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Intrinsic Mode Analysis of Human Heartbeat Time Series

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Abstract—The human heartbeat interval is determined by complex nerve control and environmental inputs. As a result, the heartbeat interval for a human is a complex time series, as shown by previous studies. Most of the analysis algorithms proposed for characterizing the profile of heartbeat time series, such as detrended fluctuation analysis and multi-scale entropy, are based on various characteristics of dynamics. In this study, we present an empirical mode decomposition-based intrinsic mode analysis, which uses the appearance energy index (AEI) to quantify the property of long-term correlation, and structure index (SI) to characterize the internal modulation of data. This presented algorithm was used to investigate the human heartbeat time series downloaded from PhysioBank. We found the profiles of human heartbeat time series of subjects with congestive heart failure (CHF) or atrial fibrillation (AF) are significantly different from those of healthy subjects in internal modulation as shown by SI. Moreover, AEI is the critical characteristics for verifying subjects with CHF from subjects with AF in a degree of long-term correlation. Both AEI and SI contribute to presenting the characteristic profiles of a human heartbeat time series.

Keywords—Heart beat interval, Empirical mode decomposition, Detrended fluctuation analysis, Intrinsic mode analysis, Appearance energy index, Structure index.

INTRODUCTION

It has been established that the heartbeat interval is a complex time series and so quantifying the complexity of such signals is a powerful tool to understand the underlying controlling mechanisms of the heartbeat and other related physiological conditions. Previous studies[9,16–18] have used various approaches, such as multi-scale entropy,[2] detrended fluctuation analysis (DFA),[9] and the rank order statistics of symbolic sequences[22] to verify various physiological and pathological conditions with some degree of success. These analysis algorithms successfully showed the particular characteristics (i.e., entropy, long-term correlation, and statistical properties of symbolic sequences) for dynamics of complex time series.

Different from these analysis algorithms for dynamics of complex time series, three main spectral components have been identified in the heart rate variability (HRV) spectra in spectral analysis methods. There are a very low-frequency (LF) component below 0.04 Hz; an LF component, from 0.04 to 0.15 Hz; and a high-frequency (HF) component, from 0.15 to 0.4 Hz.[19] The power of the HF component mainly reflects the efferent vagal activity and the LF component reflects both sympathetic and vagal activities.[19] In general, a linear method (e.g., Fourier transform) generates comparable results,[19] but assumes stationary conditions that are difficult to achieve, even in short-term records under physiologically stable or autonomic-controlled conditions. However, both linearity and stationary assumptions are not totally adequate to be used in analyzing a human heartbeat time series, which performs non-linear and non-stationary characteristics.

In 1995, empirical mode decomposition (EMD) was first proposed to decompose the intrinsic mode functions (IMFs) from non-linear and non-stationary signals adaptively to the nature of signals.[6,7,10] This decomposition has the advantage of automatically identifying the intrinsic time scales of the data without any presuppositions regarding the data's form. Hence, the IMFs derived by EMD may carry actual physical significance.[10] Therefore, EMD was applied to extract at least four main components localized in the autonomic bands of the HRV signals under controlled breathing maneuvers.[5] It overcame the difficulty of achieving strictly stationary conditions and appropriately reflected the non-linear contents of humans' heartbeat time series. In such applications of HRV

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analysis, EMD was considered to perform an innovative technique of decomposition. Furthermore, recent studies show that EMD can be used to quantify the fractal property of non-linear signals via the characteristic frequencies and power densities of the decomposed IMFs.[8,21] Fractal property has been considered to be an important characteristic of non-linear time series. Hence, we conducted this study to develop a different application of human heartbeat analysis based on EMD.

In these further studies using EMD,[8,21] Fourier transform and mean square energy were used to derive two characteristic parameters (i.e., energy density and averaged period) of each IMF, which reflect the characteristic frequency and energy density of an intrinsic component. Moreover, the plot of energy densities against their corresponding averaged periods shows some hidden information about the non-linear dynamics of the signal. Thus, we conducted this approach to quantify the characteristics of human heartbeat time series via the distribution of energy densities and averaged periods of IMFs in the EMD-based human heartbeat analysis. Consequently, we defined two parameters used in the human heartbeat analysis.

As the first parameter, appearance energy index (AEI) was defined to quantify the characteristic of energy–density distribution for IMFs decomposed from human heartbeat time series via the slope of logarithmic energy density/averaged period plot. According to correlative studies,[8,21] the slope of the logarithmic energy density/averaged period plot reflects the fractal property (i.e., long-term correlation) of a Gaussian noise. In this approach, accuracies of both assessments of AEI and Hurst exponent were examined in a numerical experiment using simulated time series of Gaussian noises. According to the results of our numerical experiment, AEI was proven as an accurate assessment for the long-term correlation of Gaussian noises. Hence, AEI was used to quantify the fractal property (i.e., the property of long-term correlation) of human heartbeat time series in this EMD-based approach.

In addition, the distribution of averaged periods of IMFs also performs to quantify a different profile of human heartbeat time series, which is different from AEI. It shows an internal self-modulation of human heartbeat time series. For healthy subjects, the internal self-modulations of human heartbeat time series are significant and can be observed via the distribution of averaged periods of IMFs. In contrast, when the internal self-modulation is weakened because of heart disease, such as congestive heart failure (CHF) and atrial fibrillation (AF), human heartbeat time series become stochastic. Thus, we defined the second index, named structural index (SI), as a new assessment for underlying self-modulation in this approach.

Finally, we used a receiver operating curve (ROC) to check the sensitivities and specificities of AEI and SI in different classifications. ROC curves show that AEI appears to be a good indicator for distinguishing ill subjects with CHF from AF. SI is the critical parameter to distinguish healthy subjects from subjects with heart disease (either CHF or AF) via the underlying modulation of human heartbeat time series. These two parameters reflect two different underlying characteristics of a human's cardiac systems: AEI is an appropriate assessment of long-term correlation for a human's heartbeat time series, which reflects the difference of physiological characteristics between subjects with CHF and AF; SI appears to be an assessment of self-modulation in human's cardiac systems. Therefore, we can get further understanding of a human's cardiac system via characteristics of the self-modulation and long-term correlation reflected by AEI and SI.

METHODS

Empirical Mode Decomposition

The EMD method derives the envelopes of a given time series via cubic spline connecting local maxima and minima separately. Then, sifting process decomposes the IMF from the time series by subtracting the mean of envelopes to itself. Sifting process should repeat until the component satisfies two conditions[22]: (1) For the entire time series, the difference between numbers of extrema and zero-crossing must equal to zero or one. (2) At any data point, the mean value of upper and lower envelopes is zero. The component that satisfies those two conditions mentioned above is called an IMF, denoted as C_k. The difference between time series and the kth IMF is the kth residue, denoted as r_k, and treated as the data for decomposing the next IMF. Decomposition process should be repeated until the residue becomes monotonic or only one extremum remains. The original data, $X(t)$, can be reconstructed by the summation of n IMFs and the nth residue:

$$X(t) = \sum_{k=1}^{n} C_k + r_n. \tag{1}$$

Characteristics of Frequency-Energy Distribution of Noise Using EMD

Hilbert transform is a common method used to derive time–frequency–amplitude distribution for a non-stationary periodical function. Most previous applications of EMD used Hilbert transform to derive the instantaneous frequency and amplitude for each

IMF. The combination of EMD and Hilbert transform is named as Hilbert Huang transform. In this approach, we focused on the investigation to the dynamical characteristics of human heartbeat time series via the spectral characteristics of IMFs, but not the time–frequency–amplitude distribution. Therefore, the spectral characteristics of each IMF should be defined first in this approach.

Recently, Wu and Huang[21] conducted a fundamental study on the characteristics of white noise using EMD. In their study, characteristic period was derived as an averaged period from Fourier spectrum of an IMF and energy density was mean square energy of time series of an IMF. Accordingly, energy density and its corresponding averaged period of the kth IMF can be calculated using

$$E_k = \frac{1}{N}\sum_{j=1}^{N}[C_k(j)]^2 \tag{2}$$

$$\bar{T}_k = \int S_{\ln T,k}\, d\ln T\left(\int S_{\ln T,k}\frac{d\ln T}{T}\right)^{-1} \tag{3}$$

where E_k is the energy density of the kth IMF; $C_k(j)$ is the kth IMF at position j; $S_{\ln T,k}$ is the Fourier spectrum of the kth IMF as a function of T, the period of the local wave form; $d\ln T$ is the differential of logarithmic period; and $\bar{T}_k$ is the averaged period of the kth IMF.

Moreover, the plot of logarithmic energy densities against their corresponding averaged periods presents a pseudo-spectrum, which indeed has the physical meaning of a spectrum. According to Wu and Huang's[21] study, the logarithmic plot of energy densities against their corresponding averaged periods for IMFs is a straight line with the slope of -1 and the straight line passes through the origin for a white noise with a norm of 1. Furthermore, Flandrin *et al.*[8] conducted a similar study to investigate the characteristics of Gaussian noises with various fractal properties. Their study showed that the slope of the logarithmic energy density/averaged period plot depends on Hurst exponent (H) for a fractal Gaussian noise.[8,21] Here, Hurst exponent is a common assessment of long-term correlation for Gaussian noises.[11,13] $H > 0.5$ induces a positive long-term correlation and $H < 0.5$ induces a negative correlation. White noise is a special case of Gaussian noise with $H = 0.5$.

Definition of AEI for Long-Term Correlation of Gaussian Noises

According to the results shown in previous studies,[8,21] the slope of the logarithmic energy density/averaged period plot of IMFs reflects a power–law correlation of a non-linear time series. This finding motivated us to define a new assessment of long-term correlation for quantifying the fractal property of a human's heartbeat time series based on EMD. To define this new assessment for long-term correlation, we conducted a numerical experiment for long-term correlation quantification using simulated time series of fractal Gaussian noise with Hurst exponents from 0.1 to 0.9. In this numerical experiment, the simulated times series of fractal Gaussian noise with data length of $N = 4096$ were generated using the Wood and Chan[20] algorithm. These simulated times series of fractal Gaussian noise were decomposed to the first five IMFs by EMD. The characteristic of long-term correlation of simulated time series was presented using a logarithmic plot of energy densities against their corresponding averaged periods.

For a white noise (as a simulated fractal Gaussian noise with Hurst exponent of 0.5), the slope of logarithmic energy density/averaged period plot is -1. The values of slope are higher than -1 for a simulated time series of fractal Gaussian noise with positive long-term correlation and the values are less than -1 for a time series with negative long-term correlation. Thus, we defined AEI using the value of slope of logarithmic energy density/averaged period plot plus 1 to quantify a positive correlation with positive value of AEI and a negative correlation with negative AEI. Hence, we conducted a numerical experiment to prove that AEI is a good assessment of long-term correlation for non-linear time series. In this experiment, 1000 simulated time series for each fractal Gaussian noise with different Hurst exponent from 0.1 to 0.9 and step of 0.2 was used to examine the accuracy of AEI in long-term correlation evaluation. The average and standard deviation derived from 1000 values of AEI for the simulated time series of each fractal Gaussian noise with different Hurst exponent is shown in Fig. 1b. Analysis results of AEI were compared with results the derived by a referred method (i.e., Rescaled range analysis, R/S) as shown in Fig. 1a. R/S analysis acts to derive a direct assessment of Hurst exponent for a non-linear signal.

Figure 1 shows the analysis results using the scaling exponents of R/S analysis and AEI for the simulated time series of fractal Gaussian noise with Hurst exponent from 0.1 to 0.9. In these graphic presentations, both assessments (i.e., the scaling exponent of R/S analysis and AEI) perform significantly positive correlations with the fractal property of the simulated time series. Hence, we used Pearson's correlation coefficient to quantify the consistence between the assessment of fractal property and the Hurst exponent of the simulated time series. According to the results of our numerical experiment, we found the value of

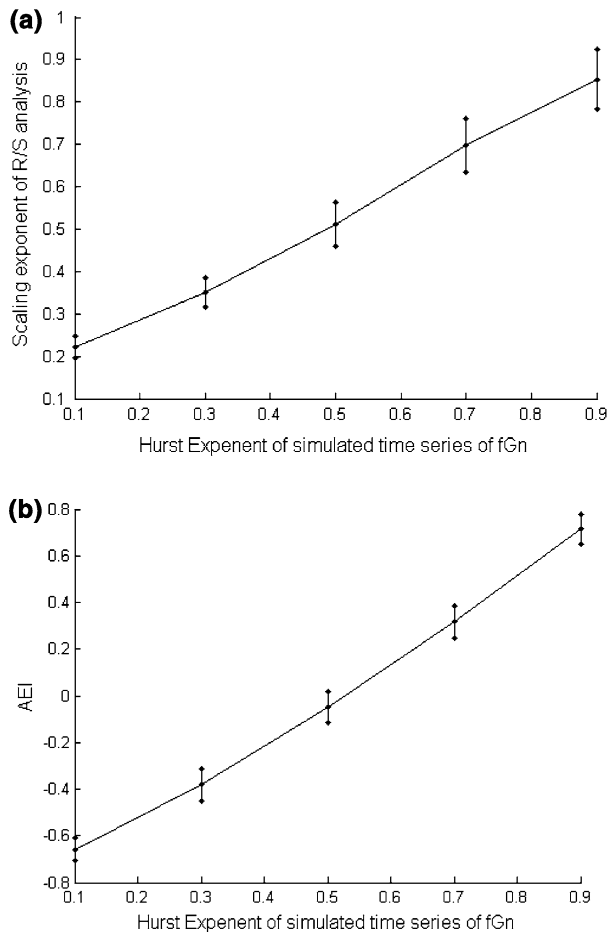

FIGURE 1. Analysis results using the scaling exponents of R/S analysis and AEI for the simulated time series of fractal Gaussian noise with Hurst exponent from 0.1 to 0.9. (a) Results of scaling exponent of R/S analysis; (b) results of AEI index in EMD-based analysis.

Pearson's correlation coefficient between the AEI and the original fractal properties of the simulated time series of Gaussian noises ($p = 0.986$) is higher than that between the assessment derived by R/S analysis and the original fractal properties of simulated time series ($p = 0.963$). It showed AEI performs more accurately in the evaluation of long-term correlation than R/S analysis does. Thus, AEI is proven as an effective indicator for long-term correlation and can be used as the first parameter in the EMD-based human heartbeat analysis.

Define Structure Index Using the Function of Dyadic Filter Bank

According to previous studies, EMD acts as a dyadic filter bank for a broadband time series, which contains no significant components. As a dyadic filter bank, EMD performs a wavelet-like decomposition to a broadband time series and the distribution of averaged periods of IMFs is a geometric series with a ratio of 2. Moreover, EMD also acts as an adaptive decomposition to a broadband time series adaptive to the nature of a signal. According to the results of previous studies[8,21] and our numerical experiment, the averaged periods of IMFs are the critical parameters for identification of a stochastic time series. Since EMD acts as a dyadic filter bank for such signals, averaged periods of the following IMFs depend on the averaged period of IMF 1. To a totally stochastic time series (i.e., white noise as fractal Gaussian noises with $H = 0.5$), averaged period of IMF 1 is close to a constant of 2.87 sampling intervals. In a human's heartbeat time series analysis using EMD, we found that the averaged period of IMF 1 reflects the internal modulation with a fixed period of around 4 s (5 beats for heart rate of 75 bpm) for a healthy subject, but the averaged period of IMF 1 is similar to that decomposed from a stochastic time series for subjects with heart disease (either CHF or AF). Moreover, distributions of averaged periods of IMFs decomposed from human heartbeat time series are similar to geometric series with a ratio of 2 for both a healthy group and a group with heart disease. Thus, we defined the SI to present the characteristic of internal modulation via averaged-period distribution of IMFs decomposed from human heartbeat time series.

TABLE 1. Values of averaged periods for IMF 1–5 decomposed from the simulated time series of white noise.

	IMF				
	1	2	3	4	5
Averaged periods in linear scale	2.87	6.08	12.61	25.85	52.75
Averaged periods in logarithmic scale	1.056	1.806	2.534	3.252	3.966

1000 simulated time series of white noise were used to derive these ensemble values of averaged periods of IMF 1–5. Averaged period is shown in number of sampling intervals.

Furthermore, in order to define this new index of internal modulation, we had to establish a baseline of total stochastic time series to derive a measurement different from the baseline for a human's heartbeat time series with a significant internal modulation, but not stochastic. In this study, white noise is considered as the representative of totally stochastic time series and was used as the baseline of this new assessment of internal modulation. Hence, an ensemble result of averaged periods of IMF 1–5 derived from 1000 simulated time series of white noise was used as the baseline for the new assessment. Values of the baseline (averaged periods of IMF 1–5) are shown in Table 1 in unit of the sampling intervals (i.e., beat number of heartbeat time series).

Thus, SI, which performs the new assessment of internal modulation, is defined as the difference between the distributions of averaged periods for two sets of IMFs, which are derived from the evaluated human heartbeat time series and baseline. Moreover, the energy density of each IMF was considered to contribute as the weighting factor in the calculation of SI. Thus, SI can be calculated by the following equation:

$$I_S = \frac{\sum_{k=1}^{n} \left|\ln T_{s,k} - \ln T_{r,k}\right| \cdot (E_{s,k})}{n \cdot \sum_{k=1}^{n} (E_{s,k})} \tag{4}$$

where $T_{s,k}$ and $E_{s,k}$ represent averaged period and energy density of the kth IMF extracted from a human heartbeat time series; $T_{r,k}$ represents the kth averaged period of baseline; and n is the number of IMFs.

According to the definition of SI, a value of SI close to 0 means that the internal modulation of a time series is similar to that of a stochastic time series. In contrast, a value of SI far from 0 shows that a time series contains an internal modulation different from that of a stochastic time series. Hence, SI was used as the second parameter in this EMD-based approach of human heartbeat analysis. It is a powerful indicator used to verify the internal modulation of a human's heartbeat time series based on the function as a dyadic filter bank of EMD.

MATERIALS

In this investigation, a database downloaded from PhysioBank[4] was used as the study material. This database includes 40 healthy subjects with subgroups of young and elderly (20 young and 20 elderly), 43 subjects with severe CHF, and 9 subjects with AF. This database has been used in many previous studies of human heartbeat analysis using different analysis algorithms. It provides samples of human heartbeat time series for four groups (i.e., healthy young, healthy elderly, subjects with CHF, and subjects with AF). Therefore, the analysis results of this proposed EMD-based algorithm can be compared with results of previous studies to illustrate the advantages.

RESULTS

In this approach, we developed a two-parameter analysis algorithm to investigate a human's heartbeat time series downloaded from PhysioBank. The first parameter is a new assessment for the property of long-term correlation. In a previous study,[15] DFA was also proposed as an assessment of long-term correlation for non-linear time series and applied in human heartbeat analysis using the same database. Therefore, we examined the performances of AEI and scaling exponent of DFA in human heartbeat analysis by three classifications: (1) classification between groups of healthy young and healthy elderly; (2) classification between healthy groups and groups with heart disease; (3) classification between groups of CHF and AF. Table 2 shows the results of classifications using AEI or scaling exponent of DFA as the assessment of the long-term correlation for human heartbeat time series. In Table 2, we found similar performances for AEI and scaling exponent of DFA used in three different classifications. This proves that AEI performs as the first parameter for quantification of long-term correlation in this EMD-based approach with some degree of success as the original method of DFA does. Physiologically, the property of long-term correlation is a useful indicator for a subject with CHF or AF, but not a useful indicator for diagnosing subject with/without heart disease.

TABLE 2. Results of three different classifications using AEI and scaling exponent of DFA.

	Scaling exponent of DFA		AEI	
Classification	Set-point	Correct rate (%)	Set-point	Correct rate (%)
Young and elderly	0.453	72.5	1.205	72.5
Healthy subjects and subjects with heart disease	0.257	63.9	0.771	63.0
With CHF or AF	0.093	98.1	0.132	98.1

Values are shown in the best correct rate and its corresponding set-point in each classification.
Set-point is the value of cutoff point for each classification and the correct rate is the percentage of subjects which are classified correctly.

Therefore, we defined the second parameter via the distribution of averaged periods in this approach. According to statistical results of averaged periods of the first five IMFs for four groups (i.e., healthy young, healthy elderly, CHF, and AF) as shown in Fig. 2, EMD actually acts as a dyadic filter bank to a human heartbeat time series. Distribution of averaged periods is similar to a geometric sequence with a ratio of 2. For the groups with heart disease (i.e., CHF or AF), the averaged periods of IMF 1 are close to 3.2 beats (1.2 in logarithmic scale), but they are around 6–8 beats for healthy subjects. According to the results of previous studies,[8,21] the averaged period of IMF 1 for a white noise is around 2.87 sampling intervals. So, it is obvious that the internal modulations of heartbeat time series for healthy subjects are different from those for subjects with heart disease.

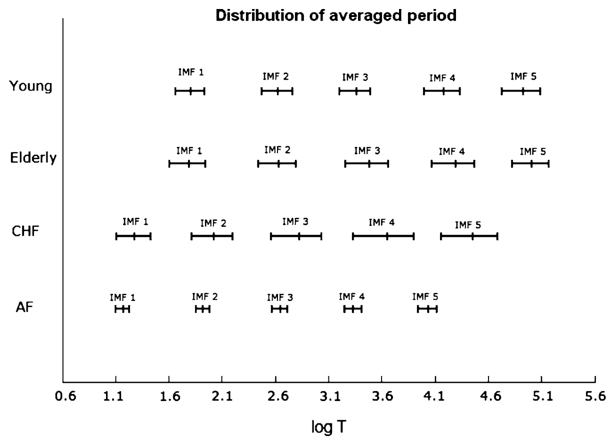

FIGURE 2. Distributions of averaged periods for IMF 1–5 decomposed from human heartbeat time series for four groups (i.e., healthy young, healthy elderly, CHF, and AF). *X*-axis is the logarithmic averaged period. Data are shown with means and standard deviations.

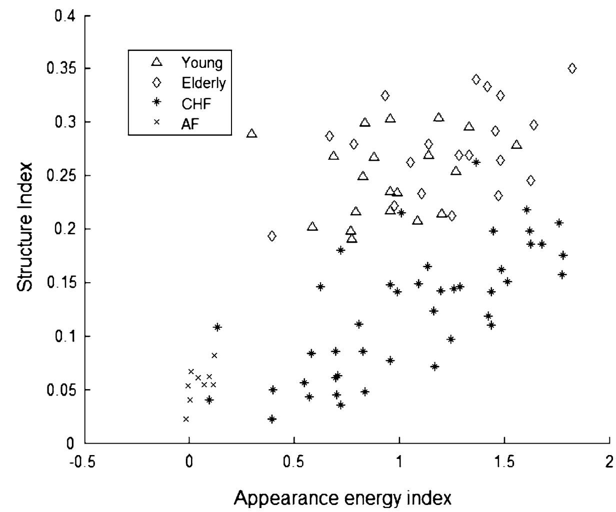

FIGURE 3. Analysis results of the database of human heartbeat time series using AEI and SI in EMD-based intrinsic mode analysis.

TABLE 3. Averaged period of the first IMF for Gaussian noises with different fractal properties.

Hurst exponent	0.1	0.3	0.5	0.7	0.9
Averaged period	2.746	2.808	2.877	2.956	3.051

In addition, according to the results of our numerical experiment, averaged periods of the first IMF decomposed from simulated time series of fractal Gaussian noises with different values of Hurst exponent depend on the fractal property of Gaussian noise. Table 3 shows the ensemble results for averaged periods of the first IMF derived from 100 simulated time series of Gaussian noise with different fractal properties. Heartbeat time series for a subject with heart disease (CHF or AF) performs internal modulation similar to that of fractal Gaussian noise with positive long-term correlation. (Averaged periods of IMF 1 are around 3.2 for heartbeat time series of subjects with heart disease, which are close to averaged periods of Gaussian noises with positive long-term correlations $H > 0.5$.) However, it seems to have an internal modulation with a rhythm similar to respiration[1,3] in IMF 1 for the healthy subjects.

Thus, the second parameter, SI, acts as an assessment of internal modulation of human heartbeat time series. The internal modulation of human heartbeat time series for a healthy subject is different from that of a stochastic time series, but that for a subject with either CHF or AF is similar to that of a stochastic time series. To integrate the analysis results of both AEI and SI, a two-dimensional plot was used to present the distribution for subjects of four groups as shown in Fig. 3. In this figure, SI performs as a parameter different from the assessment of long-term correlation as AEI does. In the previous approach using DFA, the internal modulation of human heartbeat was ignored in analysis. In this approach, the functions of EMD lead us to find the internal modulation of a human's cardiac system, not only the physical property of long-term correlation.

In addition, receiver operating characteristic (ROC) curve has often been used to evaluate the sensitivity and specificity of classification using different parameters.[12] ROC curve reflects relative true positive-, true negative-, false positive-, and false negative-values, termed specificity and sensitivity. Thus, for the purpose to examine that AEI and SI perform different sensitivities and specificities in different classification models considering different underlying physiological characteristics, two classifications were conducted for examination. Moreover, the performances of DFA in two classifications were estimated using ROC curve in comparisons with those of AEI and SI. Figure 4a shows the ROC curve for classification to subjects with CHF or AF. AEI and DFA obviously perform better than SI does in this classification. Physiologically, heartbeat time series of subjects with CHF has a higher degree of long-term correlation than those of subjects with AF. Figure 4b shows the sensitivity for classification to healthy subjects and subjects with heart disease (i.e., CHF or AF). SI obviously performs better than AEI and DFA do in this classification. Since both the scaling exponents of DFA and AEI are assessments of long-term correlation for non-linear time series, these two parameters perform similar sensitivities and specificities in both classifications. Physiologically, heartbeat time series of subjects with heart disease (i.e., CHF or AF) loses its internal self-modulation and performs more stochastic than that of a healthy subject does.

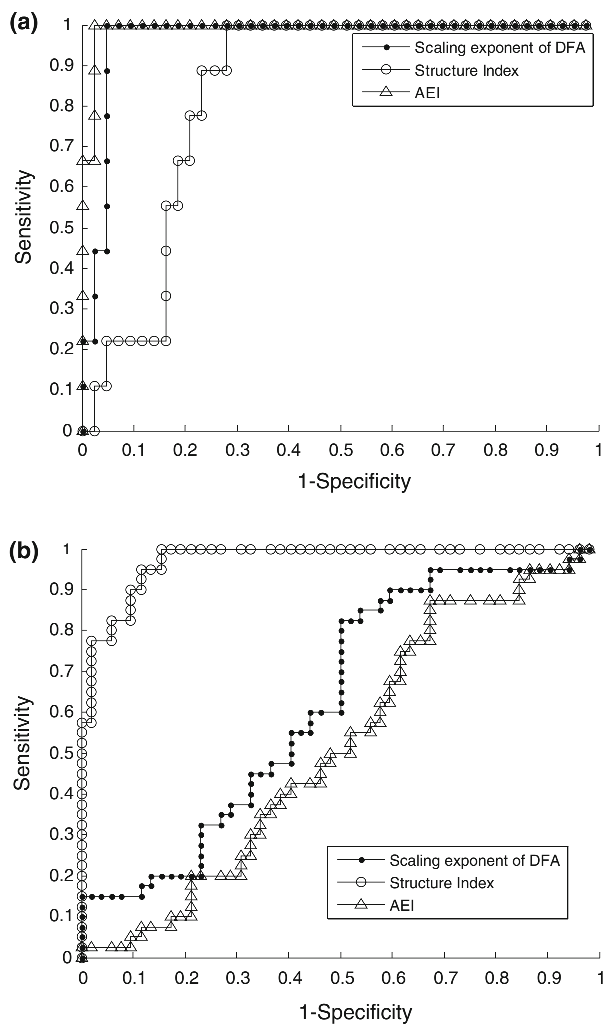

FIGURE 4. Analysis results of ROC curves for various classification models using the parameters of scaling exponent of DFA, AEI, and SI. (a) Classification between groups of CHF and AF; (b) classification according to whether subjects have heart disease or not.

DISCUSSIONS AND CONCLUSIONS

In this study, we introduced two parameters derived from spectral characteristics of IMFs for quantification of the property of long-term correlation and internal modulation of human heartbeat time series in the EMD-based analysis. AEI contributes as a new assessment for the property of long-term correlation and performs with higher accuracy than a common assessment of Hurst exponent derived by R/S analysis in the numerical experiment using simulated time series of Gaussian noises with different fractal properties. In the application of human heartbeat analysis, AEI performs the final classification results in cardiac system identification similar to those derived by a relative method of DFA published before.[14,15] It shows that the physical property of long-term correlation is actually a parameter suitable in some cases of verifications for human's cardiac systems. However, long-term correlation only presents a part of the functions of a human's cardiac systems for an underlying mechanism of long-term self-organization.

In this EMD-based approach, we found that the internal modulation of a human's heartbeat time series is more useful than fractal property in diagnosis of cardiac systems with or without CHF/AF. Physiologically, SI acts as an assessment for the self-modulation of a human's cardiac system. As is well known, interaction between heartbeat and respiration is reflected as a fundamental mechanism of auto-regulation in a cardiac system. Therefore, a heartbeat time series of a healthy human is not stochastic but with a basically underlying modulation. Since both diseases of CHF and AF weaken this modulation, a human's heartbeat time series for a subject with CHF or AF is similar to a stochastic time series. AEI is suitable to distinguish the difference between heartbeat time series of subjects with CHF and AF, but it is not suitable to verify the internal modulation of human heartbeat time series. Therefore, heartbeat time series of a subject with CHF/AF is similar to a stochastic time series (such as Gaussian noise) with positive long-term correlation ($H > 0.5$) and that of a subject with AF is similar to a totally stochastic time series (Gaussian noise with $H = 0.5$). In this approach, functions of EMD lead us to quantify the long-term correlation of human heartbeat time series via AEI and SI could be the key parameters to diagnose ill conditions of a human's cardiac systems.

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