Biomedical Signal Processing and Applications

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Abstract

In biomedical signal processing, the aim is to extract clinically, biochemically or pharmaceutically relevant information in order to enable an improved medical diagnosis. All living things, from cells to organism, deliver signals of biological origin. Such signals can be electric, mechanical, or chemical. All such signals can be of interest for diagnosis, for patient monitoring and biomedical research. The main task of processing biomedical signals is to filter the signal of interest out of from the noisy background and to reduce the redundant data stream to only a few, but relevant parameters. This paper will cover biomedical signal processing as used in diagnostic instrumentation. A number of current research projects will also be outlined with emphasis on intelligent medical diagnosis system.

Keywords
Diagnostic instrumentation, signal processing, biomedical signal, fetal electrocardiography, stochastic processes.

1. Introduction
Biomedical signal processing is mainly about the innovative applications of signal processing methods in biomedical signals through various creative integrations of the method and biomedical knowledge. It is a rapidly expanding field with a wide range of applications. These range from the construction of artificial limbs and aids for the disabled to the development of sophisticated medical monitoring systems that can operate in a noninvasive manner to give real time views of the workings of the human body. There are a number of medical systems in common use. These include ultrasound, electrocardiography and plythesmography are widely used for many purposes.

2. Biomedical Signal Processing
The processing of biomedical signals usually consists of at least four stages:

- Measurement or observation, that is, signals acquisition
- Transformation and reduction of the signals
- Computation of signal parameters that are diagnostically significant, and
- Interpretation or classification of the signals

Bio-signal processing stages are shown as in Figure 1.

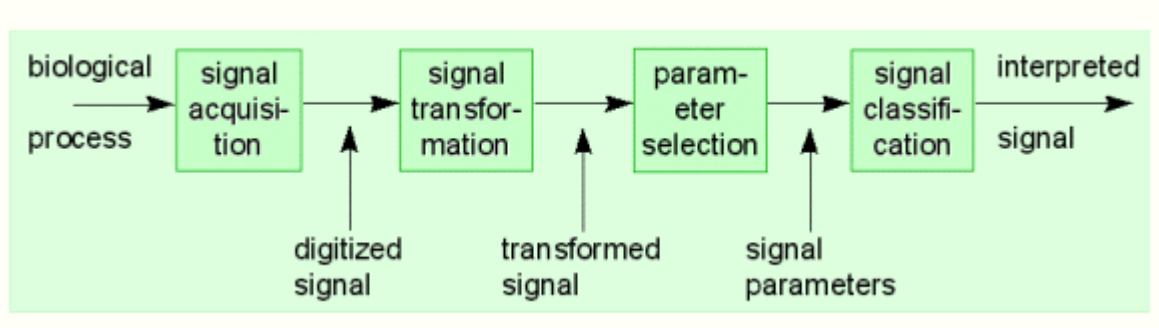


Figure 1: Bio-signal processing stages

Types of biological signals classified into two main groups: the deterministic and the stochastic (or statistical) signals. Such as a beating heart or respiration generates signals that are also repetitive. The deterministic group is subdivided into periodic, quasiperiodic, and transient signals. The stochastic signals are subdivided into stationary and non-stationary signals [1]. Groups of cells depolarise in a more or less random fashion such as muscle cells generating electromyography or nerve cells in cortex. Time varying signal wave shapes are shown as in Figure 2.

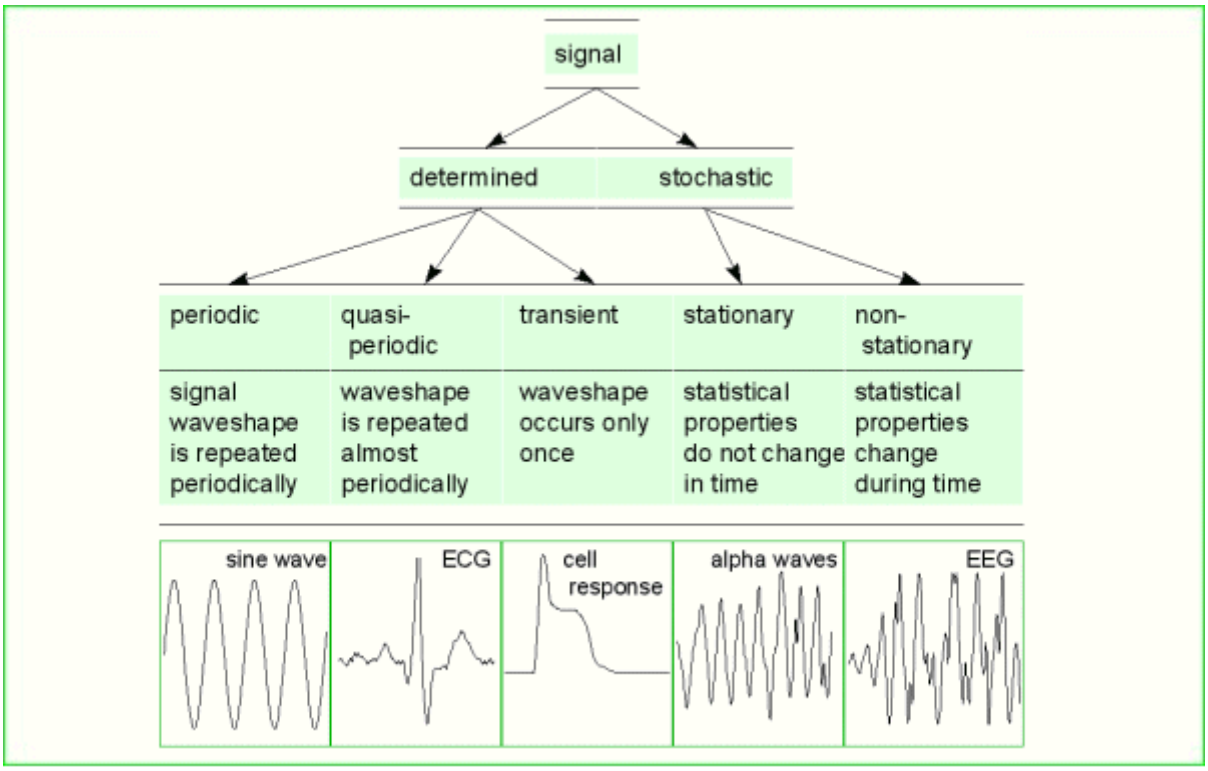


Figure 2: Signal wave shapes

2.1 Acquisition of Bio-signals

Real-time acquisition of data directly from the source by direct electrical connections to instruments avoids the need for people to measure, encode, and enter the data manually. Sensors attached to a patient convert biological signals, like blood pressure, pulse rate, mechanical movement, and electrical activity, e.g., of heart, muscle and brain, into electrical signals, which are transmitted to the computer. The signals are sampled periodically and are converted to digital representation for storage and processing. Automated data-acquisition and signal-processing techniques are particularly important in patient monitoring settings [2].

2.2 Digitization of Bio-signals: Sampling and Quantization

Most naturally occurring signals are analogue signals, i.e., signals that vary continuously. A digital computer stores and processes values in discrete units. Before processing is possible, analogue signals must be converted to discrete units. The conversion process is called analogue-to-digital conversion (ADC). ADC can be thought of as *sampling* and *rounding* - the continuous value is observed (*sampled*) at fixed intervals and rounded (*quantized*) to the nearest discrete unit. Two parameters determine how closely the digital data match the original analogue signal: the precision with which the signal is recorded and the frequency with which the signal is sampled. Precision describes the degree of accuracy of a sample observation of a signal. It is determined by the number of bits (quantisation) used to represent a signal and their correctness; the more bits, the greater the number of levels that can be distinguished. Precision also is limited by the accuracy of the instrument that converts and transmits the signal.

Ranging and calibration of the instruments, either manually or automatically, is necessary for signals to be represented with as much precision as possible. Improper ranging will result in information loss. For example, a change in a signal that varies between 0.1 and 0.2 volts will be undetectable if the instrument has been set to record changes between 0.0 and 1.0, in 0.25-volt steps. The sampling rate (sampling frequency) is the second parameter that affects the correspondence between an analogue signal and its digital representation. A sampling rate that is too low relative to the rate at which a signal changes value will produce a poor representation [3]. On the other hand, oversampling increases the expense of processing and storing the data [4].

As a general rule, we need to sample at least twice as frequently as the highest-frequency component needed from a signal. For instance, looking at an ECG, we find that the basic repetition frequency is at most a few per second, but that the QRS complex contains useful frequency components on the order of 150Hz [5]. Thus, the data sampling rate should be at least 300 measurements per second. This rate is called the *Nyqu`ist frequency*.

2.3 Noise

Another aspect of signal quality is the amount of noise in the signal - the component of the acquired data that is not due to the specific phenomenon being measured. A primary source of noise is the electrical or magnetic signals produced by nearby devices and power lines. Moreover, inaccuracies in the sensors, poor contact between sensor and source (patient), and disturbances from signals produced by physiological processes other than the one being studied (e.g., respiration interferes with the recording of ECG) are other common sources of noise.

A characteristic of noise is its relatively *random* pattern in most cases. *Filtering algorithms* can be used to reduce the effect of noise [6]. Repetitive signals, such as an ECG, can be integrated over several cycles, thus reducing the effects of random noise. When the noise pattern differs from the signal pattern, *Fourier analysis* can be used to filter the signal in the frequency domain.

2.4 Precision and Accuracy

Precision refers to the fidelity of the measurement; if the measurement is repeated on the same subject, the same result will be obtained. Accuracy refers to the tendency of measured values to be symmetrically grouped around the variable's true value. Variability of medical data can arise from intra- and inter- instrumental and observer variations (analytical or metrological variability) or intra- and inter- individual variations (biological variability); the total is the combination of these.

2.5 Abstraction and Analysis

Once the data have been acquired and filtered, they typically are processed to reduce their volume and to abstract information for use by interpretation programs. Often the data are analyzed to extract important parameters, or features, of the signal, e.g., the duration or intensity of the ST segment of an ECG. The computer can also analyze and classify the shape of the waveform by comparing the signal to models of known patterns. Further analysis (in connection with a suitable knowledge base) is necessary to determine the meaning or importance of the signals, e.g., to allow automated ECG-based cardiac diagnosis.

3. Application Area

It is a well known fact that a fetal ECG (FECG) signal is obtained from the abdominal ECG (AECG) of a pregnant woman that has the potential of being an effective diagnostic tool for determining the overall condition of the fetus during the delivery, as well as for the detection of pathological phenomena. The fetal contribution to the AECG is minor; therefore, it is not uncommon to record a much corrupt signal from which even the fetal heart rate can hardly be monitored [7]. The detection of the FECG is yet a difficult task even when the maternal component of the signal has been reduced. In order to observe the FECG, some technique should be applied for improving the signal to noise ratio (SNR) and eliminating the maternal contribution to the signal.

Several methods have been proposed for detecting fetal heart rate (FHR) by extracting the FECG signal from AECG signal. Two fundamental methods can be considered: a peak detection method and a transform method [8]. Using the peak detection method, a small segment of the FECG is observed at a time and searched for the fetal R wave. Mainly, the result of the search depends on the algorithm used, and on the local SNR in the above mentioned data segment. Due to the unpredictable nature of the AECG signal, the local SNR value fluctuates about the SNR value of the entire signal and might sometimes be much smaller. Therefore, missing some peaks is a common experience

while applying peak detection methods to noisy FECG signals. On the other hand, using the transform method, a new function of one or more parameters is constructed from the historical signal. Each value of the new function represents a property of the entire signal. Consequently, each value depends not on the local SNR but on the SNR of the entire signal. Therefore, when the FECG is obscured by noise with unwanted signal and the peak detection algorithm fails to detect, a transform method might still detect the FHR.

In recent years, Doppler ultrasound has become a popular technique of monitoring the FHR abdominally, but attempts to produce a portable system have not been successful, because of its sensitivity to movements. The expectant mother needs to be in the recumbent position and limit her physical activity during ultrasound monitoring. In addition, changes in the position or orientation of the transducer with respect to the fetus will also affect the signal, rendering this technique unsuitable for long-term FHR monitoring.

FHR and maternal heart rate (MHR) sample traces recorded by signal processing system are displayed in Figure 3. The measurement of the maternal heart rates was successful in most cases. The performance of the system in determining the FHR depends upon the FECG signal, which is obtained by subtracting the average maternal ECG (MECG) from the AECG signal.

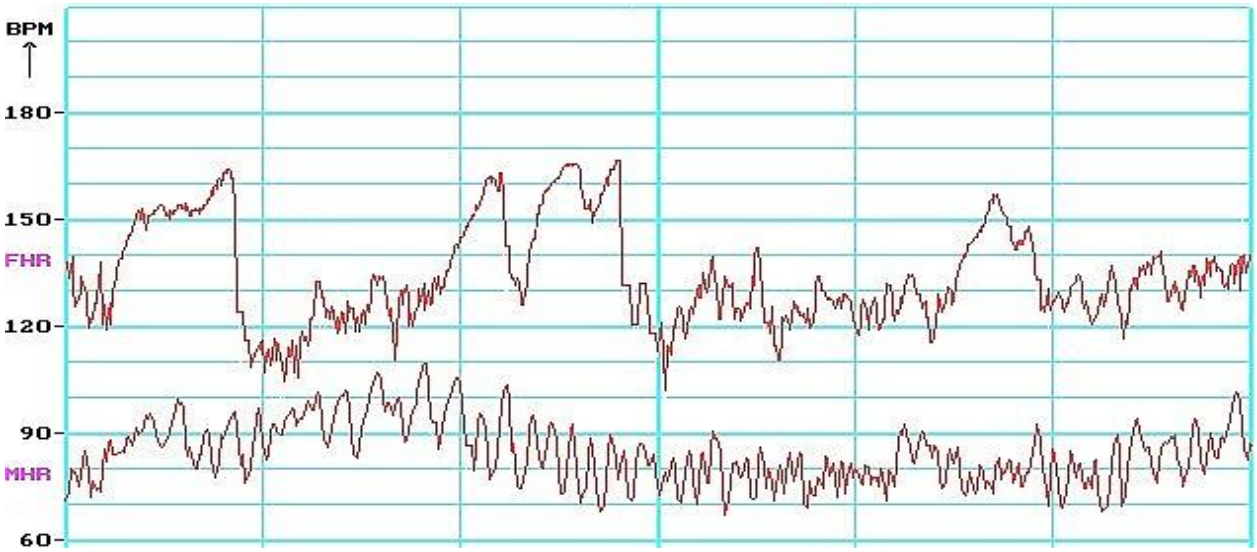
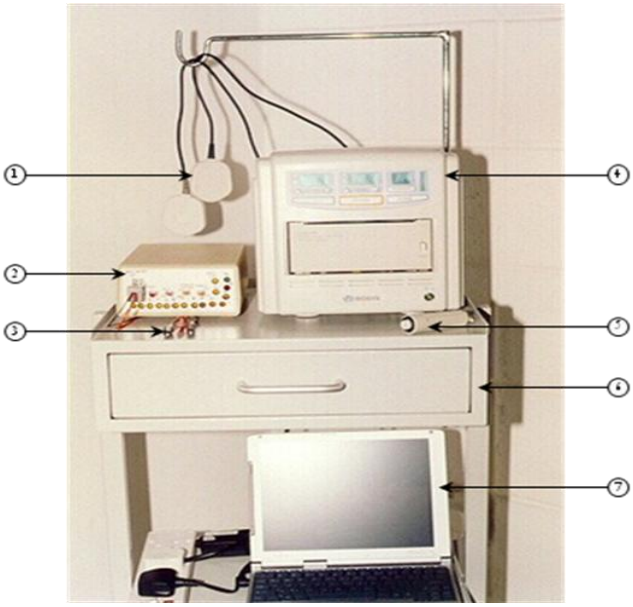


Figure 3: FHR (upper) and MHR (lower) traces using the signal processing system (each vertical division = 90 sec.)

3.1 Comparison with Doppler Ultrasound

In an effort to assess the reliability of the algorithm the detected FHR obtained from the maternal abdominal signal has been compared with the FHR given by a commercial instrument Ultrasound Fetal Monitor IFM-500 (BiOSYS Co., Ltd.). This commercial fetal monitor measures the heart rate by using the Doppler frequency shift between incident and reflected ultrasound waves at 2 MHz. A laptop computer in conjunction with software (ICM-1000 from BiOSYS Co., Ltd) was used for logging the heart rate data from the ultrasound fetal monitor to a PC via a serial RS232 interface. A photograph of the set-up is shown in Figure 4.



(1) Doppler Transducer of IFM-500 Fetal Monitor
(2) Portable Fetal and Maternal Heart Rate Recorder
(3) Electrode Leads of PIC17C44 System
(4) IFM-500 Fetal Monitor
(5) Marker of IFM-500 Fetal Monitor
(6) Trolley
(7) Laptop Computer

Figure 4: Set-up for the algorithm evaluation

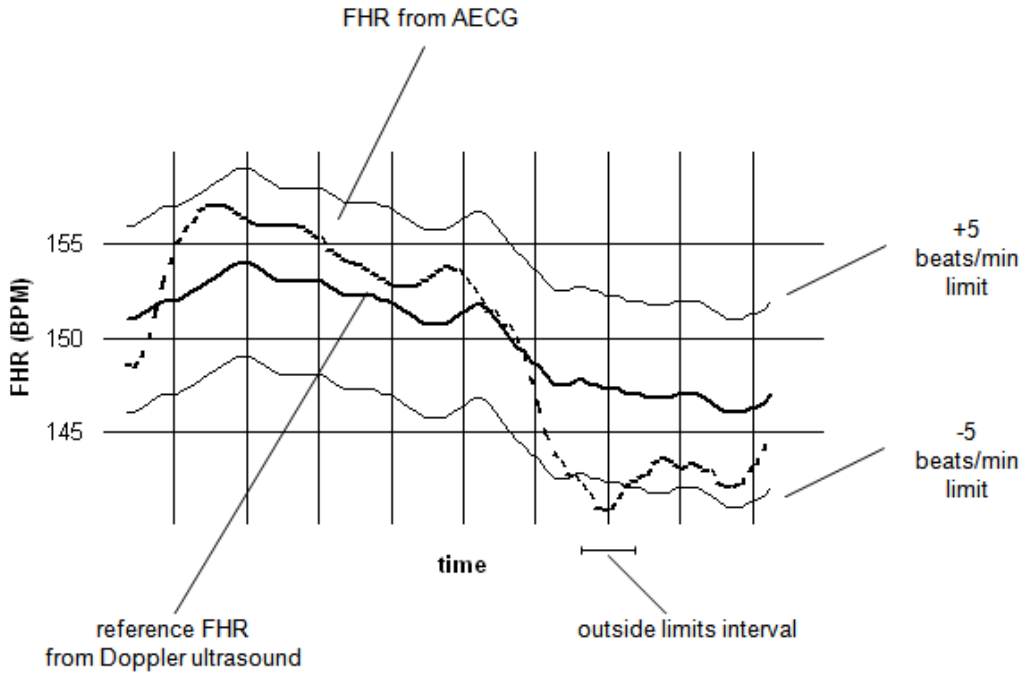


Figure 5: Comparison of FHR from ultrasound (solid line) and that of using signal processing system (dotted line) (each vertical division = 5 sec.)

The FHR curve (using the signal processing system) in Figure 5 remains inside the ±5 beats/min tolerance band on average 85% of the total time. This means that most of the time, the FHR curves obtained from AECG agreed with the ultrasound method.

5. Futures Considerations

The field of biomedical signal processing seems to hold a very promising future. The field is still in its early stages and extensive research is being held in many institutions around the globe. Physiological modelling using deep knowledge on the observed physiological system is required to achieve significant progress in the area of biomedical signal processing. Hence, interdisciplinary work groups are necessary to reach this goal.

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