A fractal-based approach for suppressing chest compression noise in ECG signal

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Abstract

In current study, we derived a technique based on regularization dimension, named as RD filter. It analyzed ECG fractal characteristics and thoracic impedance signal to achieve noise reduction. We compared RD filter against adaptive filter based on compression rate (CR filter). SNR of RD filter was improved by more than 40% on average comparing SNR of CR filter. RD filter output had DTW distance smaller than CR filter result. These findings suggest RD filter is a potential technique for CPR that can suppress compression noise and ensure discriminative features of ECG rhythms.

1. Introduction

When a patient suffers cardiac arrest (CA), blood circulation stops and irreversible brain damage occurs within minutes [1,2]. Cardiopulmonary resuscitation (CPR) is designed against these disorders. It involves a series of actions, including chest compressions, defibrillations and other life supports. First aid provider repeats these life-saving actions sequentially, most of the time on chest compressions. Study found compression quality have vital effects on resuscitation. Guidelines consistently emphasizes the importance of high-quality CPR, requiring rescuer to minimize number and duration of interruptions during compressions [3]. But chest compression quality is greatly affected by defibrillation. First aid providers observe the ECG rhythm type and decide to defibrillate or not. Since ECG signal is disrupted by chest compressions, aid providers must pause chest compressions [4]. In this way, chest compressions are interrupted for a long time.

Studies found that filtering technique can reduce chest compression noise [5,6]. If appropriate filtering can help discriminate ECG rhythms and decide to discharge or not during chest compression, the number and duration of chest compression interruptions will decrease. Filtering techniques for chest compressions noise has therefore received extensive attentions [7–10]. Various techniques were adopted, including Kalman filtering, adaptive filtering, etc. However, a major problem of these techniques is that they substantially change ECG morphology [4,10]. The morphology of ECG is essential for distinguishing rhythms, e.g., ventricular fibrillation displays rapid fluctuations but pulseless electrical activity has slow waveform change. Literature suggests the ideal filtering solution need to both suppress chest compression noise and keep rhythmic morphology of ECG [5,6].

Fractal analysis in mathematics focuses on structural complexity and can analyse morphological features of signals and graphs [11]. Regularization dimension is a specific measurement in fractal analysis, defined to measure signal irregularity [12]. Regularization can be regarded as detail removal, i.e., erase subtle changes in time series data within certain scale. Signals become more regular and has a finite length after removing subtle changes, assuming irregular signal has infinite length [11,12]. When time scale for removing subtle changes tends to zero, the left signal approximates the original signal with infinite length. This process of removing subtle changes is used to analyse irregularity of signals, defined as regularization dimension.

Assuming significant difference in ECG and chest compression noise irregularity, this study designed a filter to reduce compression noise with expectation of retaining ECG rhythm morphology at the same time. This study measured ECG and chest impedance signals of CA patients during CPR. The experiment observed denoising performance and further provided comparison between the proposed filter and conventional adaptive filter in terms of noise reduction and morphology retention.

2. Method

2.1. Data Collection

Multicentre data collection was performed at three hospitals. Family of subjects signed an informed consent form and voluntarily participated in data collection. The experiment followed clinical ethical standards, approved by the medical ethics committee of each hospital.

Patient inclusion criteria were age not less than 8 years and receiving CPR in the emergency department.

Exclusion criteria included refusal of CPR, inability to attach electrode pads due to skin damage, or perform chest compressions due to trauma or pregnancy. The resuscitation was performed by professional physicians in each hospital. Equipment used in CPR was BeneHeart D3 (Shenzhen Mindray Bio-Medical Electronics Co., Ltd). BeneHeart D3 is an automated external defibrillator and can record ECG and chest impedance signal simultaneously.

According to the inclusion and exclusion criteria, data were collected from 32 CA patients during CPR (25 males and 7 females). Patients' age was from 23 to 89 (average value: 58.5 ± 17.4 years), body height was from 1.6 to 1.78 m (1.69 ± 0.05 m) and body weight was from 45 to 80 kg (65.5 ± 10.5 kg). These patients involved acute pulmonary embolism, acute myocardial infarction, and haemorrhagic shock, etc.

Four ECG rhythms were labelled by physicians retrospectively, including: organized rhythm (ORG), asystole (ASY), pulseless electrical activity (PEA) and ventricular fibrillation (FIB) [4]. After selection, a total of 40 ECG segments without interference of chest compressions or ventilation, were obtained, including 6 ORG segments, 9 ASY segments, 13 PEA segments and 12 FIB segments, with lengths from 15 to 20 seconds. In addition, 13 ECG ASY segments from patients under chest compressions were selected by physician and used as compression noise. The chest impedance signals related to these 13 ASY segments were also recorded.

2.2. Signal Processing and Construction

BeneHeart D3 can record ECG and chest impedance using electrode pads. Chest impedance is the resistance between the electrode that defibrillators overcome to deliver discharge. The status of impedance is related with chest compressions. Thus, impedance signal is considered as a reference signal for the compression-related noise in ECG. Signals of ECG (in millivolts) and chest impedance (in ohms) were put through the built-in Mindray processing algorithm before usage [13,14]. Sampling frequency of signal was 250 Hz.

Simulation data s_{nECG} was generated by superimposing ECG with chest compression noise, i.e., $s_{nECG} = s_{ECG} + C \cdot s_{noise}$, where s_{ECG} is ECG signals free of chest compression noise, s_{noise} is compression noise forged by normalized asystole rhythms during chest compressions, and C is the coefficient to adjust noise amplitude. This process was referred to the study of Adun Langhelle et al [5]. This signal construction process ensures that filter performance can be assessed with actual rhythms, i.e., s_{ECG}. Signal-to-noise ratio of construction was defined as $SNRc = 10log_{10}(\sigma^2_{ECG}/\sigma^2_{noise})$, where σ^2_{ECG} and σ^2_{noise} are the variance of s_{ECG} and s_{noise}, respectively. In this study, the simulated data with $SNRc$ of -5, 0 and 5 dB was constructed by adjusting C. A total of 520 segments were generated for filtering tests.

2.3. Filter Design

Practical calculation of regularization dimension utilizes Gaussian kernel convolution. When Gaussian kernel width tends to zero, the length of smoothed signal converges to the original signal with certain speed [11,12]. The speed of convergence is a measure of regularization dimension, defined as follows when the limit exists:

$$D_{Rg} = 1 - \lim_{\delta \to 0}(lnl_\sigma / ln\sigma) \quad (1)$$

D_{Rg} is regularization dimension, σ defines kernel width and l_σ is smoothed signal length [15].

Filter design based on regularization dimension (RD filter) consists of four steps: noise irregularity estimation, original signal regularization, noise content identification and final denoise computation.

Noise irregularity estimation was to calculate chest impedance signal regularization dimension D_{imp}. Chest impedance changes and ECG compression noise are related with each other and thus assumed to have similar irregularity. Noise irregularity was indirectly obtained from chest impedance signal.

Original signal regularization made a collection of signals with varied irregularity from input, by smoothing the input with varied-scale Gaussian kernels, i.e., $s_\sigma = s * g_\sigma$, where s is the input to be filtered, g_σ is the Gaussian kernel with width of σ, and s_σ is the output after smoothing.

Noise content identification started with comparing the irregularity of chest compression noise (D_{imp}) and input (D_s). If D_{imp} is lower than D_s, compression noise mainly exists as low irregularity content, otherwise compression noise was high irregularity content. With the collection of signals obtained by original signal regularization, chest compression noise estimation $\hat{s}_{noise}$ could be obtained by following:

$$\begin{aligned} &\text{If } D_{imp} < D_s, \hat{s}_{noise} = \\ &\quad \underset{s_\sigma}{argmin}\left(D_{imp} - D_{s_\sigma}\right)^2 \\ &\text{If } D_{imp} > D_s, \hat{s}_{noise} = \\ &\quad s - \underset{s_\sigma}{argmin}(D_{imp} + D_{s_\sigma} - 2 \cdot D_s)^2 \end{aligned} \quad (2)$$

D_{s_σ} is regularization dimension of smoothed data with Gaussian kernel width σ.

The final denoise computation removed compression noise estimation ($\hat{s}_{noise}$) from the input (s), i.e., filtered output $= s - \hat{s}_{noise}$. Regularization dimension calculation was referred to open source software FracLab (version 2.2). This study also implemented an adaptive filtering, i.e., analyzing chest impedance for compression rate then achieving noise reduction (CR filter) [3].

2.4. Statistical Analysis

Signal-to-noise (SNR) ratio was used to quantify noise reduction: $SNR = 10log_{10}(\sigma_{ECG}^2/\sigma_{\Delta}^2)$, where σ_{ECG}^2 and σ_{Δ}^2 represent variance of s_{ECG} (expected filter output) and remaining noise (difference between s_{ECG} and filtering output), respectively. For evaluation of morphology retention, distance based on Dynamic Time Wrapping (DTW) was introduced to measure time series similarity between filter output and s_{ECG} [16]. Data were not normally distributed. Wilcoxon signed rank test was applied, and median with upper and lower quartiles was presented, performed by SPSS 13.0 with P < 0.05 as significant different.

3. Result and discussion

As shown in Table 1, SNR of two filters' output is given. RD filter generally had greater SNR than CR filter. Figure 1 shows DTW comparison. For ASY and PEA, DTW distance of two methods was close. But for FIB and ORG, RD filter presented lower DTW distance than CR filter. Figure 3 gives examples of RD and CR filter, where varied columns and rows present results of varied $SNRc$ and ECG rhythm. Both methods reduced noises but RD filter output is closer to original ECG for FIB than CR filter output.

Table 1. SNR comparison between RD and CR filter. Data presents by median with upper and lower quartiles.

Rhythm	$SNRc$	CR	RD	P - value
ASY	-5 dB	-0.33 (-3.01, 0.36)	-0.12 (-1.67, 0.87)	**< 0.05**
	0 dB	1.25 (0.34, 1.76)	1.59 (0.66, 3.01)	**< 0.01**
	5 dB	5.07 (2.88, 6.50)	3.44 (1.62, 5.34)	**< 0.01**
PEA	-5 dB	0.32 (-0.08, 0.69)	-0.06 (-1.17, 0.56)	**< 0.01**
	0 dB	1.11 (0.66, 1.60)	1.63 (0.98, 2.45)	**< 0.01**
	5 dB	1.36 (0.89, 2.01)	2.41 (1.49, 4.00)	**< 0.01**
FIB	-5 dB	0.35 (0.01, 0.62)	0.38 (0.20, 1.02)	**< 0.05**
	0 dB	1.08 (0.77, 1.51)	2.11 (1.32, 3.04)	**< 0.01**
	5 dB	1.38 (1.06, 1.81)	3.14 (1.92, 5.56)	**< 0.01**
ORG	-5 dB	0.79 (0.52, 1.02)	1.30 (0.02, 2.00)	0.40
	0 dB	1.66 (1.29, 1.87)	2.75 (1.13, 3.71)	**< 0.01**
	5 dB	1.94 (1.70, 2.24)	3.37 (1.55, 5.29)	**< 0.01**

Heart electrophysiological activity is very complex and many physiological activities occur during heart electrophysiological process [4]. In contrast, chest compression noise is generated from simple mechanical movements [3]. This leads to irregularity difference between ECG and chest compression noise and makes it possible to reduce compression noise with fractal analysis. Results show that RD filter reduced chest compression noise and outperforms CR filter in terms of SNR. According to findings of DTW distance, RD filter maintained morphological characteristics of ECG rhythm better than CR filter.

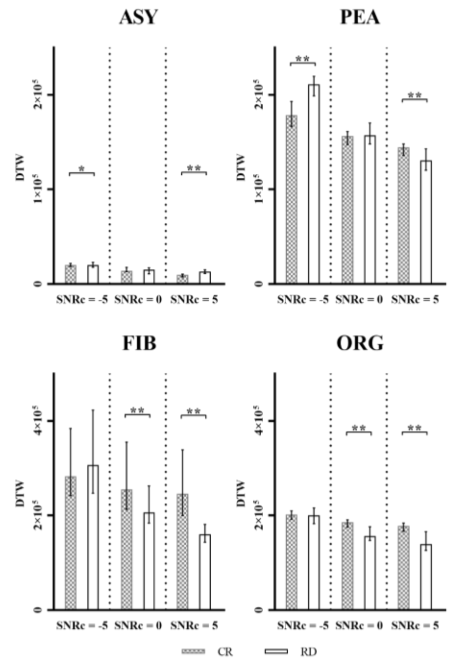

Figure 1. DTW distance of RD and CR filter for data with $SNRc$ of -5, 0 and 5dB (bars are medians, error lines are 95% confidence intervals, *: P < 0.05, **: P < 0.01).

Data further reveals that the improvement of RD filter compared with CR filter was more noticeable for FIB and ORG than for ASY and PEA. This relates to the irregularity difference of ECG rhythms. Cardiac electrophysiological activity during ASY and PEA is weak and simple [6], but during ORG is almost complete [7], while patients with FIB have rapid fibrillation [9]. Irregularity of ASY and PEA rhythm can be close to that of compression noise, but irregularity of ORG and FIB rhythm is higher. Irregularity estimation also supports this opinion. Regularization dimension of FIB and ORG, presenting by median with upper and lower quartiles were 1.43 (1.34, 1.50) and 1.56 (1.50, 1.62), but ASY and PEA were 1.34 (1.26, 1.38) and 1.32 (1.27, 1.40). The latter two are significantly smaller than the former two (p < 0.01). Artificial noise for signal construction and related chest impedance signal had regularization dimension of 1.27 (1.26, 1.32) and 1.31 (1.30, 1.35), much similar with ASY and PEA rather than FIB and ORG. This suggests irregularity difference between rhythm and chest compression noise can affect RD filter performance.

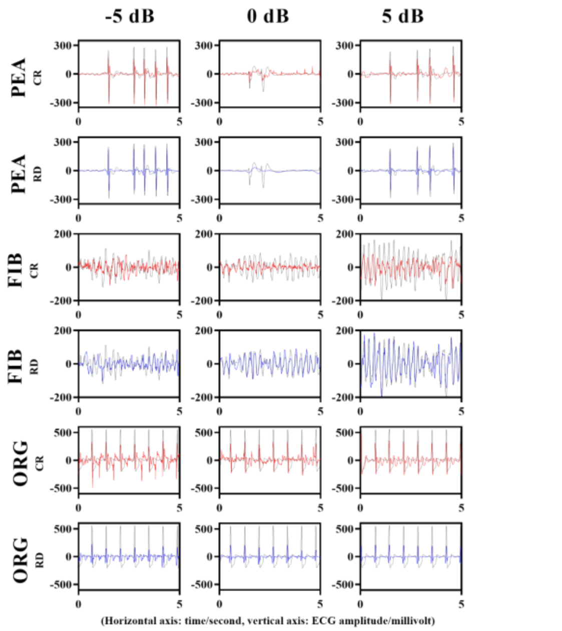

Figure 2. RD and CR filter result for data with $SNRc$ of -5, 0 and 5dB. Red, blue and black line are CR outcome, RD outcome and ECG rhythm without compression noise.

The proposed technique is of clinical value since it can maintain ventricular fibrillation rhythm. Defibrillation requires identification of ventricular fibrillation for timing of discharge, where maintaining ventricular fibrillation morphology is of great help [4]. In addition, the proposed method only requires ECG and chest compression data. In contrast to algorithms requiring compression plates for acceleration measurement [7], RD filter is more applicable to the widely used devices. However, the method proposed is still a preliminary implementation and need further improvement. Besides, the accuracy of rhythm identification of RD filter output has not been directly analyzed, which needs to be explored in future.

4. Conclusion

RD filter based on fractal analysis was implemented for reducing chest compression noise during CPR. The comparison with existing adaptive filter demonstrates that the proposed method can better reduce noise and maintain morphological characteristics of ECG rhythms. Our study provides a possible filter technique to reduce interruptions in chest compressions during CPR.

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