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ORIGINAL ARTICLE

An intelligent approach for variable size segmentation of non-stationary signals

Hamed Azami [a,*], Hamid Hassanpour [b], Javier Escudero [c], Saeid Sanei [d]

[a] *Department of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran*
[b] *School of Information Technology and Computer Engineering, Shahrood University, Iran*
[c] *Institute for Digital Communications, School of Engineering, The University of Edinburgh, UK*
[d] *Department of Computing, Faculty of Engineering and Physical Sciences, University of Surrey, UK*

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A B S T R A C T

In numerous signal processing applications, non-stationary signals should be segmented to piece-wise stationary epochs before being further analyzed. In this article, an enhanced segmentation method based on fractal dimension (FD) and evolutionary algorithms (EAs) for non-stationary signals, such as electroencephalogram (EEG), magnetoencephalogram (MEG) and electromyogram (EMG), is proposed. In the proposed approach, discrete wavelet transform (DWT) decomposes the signal into orthonormal time series with different frequency bands. Then, the FD of the decomposed signal is calculated within two sliding windows. The accuracy of the segmentation method depends on these parameters of FD. In this study, four EAs are used to increase the accuracy of segmentation method and choose acceptable parameters of the FD. These include particle swarm optimization (PSO), new PSO (NPSO), PSO with mutation, and bee colony optimization (BCO). The suggested methods are compared with other most popular approaches (improved nonlinear energy operator (INLEO), wavelet generalized likelihood ratio (WGLR), and Varri's method) using synthetic signals, real EEG data, and the difference in the received photons of galactic objects. The results demonstrate the absolute superiority of the suggested approach.

Introduction

Generally speaking, signals can be categorized in two main types, namely, deterministic signals and non-deterministic signals. A non-deterministic signal is the one with varying statistical properties and can be considered random in analysis. Most of physiological signals, such as electroencephalogram (EEG) and electrocardiogram (ECG) signals, are of this type. Attending at the process, random signals can be divided into two main classes: stationary and non-stationary signals. Unlike in non-stationary signals, the statistical properties,

* Corresponding author. Tel.: +98 121 2254248, +98 9111251101.
E-mail addresses: hmd.azami@gmail.com, hmd.azami@yahoo.com (H. Azami).

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such as mean and variance, do not change in stationary signals.

Since processing stationary signals is much easier and less complicated than non-stationary ones, the signal is often broken into segments within which the signals can be considered stationary. In this way, each part can be analyzed or processed separately [1–3]. This approach is taken in a number of signal processing applications such as tracking the changes in brightness of galactic objects [1] and EEG signal processing [2].

Generally, there are two types of segmentations for non-stationary signals. In the first type, the signal is segmented into equal parts. This process is called fixed-size segmentation. Although computing fixed-size segmentations is simple, it does not have sufficient accuracy [4]. In the second technique used for non-stationary signals, which is called adaptive segmentation, the signals are automatically segmented into variable parts of different statistical properties [2].

The generalized likelihood ratio (GLR) method has been suggested to obtain the boundaries of signal segments by using two windows that slide along the signal. The signal within each window of this algorithm is modeled by an auto-regressive model (AR). In the case where the windows are placed in a segment, their statistical properties do not differ. In other words, the AR coefficients remain roughly constant and equal. On the other hand, if the sliding windows fall in dissimilar segments, the AR coefficients change and the boundaries are detected [5]. Lv et al. have suggested using wavelet transform to decrease the number of false segments and reduce the computation load [6]. This method has been named wavelet GLR (WGLR) [6].

Agarval and Gotman proposed the nonlinear energy operator (NLEO) in order to segment the electroencephalographic signals using the following equation [7]:

$$\psi_d[x(n)] = x^2(n) - x(n-1)x(n+1) \tag{1}$$

If $x(n)$ is a sinusoidal wave, then, $\psi[x(n)]$ will be defined as follows:

$$Q(n) = \psi[A\cos(\omega_0 n + \theta)] = A^2 \sin^2 \omega_0 \tag{2}$$

when ω_0 is much smaller than the sampling frequency, then $Q(n) = A^2\omega_0^2$. In fact, any change in amplitude (A) and/or frequency (ω_0) can be discovered in $Q(n)$. In the case of a multi-component signal, Hassanpour and Shahiri [8] demonstrated that the linear operation creates cross-terms, something that defeats the purpose of the NLEO method in properly segmenting the signal. In order to reduce the effects of cross-terms in the NLEO method, using the wavelet transform has been proposed [8]. This new method is known as improved nonlinear energy operator (INLEO).

A novel approach for non-stationary signal segmentation in general, and real EEG signal in particular, based on standard deviation, integral operation, discrete wavelet transform (DWT), and variable threshold has been proposed [9]. In this paper, it was illustrated that the standard deviation can indicate changes in the amplitude and/or frequency [9]. In order to take away the impact of shifting and smooth the signal, the integral operation was utilized as a pre-processing step although the performance of the method is still relevant on the noise components.

Several powerful image segmentation methods using hidden Markov model (HMM) [10], triplet Markov chains (TMC) [11], and pairwise Markov model (PMM) [11] have been proposed by Lanchantin et al. [11]. These methods have been validated by different experiments, some of which are related to semi-supervised and unsupervised image segmentation. It should be mentioned that these approaches can be used and discussed in non-stationary and stationary signal segmentation approaches too.

Inasmuch as real time series are usually nonlinear and to extract important information from the measured signals, it is significant to utilize a pre-processing step, such as a wavelet transform (WT), to reduce the effect of noise [12]. DWT represents the signal variation in frequency with respect to time.

After decomposing the signal, fractal dimension (FD) is employed as a relevant tool to detect the transients in a signal [13]. FD can be used as a feature for adaptive signal segmentation because FD can indicate changes not only in amplitude but also in frequency. Fig. 1 shows when the amplitude and/or frequency of a signal are changed, the FD changes. The original signal consists of four segments. The first and second segments have the same amplitude. The frequency of the first part is, however, dissimilar from that of the second part. The amplitude of the third segment is different from that of the second segment. The fourth segment is different from the third one in terms of both amplitude and frequency. This signal illustrates that if two adjacent epochs in a time series have different frequencies and/or amplitudes, the FD will change.

Two key parameters for FD-based detection of transients in the signals are determined experimentally. These are the window length and the overlapping percentage of successive windows. Small windows might not be fully capable of clarifying long-term statistics suitably whereas long windows may overlook small block variations. The overlapping percentage of the successive windows influences both the correctness of the segmentation results and the computational load.

To achieve accurate segmentations, here we investigate the use of particle swarm optimization (PSO), new PSO (NPSO) and PSO with mutation, and bee colony optimization (BCO) to estimate the aforementioned parameters. These algorithms are fast search techniques that can obtain precise or locally optimal estimations in the desired search space.

The other sections of this paper are organized as follows. In 'Fractal dimension' Katz's method to calculate the FD has been explained in brief. 'Evolutionary algorithms' introduces

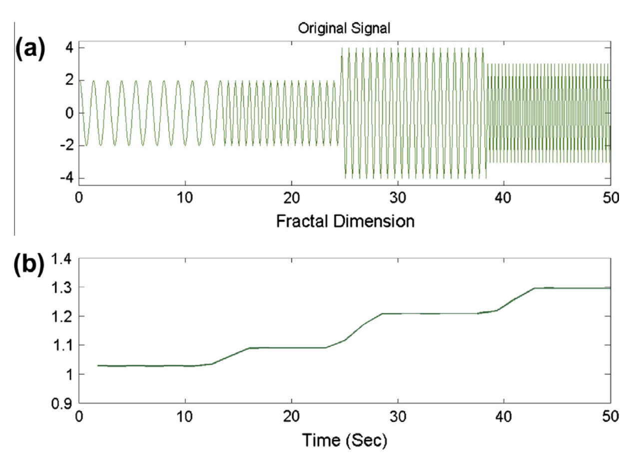

Fig. 1 Variation in FD when amplitude or frequency changes.