CARDIOPULMONARY RESUSCITATION PATTERN EVALUATION BASED ON ENSEMBLE EMPIRICAL MODE DECOMPOSITION FILTER VIA NON-LINEAR APPROACHES.

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ABSTRACT

Out-of-hospital cardiac arrest (OHCA) is a critical cardiac disorder. The OHCA survival rate is still relatively low. Cardiopulmonary resuscitation (CPR) is very essential with the cardiac arrest. This study evaluates a non-linear approximation of the CPR given to patients, especially asystole patients. In order to clean the electrocardiography (ECG) signal which is collected by the automated external defibrillator (AED), the raw signal is filtered using ensemble empirical mode decomposition (EEMD), and the CPR-related IMFs are chosen to be evaluated. Sample entropy (SE), complexity index (CI), detrended fluctuation algorithm (DFA) and statistical analysis using Anova are utilized. The CPR evaluation compares the patient survival rates after two hours of the cardiac arrest. The CPR pattern of the 951 asystole patients are analyzed. In the CPR-related IMFs peak-to-peak interval analysis, for both classes, patient groups who are younger than or older than 60 years, does not have any significance. Furthermore, the amplitude difference evaluation, both classes do not have any significant difference for SE ($p = 0.28$) and DFA ($p = 0.92$) except for the CI ($p = 0.028$). The results show that patients group aged younger than 60 years have higher survival rate with high complexity of the CPR-IMFs amplitude differences.

Keywords: Out-of-hospital cardiac arrest, cardiopulmonary resuscitation, ensemble empirical mode decomposition, sample entropy, complexity index, and detrended fluctuation analysis.

1. Introduction

Yearly, abundance of people over the world suffer out-of-hospital cardiac arrest (OHCA) [1, 2]. OHCA can be categorized as a typical situation associated with tremendous mortality rate [3, 4]. Its cause is noticed to be due to the acute coronary syndrome [5]. The main cause of OHCA, based on some studies, is due to severe coronary disorder, including the acute coronary occlusion [6-8]. According to Eisenberg et. al., the accomplishment of the patient resuscitation for OHCA is based on certain factors, such as the general condition of the patients, the type and vitality of the events, the distance to cardiac arrest to begin the bystander cardiopulmonary resuscitation

(CPR), and following with the advanced cardiac life support (ACLS) [9].

CPR is one of the fundamental and chain survival parts for the treatment of the OHCA patients. When the connections between each other is well performed, the survival rate will increase significantly [10]. On the other hand, the unexpected cardiac rhythm can be escalated when one of these connections is postponed [11, 12]. An essential chest compression itself is an effective pressure, at sternum fabricating the stream of blood and oxygen to the myocardium and brain [13]. The chest compression condition is a dominant index of the CPR accomplishment [14-16]. CPR is crucial for the re-forming the spontaneous circulation [17, 18]. It also increases the percentage of the survival rate compare to the no-CPR cardiac arrest cases [19].

In order to evaluate the CPR data, the noise is an essential concern. The filtering method should be performed in advanced in order to extract the correct information from the continuous signal. Empirical mode decomposition (EMD) filtering algorithm, proposed by Huang, et. al., [20, 21], has been used for studies related to signal filtering problem. EMD based-filter also has been used broadly for the narrow-band signal such as ECG [22] and blood pressure [23].

In advanced, the filtered signal is extracted to achieve the information contained its characteristics. The entropy algorithm, one of those methods, was used in information theory [24] to face the nonlinearity problems. An entropy algorithm was also applied to the ECG signal studies [25, 26]. A study by Costa, et. al, applying the extended sample entropy, was applied to evaluate the feature extraction of ECG using the multi-scale entropy [27]. Another non-linear method, detrended fluctuation analysis (DFA), was originally utilized for the DNA sequence [28].

Studies related to the purifying the signal and extracting information for the cardiac arrest cases have been done for several years. For the filtering area, a study utilizing multi-channel Wiener filter and a matching pursuit-like way was done to remove CPR artifact from ECG [29].

The least mean-square (LSM) filtering has also been utilized to remove the CPR problem [30]. A new method combining the noise-assisted multivariable EMD (N-A MEMD) and least square mean (LSM) filtering was implemented by Lo et. al., [31]. The application of the sample entropy for the shock outcome predictor [32]. The extended of the sample entropy, multiscale entropy, was also applied for the cardiac arrest problem [33]. Another non-linear method, detrended fluctuation analysis was utilized by Lin et. al., for the study of ventricular fibrillation in OHCA cases [34]. Therefore, the purpose of this study is to evaluate the CPR pattern by utilizing the EEMD to purify the CPR signal and the ECG data by applying the non-linear algorithms to see the survival rate.

2. Data Acquisition and Algorithm

2.1 Data acquisition

The dataset is retrospectively collected from the New Taipei City fire-based of emergency medical service (EMS). All the staff have been trained for the basic life support, early defibrillation and advanced life support. All the ambulance units are equipped with a ForeRunner AED (Philips, Seattle, WA, USA). The ECG signal is logged into the AED card data, sampled for 200 Hz. The logging lead was placed on the patient chest.

This study utilizes data from the whole year of 2010. Originally, the total of 1207 patient ECGs, sampled for 200 Hz, is divided into two groups, trauma and non-trauma cardiac arrest. Focusing on the non-trauma patients only, the data is parted into another two groups, either patients have AED shock or non-shock-able signal. In order to evaluate the pure CPR without any help of the AED, all the 1001 non-shock-able patients, which eventually becomes 951 sets after filtering for the quality of the data, is divided according to their age with the threshold of 60 years, as shown in Fig. 1. After having the two different group signals, the outcome of the patient is evaluated after 2 hours based on their conditions. The evaluation is analyzed in MATLAB language (Mathwork Inc).

2.2 Empirical Mode Decomposition-Based Filter

2.2.1. Empirical Mode Decomposition (EMD)

EMD is initially proposed by Huang et al. in 1998 [14]. EMD is a convincing algorithm to decompose the specific frequency range of the data into a finite number of intrinsic mode decompositions (IMFs). These decomposed IMFs illustrate certain characteristics. However, for the real-world signals, the mode-mixing disturbs the regularity of the IMFs. Due to this reason, the ensemble empirical mode decomposition (EEMD) was proposed to deal the mode-mixing difficulties.

2.2.2. Ensemble Empirical Mode Decomposition

The intermittence corrupts the consistence of the IMFs. The subsequent mode function will be affected, hence the physical meaning of those IMFs that cannot be parted based on their characteristics. Wu and Huang [35] proposed EEMD using noise-assisted method to overcome this phenomenon. In EEMD, the white noise is added to the original signal to form a mixed combination of noise and signal in order to remove the intermittence and generate consistent IMFs. EEMD study was also conducted to an ECG noise filtering problem [36].

2.3 Feature Extraction Algorithms

2.3.1. Sample Entropy and Complexity Index

The entropy is initially recognized in the thermodynamics property to evaluate the regularity.

The higher entropy means the less regular the pattern or the sequence to be recognized. For more detail can be referred to the previous study by Costa et. al., [37]. For the multiscale entropy, the coarse grained time series is based on the scale factor. The coarse grained time series will be evaluated by entropy algorithm. The result of the entropy corresponds to the each scale is called multiscale entropy. The complexity index (CI) is defined as measurement of the signal complexity. It is calculated by the evaluation of the area under curve of the multiscale entropy. The calculation from the recreated time series based on the coarse grained information will affect the area under the area of the curve.

2.3.2. Detrended fluctuation analysis

Fractal analysis is one of the most prosperous access to get those features. Detrended fluctuation analysis (DFA) is a non-stationary algorithm for statistical analysis. A considerably physiology-related problem is a non-stationary time series one. This method originally proposed by Peng et. al., [38].

3. Results and Discussion

In this study, the original ECG logged from the AED machine, sampling frequency of 200 Hz, is filtered by the EEMD algorithm, shown in Fig. 2 to Fig. 4. From those figures, it can be seen that IMF 2 to IMF 4 are relatively similar to the CPR pattern having the dominant frequency as described as previous study conducted by Lo et. al., [22]. Figs. 5 and 6 also show the time frequency evaluation shows the differences between the raw ECG and the reconstructed-CPR, by combining the CPR-related IMFs, signal after the EEMD filter. Figs. 5a and 6a give the information about the time-frequency information. For Fig. 5a, the dominant signal occurs mostly in below the CPR frequency ranges, lower than 0.5 Hz, indicated by the red area.

Meanwhile, for Fig. 6a, after the EEMD filter, the dominant frequency shifts to the range of 2 Hz to 4 Hz, indicated by the red aquare. This filter also automatically reduces the baseline noise of the signal that can be seen by the Figs. 5b and 6b.

All the maxima points are detected from the reconstructed IMFs that have the CPR frequency, by evaluating the changing of the slopes from positive to negative as shown in Fig. 7,. Furthermore, the maxima points are evaluated to obtain the maxima interval (**I**) and maxima amplitude differences (**dA**) from the IMF-combined CPR, shown in Fig. 7. Furthermore, both signals, **I** and **dA,** are estimated by utilizing SE, CI and DFA.

The evaluation results of the 951 patient ECGs of non-trauma and non-shock-able rhythm using a threshold of 60 years of age are shown in Table 1. For the interval analysis, it initiates with patients of age greater 60-year old. The total patients for this category is 579 patients who died and 116 patients who survived. In this category, died patients have SE mean value of 1.91±0.58 and the survived patients have 1.87±0.56 ($p > 0.05$). For the CI evaluation, died patients have 13.26±4.46 and the survived have 13.48±4.67 ($p > 0.05$). The DFA evaluation produces 0.86±0.145 for died patients and 0.833±0.136 for the survival ($p > 0.05$).

The next interval evaluation is for the patients having age less than 60 years. The total number of patients for this class is less than half as much as the greater than 60-year-old patients. The SE has 1.86±0.61 and 1.81±0.6 respectively for died and the survived, p-value is greater than 0.05. The CI has 13.12±4.9 and 12.03±4.26, respectively for died and survived, and has no significant differences. For the DFA, it has 0.839±0.15 and 0.845±0.12 respectively for died and NYM patients, and also not significantly different.

From the amplitude difference point of view, for the patients' age is greater than 60, died patients have SE mean value of 0.22±0.236 and for the survive patients have 0.226±0.244 (p >

0.05). For the CI evaluation, died patients have 1.23±1.24 and survived have 1.195±1.184 ($p > 0.05$). The DFA produces 0.115±0.126 for died patient and 0.099±0.116 for survived ($p > 0.05$).

For cases of the category of age of less than 60 years, the SE has 0.2±0.23 and 0.24±0.16, respectively of died and alive patients, and have no significant differences. The CI has 0.983±1.03 and 1.378±1.173, respectively for died and survived, this case is significantly different ($p < 0.05$). The DFA case creates 0.105±0.168 and 0.107±0.098 ($p > 0.05$).

Several studies were conducted earlier related to the age and the CPR to the outcome of the survival. A study by Longstreth et. al. evaluated the 5-year period about the relation of the age and the CPR. This study stated that the CPR can benefit the elderly as well as the younger patients [40]. Another study conducted by Wuerz et. al., also produced no significant different for younger and elderly patient for the return of spontaneous patients and survived to the hospital discharge [41].

However, a study conducted by Herlitz et. al, for 23461 patients, concluded that age also is a serious factor in the cardiac arrest cases. The survival rate decreases by the age [42]. Another study of 503 cases conducted by Murphy at. al., carried out the information that the elderly having out-of-hospital cardiac without any witness or with the asystole made the CPR barely effective [43]. For the long-term-care population, even though the CPR is performed by the qualified and professional team, the elderly had a very small benefit [44].

4. Conclusions and Future Work

This study evaluates a total of 951 of the non-shock-able patient ECGs, using the ensemble empirical mode decomposition filtering and utilizing non-linear approaches. The IMF-combined CPR maxima interval and the amplitude are evaluated. Even though most of all evaluations do not have any significant different, the evaluation of CI for the maxima amplitude has difference significantly. According to the results, it can be concluded that the patients with age younger than 60 years have higher survival rate by having more complexity in CPR amplitude differences. This result can be considered as the information of the automated CPR machine design with the force given by the machine may be dynamics.

This study has several limitations. The first one is when the noise has the same frequency range of those CPR IMFs, affecting to the raw ECG signal, is still in the evaluation. This condition may affect the result, especially for the slope evaluation. Another limitation is the survival and died patient portion data are relatively not balance.

For future study, the application of the advanced time-domain filter should be applied to purify the unfiltered noise on the frequency domain filter.

Acknowledgments

The authors wish to thank National Taiwan University Hospital (NTUH) doctors, nurses and other officials who have given their best helps for this research. This research is financially supported by the Ministry of science and technology (MOST) of Taiwan (MOST103-2627-M-155-001).

Conflict of Interest

The authors declare no conflict of interest.

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Figures and Tables

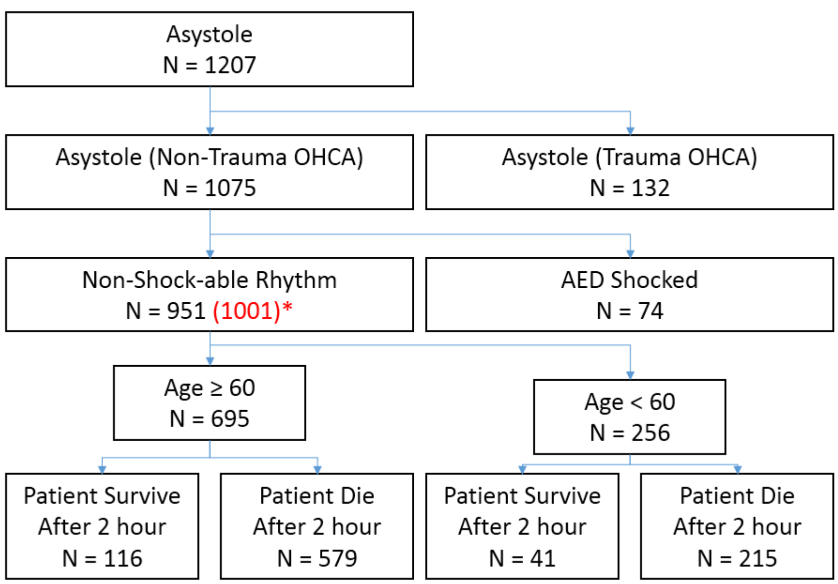


Figure 1: The flowchart of the CPR evaluation.

***Note**: The original 1001 ECG signal have to be reduced due to the quality of the data.

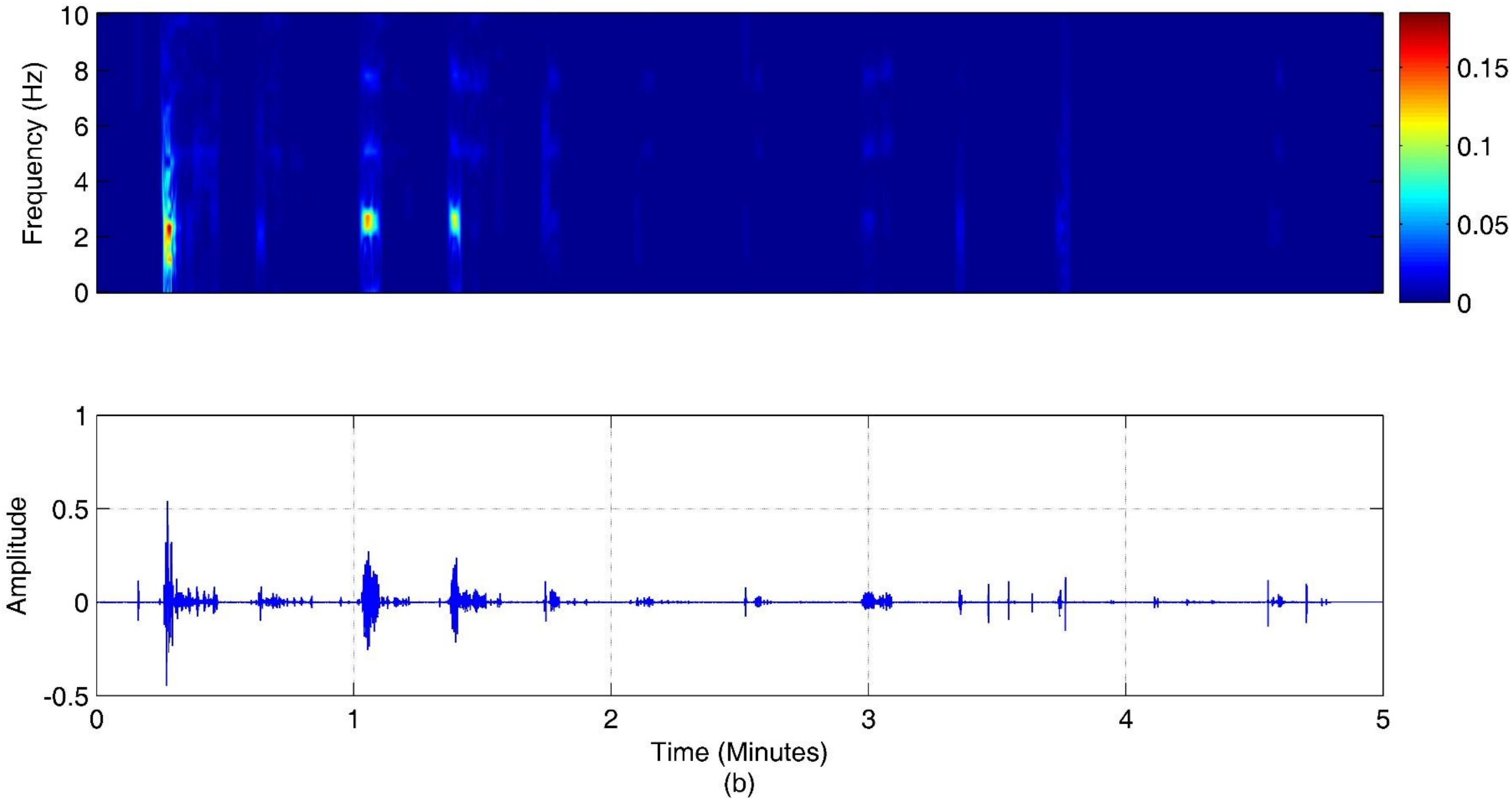
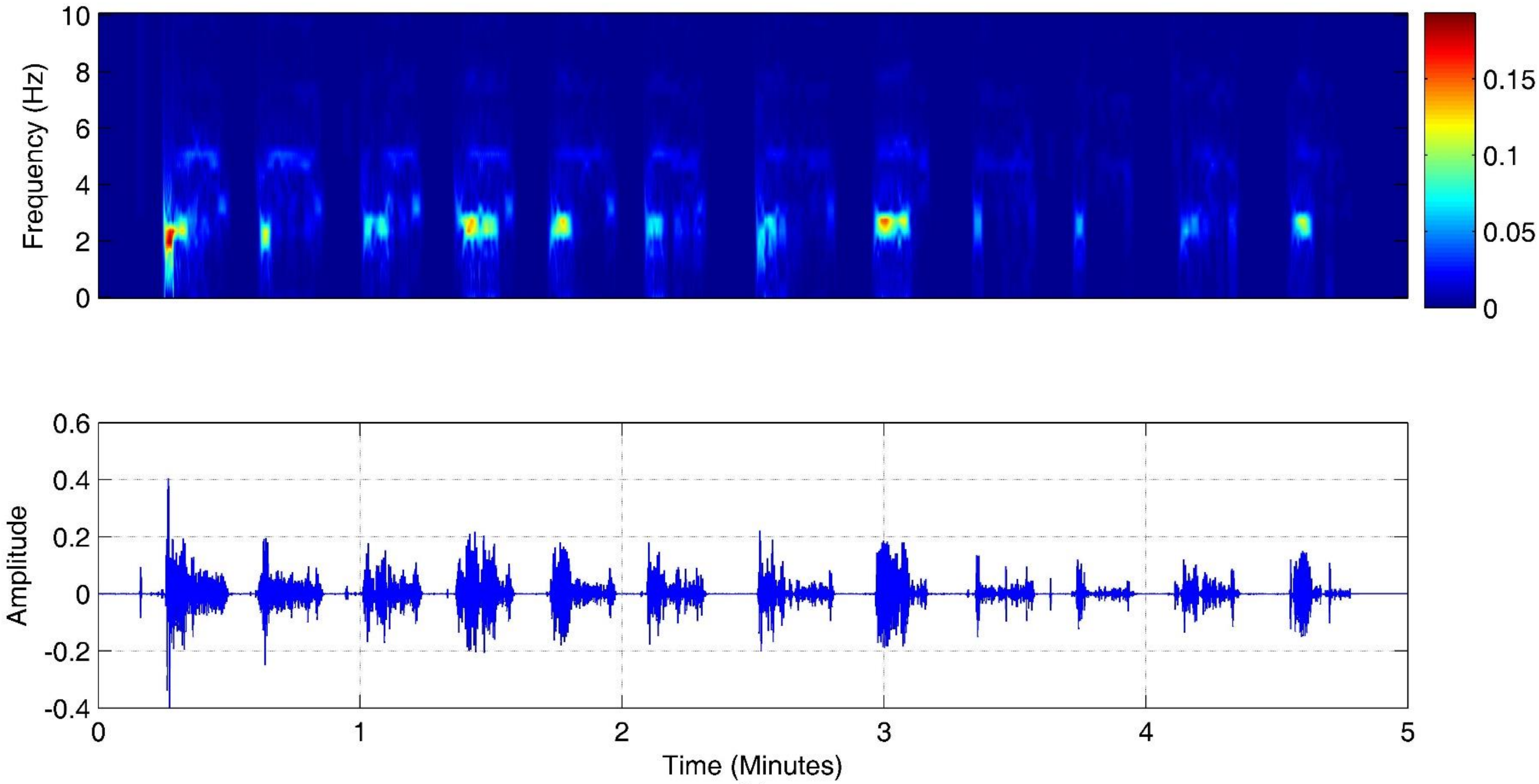
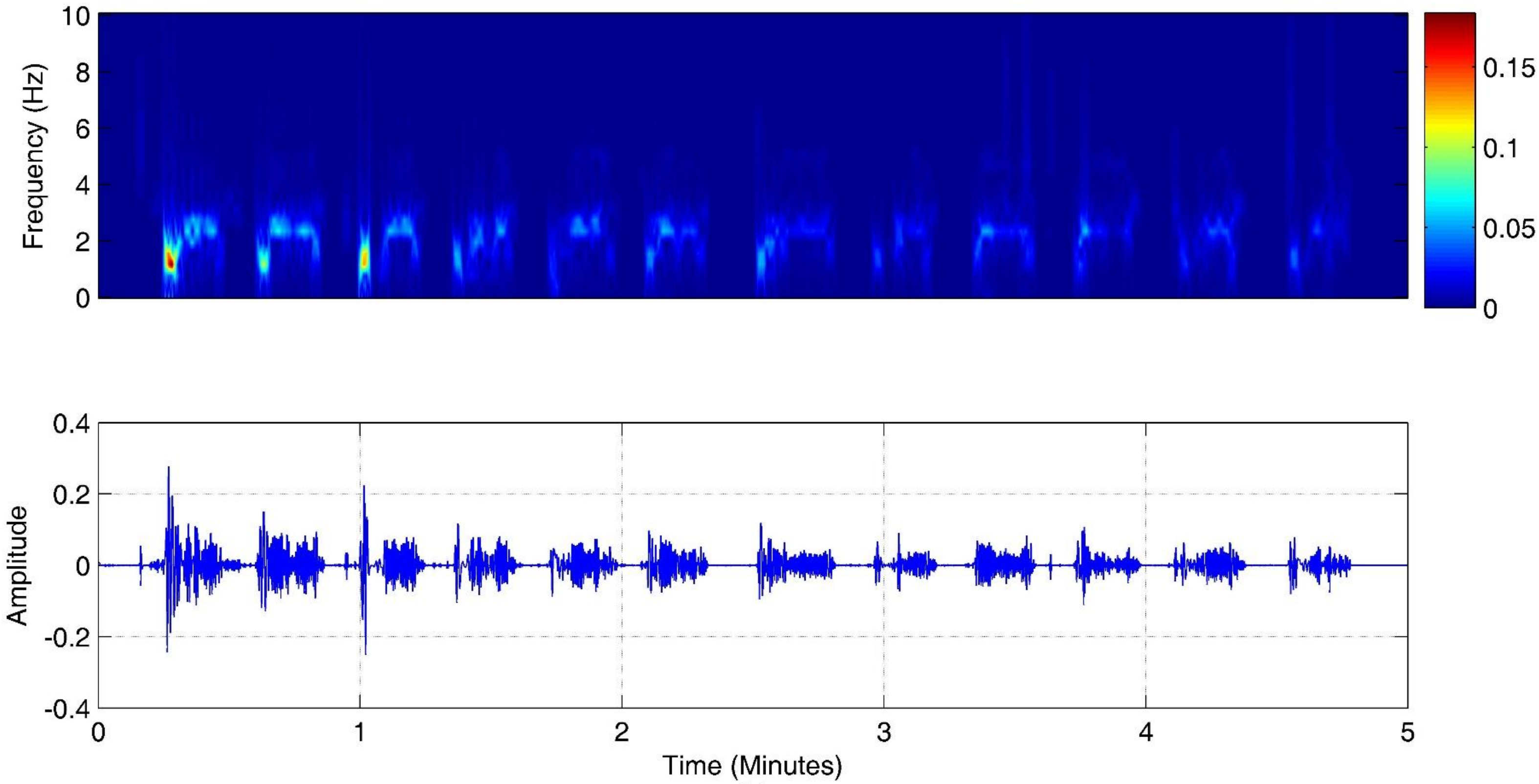


Figure 2: EEMD-extracted CPR and the time-frequency information of IMF 2.



(b)

Figure 3: EEMD-extracted CPR and the time-frequency information of IMF 3.



(b)

Figure 4: EEMD-extracted CPR and the time-frequency information of IMF 4.

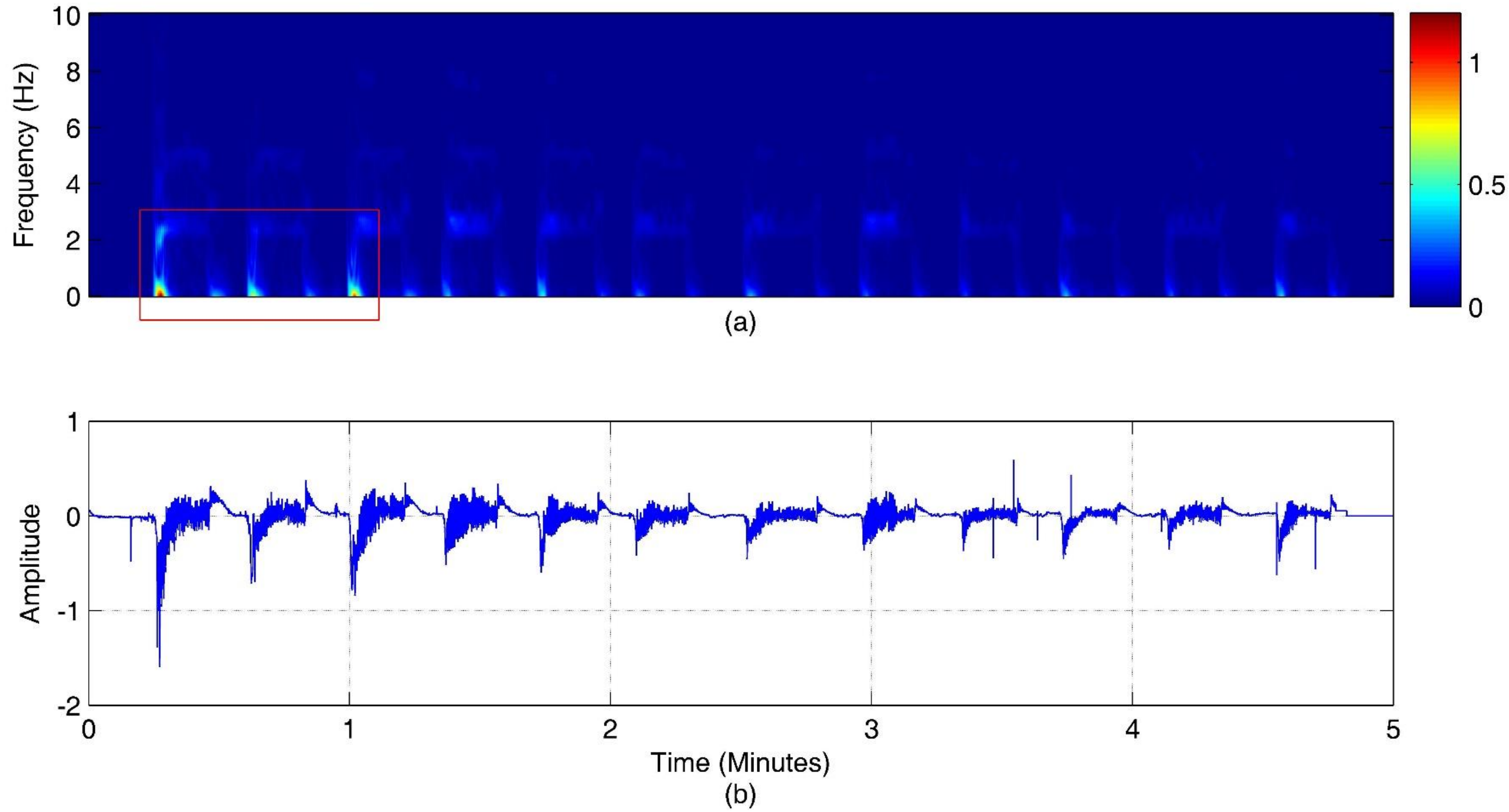


Figure 5: Raw signal from AED machine. a) Time-frequency result; b) The raw signal.

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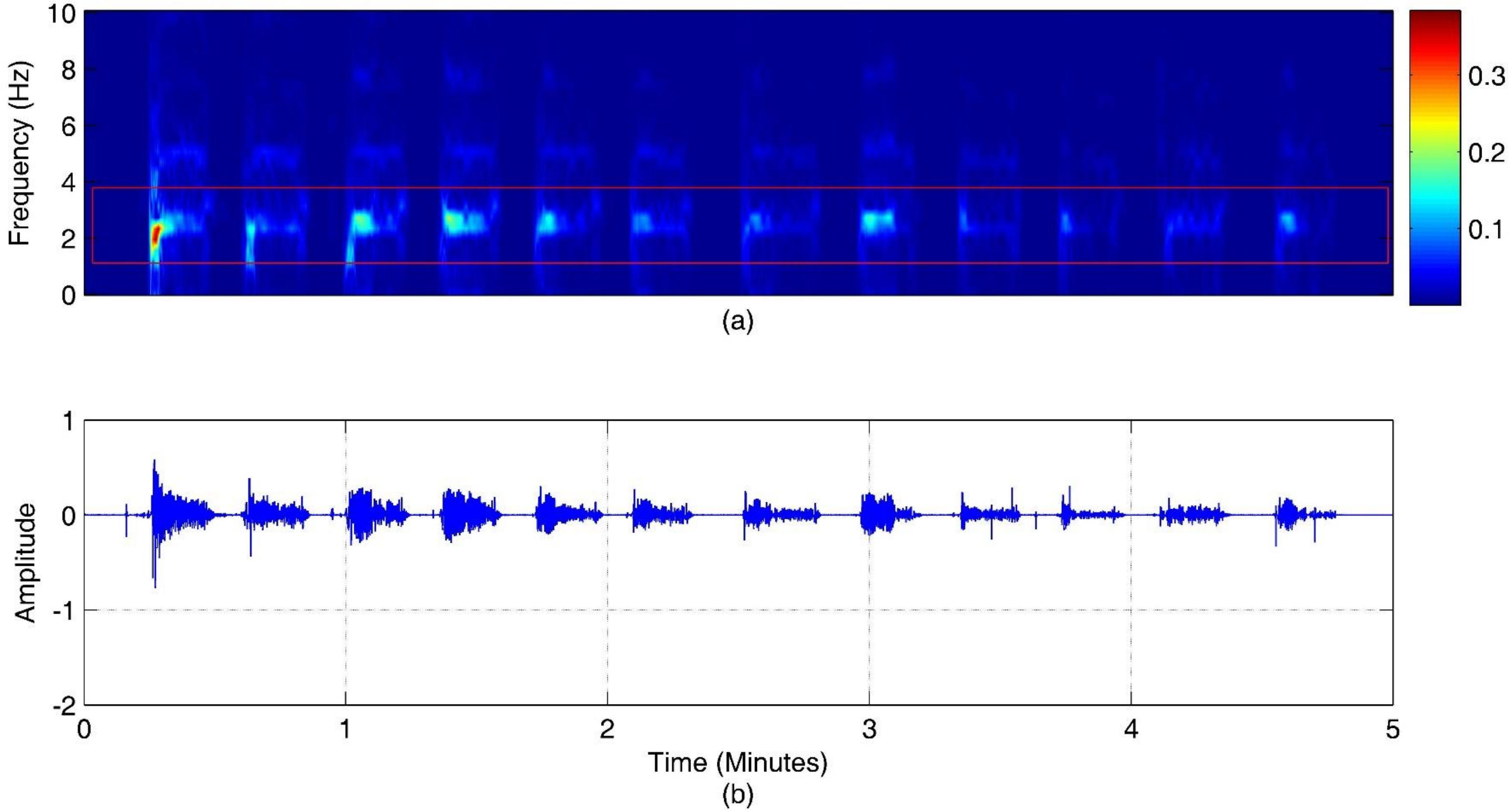

335 Figure 6: EEMD-reconstructed CPR signal. a) Time-frequency result; b) The reconstructed signal.

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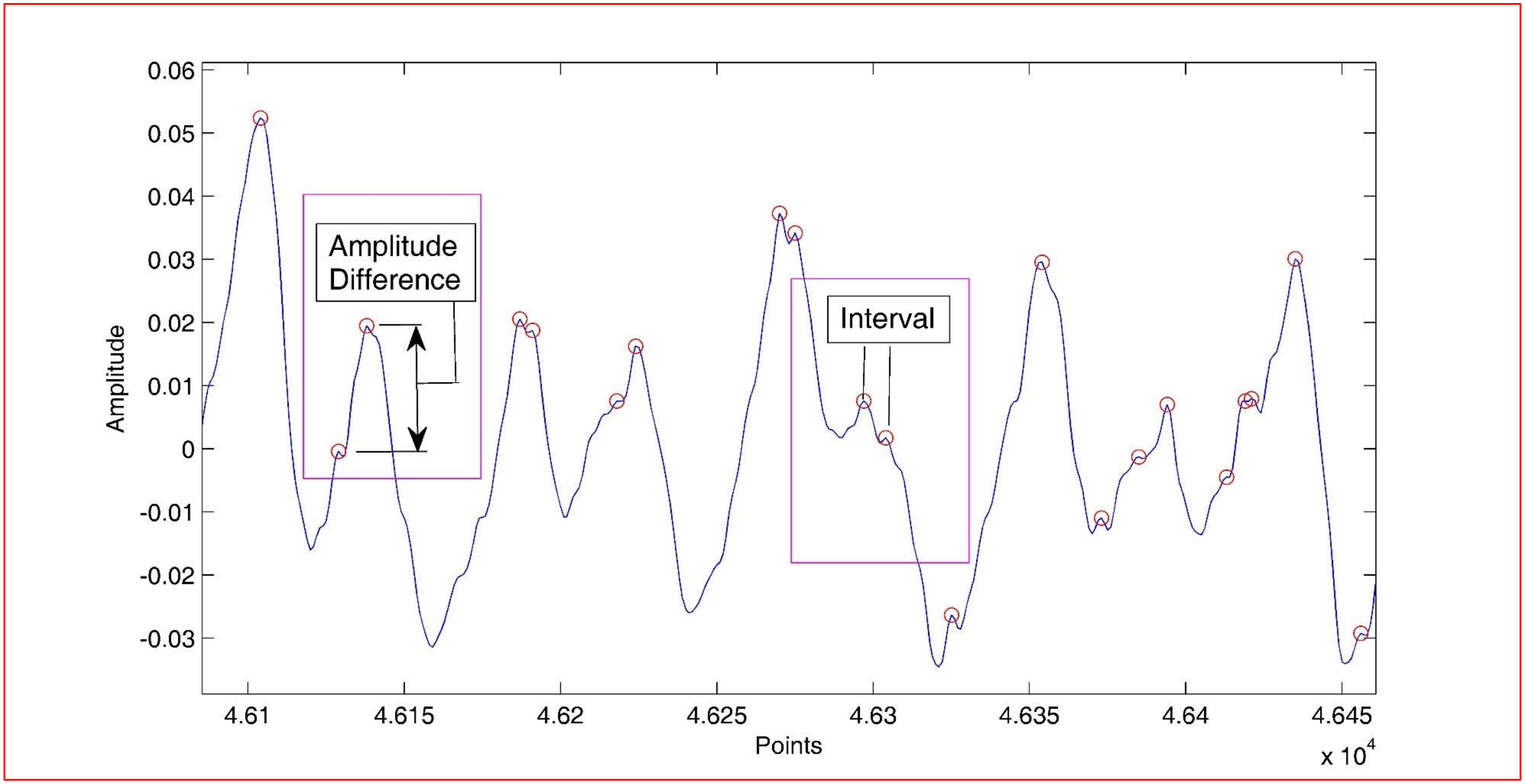

Figure 7: CPR IMFs maxima information evaluation

Table 1: The statistical evaluation of the CPR IMFs result.

Evaluation	Age	Feature	Status	Mean	Standard Deviation	*p-value* *($p<0.05$)*
INTERVAL	> 60 (579,116)	SE	Died	1.91	0.58	0.556
			Survival	1.87	0.56	
		CI	Died	13.26	4.46	0.62
			Survival	13.48	4.67	
		DFA	Died	0.86	0.145	0.06
			Survival	0.833	0.136	
	< 60 (215,41)	SE	Died	1.86	0.61	0.575
			Survival	1.81	0.6	
		CI	Died	13.12	4.9	0.234
			Survival	12.03	4.26	
		DFA	Died	0.839	0.15	0.825
			Survival	0.845	0.12	
AMPLITUDE	> 60 (579,116)	SE	Died	0.22	0.236	0.825
			Survival	0.226	0.244	
		CI	Died	1.23	1.24	0.781
			Survival	1.195	1.184	
		DFA	Died	0.115	0.126	0.215
			Survival	0.099	0.1165	
	< 60 (215,41)	SE	Died	0.2	0.23	0.28
			Survival	0.24	0.16	
		CI	Died	0.983	1.03	***0.028**
			Survival	1.378	1.173	
		DFA	Died	0.105	0.168	0.912
			Survival	0.1077	0.0983	

NOTE**: **SE** means sample entropy, **CI** complexity index, **DFA** detrended fluctuation analysis, "**" significant different parameter.