31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Morphological Processing of Physiological Signals for Feature Extraction

B. Samanta, *Senior Member, IEEE*

Abstract— **The paper proposes a novel method of extracting features from physiological signals using intrinsic mode decomposition (IMD) and morphological signal processing (MSP). The complex, nonlinear and non-stationary biomedical signals are first decomposed into intrinsic mode functions (IMF). Next each IMF is subjected to MSP for extracting features, namely, pattern spectrum entropy, that characterize the shape-size complexity of the component signals. These along with other features like energy and sample entropy are extracted from the individual IMF as well as the cumulative sums of IMF for characterizing the signals. The procedure is illustrated using heart sound signals digitally recorded during cardiac auscultation representing different cardiac conditions.**

I. Introduction

In living systems, a rich variety of dynamical behaviors are manifested through physiological signals that are complex, nonlinear and non-stationary. Several techniques have been proposed for analyzing such biomedical signals [1-5]. Huang et al. [6] proposed an intuitive signal processing technique, empirical mode decomposition (EMD), suitable for nonlinear, non-stationary biomedical signals. Approximate Entropy (ApEn) and Sample Entropy (SampEn) have been proposed as measures of regularity and complexity of time series signals [4, 5]. ApEn and SampEn are used for short and noisy physiological signals as alternatives to other nonlinear system measures like Lyapunov exponent and correlation dimension (D_2) [2]. However, these entropy based features are sensitive to the low-frequency trend of the noisy signal. Amoud et al. [7] proposed intrinsic mode entropy (IMEn) as the SampEn of the EMD extracted intrinsic mode functions (IMF) for reducing the sensitivity to low-frequency trend and noise.

Mathematical morphology (MM) was introduced to analyze geometrical features of images through basic morphological operations of erosion (contraction), dilation (expansion), opening (erosion followed by dilation) and closing (dilation followed by erosion) using a structuring element (SE) of simpler shape and size [8-10]. Though the initial applications of MM were mainly in the field of image processing and analysis, there have been growing interests in other domains including biomedical signal processing [11]. Morphological signal processing (MSP) is used to extract multi-scale pattern spectrum (PS) [10]. Recently, the author has proposed a novel entropy based feature from PS as a health index for prognostics of machinery conditions [12].

This paper presents a hybrid technique combining EMD for decomposition of physiological signals into IMF and MSP for extraction of PS entropy based features. Figure 1 shows the schematic of the feature extraction process with three major stages-1: data acquisition, 2: signal processing and 3: feature extraction. Features based on PS entropy and SampEn are extracted from individual IMF and their cumulative sums. The procedure is illustrated using digitally recorded heart sound (HS) signals during cardiac auscultation [13, 14].

Rest of the paper is organized as follows. Section II presents a brief introduction to MSP and PS entropy. In Section III, IMD and IM entropy based features are briefly discussed. Section IV presents HS signals considered in this paper. Results and discussions are presented in Section V. Salient features of the present work are summarized in conclusions.

II. Morphological Signal Processing (MSP)

MSP is based on a set-theoretical method of nonlinear analysis called MM. In MM, the geometric features of images and signals are modified locally through basic morphological operations of erosion, dilation, opening and closing. In this section, analysis of time domain signals using MSP is briefly discussed, see [8-10] for details.

A. Basic Morphological Operations

The basic idea of MSP is to modify and extract the geometrical features of a signal by its morphological convolution with another object of simpler shape and size, termed as structuring element (SE). The SE can be of different shapes including flat, triangular, semi-circular, disk and any irregular curve. The size (scale) of SE, in both length and height, depends on the type of signal to be analyzed. The selection of SE, in terms of shape and size, is an important issue in MSP. The basic morphological operations of erosion, dilation, opening and closing are defined for a one-dimensional sampled function, f(i), with a discrete-valued SE, g(j), ($i \in I$, $j \in J$, $J<I$) as follows:

Erosion: $$(f \ominus g)(i) = \min(f(i+j) - g(j)), \quad (1)$$

Dilation: $$(f \oplus g)(i) = \max(f(i-j) - g(j)), \quad (2)$$

Opening: $$(f \circ g)(i) = ((f \ominus g) \oplus g(j)), \quad (3)$$

Closing: $$(f \bullet g)(i) = ((f \oplus g) \ominus g(j)), \quad (4)$$

where $\ominus$, $\oplus$, $\circ$ and $\bullet$ denote the morphological operators for erosion, dilation, opening and closing respectively.

Manuscript received April 7, 2009.

The author is with Department of Mechanical Engineering, Villanova University, Villanova, PA 10985, USA (phone: 610-519-7018; fax: 610-519-7312; e-mail: biswanath.samanta@ villanova.edu).

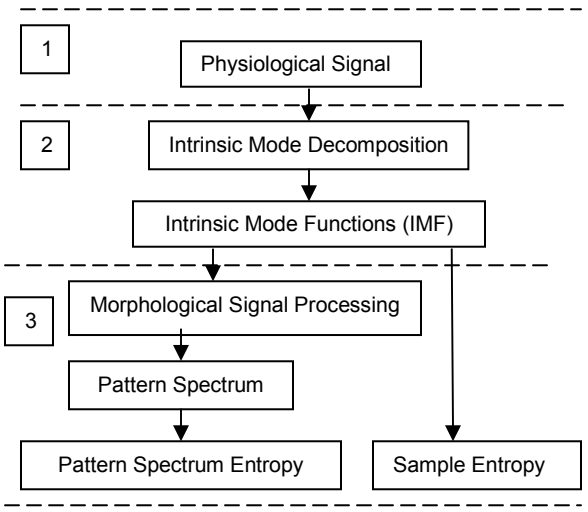

Fig. 1. Schematic of feature extraction process.

B. Multiscale Morphology Analysis and Pattern Spectrum

Most of the traditional MM used single-scale analysis with a SE of fixed scale selected a priori based on the nature of the signal [8-10]. To overcome the necessity of assigning a fixed scale, multicsale morphological filters and PS were introduced [10]. For a nonnegative sampled signal, f(i), $i \in I$ and a SE, g, PS are defined as follows:

$$PS(f,g,+n) = S[f \circ ng - f \circ (n+1)g], \quad 0 \le n \le N, \tag{5}$$

$$PS(f,g,-n) = S[f \bullet ng - f \bullet (n-1)g], \quad 1 \le n \le K. \tag{6}$$

Where $S(f) = \sum_i f(i)$, N is the maximum size of n with f having sufficient dc-bias such that $f \circ g \ge 0, \forall n \le N$ and K is the minimum size of n.

The PS contains useful qualitative information about the signal (f) shape and size relative to the SE (g). The degree of shape content of g in f is given as normalized PS: $q(n) = PS(f,g,n)/S(f)$.

C. Pattern Spectrum Entropy

The quantitative measure of shape-size complexity of a signal relative to a SE pattern is obtained as an average roughness from its PS using the concepts of information theory [10]:

$$H(f/g) = -\sum_{n=0}^{N} q(n) \log q(n). \tag{7}$$

The H(f/g) is termed as PS entropy and its normalized form is defined as $H_r(f/g) = H(f,g,n)/\log(N+1)$. PS entropy (PSEn) gives a quantitative measure of the shape-size complexity of the signal.

III. INTRINSIC MODE DECOMPOSITION (IMD)

Huang et al. [6] presented an intuitive method of decomposing a time series signal into IMF modulating both in amplitude and frequency. The iterative extraction of IMF is on the basis of the local representation of the signal as the sum of an oscillating component (first IMF) and a local trend (residual). The residual signal is further represented as the sum of another (second) IMF and the next residual. The process of IMF extraction is repeated till the residual becomes a monotonic function without any extrema. The original signal, x(t), is represented as the sum of all IMF ($c_k(t)$, k=1,..,K) and the residual r(t) as follows:

$$x(t) = \sum_{k=1}^{K} c_k(t) + r(t), \tag{8}$$

The cumulative sum of IMF up to the level k, $C_k(t)$, defined in Eq. (9), represents the sum of multilevel filtered components:

$$C_k(t) = \sum_{i=1}^{k} c_i(t) \tag{9}$$

Features can be extracted from these IMF ($c_k(t)$) and their cumulative sums ($C_k(t)$, k=1,…,K) for characterizing the signal.

A. Intrinsic Mode Entropy (IMEn)

SampEn is defined as the negative logarithm of the conditional probability that two sequences that are similar for m points (dimension m), remain similar at the next point (m+1), within a tolerance r, Eq.(10). The probability density function is estimated using Eq. (11), where Λ represents Heaviside function and N is the length of the time series [5].

$$SampEn(m,r,N) = -\ln\left(\frac{A^{m+1}(r)}{A^{m}(r)}\right) \tag{10}$$

$$A^{m}(r) = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1}^{N} \Lambda\left(r - \left\| x_i^m - x_j^m \right\|\right) \tag{11}$$

Amoud et al. [7] proposed intrinsic mode entropy as the SampEn of the cumulative sum of IMF, upto level k, to make it insensitive to the low frequency trend or bias. In the present work, IMEn is defined as the SampEn of individual IMF as follows:

$$IMEn(k,m,r) = SampEn(c_k(t), m, r) \tag{12}$$

B. Intrinsic Mode PS Entropy (IMPSEn)

In this work, intrinsic mode pattern spectrum entropy (IMPSEn) is proposed for individual IMF, similar to Eq. (7), as follows:

$$IMPSEn(k,g) = H(c_k(t)/g). \tag{13}$$

C. Cumulative IM Features

The cumulative sums of IMF, $C_k(t)$, have been used to define the sample entropy of cumulative IMF, cIMEn, similar to [7], as follows:

$$cIMEn(k,m,r) = SampEn(C_k(t), m, r) \tag{14}$$

The cumulative intrinsic mode PS entropy (cIMPSEn) has been proposed as follows:

$$cIMPSEn(k,g) = H(C_k(t)/g). \tag{15}$$

IV. HEART SOUND (HS) SIGNALS

Heart beats make two sounds ("lub-dub") with no sounds

in between under normal conditions. However, there may be extra sounds or 'heart murmurs' which may or may not have pathological significance. The heart murmurs can be of different types depending on the blood flow conditions in the heart. These murmurs can be analyzed for an initial assessment of heart conditions and would serve as a basis of further investigations for firm diagnosis and rational treatment [13]. In this paper, heart sound data for five different cardiac conditions were considered: (a) normal (N), (b) systolic murmur (S1, S2), and (c) diastolic murmur (D1, D2). Figure 2 shows the single cycle HS signals.

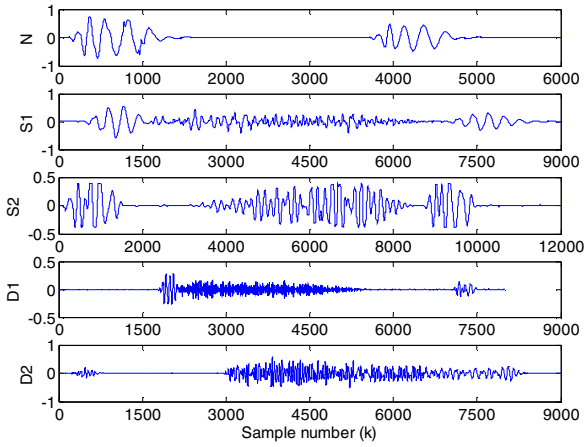

Fig. 2. Heart sound signals (from top): N: Normal, S1, S2: Systolic murmur, D1, D2: Diastolic murmur.

V. RESULTS AND DISCUSSIONS

In this Section, features extracted from HS signals are presented. First the features were extracted from the original signals. Next, each HS signal was decomposed into IMF. Features were extracted from individual IMF, $c_k(t)$, as well as their cumulative sums, $C_k(t)$, k=1, K.

A. Overall Signal Features

HS signals (N, S1, S2 and D1, D2) were analyzed for determining correlation dimension, D_2 [2]:

$$D_2 = \lim(r \to 0)\left(\frac{\log C(r)}{\log r}\right) \qquad (16)$$

where r is cell size and C(r) is correlation sum. Figure 3 shows the variation of logC(r) versus logr for all five types of HS signals. The slope of the linear portion of each curve was used as the estimate of D_2 [2].

Table 1 presents normalized signal energy (E), correlation dimension (D_2), SampEn and PSEn for HS signals.

B. Intrinsic Mode Functions (IMF)

Each HS signal was decomposed into IMF using EMD. Figure 4 shows the IMF for signal S1. First the original signal, x(t), is shown followed by six IMF ($c_k(t)$, k=1,6) and the residual (r(t)). IMF at levels 1-4, i.e., $c_k(t)$, k=1-4, are found to be dominant. IMF at levels 5-6 show relatively low-amplitude slow trends. IMF of other HS signals were similarly obtained.

C. Intrinsic Mode (IM) Features

Each of IMF was further processed to extract features –IM Entropy (IMEn) and IM pattern spectrum entropy (IMPSEn). Figures 5(a) and (b) show these features for each IMF of HS signals. IMPSEn show better distinction among HS signals than IMEn. For signals N and S1, IMPSEn of third IMF was found to be most dominant. For S2, fourth and fifth IMPSEn, and for D1 and D2, first three IMPSEn were prominent.

D. Cumulative Intrinsic Mode (cIM) Features

Features were next extracted from the cumulative sums of IMF ($C_k(t)$, k=1,K). Figures 6(a) and (b) show the features for each $C_k(t)$ of HS signals. Distinction among HS signals is more prominent in cIMPSEn than cIMEn. The contributions of individual IMF are evident from the large differences of cIMPSEn between successive IMF indices.

VI. CONCLUSIONS

The study presents a hybrid approach of feature extraction from physiological signals combining EMD and MSP. The approach combines the advantages of both techniques in analyzing nonlinear, non-stationary biomedical signals. MSP based features show better distinctive property than sample entropy. In this work, feasibility of using these techniques has been investigated using a limited set of available HS signals. In the next phase, the approach will be validated through extended datasets including other biomedical signals.

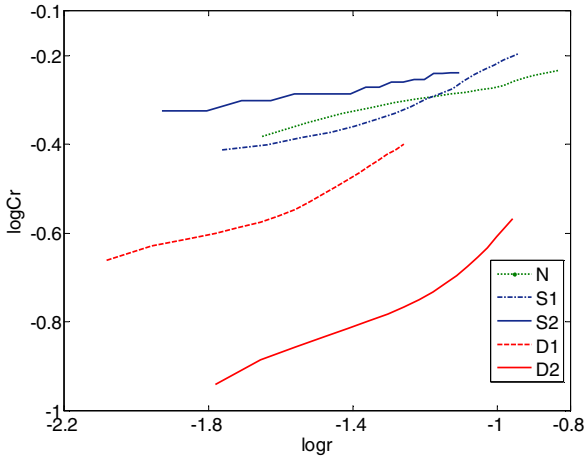

Fig. 3. Variation of logC(r) versus logr for HS signals

TABLE 1: OVERALL SIGNAL FEATURES

HS Type	E	D_2	SampEn	PSEn
Normal	0.2576	0.1683	0.0064	0.1194
Systolic 1	0.2080	0.2878	0.0041	0.0703
Systolic 2	0.1717	0.1134	0.0107	0.0778
Diastolic 1	0.1860	0.3230	0.0027	0.0536
Diastolic 2	0.1788	0.4271	0.0300	0.1415

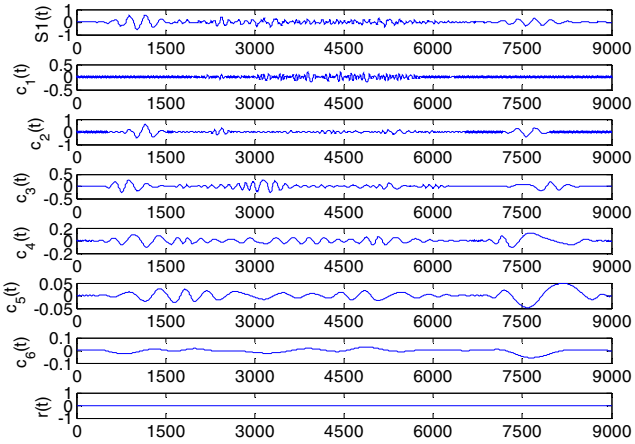

Fig.4. Intrinsic Mode Functions (IMF) of HS signal S1

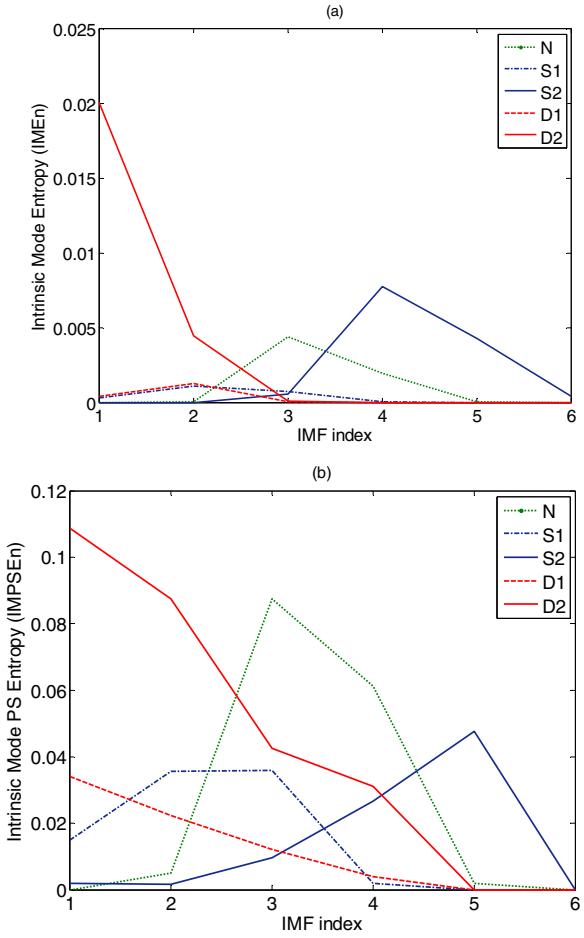

Fig. 5. IM features (a) IMEn, (b) IMPSEn.

REFERENCES

[1] Goldberger, AL, Amaral, AN, Glass, L Hausdorff JM, Ivanov, PC, Mark, RG, Mietus, JE Moody GB, Peng C-K and Stanley HE, PhysioBank, PhysioToolkit, and PhysioNet components of a new research resource for complex physiologic signals, *Circulation* 2000; 101: 215-220.

[2] Henry B, Lovell N, Camacho F. Nonlinear dynamics time series analysis. *Nonlinear Biomedical Signal Processing, Volume 2, Dynamic Analysis and Modeling*, Metin Akay (Editor), 2002, ISBN: 9780780360129.

[3] Cerutti, S. Biomedical signal processing. IEEE Reviews in Biomedical Engineering 2008; 1:8-11.

[4] Pincus SM. Approximate entropy as a measure of system complexity. *Proc Natl Acad Sci USA* 1991; 88: 2297-2301.

[5] Richman JS, Moorman, JR. Physiological time-series analysis using approximate entropy and sample entropy. *Am J Physiol Heart Circ Physiol* 2000; 278:2039-2049.

[6] Huang N, Shen Z, Long S, Wu M, Shih HH, Zheng NC, Yen NC, Tung C, Liu H. The empirical mode decomposition and Hilbert spectrum for nonlinear and nonstationary time series analysis. *Proc. Royal Society A* 1998; 454:903-995.

[7] Amoud H, Snoussi H, Hewson D, Doussot M, Duchene J. Intrinsic mode entropy for nonlinear discriminant analysis. *IEEE Signal Proc. Lett.* 2007; 14:297-300.

[8] J. Serra, *Image analysis and Mathematical Morphology*. New York: Academic Press, 1982.

[9] Maragos P. A representation theory for morphological image and signal processing. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 1989; 11:586-599.

[10] Maragos P. Pattern spectrum and multiscale shape representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1989; 11:701-716.

[11] Sun P, Wu QH, Weindling AM, Finkelstein A, Ibrahim K. An improved morphological approach to background normalization of ECG signals. *IEEE Transactions on Biomedical Engineering* 2003; 50: 117-121.

[12] Samanta B, Nataraj C. Prognostics using morphological signal processing and computational intelligence. *1st IEEE intl. Conf. PHM2008*, Denver, CO, doi: 10.1109/PHM.2008.4711461.

[13] Chizner, MA. Cardiac auscultation: rediscovering the lost art. *Curr Probl Cardiol* 2008; 33:326-408.

[14] Samanta B, Nataraj C. Automated diagnosis of cardiac state in healthcare systems using computational intelligence. *International Journal of Services Operations and Informatics* 2008; 3:162-177.

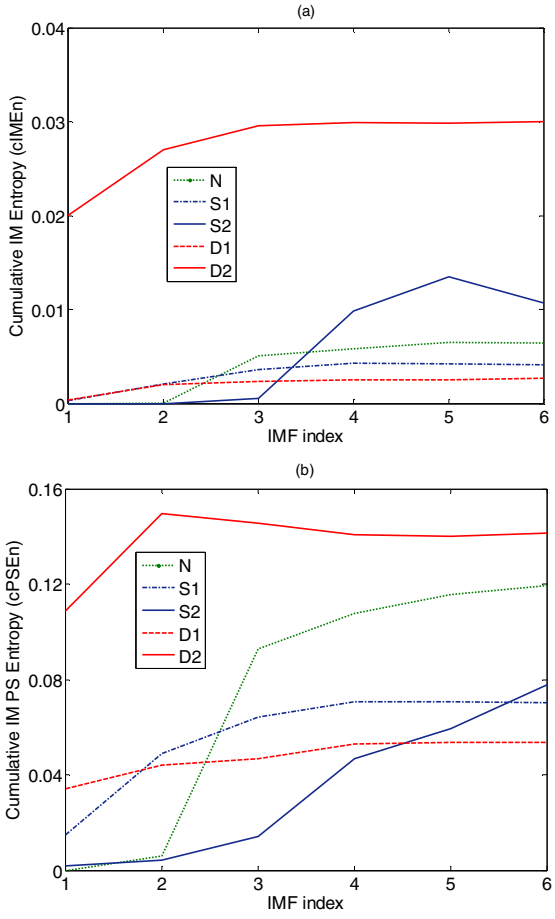

Fig. 6. Cumulative IM features (a) cIMEn, (b) cIMPSEn.