in an irregular way with a low number of overlapped boxes. The curve is almost uniformly distributed over the 40×40 grid, with relatively few overlaps. For a normal sinus rhythm (SR), however, the curve in the phase space diagram shows a regular structure which fills only small parts of the total area, and the curve is concentrated in a limited part of the plot with a large number of the overlaps within a small number of boxes.

The extended time delay algorithm (ETD) is based on a 3D plot which consists of the same 2D phase space reconstruction as TD on the x and y axes but adds the number of overlapped boxes (i.e., $N_{(x(t),\, x(t+\tau))}$) on the z axis to address the problem of undercounting visited boxes. Because ETD analyzes signals not only to identify a dynamic low or random behavior but also to count the number of overlaps due to changes in heart rates and baselines, it can properly remedy the above mentioned weaknesses of TD algorithm.

Figure 3 shows how the ETD algorithm works. We determine the area of the plot filled by the curve and the density of the visited boxes. To achieve this, we produce a 40×40 grid ranging from 0 to the maximum value of the investigated raw ECG signal (β).

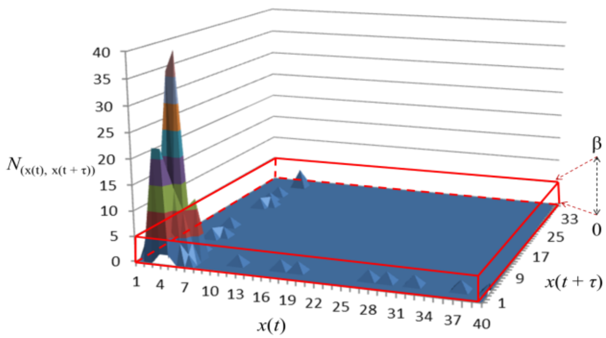


Figure 3. 3D Phase space reconstruction plots of ETD (CUDB patient 1)

The areas with high peaks indicate the existence of baseline from SR. The decision criterion of the ETD value, E, is calculated by summing all visits as:

$$E = \Sigma_{all}\,(N_{(x(t),\, x(t+\tau))}) \qquad (1)$$

Where $N_{(x(t),\, x(t+\tau))}$ is from 0 to β ($0 < N_{(x(t),\, x(t+\tau))} < \beta$; $\beta = 5$). If E is higher than a prescribed threshold E_0, we classify the corresponding ECG segment as VF. We choose τ = 0.5seconds and the threshold $E_0 = 450$ according to an optimal threshold value algorithm proposed in [16].

Algorithm 1 shows the detailed pseudo code of the ETD algorithm:

Algorithm 1: An algorithm for ETD

```
Determine Integer Array E [40, 40], β = 5, W = 8s, F = 62.5 Hz, τ = 0.5 sec
for ECG [i] from 0 to W×F by 1
  if (i > τ)
    then x(t + τ) = Scaled ECG [i]
         x(t) = Scaled ECG [i - τ]
         Increment E [x(t + τ), x(t)]
         if ((E [x(t + τ), x(t)] > 0 ) && (E [x(t + τ), x(t)] <= β))
           then Increment E (β, W);
         end-if
  end-if
end-for
```

Let us use the same examples in Figures 1 and 2 for illustration. Figure 1 (c), (f) and Figure 2 (c), (f) are the corresponding 3D plots from ETD for the same data respectively. If the tested ECG signal is clear (without noise) as in the case of patient 1, both TD and ETD can easily distinguish between normal SR and VF attack. However, for the two ambiguous cases with the changing baseline (patient 2) or changing heart rates (patient 26), TD cannot detect the right result as shown in Figure 2(b) and (e). On the other hand, the patients are considered normal by ETD because the algorithm keeps track of overlapped values on the z-axis (Figure 2(c) and (f)). Also, the corresponding E values, 345 and 426, are smaller than the threshold value (450); thus, they are correctly classified as normal signals.

IV. Performance Evaluation

We first conduct comparative analyses over six VF detection algorithms: Threshold Crossing Intervals algorithm (TCI) [13], VF filter algorithm (VFF) [14], Pan and Tompkins algorithm (TOMP) [15], Threshold Crossing Sample Count algorithm (TCSC) [8], TD [12] and ETD. All six algorithms are analyzed in terms of common quality metrics -- sensitivity (*Sn*), specificity (*Sp*), positive predictivity (*Pp*), accuracy (*Acc*) -- and a receiver operating characteristic (ROC) curve using the popular Creighton University (CU) VT databases [17] with an 8 second window and *filtering.m* method [18]. For better comparison between TD and ETD, we set similar sensitivity results for both methods, so that the other three measures can be fairly compared. We then provide an in-depth analysis between the TD and ETD algorithms using the same quality measures and an aggregate measure, the area under ROC curve (AUC).

Table I shows the comparative results in terms of the four quality measures across the six VF algorithms, where the top two best results are **highlighted** and the worst results for each measure are in red color or *italic* style. As shown, VFF performs the best in terms of *Sp*, *Pp* and *Acc*; however, it performs the worst in terms of *Sn*; thus, it cannot be considered as a good method. On the other hand, both TD and ETD have good performance in all four measures, with ETD slightly better than TD.

TABLE I. COMPARISON OF PERFORMANCE FOR SIX VF ALGORITHMS

Algorithms	Sn (%)	Sp (%)	Pp (%)	Acc (%)
TCI	69.64	62.39	38.31	64.21
VFF	*36.23*	**99.67**	**97.16**	**84.44**
TOMP	**73.50**	*54.85*	*34.63*	*59.43*
TCSC	63.24	81.29	51.9	76.92
TD	**80.52**	81.83	55.85	81.54
ETD	**80.52**	**85.90**	**61.98**	**84.71**

Figure 4 compares the ROC curve of the six algorithms. These results also clearly support the conclusion that both ETD and TD outperform the other four algorithms, with ETD slightly better than TD, as well as the fact that VFF did not perform well in terms of *Sn*. Across the 35 data sets used, TD and ETD obtained the same results for 8 data sets. Thus, we removed these data sets from further analysis. Table II summarizes the average results from this differential analysis. As shown, under equal sensitivity, ETD performs better than TD in terms of *Sp*, *Pp*, *Acc*, and *AUC* by 5.19%, 7.64%, 4.06% and 2.60% respectively.

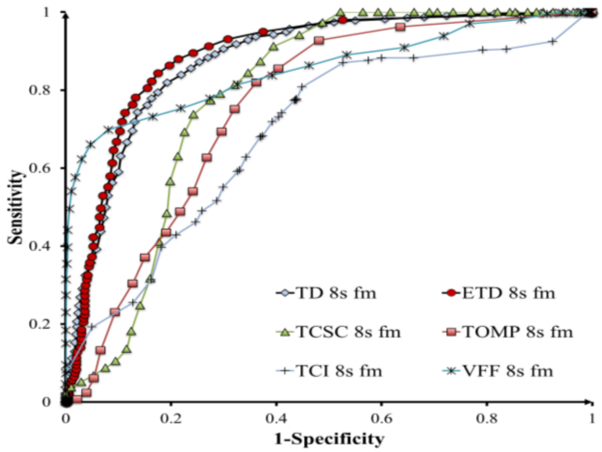


Figure 4. Comparison of ROCs for six VF detection algorithms (fm: *filtering.m)*

TABLE II. COMPARISON OF PERFORMANCE BETWEEN ETD AND TD ALGORITHMS BASED ON SELECTED PATIENTS

Algorithms	Sn (%)	Sp (%)	Pp (%)	Acc (%)	AUC (%)
ETD	77.18	**85.78**	**60.08**	**83.91**	**81.48**
TD	77.18	80.58	52.44	79.84	78.88
Deviation	0	5.19	7.64	4.06	2.60

V. CONCLUSION AND DISCUSSION

In this paper, we proposed an extension of the time delay algorithm, called ETD, which uses a 3D phase space plot to address the weaknesses of the TD algorithm for VF detection. Our comparative analyses show that under equivalent conditions (i.e., same filtering method, window segmentation, optimized threshold values, data sets and system) both TD and ETD perform better than the other four algorithms in the comparison in terms of common quality measures and ROC curve. Our study also shows that with the same sensitivity setting, ETD improves upon TD performance in three other quality measures by up to 7.64%. In terms of aggregated accuracy, the ETD algorithm shows an improvement of 2.6% of the area under curve (AUC) compared to TD.

In particular, with the extension, the performance of ETD was quite robust as it was not much impacted by signal noise such as baseline drift and changing heart rate. This can be seen from the results in Figure 2, where the two unclear cases, baseline wave and the variable interval of QRS complexes, are shown. These cases were problematic for the TD algorithm, because they prevented accurate discrimination of SR from VF.

Although the 3D plot of ETD slightly improves on detection accuracy, problems with baseline wave and R-peak interval still need to be resolved. The baseline wave moves the hot-spot area of the phase space plot so that it disrupts the high peak of the ETD plot. Since this issue is closely related to baseline tracking and the scaling process in the ETD algorithm, the adaptive process approach, which makes the baseline of ECG signal stable so that the hot-spot area is concentrated in the same spot, may be able to resolve the issue. Moreover, the R-peak interval problem affects uniform positioning of two lines in the phase space plot. As a result, it increases the 2D plot area in the number of visited boxes. This issue is also connected to using a fixed τ time delay.

Compared to common performance metrics, the AUC is a better way to judge the performance of different algorithms by one single value. However, similar to how the four performance metrics are decided by the threshold value, the threshold value we selected also affects the value of the AUC. Because we use ECG signals from 35 patients in the CU database, any given threshold may not be a proper decision value for some datasets. For more accurate evaluation, a dataset-specific threshold values may be able to enhance the validity of VF detection algorithms.

REFERENCES

[1] Pantelopoulos, A. and Bourbakis, N. G., “A survey on wearable sensor-based systems for health monitoring and prognosis,” *IEEE Trans on Systems, Man and Cybernetics – Part C: Applications and Reviews*, vol. 40, pp. 1 - 12, Jan. 2010.

[2] Weaver, W. D., Cobb, L. A., Hallstrom, A. P., Copass, M. K., Ray, R., Emery, M. and Fahrenbruch, C., “Considerations for improving survival from out-of-hospital cardiac arrest,” *Annals of Emergency Medicine*, vol. 15, pp.1181-1186, Oct. 1986.

[3] Jekova, I. and Krasteva, V., “Real time detection of ventricular fibrillation and tachycardia,” *Physiol. Meas.*, vol. 25, pp. 1167-1178, 2004.

[4] Amann A., Tratnig, R. and Unterkofler, K., “Reliability of old and new ventricular fibrillation detection algorithms for automated external defibrillators,” *BioMed. Eng.* Online vol. 4, p. 60 Oct. 2005.

[5] Amann, A., Tratniq, R. and Unterkofler, K., “A new ventricular fibrillation detection algorithm for automated external defibrillators,” *Comput Cardiol*, vol. 32, pp. 559-562, 2005.

[6] Ismail, A. H., Fries, M., Rossaint, R. and Leonhardt, S., “Validating the reliability of five ventricular fibrillation detecting algorithms,” in *ECIFMBE 2008, IFMBE Proceedings*, vol. 22, pp. 26-29, 2008.

[7] Abu, E. M. A., Lee, S. Y. and Hasan, M. K., “Sequential algorithm for life threatening cardiac pathologies detection based on mean signal strength and EMD functions,” *BioMed. Eng.* Online vol. 9, p. 43, 2010.

[8] Arafat, M. A., Chowdhury, A. W. and Hasan, M. K., “A simple time domain algorithm for the detection of ventricular fibrillation in electrocardiogram”, *SIViP*, vol. 5, pp. 1-10, 2009.

[9] Fokhenrood, S., Leijdekkers, P. and Gay, V., “Ventricular tachycardia/fibrillation detection algorithm for 24/7 personal wireless heart monitoring,” *ICOST 2007*, LNCS vol. 4541, pp. 110-120, 2007.

[10] Zhang, Z. X., Tian, X. W., Lim, J. S., “Real-time algorithms for a mobile cardiac monitoring system to detect life-threatening arrhythmias” *in The 2nd International Conference on Computer and Automation Engineering (ICCAE)*, vol. 4, pp. 232-236, 2010.

[11] Rospierski, M., Segura, M., Guzzo, M., Zavalla, E., Sisterna, C., and Laciar, E., “Ventricular fibrillation detection algorithm implemented in a cell-phone platform”, *Congreso Argentino de Sistemas Embebidos*, pp. 168-173, 2011.

[12] Amann, A., Tratniq, R. and Unterkofler, K., “Detecting ventricular fibrillation by time-delay methods,” *IEEE Trans. Biomed. Eng.* Vol. 54, pp. 174-177, 2007.

[13] Thakor, N. V. and Pan K., “Ventricular tachycardia and fibrillation detection by a sequential hypothesis testing algorithm,” *IEEE Trans. on Biomedical Engineering*, vol. 37, pp. 837-43. Aug. 1990.

[14] Kuo S. and Dillman R., “Computer detection of ventricular fibrillation,” *Computers in Cardiology*, pp. 347-349, 1978.

[15] Pan, J. and Tompkins, W., “A real-time QRS detection algorithm,” *IEEE Trans Biomed Eng.* vol. 32, pp. 230-236, 1985.

[16] Kim, JY, Chu, CH, Zhou, S. and Shin, S., “Analysis and modeling of energy consumption for wearable ECG devices.” (Working Paper), Penn State University, PA.

[17] Goldberger, A. L., et al., “PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals,” *Circulation*, vol. 101, no. 23, pp. e215-e220. Available: http://www.physionet.org/physiobank/database/cudb

[18] filtering.m [Online]. Available: https://homepages.fhv.at/ku/karl/VF/filtering.m