A BIOMEDICAL DIAGNOSIS PREDICTIVE USING FRACTAL ANALYSIS: STUDY OF CARDIAC RECORDINGS

Ajit Sadana and Anand Ramakrishnan
Chemical Engineering Department
University of Mississippi
University, MS 38677-9740

Submitted to: Proceedings of the Memphis Area Engineering Societies Conference
Abstract

A novel diagnostic approach based on fractal analysis is presented to help distinguish between normal and pathological conditions. A FractalVision software program is utilized to obtain the fractal dimension, \( D_f \) values for the normal and different pathological conditions. A comparison of the \( D_f \) values obtained is made for the normal condition, and for the different pathological conditions. The decrease in the \( D_f \) value (or degree of heterogeneity) of the signal with the onset of a pathological condition is consistent with current theory. Even though the changes in \( D_f \) exhibited are small as one goes from a normal state to a heart attack state, the simple and rapid diagnostic procedure does demonstrate potential as a useful method to provide physical insights into the complex dynamics of processes that lead to an arrhythmic state from the normal state. The refinement of the technique should make it more reliable and more accurate. This should facilitate in its application as a supplemental method to support the diagnosis of a pathological or normal heart condition.
Introduction

The analysis of the dynamics of human biomedical or biological signals is an important area of investigation to help control and to be able to predict the onset of pathological conditions. Nonlinear dynamics theory exhibits the potential to help understand complex engineering and biological systems. Chaotic behavior is exhibited by the brain by EEG signals (Hively et al., 1995), and is also present in cardiac (ECG) signals. In fact, it has been indicated that chaotic behavior is present in quite a few biological processes that are occurring in the human body, and these give rise to the fractal structures that are prevalent in the body (Goldberger et al., 1990a). The principles of nonlinear dynamics including chaos theory and fractal concepts have been investigated to provide a better understanding of the transition(s) that occur during the transition from a healthy to a pathological state (Goldberger et al., 1985, 1988, 1990b,c, 1992). These authors emphasize that it is the degree of variability, in say for example, the heart rate, that is a characteristic of a healthy individual. A gradual decrease in the ‘variability’ indicates a transition from a healthy state to a pathological state.

Analysis of heart failure is of tremendous significance since it is a major medical problem that afflicts about 700,000 individuals per year in the United States alone (Abraham and Bristow, 1997). The annual costs are staggering and estimates range from $10 - 40 billion annually. The approximate average per capita cost is estimated to be $140,000 to 560,000. Olson et al. (1988) classify heart failure as the major manifestation of dilated cardiomyopathy. Furthermore, Gray et al. (1998) indicate that asynchronous contraction of cardiac muscle fibers (cardiac fibrillation)
is the leading cause of death in the industrial world, and still its mechanism of action is not precisely clear (Myerburg, 1990).

Some forms of heart failure are heritable and genetic in nature. Olson et al. (1998) indicate that actin mutations (cardiac actin gene ACTC) may lead to a defective transmission of force in cardiac myocytes. This eventually leads to heart failure. Barinaga (1998) has very recently summarized the different genes that can lead to heart defects. Some of the genes that lead to hypertrophic cardiomyopathy (HCM) include β myosin heavy chain, myosin essential light chain, myosin regulatory light chain, troponin T, troponin I, and α troponysin. These genes are involved in muscle contraction and in force generation.

Skinner (1994) emphasizes that all fractal dimensional systems are chaotic and that the data they generate will be aperiodic, complex, and apparently unpredictable. A characteristic feature of chaotic behavior is the sensitivity to initial conditions. The nonlinear analysis methods provide insights into the dynamics of the mechanisms generating the EEG signals. Correlation dimensions and Lyapunov exponents have been established from EEG recordings to help delineate the pathology of brain disorders, especially epilepsy.

Poon and Merrill (1997) indicate that cardiac chaos decreases in congestive heart failure (CHF) as compared to a healthy heart. This may be used as a diagnostic tool to help predict the onset of CHF. Skinner (1990) emphasizes that all fractal dimensional systems are chaotic, and that the
data they generate will be aperiodic, complex, and apparently unpredictable. A characteristic feature of chaotic behavior is the sensitivity to initial conditions. Fractals are self-similar objects. The object may be composed of sub-units, sub-sub units, etc. These sub-units resemble (but are not identical to) the larger scale picture (Goldberger, 1996). This author further indicates that fractal nature is present in respiration (Szeto et al., 1992), systemic blood pressure (Marsh et al., 1990), and in white blood cells counts (Goldberger et al., 1986).

Chaotic studies have analyzed quite a few different systems (Skinner, 1994; Garfinkel et al., 1992; Shinbrot et al., 1993; Ott et al., 1990; Schiff et al., 1994; Moss, 1994; Hunt, 1990; Roy et al., 1991; Petrov et al., 1993; Femat et al., 1996; Peng et al., 1994). It has been emphasized that the demonstration of chaotic behavior in humans opens out the possibility of diagnostic and of therapeutic control of diseases ranging from epilepsy to cardiac arrest (Moss, 1994). This became especially true after it was predicted that chaotic physical systems may be controllable by small perturbations. (Ott et al., 1990).

Different computational procedures have been utilized to analyze time-series data (Barahona and Poon, 1996; Marmarelis, 1998; Trucott and Teich, 1996). Different approaches to analyze the heart structure itself, and the dynamics of blood flow have been proposed (Aliev naf Panfilov, 1996; Kilner, 2000; Schreiner et al. 1996; Taber and Eggers, 1996; Zamir, 1999). All of the above techniques though promising are relatively complex in nature and require quite a bit of processing before one is able to make a judgement on the pathological or normal heart condition.
What is required are rapid, sensitive, and precise methods by which one may gain further insights into the heart condition.

Peng et al. (1993) indicate that the healthy heart beat shows more complex fluctuations (more heterogeneity) when compared to the diseased heart rate fluctuation pattern that is close to ‘random walk’. Moss (1994) emphasizes that drawbacks that are involved in the control of chaotic systems, particularly of a biological origin. Furthermore, there are various ways by which one may get false impressions about detecting chaos in biological systems (Rapp, 1994). Up until now chaotic time series analysis have been utilized, notwithstanding all the drawbacks involved, to help characterize EEG recordings of non-seizure and seizure states. A better understanding of the non-linear dynamics exhibited would provide insights into the mechanisms that underlie these dynamics. The eventual goal of these analysis is to help control or constrain these periods of seizure activity by noninvasive methods, if possible.

The seizure or non-seizure recordings are basically of a heterogeneous nature. In the normal (non-seizure) state the randomness of the brain activity is reflected in a relatively higher degree of heterogeneity in the signal. In the pathological state (for example, during an epileptic seizure), however, the pathology dominates the brain activity by producing more ‘order’ or a lesser degree of heterogeneity in the signal or recording.
We do recognize that by examining the shape of the ECG recording, and by looking at different segments of the PQRST curve one may be or is able to indicate that precise nature and location of the cardiac trouble. As is to be conservatively expected one often obtains two or more indicators to more precisely arrive at a prognosis. The technique we will be presenting is statistically based, and provides a lumped parameter. This is an initial attempt to diagnose a pathological heart condition and distinguish it from a healthy condition. The technique to be presented is of a general nature and the precise nature of the heart ailment may or may not be available at the time of analysis. At a later stage modifications of the technique may be developed to examine different sections of the PQRST curve, and thus further pinpoint the actual heart condition.

In this paper we will obtain, renalyze, and compare the fractal dimension values estimated from the ECG recordings of the normal state, the ventricular trigeminy state, the concealed bigeminy state, and the dilated cardiomyopathy state. The fractal dimension or the degree of heterogeneity, and the changes therein exhibited with time, are then used to help characterize the different states from ECG recordings.

**Procedure for Analysis**

ECG recordings were taken from the literature, and were transferred to a diskette using a HP
ScanJet 4C scanner. The fractal dimensions of the scanned recordings were obtained using FractalVision (Windows version 1.04) (Hoviss et al., 1980). It is developed by Cedar Software, Wolcott, VT. Basically, it is a ‘box-counting’ program, wherein different size boxes are used to ‘cover-up’ the recording to be analyzed. One obtains an average fractal dimension that is accurate to 7 significant digits.

Results and Discussion

In this work, we utilize experimental time-series data from previous studies and use our approach for analysis.

Peng et al. (1993) have recently presented long-range antcorrelations and have indicated the non-Gaussian behavior of the heartbeat. These authors noted that cardiac beat-to-beat intervals of healthy subjects display scale-invariant, long-range anticorrelations (up to $10^4$ heart beats). They also indicate that the histogram of heartbeat increments is reasonably described by a Levy distribution. Though this distribution remains the same for a group of subjects with severe heart disease, these authors noted that the long-range correlations vanish. Peng et al. (1993) emphasize that these nontrivial long-range correlations in healthy heart rate dynamics indicates adaptive behavior. The loss of these correlations with the pathological condition indicates and is consistent with the loss of adaptive behavior.

Figure 1 shows the interbeat interval $B_L(n)$ after low-pass filtering for (a) healthy subject, and (b)
a patient with severe cardiac disease (dilated cardiomyopathy). Table 1 shows the fractal
dimension, $D_f$ values obtained for the normal case, as well as when severe cardiac disease is
present. Note that the fractal dimension, $D_f$ value for the normal state is 1.4375. During the
heart attack the $D_f$ value is lower, and is equal to 1.1838. There is a 17.6% decrease in the
fractal dimension value. This decrease in the fractal dimension value indicates a decrease in the
heterogeneity of the cardiac recording. This is consistent with the loss of adaptability with the
onset of the pathological condition.

The advantage of this method is that the fractal dimension values are obtained very quickly, no
reconstruction of the data or ‘filtering’ is required, and the procedure can readily be incorporated
‘on line’ to provide a continuous stream of $D_f$ values. This should be of assistance in helping to
predict (and to possibly control) the onset of a pathological condition, which is indicated by a
drop in the $D_f$ value. The decrease in the $D_f$ value is reasonable, and is presumably prone to
errors in interpretation. Nevertheless, refinements in the procedure should presumably alleviate
this problem.

The fractal analysis is worthwhile exploring further considering (a) its simplicity and its rapid
nature in application, and in obtaining fractal dimensions quickly, and (b) the possibility of its
incorporation into a ‘real-time’ system that helps predict the onset of a pathological condition
when there is a ‘significant’ (to be determined) decrease in the fractal dimension value. Quite a
few pieces of data from different sources need to be processed to determine the magnitude of
changes in the fractal dimension obtained on going from a normal condition to a pathological one, and vice-versa.

In another study we analyze the data related to complex cardiac arrhythmias using chaos theory (Glass et al., 1987). These authors presented Holter recordings from two patients who display frequent ectopy. Figure 2 shows the ambulatory ECG record of (a) an elderly man with Cheyne-Stokes breathing exhibiting episodes of ventricular trigeminy, and (b) of a middle-aged man with frequent ectopic betas (concealed bigeminy). Table 2 shows the fractal dimension values for both of these cases. The $D_f$ values estimated for the ventricular trigeminy and the concealed bigeminy were 1.3285 and 1.1595, respectively. Note that the $D_f$ value for the ventricular trigeminy is 14.7% higher than that observed for concealed bigeminy. Since no record for a healthy person was provided, we are not able to compare the $D_f$ values estimated for the two different pathological conditions with the normal condition. One would expect, however, that the $D_f$ value for a healthy person (man in the ambulance) would be higher than those obtained for a pathological condition. As a limit for a ‘dead’ person, whose heartbeat is presumably a ‘flat line’, the estimated fractal dimension value should be equal to one.

It would be of interest to analyze other arrhythmias, induced or not, using the fractal analysis method. The concept is simple to use, the results are obtained rapidly, and the procedure is non-invasive. It would also be of interest to apply this fractal analysis approach to other arrhythmias, induced or not, in animals, and to cardiac recordings from humans who are in the normal state,
and have undergone arrhythmias. A framework of such fractal dimension value data would be of considerable assistance in better understanding the dynamics of the human heart beating under normal conditions, and during the transition and onset of cardiac arrests. The therapeutic and diagnostic potential and the value of such a procedure is enormous. It is definitely worthwhile exploring further the therapeutic and diagnostic potential exhibited by the fractal analysis method for analyzing the dynamics of human behavior (normal or pathological). Hopefully, this type of analysis would, by noninvasive means, either help constrain, control, or rectify human behavior. More importantly, it would provide indications of the onset of pathological behavior. The earlier one obtains the trends in pathological behavior, the higher the probability of ‘quick’ corrective action accompanied with a minimum of permanent damage.
Figure Captions

1: Interbeat interval, B_L(n) after low-pass filtering for (a) a healthy subject, and (b) a patient with dilated cardiomyopathy (severe cardiac disease (Peng et al., 1993).

Figure 2:

Ambulatory ECG record of (a) an elderly man showing ventricular trigeminy, and (b) a middle-aged person showing frequent ventricular ectopic beats (or concealed bigeminy).
<table>
<thead>
<tr>
<th>Pathological Condition</th>
<th>Fractal Dimension, $D_f$</th>
<th>% Change in $D_f$</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>normal</td>
<td>1.4374</td>
<td>---</td>
<td>(Peng et al., 1993)</td>
</tr>
<tr>
<td>dilated cardio myopathy</td>
<td>1.1838</td>
<td>-17.6</td>
<td>(Peng et al., 1993)</td>
</tr>
<tr>
<td>cardiomyopathy</td>
<td></td>
<td></td>
<td>---</td>
</tr>
<tr>
<td>Pathological Condition</td>
<td>Age</td>
<td>Fractal Dimension, $D_f$</td>
<td>% change in $D_f$</td>
</tr>
<tr>
<td>------------------------</td>
<td>--------------</td>
<td>--------------------------</td>
<td>-------------------</td>
</tr>
<tr>
<td>ventricular trigeminy</td>
<td>elderly man</td>
<td>1.3285</td>
<td>------</td>
</tr>
<tr>
<td>concealed bigeminy</td>
<td>middle-aged</td>
<td>1.1585</td>
<td>- 14.7</td>
</tr>
<tr>
<td></td>
<td>aged man</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
References


Goldberger, A.L. Is the normal heartbeat chaotic or homoeostatic? News Physiological Sci., 6,


Levine, R.J.C., Yang, Z., Epstein, N.D., Fananapazir, L., Stull, J.T., and Sweeney, H.L., Structural and functional responses of mammalian thick filaments to alterations in myosin


Ruelle, D. Where can one hope to profitably apply the ideas of chaos? Physics Today, 47, 24-30 (1994).


