Vietnam Journal of Science and Technology ***57*** *(1) (2019) 92-101*

doi:10.15625/2525-2518/57/1/12964

A VARIATIONAL MODE DECOMPOSITION BASED APPROACH FOR CARDIOPULMONARY RESUSCITATION ESTIMATION AND ASSESSMENT

Thi-Thao Tran, Van-Truong Pham*

Hanoi University of Science and Technology, No.1 Dai Co Viet, Ha Ba Trung, Ha Noi

*Email: truong.phamvan@hust.edu.vn

Received: 14 August 2018; Accepted for publication: 20 November 2018

Abstract. Cardiac arrests remain leading causes of deaths for thousands of people annually. One of the most common methods for cardiac arrest treatment is cardiopulmonary resuscitation (CPR) that provides chest compressions. It has been shown that the quality of chest compression is considered as one of key indicators for assessment of CPR performance. In this paper, we present an approach for CPR quality evaluation using ECG contaminated with CPR artifact and thoracic impedance. The proposed approach contains two key steps: First, the CPR artifact signal is estimated via variational mode decomposition (VMD) and a mode selection algorithm based on mode's frequency and frequency of thoracic impedance signal. In the second step, CPR parameters performed on the estimated CPR signals are computed and compared with those derived by reference CPR. The proposed approach is applied for a dataset including patients presenting with asystole, ventricular tachycardia, and pulseless electrical activity. Quantitative results validate the performance of the proposed approach for CPR quality assessment.

Keywords: cardiopulmonary resuscitation, spectrum analysis, thoracic impedance, cardiac arrest, variational mode decomposition.

Classification numbers: 4.2.3; 4.10.2.

1. INTRODUCTION

Cardiac arrest is a medical emergency, that causes sudden cardiac death if cardiac arrest is not treated immediately. A good quality of cardiopulmonary resuscitation (CPR) can help increase survival rates from the cardiac arrest [1, 2]. Therefore, it is necessary to assess the CPR performance performed by emergency medical technicians. In the treatment of cardiac arrest, it has been proved that the chest compressions play a key role. According to guideless in [2], the compressions should be 100 to 120 compressions per minute (cpm), to allow full chest recoil and minimum interruptions in compressions [1, 2, 3]. To improve the delivery of CPR, the quantitative assessment of CPR quality is of high demand.

There have been many works on estimation of cardiopulmonary resuscitation quality. The most common approach for estimation of CPR is the use of extra signals acquired from accelerometers like thoracic impedance, in combination with an adaptive filter. Abella et al. [4,

5] and Wik et al. [6] used accelerometer interface between the rescuer and the patient's chest to measure the presence and the frequency of chest compressions. To quantify the chest compression quality, Valenzuela et al. [7] used automated external defibrillator electrocardiograms. Irusta et al. [8] proposed an algorithm for CPR artifact removal based on the compression frequency using a least mean square filter. Ayala et al. [9] used adaptive filter approach using the compression depth and thoracic impedance signals to characterize the chest compression. Recently, the approaches of using Empirical Mode Decomposition (EMD) [10] have been introduced. Lin et al. [11] used EMD and autocorrelograms to automatically quantify the chest compression performance from ECG signal acquired by AEDs. Lo et al. [12] proposed a framework to identify the CPR fluctuations by combining dominant modes from EMD to reconstruct a CPR-related fluctuation and applying a least mean square based adaptive filter to estimate the CPR artifact. Though having advantages in chest compression estimation, the adaptive filter and Empirical Mode Decomposition, have shortcomings. In the adaptive filter approach, the artifact removal performance is sensitive to the reference signal. In the Empirical mode decomposition, the mode-mixing problem should be handled, and the periodic properties of the mode might not to be offered. As an alternative to the EMD approach, variational mode decomposition (VMD) has been proposed to address shortcomings of EMD.

Since first introduced in 2014 by Dragomiretskiy and Zosso [13], VMD has attracted a lot of interests from many researchers in various signal processing applications such as wheel set bearing fault diagnosis, detecting rub-impact fault of the rotor system, and power quality events. In this paper, inspired by the VMD, we present an automatic method to detect the chest compressions using the ECG acquired from defibrillators and thoracic impedance (TI) signals. The ECG signal that is contaminated with CPR artifact, is first decomposed into different subsignals (also called modes) by the VMD. After decomposition of the ECG signal, the instantaneous frequencies of the modes are calculated and compared with the fundamental frequency of the thoracic impedance signal. The mode whose frequency coincides with TI frequency will be assigned as the estimated CPR signal. Based on the estimated CPR signals, the CPR quality parameters are computed and validated.

2. BACKGROUND

2.1. ECG signals and abnormal heart rhythms

An electrocardiogram (ECG) is a recording of the electrical activity of the heart muscles as it changes over time [14]. The ECG signals can provide valuable information about abnormalities in the heart function. Cardiac arrest is the abrupt loss of heart function in a person who may or may not have diagnosed heart diseases. Cardiac arrest is resulted from the heart's electrical system malfunctions, and the cardiac arrest death results when the heart suddenly stops working properly [2]. This is caused by abnormal, or irregular, heart rhythms which called arrhythmias. The arrhythmias of the cardiac arrest can be analyzed by automated external defibrillators (AED) to shockable or un-shockable rhythm. The un-shockable rhythm is treated by CPR [11].

The arrhythmias are categorized into four groups: Ventricular fibrillation, Ventricular tachycardia, Asystole, and Pulseless electrical activity [15]. Ventricular fibrillation (VF) is a condition in which there is uncoordinated contraction of the cardiac muscle of the ventricles in the heart, making them quiver rather than contract properly. Ventricular fibrillation is the most commonly identified arrhythmia in cardiac arrest patients. Ventricular tachycardia (VT) is a fast

heart rhythm that originates in one of the ventricles of the heart. This is a potentially life-threatening arrhythmia because it may lead to ventricular fibrillation, asystole, and sudden death. Asystole (AS) is a state of no cardiac electrical activity. This arrhythmia is often treated with chest compressions and ventilations. Pulseless electrical activity (PEA) occurs when there is an organized electrical activity but there is no pulse.

2.2. Thoracic impedance signal and chest compression

The electrical impedance of biological tissue is found via measuring the voltage drop when passing a current through the tissue and using the Ohm's law. The tissue impedance changes with the distance between electrodes, the redistribution and movement of fluids contained in the tissue. Since the acquired impedance signal is sensitive to the movement, the CPR causes artifacts in analyzing the heart rhythm [16].

Pressure signal is acquired from the sensor fitted on the extra-pad of the defibrillator. The sensor is sensitive to the movement of the chest, and the information on a card fitted to the defibrillator is delivered [17]. The chest compressions are done by pressing the chest between the breastbones generally from 4 to 5cm and necessary to provide the vital organ with circulation of blood. These compressions should be repeated with the rate from 100 to 120 compressions per minute (cpm).

2.3. Variational Mode Decomposition

Variational Mode Decomposition (VMD) [13] is a signal processing technique that decomposes a real-valued signal $f(t)$ into different subsignals (called levels modes) u_k. These modes have specific sparsity properties. It is assumed that each mode k to be concentrated around a center pulsation ω_k determined during the decomposition process. Thus, the sparsity of each mode is chosen to be its bandwidth in spectral domain.

The decomposition process of VMD is realized by solving the following optimization problem:

$$\begin{aligned} &\min \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \\ &\text{s.t.} \quad \sum_k u_k = f(t) \end{aligned} \tag{1}$$

where $f(t)$ is the main signal to be decomposed; $\{u_k\}=\{u_1,\ldots,u_k\}$ and $\{\omega_k\}=\{\omega_1,\ldots,\omega_K\}$ implicates the set of all modes and their center frequencies, respectively. $\delta(t)$ is the Dirac distribution, and * denotes convolution. In order to address the constraint, both penalty term and Lagrangian multipliers λ are considered. The combination of the two terms benefits both from the nice convergence properties of the quadratic penalty at finite weight, and the strict enforcement of the constraint by the Lagrangian multiplier. Therefore, the above optimization problem is changed to unconstraint one as below:

$$\begin{aligned} L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ + \left\| f(t) - \sum_k u(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k \right\rangle \end{aligned} \tag{2}$$

Then the alternate direction method of multipliers (ADMM) is used for solving the original minimization problem (2) by finding the saddle point of the augmented Lagrangian $\boldsymbol{L}$ in a sequence of iterative sub-optimizations. Plugging the solutions of the sub-optimizations into the ADMM, and directly optimizing in Fourier domain.

3. METHODOLOGY

3.1. Signal Preprocessing and analysis

All ECG data acquired from defibrillators were recorded with a sampling rate of 250 Hz. The acquired ECG data are contaminated with CPR artifact. The thoracic impedance signals are used in the proposed algorithm to separate the CPR artifacts from the ECG signals. In addition, the compression depths are also available and used as the reference CPR signals to evaluate the performance of the automatic CPR estimation algorithm. The reference CPR and thoracic impedance signals are all resampled to 250 Hz, sampling rate of ECG signals, for conventional interpretation. Input signals are first filtered with a 4th order Butterworth band-pass filter (0.5-30Hz for ECG signal, and 0.7 - 5 Hz for TI and reference CPR signals) to remove baseline wander and high frequencies. The data is analyzed in one-minute segments, each segment is divided into ten-second epochs.

3.2. ECG signal decomposition

After being filtered by bandpass filter, the ECG signals are applied to the VMD method [13]. By the VMD algorithm, the signal can be separated into modes. Figure 1 shows an example of the decomposition step by VMD for a representative segment. In this segment, the VMD decomposes the ECG signal into 5 modes. The frequency obtained by performing Fast Fourier Transform (FFT) for each mode is also provided in the time-series plot of each mode. The spectrograms of ECG signal and modes are also provided.

3.3. ECG mode's frequency and mode elimination

As validated in previous studies [8,9], the fundamental frequency of thoracic impedance signal is associated with the chest compression depth. In other words, the frequency of the TI signal can be used for estimation of the fundamental frequency of CPR signal. The association between the input ECG, TI and the reference CPR signals is interpreted in Figure 2. In this figure, the time-frequency via Gabor spectrograms, and frequency distributions of these signals are also provided. As can be observed from the figure, the frequency of TI signal (1.76 Hz), is close to the fundamental frequency of the reference CPR signal (1.83 Hz, equivalent to 110 compressions per minute). The frequency of the CPR signal is coincided with the highest peak in the frequency distribution of the ECG signal, that is contaminated by CPR artifact. Back to Figure 1, we can see that the reference CPR frequency is also coincided with the frequency of the IMF 1 (mode 1), one of decomposed modes by VMD on the ECG signal.

Based on ECG and TI signals, in this study, we propose a new approach for CPR estimation. Our approach stems from the fact that the acquired ECG signal is contaminated with CPR artifact, and the artifact presents an almost periodic waveform, whose fundamental frequency is of the chest compressions. Accordingly, it is reasonable to estimate the CPR signal from the decomposed ECG's modes. The idea behind using TI to estimate the CPR is that the TI

signal is normally available in AED acquisition system whereas the reference CPR signals are normally not available.

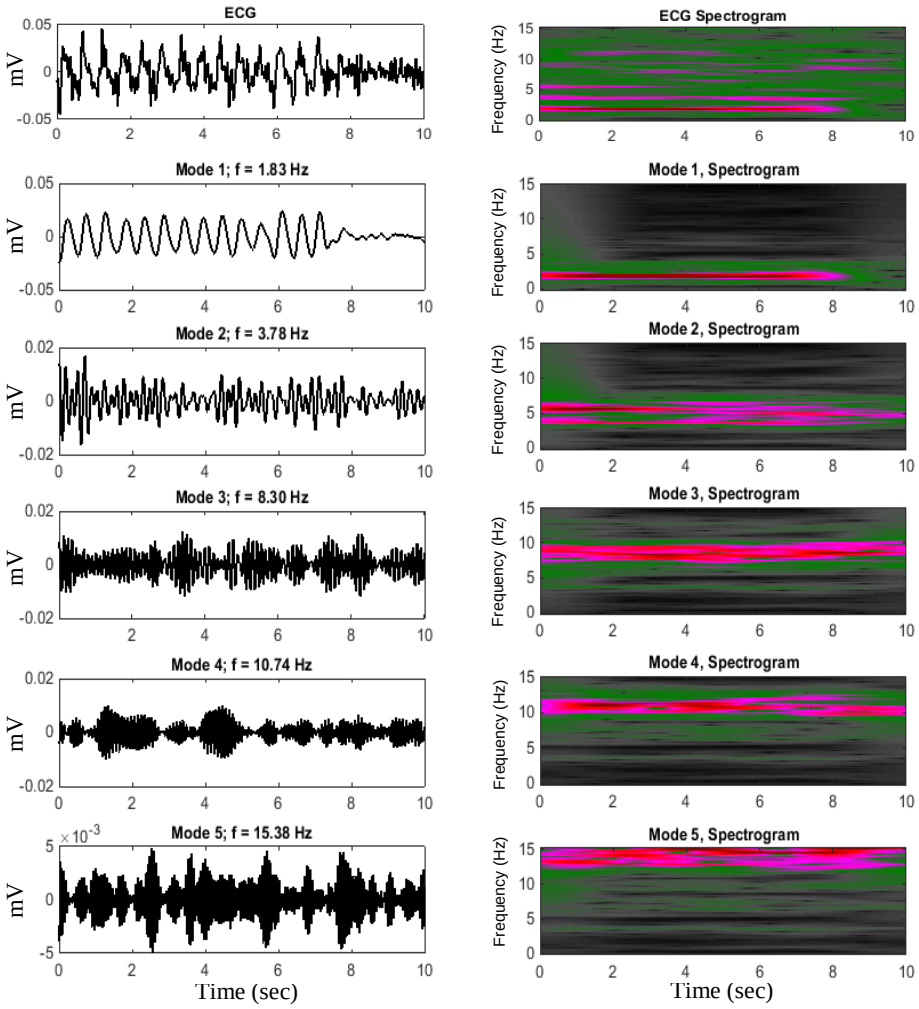

Figure 1. ECG signal and its decomposed modes, and the corresponding spectrograms: (a) signals intime domain, and (b) spectrograms.

The paradigm for the proposed approach to estimate the CPR signal is described as follows: For each signal segment, we decompose the ECG into modes, then compute the frequency of each mode. Besides, we calculate the frequency of the thoracic impedance signal (f_{TI}) of that segment. The frequencies are computed via taking the Fast Fourier Transform (FFT). Then, we compare the frequency of the modes (f_1, f_2,.., f_N) with the TI frequency. If the frequency of one mode coincides with TI frequency, with a tolerance of 0.2 Hz, it is considered as a candidate mode for the estimated CPR signal. If no candidate component is found, the estimated CPR signal is set to zero for that segment. If there exist more than one candidate modes, all modes are combined (added). The combined signal is then considered as the estimated CPR signal.

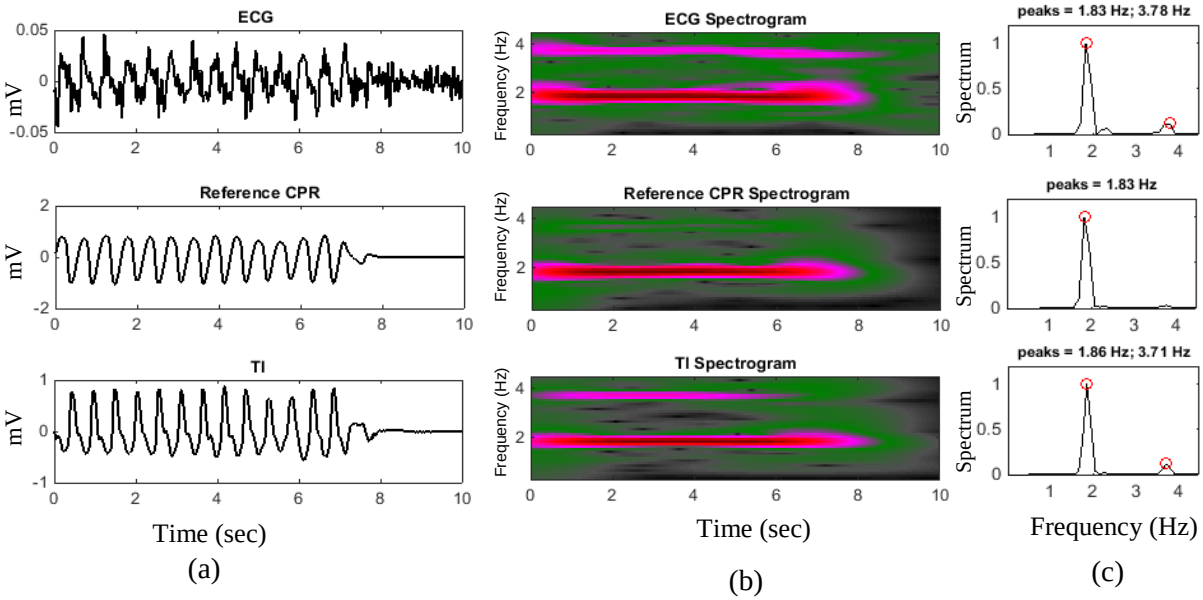

Figure 2. Signals, corresponding frequency distributions, and spectrograms of (a) ECG, Reference CPR, and TI signals. (a) Signals in time domain; (b) Gabor Spectrograms; (c) Frequency distributions. The reference CPR in this segment is with 1.83 Hz, approximate to 110 compressions per minute (cpm), coincided with that in the ECG, and close to TI frequency.

3.4. Assessment of CPR quality

To assess the CPR artifact, for one segment, the annotations of chest compressions from the estimated CPR signals are compared with annotations of chest compression from the reference CPR. The annotation of chest compressions provides us the reference to evaluate an automatic detection algorithm of chest compressions. In this study, we use two CPR quality parameters: No flow time and Compression number as the definition in the works in [3, 11]. No flow time is defined as a pause in chest compressions of more than 1.5 seconds. Compression number is the number of compressions in the segment.

4. RESULTS

4.1. CPR estimation

To show the quality of the estimated CPR signal in terms of waveform and frequency from the sample segment, we compare the results with the reference CPR signal, which is derived by compression depth. As can be seen from Figure 3, the waveform and spectrogram plots of the estimated CPR signal are in good agreement with the reference CPR signal. The fundamental frequencies from the power spectral density of the two signals are also the same, 1.83 Hz (or 110 cpm), as in the frequency distributions of each signal in this figure.

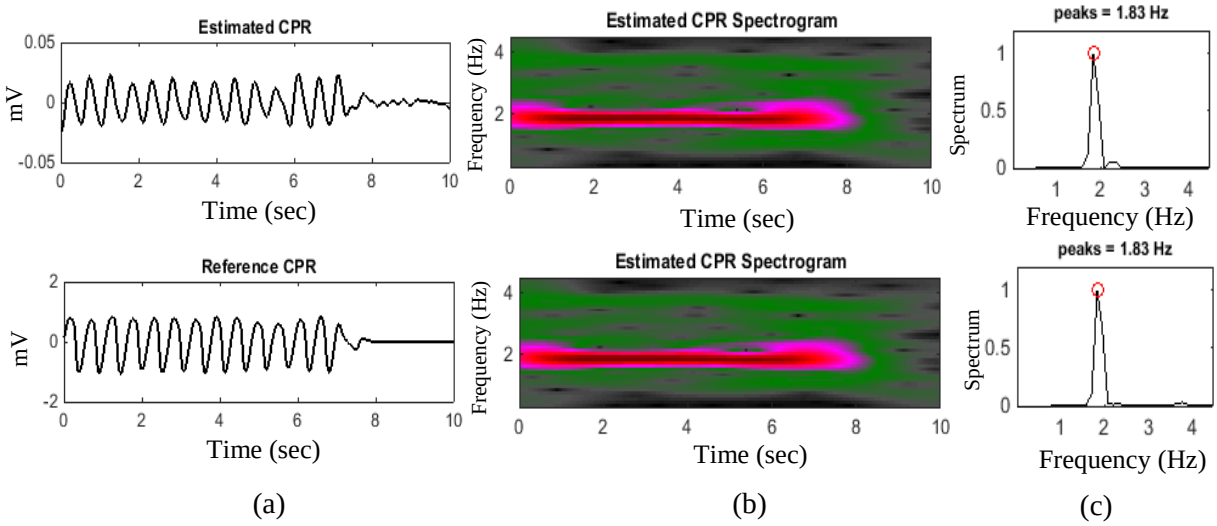

Figure 3. Comparison of Estimated CPR with the reference CPR in an epoch: (a) Signals, (b) Gabor spectrograms, and (c) Frequency distributions.

4.2. CPR quality assessment

We have applied the proposed approach to the data set acquired from patients presenting AS (segments), VFVT (segments), and PEA (segments). Each segment lasts 10 seconds, corresponding to 2500 samples of a signal, is used for analysis. The bandpass filtering, EEMD implementation, and CPR quality evaluation are implemented using Matlab (MathWorks Inc., Natick, MA).

The obtained values of CPR quality parameters on the estimated CPR signals are compared with those derived from the compression signal used as the reference CPR. Especially, the correlations of no flow time and compression number parameters of CPR quality by the proposed method and those derived from the compression signal using the scatter and the Bland-Altman mean-difference plots for AS, VFVT, and PEA patients are presented in Figures 4 and 5. As can be seen from the Bland-Altman plots for no flow time parameters in Figure 4, the CPR quality parameters obtained from the proposed automatic algorithm are in good agreements with those derived from the reference compression signals. The no flow time parameters are with adequate correlation coefficients (0.8 for AS, 0.79 for VFVT, and 0.81 for PEA) in scatter plots. Similar to the case of compression number in Figure 5, the Bland-Altman shows good agreements between the parameters from estimated CPR signals (automatic) and reference compressions (reference). The correlation coefficients are high for compression number parameters (0.83 for AS, 0.85 for VFVT, and 0.82 for PEA). The mean and standard deviation values of the parameters shown in Figures 4 and 5 are also provide in Table.1. From this table, the values for each parameter measures, no flow time and compression number, by the estimated CPR signals are close to those derived by the reference CPR.

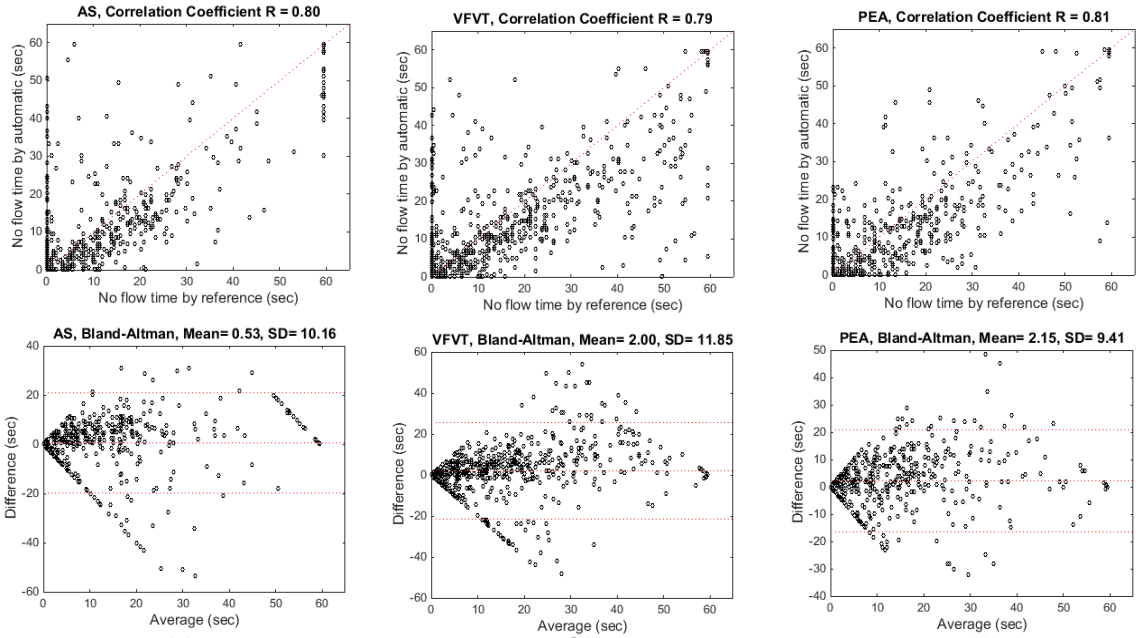

Figure 4. Scatter plots (top) and Bland-Altman mean-difference plots (bottom) to examine the correlations between the no flow time by estimated CPR and reference CPR signal for data with (a) AS, (b) VFVT, and (c) PEA.

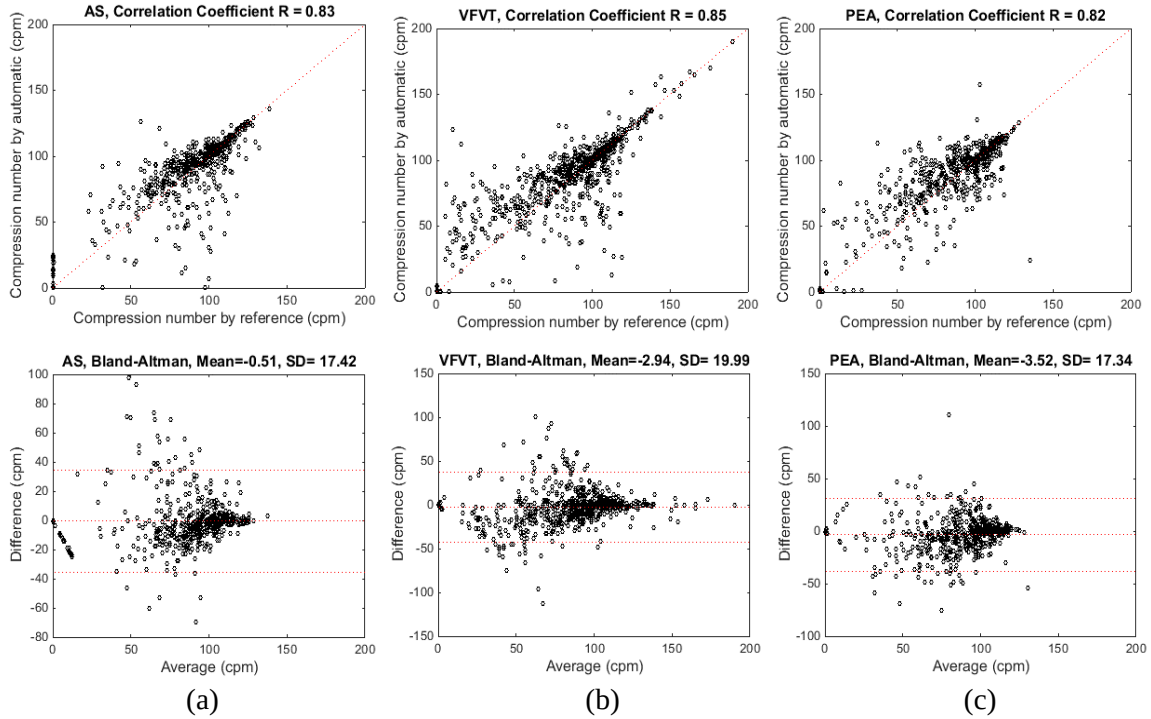

Figure 5. Scatter plots (top) and Bland-Altman mean-difference plots (bottom) to examine the correlations between the compression number by estimated CPR and reference CPR signal for data with (a) AS, (b) VFVT, and (c) PEA.

Table 1. The average values for the data set of CPR quality parameters calculated from the estimated CPR (automatic) and reference CPR (reference).

		No-flow-time (s)	Compression number (cpm)
AS	Automatic	11.9±15.4	86.0±29.6
	Reference	12.4±16.3	85.4±30.3
VFVT	Automatic	15.6±16.7	81.9±34.3
	Reference	17.6±19.0	78.9±37.1
PEA	Automatic	12.2±14.3	86.4±27.9
	Reference	14.3±15.9	82.8±29.7

5. CONCLUSIONS

The study has proposed a new approach for assessment of the CPR quality from analyzing the ECG signals retrieved from AEDs and thoracic impedance signals in patients presenting with AS, VFVT, and PEA. The ECG contaminated with CPR artifact is decomposed in to modes via variational mode decomposition approach. The frequency of each mode is computed and compared with fundamental frequency of the thoracic impedance signal. Then, the CPR signal is estimated by combining the modes whose instantaneous frequencies coincided with the frequency of thoracic impedance signal. The assessment of CPR quality of the CPR is evaluated. A good agreements and high correlation between the results by estimated CPR signal with those by reference compression signals demonstrates the performance of the proposed method.

Acknowledgements. This research is funded by the Hanoi University of Science and Technology (HUST) under project number T2017-PC-122.

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