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## **An Introduction to Biomedical Signal Processing**

Lecture Notes for BSP, Chapter 1

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Master Program Data Engineering

# 1 Introduction

Biomedical signal processing (BSP) is about algorithms for processing a particular class of digital signals which are acquired in biomedical research and clinical medicine. Biomedical signals are recordings of physiological activities of organisms, ranging from gene and protein sequences, to neural and cardiac rhythms, to tissue and organ images. Electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG) and various sensory evoked potentials are a few examples of such bioelectric signals. Such signals convey information about the structure and functioning of associated underlying biological source. However, the required information is in the most cases hidden in the signal structure and may not be immediately perceived. Before the signal can be given a meaningful interpretation, some operations must be applied on the available recordings to decode or extract the significant information. The decoding procedure is sometimes straightforward and only needs visual inspection of the signal on a computer screen or a paper printout. However, the complexity of a signal is often quite substantial, and, therefore, advanced biomedical signal processing procedures are needed for extracting clinically significant information hidden in the signal. For instance, when the visual processing mechanism of the brain is of interest, the eye is stimulated with a flash and the activity of the brain is monitored by means of surface electrodes located on the scalp. The information related to the visual activity of the brain is accompanied with the signal which is mainly due to other activities of the brain. Hence, in order to separate the desired physiological process from interfering processes and to enhance the relevant information, *noise reduction* procedure must be applied on the signal.

In addition to suppressing the noise, biomedical signal processing is often used to *extract hidden features* which are not explicitly available from the signal through visual inspection. For instance, small variations in heart rate cannot be captured by the human eye have been found to offer useful clinical information when measured using a proper signal processing technique.

In many situations, we may wish to transmit the signal from point of acquisition to a remote location for monitoring or processing. This may be the case, for example, when information recorded by means of wearable devices is required in the hospital or physician's office. In these cases, the main objective of processing is to match the signal with the requirement of the transmission channel. In other cases, we may wish to record several vital signals in a long

timescales (e.g., several days). For instance, in order to analyze the abnormal sleep patterns or to detect irregularly occurring disturbances in heart or breathing rates, long-term signals from brain, heart, muscles and eye movements are routinely recorded. Therefore, effective storing is needed such that the recorded data will require minimum amount of storing space. In both these situations, the objective of processing would be *data-compression* of digitized signal.

Another important objective in biomedical signal processing is mathematical *signal modeling* and *simulation* which provides a critical tool to understand the complex temporal phenomenology of physiological processes. For example, various mathematical models have been developed to describe how action potentials in excitable cells are initiated and propagated through the excitable tissue. Another line of examples for such bioelectrical models includes models of head and brain for localizing sources of neural activities.

A large number of processing algorithms have been particularly proposed to suppress disturbances in physiological recordings and to facilitate diagnostic feature extraction. In addition, with the aid of biomedical signal processing, biologists and neuroscientists can develop hypotheses to explain physiological functions and physicians can monitor distinct states of malfunctions/disorders.

This lecture briefly introduces bio-electrical phenomena, data acquisition procedures, filtering fundamentals, spectrum estimation and feature extraction with particular emphasis on diagnostic applications of ECG and EEG recordings. It also provides a few examples of elementary linear and non-linear modeling formalisms.

After putting the biomedical signal processing in context, the rest of this chapter gives an introduction to data acquisition and processing procedures and provides an overview to the basics of signal and systems. The main reference for this chapter is:

[1] Cohen, Arnon. Biomedical Signal Processing: Time and frequency domains analysis, Volume I. CRC-Press, 1986.

## 1.1 General measurement and diagnostic system

As depicted in Figure 1-1, a general measurement and diagnostic system consists of two substantial building units for *data acquisition* and *data processing*. Through the data acquisition (shown by the blue dashed line), the captured signal is converted to a form suitable for the final processing platform (e.g., a digital computer or a microprocessor). Transduction and pre-processing are major

steps in this unit. In transduction block, a transducer coupled to the information source collect the required information (e.g., electrical signal, sounds, mechanical pressure or concentration of a certain chemical substance) and converts it to analog voltage which is suitable for encoding into a computer. Pre- processing typically involves in two successive steps: analog signal conditioning and analog to digital (A/D) conversion. Analog signal conditioning consists of analog amplifiers and filters which provide a good match between the signals measured with a transducer and the analog-to-digital (A/D) converter. Afterwards, A/D device transforms the analog signal to a digital signal that can be represented in a computer. More details of A/D conversion is provided in chapter 3.

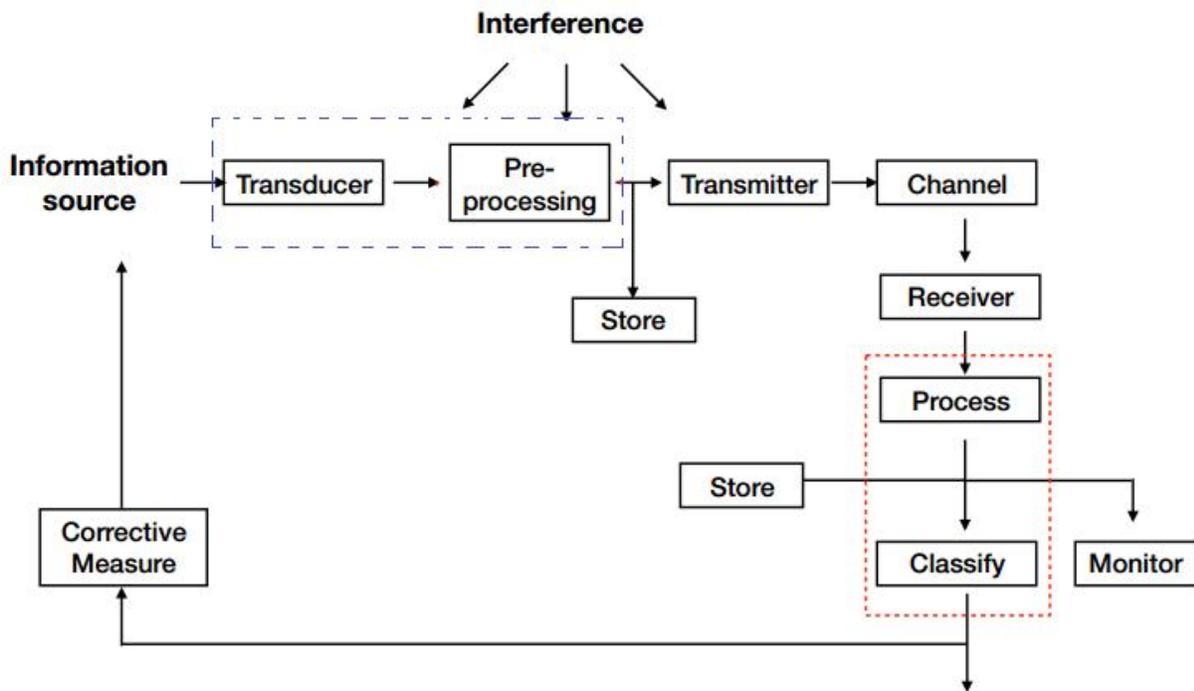


Figure 1-1: General measurement and diagnostic system [1].

In diagnostic context, the processing has to classify the signal into one of many given classes which may be the normal and various pathological classes. In a therapeutic context, after classification, an algorithm may be taken to directly modify the behavior of a certain physiological process. For instance, the algorithm of cardiac pacemaker, initially estimates the mean of the heart rate and compares it with a fixed or adaptively changing threshold. Then, based on this corrective measure it may change the patterns of cardiac activity by sending appropriate stimulating pulses.

Signal processing unit (shown in red dashed line) typically consists of the following blocks:

- **Segmentation:**  
Characteristic properties of the signal may drastically vary during time. However, we observe and process the signal only in a finite time window. The length of the time window depends on the signal source and goal of processing. In some applications such as cardiac monitoring, the signal processing is performed only on a single window with predetermined length. In others, for example in electroencephalography or sensory evoked potential or speech investigations, some scheme for automatically dividing the signal into varying length segments is required.
- **Signal Estimation or Enhancement:**  
A variety of techniques are available for the enhancement of the relevant information in the signal. *Noise attenuating and cancelling* techniques or *signal enhancement* methods are required when the signal has been corrupted with additive and multiplicative noise or in cases where the desired information constitutes only a part of the signal such that irrelevant portions are considered as artifact. Examples of the enhancement methods (also known as signal estimation methods) developed to increase the signal-to-noise ratio are discussed in chapters 5 and 7.
- **Feature extraction**  
In many cases, the signal may contain redundancies. When effective storing and transmission are required, or when the signal is to be automatically classified, the signal can be transformed into reduced set of features that contain the required information. These features are then used for storage, transmission, and classification. Reconstruction of the signal from its features is often of particular importance. The types of features used and their number is therefore, dictated by the trade-off between the data reduction rate for efficient storing and transmitting and, the error of reconstruction.
- **Classification and prediction**  
The ultimate goal in a general system is often either producing the class label for the signal or predicting a significant event in the continuations of the signal. Given a training data, namely the input recordings and their labels, supervised algorithms introduced in Machine

Learning (ML) are often used to train a linear or non-linear classifier. In this course, however, aiming at representing the signal in a way that more relevant features can be extracted, the training step won't be touched. For further reading, you can see [this ML lecture notes](#).

## 1.2 Classification of signals

Signals, generated by biological and physical systems, may possess various properties and characteristics. In order to apply the appropriate processing tools, it is important to firstly identify the general characteristics of the signal. In general, signals are classified into two main groups: *deterministic* and *random* signals (see Figure 2-1).

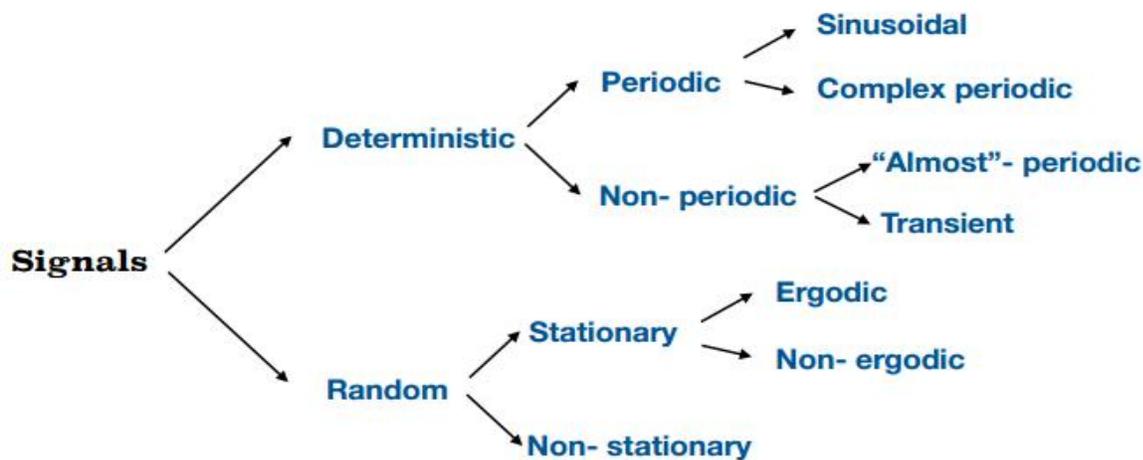


Figure 1-2: Classification of the signals [1].

1. Deterministic signals can be totally described by explicit mathematical relationships. They are free from extraneous variations and don't change from one measurement to another measurement. An example of deterministic signals is Mackey-Glass time series described by the following nonlinear time delay differential equation:

$$\frac{dx}{dt} = \beta \frac{x(t-\tau)}{1+x(t-\tau)^n} - \gamma x, \quad \gamma, \beta, n > 0$$

where  $\gamma, \beta, n$  are real numbers, and  $x(t - \tau)$  represents the value of the variable  $x$  at time  $(t - \tau)$ . Depending on the values of the parameters, this equation displays a range of periodic and chaotic dynamics (see Figure 3-1).

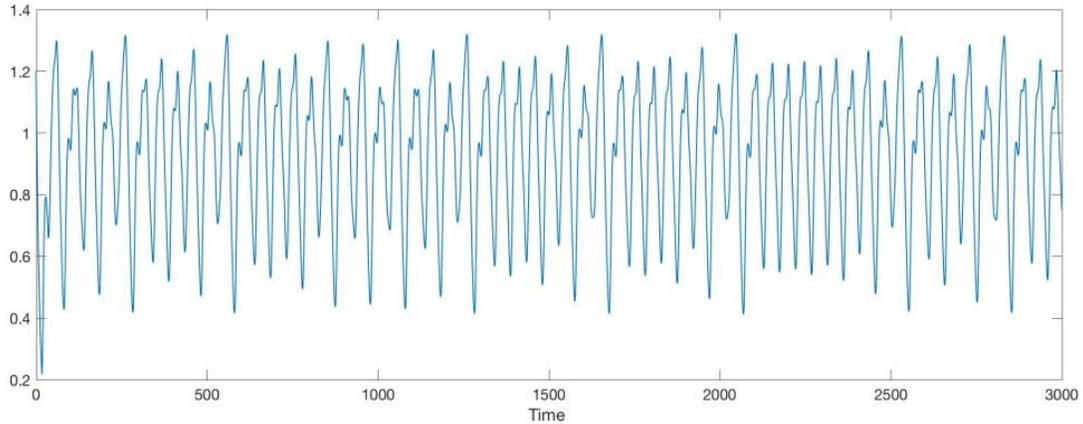


Figure 1-3: An example of deterministic chaotic signal generated from Mackey-Glass equation.

Deterministic signals are divided into two subgroups: periodic and non-periodic signals:

- Periodic signals are signals for which  $x(t) = x(t + T_0)$ , where  $T_0$  is the period and the frequency  $\omega_0 = 2\pi/T_0$  is said to be the fundamental frequency. Periodic signals are convenient since one period is sufficient for complete description. In the frequency domain, the signal is represented by means of the *Fourier series*, where only the fundamental frequency and its harmonics take part (the frequency  $n\omega_0$  is said to be the  $n$ th harmonic of  $\omega_0$  where  $n$  is an integer). More details on Fourier Transform is provided in chapter 3.
- Non-periodic signals consist of two classes: “almost periodic” and *transient* signals. A combination of several unrelated periodic signals creates an “almost” periodic signal. Although those that are not periodic in the mathematical sense, they have discrete description in the frequency domain. However, this frequency description differs from the periodic one in that the various frequencies participating are not harmonics of some fundamental frequency.

A *transient* signal in contrast to the *steady state* signal is a deterministic signal not having the properties discussed previously. Any discontinuity and sudden change in a deterministic signal is regarded as a transient. Mathematically speaking, a transient signal is represented by *infinite* number of sinusoids in frequency domain. Conversely,

any signal expressible as a finite number of sinusoids can be defined as a steady-state signal.

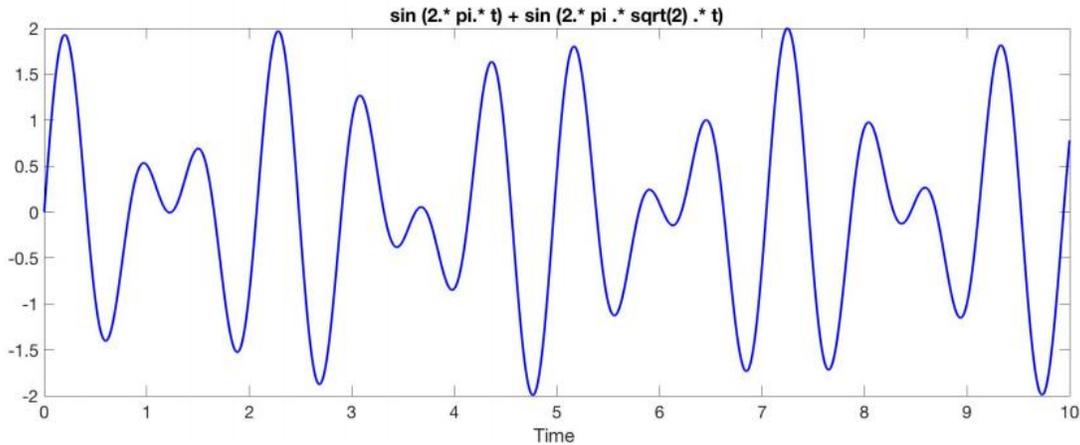


Figure 1-4: An example of an almost-periodic signal.

2. Random signals cannot be exactly expressed. It varies extraneous and it is no longer repeatable. It can be described only in terms of probabilities and statistical averages. A random signal is a sample function of a random process. One sample function of a random process differs from another in their time description. They shares, however, the same statistical properties. The complete (infinite) set of sample functions produced by the random process is called the *ensemble*. The description of the random signal is given by the joint probability density function. Random processes are of two classes: stationary and non-stationary.

  - A stationary process is a stochastic process whose statistical properties are not a function of time. Stationary process are convenient since for such a process we can calculate, for example, the expectation by averaging the values,  $x(t)$ , overall the ensembles at any time,  $t$  (see Figure 1-5, more details are provided in chapter 3). An important class of stationary random signals is the class of ergodic signals. For these signals, in order to calculate the statistical average over the ensemble, it is sufficient to calculate the time average of any

sample function over the time axis. As the course progresses, we will see that stationarity and ergodicity are properties which allow the use of practical processing methods.

- A non-stationary process is a signal whose statistical properties vary with time. It is difficult to process a non-stationary (and thus nonergodic) process. Very often we are forced to divide the process into segments, each assumed to be stationary. The length of the segments depends on the properties of the nonstationarities. For instance, in speech signals, segments are chosen with durations of about 10 *ms* while in EEG analysis segments may be of the order of a few seconds.

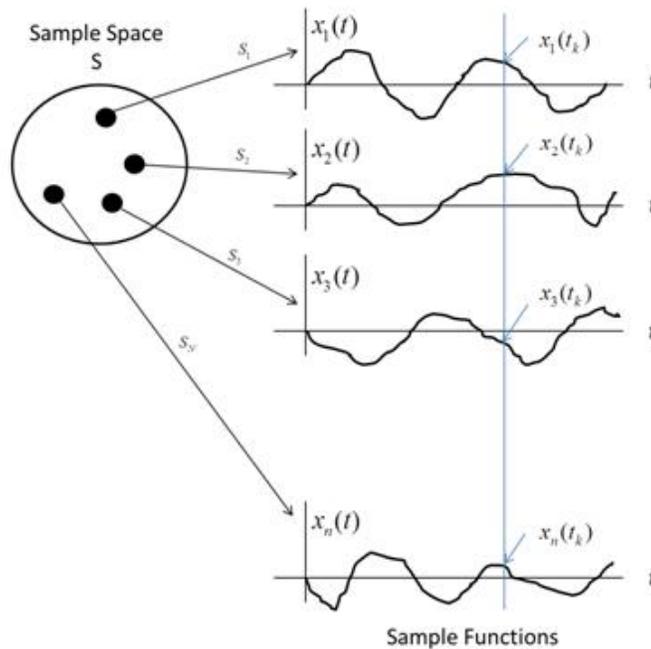


Figure 1-5: Illustration of a sample space for a random process [<https://www.vocal.com/noise-reduction/statistical-analysis-random-signals/>].

The objective and constraints of the problem at hand will determine to consider a vital signal as random or deterministic. For example, in ECG processing, if we are interested in the general characteristics of the QRS complex, we consider the recording as a deterministic signal. When we are interested in the changes of the R-R interval, we consider it a random signal. EEG signal is often viewed as a realization of a stochastic process and is modeled as a random signal. Only under

certain conditions such as before and during epileptic seizure, EEG can be modeled as chaotic deterministic process.

From the processing point of view, both deterministic and random signals are either continuous or discrete. Continuous time signals are defined at any point in time and are represented by a continuous independent variable. Fourier and Laplace transforms and other “analog” methods are applied to the processing of these signals. Discrete signals are signals that are defined only at given points in time and thus are represented by a discrete independent variable. Digital signals are discrete signals whose amplitude is also discrete. Discrete signal may arise by sampling a continuous signal in time and quantizing its amplitude, or they may be discrete by nature (i.e., generated by a discrete-time process). These signals are processed by means of discrete signal processing methods such as the Z transform and the Discrete Fourier Transform (DFT).

### 1.3 Fundamentals of signal processing in frequency domain

Filtering is a very basic tool for signal processing. Filters mostly applied on signals in frequency domain rather than in the time domain. Fourier transform simply transfers a signal from the time domain to the frequency domain where the amplitude and phase of the signal is represented as a function of frequency. A more practical transformation is Laplace transform which transfers a continuous time signal,  $x(t)$ , into the complex frequency plane. Filters are mainly designed to attenuate or completely cut off portions of the signals' frequencies to shape the spectral properties of the signal. For discrete time signals, the complex Z domain is defined.

The frequency filtering is a powerful tool for random as well as deterministic signals. When processing random signals, we apply the Fourier transform to the autocorrelation function rather than the sample function itself. We then deal with the power spectral density function. The same filter design techniques are applied here.

### 1.4 The course overview

Chapter 2 gives a brief description to the bioelectric phenomena from which vital signals arise. A review of basics in digital signal processing and random processes is provided in chapter 3. Chapter 4 briefly introduces the EEG signal, some common patterns observed in EEG and clinical

applications of EEG processing. The main theme of chapter 5, then will be artifact rejection and spectral analysis in EEG interpretation. In chapters 6 and 7, the main characteristics and clinical applications of ECG will be presented and some methods for noise reduction, beat detection and data compression will be explained.