Chapter 2
An Introduction to ECG Signal Processing and Analysis

Adam Gacek

2.1 Introduction

ECG signals are reflective of electric activities of a heart muscle. They are related to a variety of intertwined and complex chemical, electrical, and mechanical processes present in heart. They convey a great deal to valuable diagnostic information not only describing functioning of heart but also other systems such as circulation or nervous systems.

The ECG signal has been a subject of studies for over 100 years. The first recording of electrical activities of heart was realized in 1887 by an English physiologist August Waller who used surface electrodes placed on a skin and connected to the capillary electrometer. He was the first to call the registered signal electrocardiogram. Nevertheless W. Einthoven is regarded to be the father of electrocardiography who in 1902 recorded the first electrocardiogram with the use of a string galvanometer. In 1906 M. Cremer realized a recording of the first esophageal electrocardiogram with the help of a special esophageal probe (electrode) (Cremer 1906). This type of electrocardiography has been intensively developed in the 1970s of the last century to be used as a technique helpful in the differentiation of atria rhythm irregularity. Cremer recorded also the first fetal electrocardiogram. In 1924 W. Einthoven received the Nobel Prize for the invention of electrocardiography and its development. Since then there has been a substantial research in the area of electrocardiography. Since the 1940s, electrocardiography has become a routine method in heart diagnostics. There has been a significant development of diagnostic techniques based on ECG analysis (say, exercise test EKG, monitoring of patients in intensive care, high resolution electrocardiography, heart rhythm variability HRV, heart mapping).

A. Gacek (✉)
Institute of Medical Technology and Equipment, Zabrze, Poland
e-mail: adamg@itam.zabrze.pl

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ECG signal is one of the best-recognized biomedical signals. Its high diagnostic capabilities have been demonstrated. In the last decades there has been a significant growth of interest in the development of efficient methods of processing and analysis of ECG signals with intent of the formation of useful diagnostic information. Those pursuits have been realized in parallel with information technologies, especially in the realm of digital signal processing realized both in hardware and software.

In virtue of the essence of ECG signals, they often have been a source of imprecise information. In the design of diagnostic systems, it becomes of interest to make them user-friendly. These factors have triggered interest in the exploitation of the technology of Computational Intelligence (CI). In this context, it is worth recalling that the first studies in the area of intelligent systems go back to the use of techniques of Artificial Intelligence (AI) with a wealth of its symbolic processing. The description of ECG signals in terms of sequences of symbols has resulted in techniques of syntactic pattern description and classification. In essence, a continuous ECG signal is represented in the form of sequences of symbols, which are analyzed and classified based on the machinery of formal grammars. We can refer here to syntactic methods used to detect the characteristic waves of ECG signals (Horowitz 1975), detection of arrhythmias (Udupa and Murphy 1980) signal filtering (Papakonstantinou and Gritazali 1981), and ECG signal analysis (Papakonstantinou and Gritazali 1981; Skordolakis 1986; Papakonstantinou et al. 1986; Trahanias and Skordolakis 1990). There are also studies devoted to the analysis and classification of ECG signals by using combinations of syntactic and probabilistic methods.

One of the first approaches, which fully exploits techniques of AI, comes in the form of semantic nets applied to the analysis of ECG signals (Stockman and Kanal 1983). In this method the signal is represented in the form of a OR/AND graph while the classification process is concerned with a graph search. Another important collection of techniques stems from the concept of rule-based systems where an ECG signal is described in the form of “if-ten” rules (Kundu et al. 1993). The reasoning mechanism relies on the use of the so-called modus ponens. The reliance on this concept, though, requires that a knowledge base is complete meaning that for any signal there is a set of rules to be used in the inference process. The reduction of the size of the rule base along with an enhancement of reasoning processes realized in presence of uncertainty becomes possible when invoking a so-called *generalized* modus ponens (Kundu et al. 1998). For the detailed discussion the reader may refer to (Kundu et al. 2000); one of the conclusions coming from this study and the references reported therein is that the AI methods are more often used to ECG signal interpretation and quite seldom are involved in the description of the features of the signal used in its description.

Considering a certain historical framework, it is worth noting that the technology of neural networks being an integral component of Computational Intelligence has been applied to ECG signal analysis and classification. One of the first applications of neurocomputing was in ECG signal compression applied to signals collected in

Holter ECG systems (Iwata et al. 1990) and in the detection of QRS complexes (Xue et al. 1992; Xue and Reddy 1997). In the second half of the 1990s, we have witnessed a rapidly growing number of applications of neural networks to ECG signal analysis and classification. With this regard, it is worth recalling other applications such a detection of ventricular late potentials VLPs (Xue and Reddy 1997) and ECG signal analysis (Silipo and Marchesi 1998; Barro et al. 1998). For instance, radial basis function (RBF) neural networks were used in ECG signal classification (Silipo et al. 1999). Neural networks were used to arrhythmia analysis (Wang et al. 2001), determination of P waves (Botter et al. 2001), and classification of heart evolution with the use of second order cumulants (Osowski and Linh 2001). The concept of neural networks in the form of a collection of subnetworks (experts) was presented in (Hu et al. 1997). Neural networks in conjunction with the methods of frequency-temporal signal analysis were used to detect ventricular late potentials (VLPs) (Wu et al. 2001) and classification of heart evolution in an on-line mode in which case neural networks were used in conjunction with Hermite functions (Linh et al. 2003).

In the literature, we can also note a stream of studies exploiting the technology of fuzzy systems (Czogała and Łęski 2000b). For instance, fuzzy systems were used in the analysis of ECG and EEG signals in (Moon et al. 2002). Fuzzy rule-based systems were used in the detection of arrhythmias (Chowdhury and Ludeman 1994) as well as a construction of ECG signals (Wang et al. 1991). Some other applications of fuzzy sets to ECG signal analysis include a detection and classification of QRS segments (Czogała and Łęski 1998, 2000a). In this case a fuzzy signal is formed through a transformation of the numeric (standard) ECG signal into a series of membership functions. In (Łęski and Henzel 1999a, b) a fuzzy signal was used to feature extraction. In (Pedrycz and Gacek 2001a) presented was a concept of fuzzy automata (Moore and Mealy) applied to ECG signal classification. An interesting development was reported in (Pedrycz et al. 2000; Pedrycz and Gacek 2001b) where shadowed sets were used to signal granulation (quantization). Examples of information granulation to ECG signal modeling and classification were presented in (Pedrycz and Gacek 2002; Gacek and Pedrycz 2005, 2006; Bortolan and Pedrycz 2002a, b). More recently, ideas of information granulation were used to ECG signal compression and classification. With this regard used were ideas of data clustering (Gacek and Jeżewski 2003a, b) and Genetic Algorithms (GAs) (Gacek and Pedrycz 2003).

This brief analysis points at a growing role and interest of CI to ECG signal analysis, processing, and classification. It has to be noted though that the CI methods are still in the research phase and only a few medical devices commercially available use some components of CI. The limitations come from the fact that these methods quite commonly come with a considerable computing overhead, which requires the use of hardware system resources. Over time this limitation becomes less essential given the progress of information technologies. It supports a conclusion that the technology of CI will become more readily available and implemented in ECG systems including those operating in the on-line mode.

ECG signal processing and analysis comprises a sequence of steps among which the most essential include

- Amplification of signal and its A/C conversion
- Noise elimination
- Feature selection

The quality and effectiveness of the methods used at these steps imply the quality of the overall process of classification and interpretation of ECG signals. Both signal amplification and A/C conversion are realized in hardware while all filtering and noise elimination are realized through the use of advanced technologies of information processing; here we witness a growing role being played by Computational Intelligence.

2.2 A Nature of ECG Signals

ECG signals are reflective of an electric activity of heart. The ECG signal is some kind of an electric provocation spread in the heart muscle cells. Under the influence of this provocation, the heart muscle cells shrink, which as a result, causes a mechanical effect in the form of cyclic shrinking of heart atria and ventricles. As an effect of heart muscle shrinking, the blood circulates in the human organs. The propagation electric provocation in the heart muscle forms a depolarization wave of the bioelectric potentials of the neighboring heart cells. The propagation of the depolarization wave, see Fig. 2.1, is caused due to a quick movement of positive ions of sodium (Na+). After moving of the depolarization wave, the heart muscle cells return to their rest state recovering before starting resting negative potential. This state is called a repolarization phase. The depolarization and

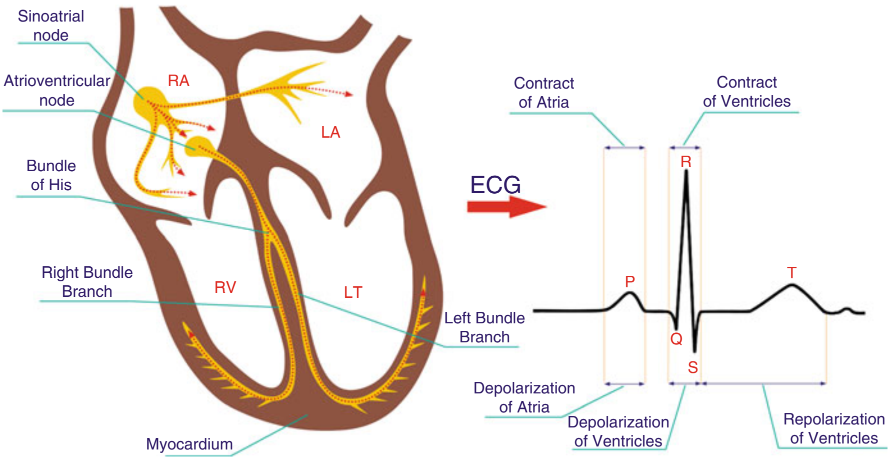

Fig. 2.1 Propagation of the depolarization wave in the heart muscle

repolarization phenomena of the heart muscle cells are caused by the movement of ions. This is the essence of the heart electric activity. Movement of ions in the heart muscle cells is the electric current, which generates the electromagnetic field around the heart. There is possibility to measure the electric potential at each point of the electromagnetic field.

The potential difference recorded at the two points of the electromagnetic field reflects the ECG signal. The shape of the ECG signal and a cyclic repetition of its characteristic parts including P-QRS-T complex, constitute essential information about operation of the electrical conduction system of the heart. By analyzing the ECG signals recorded simultaneously at different points of the human body, we can obtain essential diagnostic information related to heart functioning. It is concerned not only with the electrophysiological parameters of the heart, but it is also connected with its anatomical and mechanical properties. In essence, the ECG signal is an electric signal generated directly by the heart muscle cells. The information included in the ECG signal is directly related to the source of the signal, that is, the heart itself. As opposed to other biomedical signals, ECG signals are received directly at the recording points as electrical signal. Recorded ECG signals do not require conversion. ECG signals are recorded as a difference of electric potentials at the two points inside of the heart, on its surface or on a surface of the human body. The potential difference corresponds to the voltage recorded between two points where the measurements were taken. This voltage is the amplitude of the ECG signal recorded in the two-pole (two electrode) system. Such a two-electrode system applied to the recording of the ECG signal is referred to as an ECG lead. In this two-pole ECG recording system, one electrode is an active measurement electrode while the second electrode is the reference one. The changes during time, of voltage variation between the ECG recording electrodes, depict a course of ECG signal during time. The ECG signal recorded on paper or electronic data carrier is called an electrocardiogram.

2.3 The Main Properties of ECG Signals

ECG signals are one of the best-known biomedical signals. Given their nature, they, bring forward a number of challenges during their registration, processing, and analysis. Characteristic properties of biomedical signals include their nonstationarity, noise susceptibility, and variability among individuals. ECG signals exhibit all these properties. In particular, a highly undesirable aspect of these signals is their high susceptibility to various types of noise. The registered ECG signals are always affected by noise. The main sources of noise include:

Changes of the body-electrode impedance resulting from physic-chemical processes present in this region as well as the movement of the patient. These phenomena cause a so-called effect of a baseline wandering. These distortions are slow-varying distortions (Wiese et al. 2005; Pawar et al. 2007b).

Changes of a mutual position of heart and the electrodes caused by respiratory movements of a patient. This results in some slow-changing disturbances.

Contraction of skeletal muscles caused by the movement of the patient or inappropriate temperature of the environment. This causes so-called muscle disturbances. They are very difficult to deal with because of the broad spectrum of frequency of these disturbances, whose frequency overlaps with the frequency of the ECG signal itself (Fernandez-Chimeno et al. 2006).

Interference of electromagnetic nature (Bruce 2000). These disturbances are referred to as power interferences.

Interferences caused by high power devices such as e.g., diathermy. These disturbances are of impulse nature (Santopietro 1977; Fernandez-Chimeno et al. 2006).

By taking into consideration all causes of disturbances affecting ECG signals, their list includes the following categories:

Low frequency (slow-changing) interferences
Muscle interferences
Power-induced electromagnetic interferences
Electromagnetic interferences of impulse character

As already noted, the most difficult to deal with are interferences of low frequency and those of muscle origin. They are difficult to filter without affecting important diagnostic information contained in the original ECG signal. Depending upon the nature of the ECG test, the signals could be affected to some extent, which also depends on the location of the points of registration of the ECG signals. The ECG signals registered from various points could have a very much diversified amplitude and quite often exhibit a very low signal-to-noise ratio (SNR). Typically, the amplitudes of ECG signals collected on the body surface have amplitude of several mV. Higher signal amplitudes are those coming from heart ventricles. Whereas ECG fetal signals exhibit amplitudes in the range of μV. Similar amplitudes of ECG signals are encountered when dealing with an analysis of heart micropotentials. In these two cases we encounter a highly undesirable SNR, which could be as bad as $-20\,\mathrm{dB}$ (Jesus and Rix 1986). For some segments of the ECG signal, this detrimental SNR values are quite natural. We observe this situation in the initial region of the P, Q, and T waves when detecting delayed potentials of the ECG signal. In case of non-standard rest ECG test, such as an analysis of heart micropotentials (Ahmed and Milne 1975; Berbari et al. 2005) the amplitudes of the registered signals are in the range of μV. In spite of the fact that the patient is not moving, the muscle noise as well as noise of electronic interface itself give rise to disturbances whose amplitudes exceed many times the amplitude of the useful signal. The fetal ECG signals, registered on mother abdomen surface, have particularly unfavorable values of SNR. It is caused by the effect that the ECG signal is the joint signal coming from the mother and the fetus. In this case, the signal coming from the mother treated as a noise has amplitude in the range of mV while the fetal signal has amplitude of μV so that the useful signal is affected by noise whose amplitude is 1,000 times higher than the original source of diagnostic information. For instance, if we consider that the micropotentials have amplitude of $5\,\mu\mathrm{V}$ and visually the signal in the rest state is regarded to be noise-free when the amplitude of disturbances is no larger than $50\,\mu\mathrm{V}$, then the amplitude of disturbances is ten times higher than the useful signal. We are faced with similar problems when dealing with some specialized testing such as those involving analysis of high frequency electrocardiograms (Maniewski 2000; Mroczka et al. 2000; Narayanaswamy 2002), where in order to detect ischemic heart disease (IHD), the signals in the range of 80–150 Hz are analyzed. In this case the recorded signal is of the amplitude of a few μV. Important features of ECG concern their variability across individuals (patients) and across time. This means that the shape of the signal as well as its repeatability to the characteristic regions change over time and are dependent on each individual. If we consider a shape of the ECG signal present in a certain lead within the population of healthy individuals, there will be differences among these signals. A similar situation will be encountered in case of patients with some heart problems. This implies that in the analysis of ECG signals we cannot rely on some templates – prototypes as such do not exist. The limitation associated with this is quite substantial, as we cannot consider typical methods of signal processing and classification where we often rely on the use of such templates. For instance, in exercise tests we realize muscle noise suppression via averaging parts of the ECG signals including QRS complexes. From the averaging process we have to exclude those complexes that are of a different shape than the one which has been acknowledged to be dominant for a given patient. The algorithm has to exhibit some abilities of unsupervised learning given the fact that such a dominant shape cannot be determined in advance.

The ECG signal is reflective of interrelated processes of chemical, electrical, and mechanical nature that are present in the heart. They depend upon the features specific to a given individual, say a form of ventricles as well as the properties of the electrical conduction system of the heart (ECSH).

The mathematical description of these phenomena is still incomplete. In spite of this, cardiologists are considering the shape of the ECG signal and its key features, and are capable to assess the functioning of the heart and detect changes occurring in the heart muscle. The assessment is realized in a heuristic manner based on the existing knowledge and acquired experience.

For the purposes of ECG diagnostics defined was a typical ECG signal (viewed as normal) that reflects the electrical activity of the heart muscle place during a single heart evolution. As shown in Fig. 2.2, defined are some characteristic segments, points, and parameters used to capture the essence of the signal.

In medical diagnostics, the relationships between the shape and parameters of the signal and the functioning of the heart are often expressed in terms of linguistic statements resulting in some logic expressions. For instance, we have the terms such as “extended R wave,” “shortened QT interval,” “unclear Q wave,” elevated ST segment,” “low T wave,” etc. In all these examples we encounter some linguistic terms (which can be formalized in the language of fuzzy sets). In books about cardiological diagnostics we usually do not encounter detailed numeric relationships or formulas but instead rather verbal descriptions characterizing the relationships between the signals and functioning of the heart.

The expert cardiologist forms his/her own model of the process, which is described in a linguistic fashion. It is noted that the model is formed on a basis of acquired knowledge and experience.

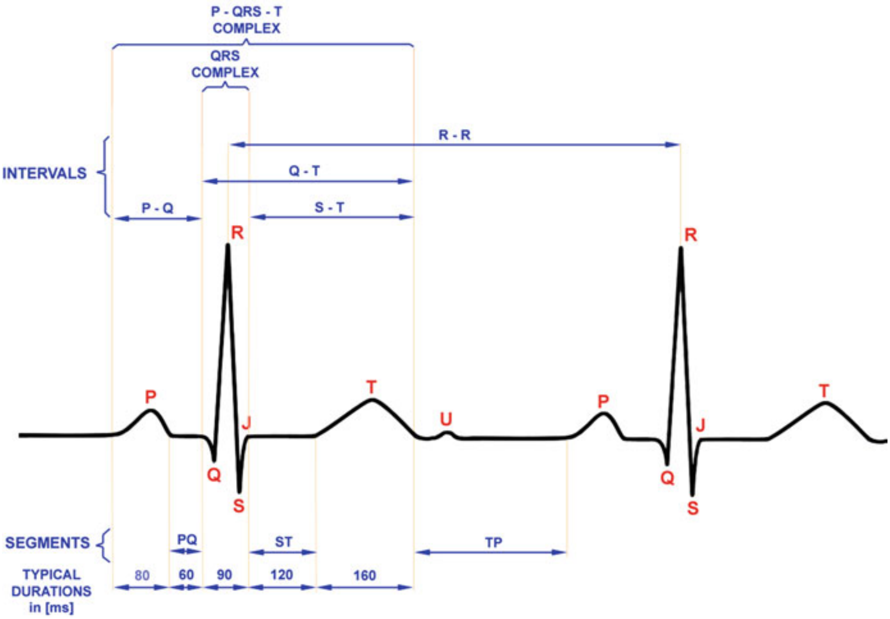

Fig. 2.2 Typical shape of ECG signal and its essential waves and characteristic points

2.4 Processing and Analysis of ECG Signals

As noted, ECG signals form a source of important diagnostic information in cardiology. In order to take advantage of it, the signals have to be properly registered and processed in such a way that we can proceed with their effective analysis and interpretation (Sornmo and Laguna 2005; Acharya et al. 2007). ECG signals are quasi-periodic of relatively low amplitude of several mV. They are often affected by noise. The registration of the signal requires their amplification and further processing in order to suppress noise to highest extent. Further ECG signal analysis is realized based on these recordings for which the noise has been suppressed. The first step of the overall processing is an analog-to-digital (A/D) conversion. In the sequel the digital ECG signal is filtered to eliminate noise and further processed to enhance effectiveness of methods of feature selection, classification, and interpretation applied to the signal. Information granulation has been regarded as one of the interesting and promising alternatives with this regard; in essence the methods arising there could be sought as a certain way of realization of data compression.

An overall process of ECG signal processing and analysis comprises the following phases, refer to Fig. 2.3

Signal amplification
A/C conversion

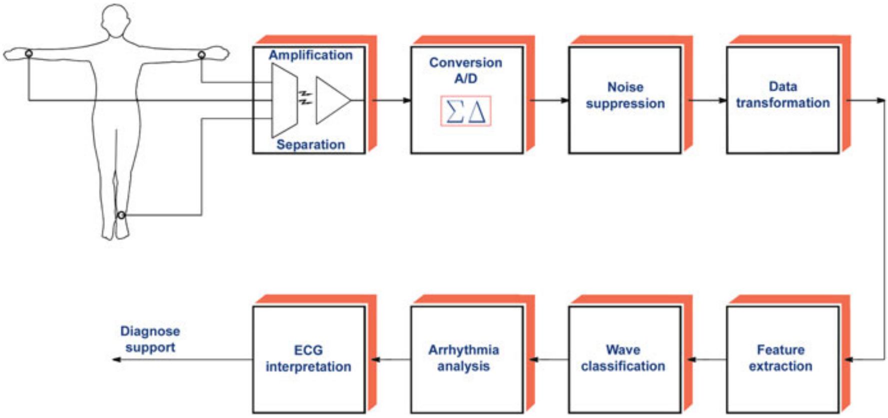

Fig. 2.3 Main phases of ECG signal processing and analysis

Noise suppression (reduction)
Data compression
Feature selection
Signal classification
Interpretation

2.4.1 Amplification of ECG Signals

Depending upon the needs, ECG signals can be registered from various parts of the body. Most commonly, the registration is realized from the skin of chest and limbs. For the needs of electrophysiological diagnostics, the signals are registered directly from the inside of atria and heart ventricles or from esophagus. Depending on the registration area, the amplitude of the signal is in the range of several μV to mV. The first step of signal processing is concerned with signal amplification under conditions of galvanic separation implied by safety requirements. In modern electrocardiographic systems, one uses signal amplifiers with galvanic separation, see (von Maltzahn and Nagel 2006). In these systems, the signal is amplified several times, typically 3–10 times. In particular applications, the ECG signal can be significantly amplified up to few hundred times. The amplifiers offer galvanic separation up to 5 kV.

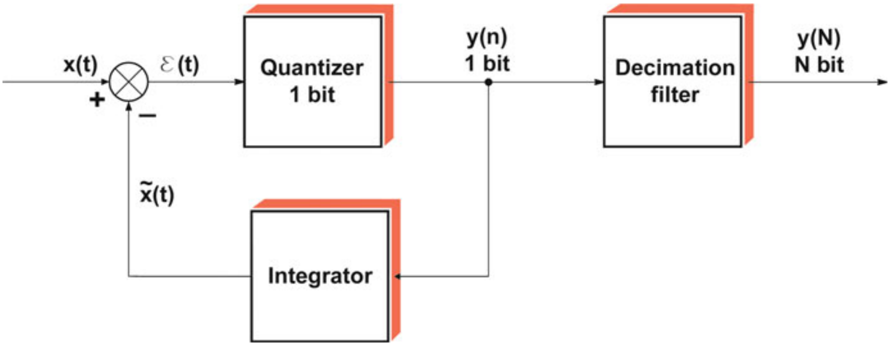

Fig. 2.4 A schematic view of the simplified 1 bit ΣΔ A/D converter

2.4.2 A/C Conversion

Once amplified, the signals are converted into its digital form. For this purpose commonly used are A/C converters of sigma-delta (ΣΔ) type of high resolution (22 bits) and a low-noise level (Stranneby 2001). These converters operate in the oversampling mode that is with the sampling frequency that significantly exceeds the one resulting from the Shannon-Nyquist sampling theorem.

Figure 2.4 illustrates a simplified scheme of a 1-bit ΣΔ A/D converter.

As shown there, the converter consists of a ΣΔ modulator combined with a decimation filter The essence of these converters comprises a rough approximation of the input signal $x(t)$, denoted here by $x^{\sim}(t)$, computation of the approximation error and its quantization. In the sequel this quantized error becomes integrated providing a new value of the approximation of the original signal.

A digital decimation filter present at the output of the A/C converter realizes three functions. It reduces a sampling frequency, increases the length of word from one to M bits, and reduces noise generated by the 1 bit ΣΔ modulator. The sampling frequency of ECG signals when the ΣΔ converters are being used is in the range of 4,000 Hz.

2.4.3 Noise Suppression

As noted earlier, ECG signals are always affected by noise. Among different types of noise, low frequency and muscle noises are the most difficult to handle.

Fig. 2.5 Low frequency noise present in ECG signal

2.4.3.1 Low Frequency Noise

This noise is a result of changes of impedance between the electrode and a body of the patient. The impedance changes as a result of changes of distances between the source of signal (heart) and the electrode caused by the movement of the patient including breathing and changes of contact between the body and the electrode, which to a significant extent is caused by the movement of the body of the patient, Fig. 2.5.

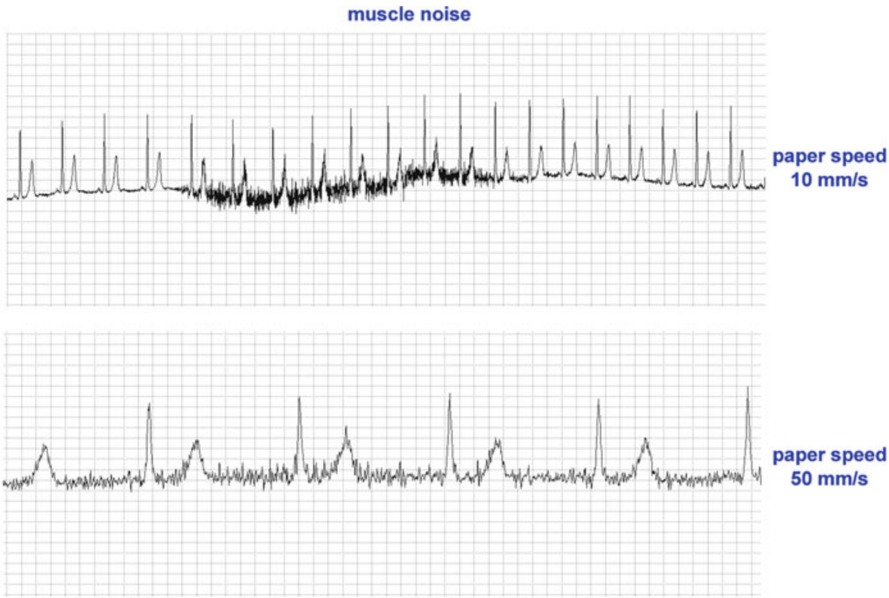

Fig. 2.6 Example of muscle noise of ECG signals

The low frequency noise is located in the frequency below 1 Hz. However, in some types of examinations, say exercise examination of ECG (Santopietro 1977; Su et al. 2007; Bailon et al. 2006), this range of frequencies is far higher and can reach the frequency of several Hz. In exercise test of ECG, the amplitude of low frequency noise becomes higher which calls for the use of more effective means of noise suppression. A similar situation appears in systems of long-term registration and monitoring of ECG signals (Holter systems).

2.4.3.2 Muscle Noise

The noise of this nature is caused by the contraction of skeletal muscles, which appear because of the movement of the patient (related with the movement or inappropriate ambient temperature in which the ECG examination is being carried out).

Muscle signals, Fig. 2.6, are always associated with ECG signals. The highest level of noise is present in stress tests. In these conditions, the noise is caused by intensive muscle contractions during running on a treadmill or the load of the patient caused by cycloergometer.

The movement of the patient is present during a long-term recording of ECG signals under normal conditions (which is present in Holter testing). In this case, the level of muscle noise depends quite significantly on a level of activity (movement) of the patient, which could vary within the testing.

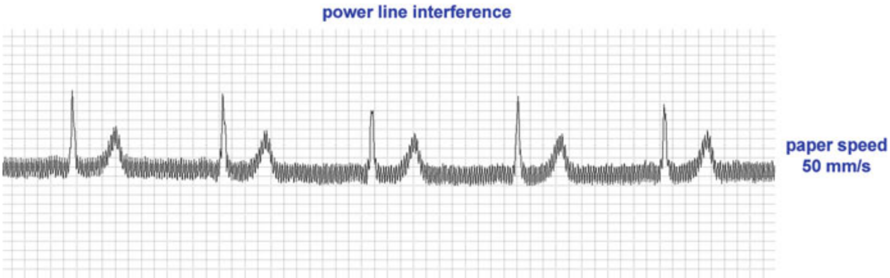

Fig. 2.7 Power line interference in ECG signal

Muscle noise becomes present in rest tests caused by involuntary contractions of skeletal muscle resulting from the ambient temperature, which could be too low or too high. This phenomenon is particularly undesirable in case of registering microvolt heart potentials, that is micropotentials recorded on the surface of the body, in the esophagus or in the heart ventricles. The main problem arises here because of the overlap of the spectrum of the signal and noise to a significant extent. The spectrum of the signal forms a range of 0.005–150 Hz whereas the noise spectrum covers the range of frequencies from 20 to 80 Hz. The attempts to filter muscle noise lead to significant distortions of the ECG signal. With the increase of the effectiveness of the muscle noise, the resulting distortions of the signal may result in incorrect classification results produced by medical doctors as well as computerized systems.

2.4.3.3 Electromagnetic Noise

The noise of this type becomes present as a result of influence of the electromagnetic field generated by power supplied to the measurement system (Fig. 2.7) or generated by other medical devices (Bruce 2000; Lin and Hu 2008).

The frequency spectrum of the power line interferences is relatively narrow and centered around the frequency of AC power supply. This noise is relatively easy to filter. For this purpose the band prohibitive filters are used with narrow frequency characteristics; the filters could be analog but most predominantly digital. An efficient way to suppress power noise is to construct registration devices in such a way so that proper shielding and noise elimination is provided.

Electromagnetic noise is also relatively easy to eliminate through band prohibitive filtering. The spectrum of this noise overlaps to a limited extent of the ECG frequencies, meaning that the required methods of noise filtering do not distort the original signal.

Among the electromagnetic noise we can distinguish noise caused by the power supplies where the amplitude of voltage and current changes with frequency of 50 or 60 Hz. In this case, we are talking about typical power supply type of noise.

The power supply could be a source of sporadic impulse-like noise. It is often caused by turning on high-power devices such as diathermy equipment, Roentgen machines, and tomography devices.

2.4.4 Data Transformation

Another important phase of the overall processing of ECG signals concerns a transformation of data (samples of signals) to some other format in order to enhance effectiveness of processing and further interpretation. In general, we can say that the transformation forms a sort of compression process. On the one hand, we reduce an amount of information to be processed and analyzed. On the other, we extract a limited number of features, which exhibit high discriminatory properties (which is of relevance in case of signal classification).

As a result of the signal transformation, the original signal can be represented in a digital format or as a series of linguistic information granules described in terms of some parameters or described in a linguistic fashion. The transformation viewed in this way is applied to on-line ECG systems, say telemedicine systems, systems for exercise test of ECG, or Holter systems.

The development of ideas and algorithms supporting the transformation of ECG signals started in the 1960s of the past century. In this period, a transformation method called AZTEC was quite popular. Following some rules, the method is aimed at the approximation of the ECG signal by a series of linear segments that are either horizontal or elevated. Since then we witness a rapid development of other methods including orthogonal transformation (Ahmed and Milne 1975), entropy coding (Ruttimann and Pibperger 1979), long-term prediction (Nave and Cohen 1993), wavelet transformations (Hilton 1997; Tai et al. 2005), SVD analysis (Kanjilal et al. 1997; Wei et al. 2001), and information granulation (Gacek and Pedrycz 2006).

2.4.5 A Detection of P-QRS-T Complex – A Region of Interest

A characteristic feature of ECG signal comes with a cyclic occurrence of its components consisting of the P-QRS-T complex. The ECG signal in this region is reflective of performance of the conduction system of the heart that pertains to a single heart evolution involving contraction of atria and ventricles. This part of the ECG signal forms a region of interest (ROI) as it contains the most essential diagnostic information. During ECG signal processing and analysis, an important task is to detect each section containing the P-QRS-T complex, refer to Fig. 2.2, and a determination ofso-called fiducial points (Sayadi and Shamsollahi 2008). These points determine the beginning and the end of location of P and T, Q, R, S, I and a location of the center of the ST interval. The most essential is the determination of the R point.

A detection of the part of the signal containing the O-QRS-T complex is realized through a detection of the most characteristic basis point of the region called FR (referred to as a centering point) that corresponds to the location of the R point in time. The time intervals between successive R points are used to determine a frequency of heart activity being one of the diagnostic indicators used in cardiology. The overall P-QRS-T complex is taken as the part of the ECG signal present in some time interval that is formed by taking $\mathrm{n_b}$ samples and $\mathrm{n_f}$ samples of the signal located before and after the location of the R point. The analysis of ECG signal in the temporal window (ROI) deals with the determination of the remaining basis points of the P-QRS-T complex.

The simplest methods of detection of the R point involve finding a sample of the signal of the highest amplitude at the point where the first derivative crosses zero or the signal exceeds a certain predetermined threshold level. Such methods, although computationally simple, are based on a single sample of the signal, which makes the method sensitive to noise. Given this, these methods are used only when dealing with noise-free signals such as those coming from rest of the examinations. Some other simple methods based on the use of three points are known as a double-level method (Rompelman et al. 1986). In this method, the centering point of $x(t)$ in the region of interest is computed as an average of two time moments t_1 and t_2 that correspond to the crossing points of the rising and falling slope of the signal determined for some level L (Rompelman et al. 1986) We obtain

$$FP = \frac{t_1 + t_2}{2},$$

where $x(t_1) = x(t_2) = L$ while the predetermined threshold level is described in the form

$$L = a \cdot \max |x(t)|.$$

Typically, the value of a is set to 0.6 (Jane et al. 1991). As presented above, the method is aimed at processing continuous signals. The discrete time version of the signal is formed by looking at the samples for which the difference between their amplitudes and the threshold L attains a minimal value. The double-level method determines the basis points FR with accuracy that is higher than the one arising from the sampling period of the signal. However, as the method is simple and lacks robustness, the result is rounded off to the closest sample.

In the literature, we encounter a number of important methods, which were proposed to detect basis points of the ECG signal, especially those present in the QRS complex. Among others, we encounter wavelet analysis (Kadambe et al. 1999; Li and Zheng 1995) and banks of filters (Afonso et al. 1999). One can also point at the methods based on slope analysis (Ahmed and Milne 1975) or the derivative analysis (Haque et al. 2002).

By a thorough analysis of the methods of the determination of the basis points, we note that there is a tendency of moving from simple methods, in which the determination of the FR point uses one or several samples of the signal to the algorithms that are more complex and where the determination of the FR point relies on the entire collection of the samples of the signal. This tendency is motivated by intent of constructing methods that are more robust to noise. Obviously, this comes with a higher computing overhead associated with the determination of the basis points. In some sense it relates with the increasing computing capabilities available today. On the other hand, we can envision that too high computing overhead might become an obstacle of using some methods. For instance, in the Holter system, when we decide to proceed with some initial preprocessing during signal acquisition in a portable registration device, the simple methods are only applicable (say, the double point method). On the other hand, if we realize the entire ECG signal analysis on a stationary Holter analyzer, we can considering using more complex methods of the determination of the centering points. Evidently, it leads to a longer analysis time or necessitates the use of computers of higher processing power.

2.4.6 Feature Extraction

The successive step of ECG signal analysis is a formation of a feature space that is a collection of descriptors that fully capture the essence of the signal. More precisely, we are interested in the features that exhibit high discriminatory power, which is of importance to any classification of ECG signals and their interpretation. Those features are mostly present in a time domain; however they could be defined in the frequency domain. It is also possible to extract features of a different nature, which relate with some unconventional features such as those exploiting methods of data approximation, data segmentation, and information granulation.

Of paramount importance are the features exhibiting some diagnostic properties. As examples, we can recall here, see Fig. 2.2,

Time intervals between consecutive R points
Distance PQ, PR, QT
Amplitudes of P, Q, R, S, T
Duration of P, R, and T waves
A location of the center of the ST interval
A slope of the ST interval.

These features, being so-called primitive features are determined directly from the ECG signal.

For diagnostic purposes extracted are also some other features, called derivative features which are constructed based on the primitive ones. For instance, we can recall here

Shift of the QRS complex versus baseline – known as offset
Areas of waves of P, R, and T
Position of the heart axis

Corrected distance Qt denoted also as Qt_c, which is determined following the Bazett equation

$$Qt_c = \frac{QT}{\sqrt{RR}}$$

where RR stands for a distance between successive R waves.

A ratio of successive intervals RR_i described as $\partial_R = \frac{RR_i}{RR_{i+1}}$.

The features of the ECG signal constructed on a basis of a shape of the signal, segments of the signal that repeat in a cyclic fashion that cover a single heart evolution, namely a P-QRS-T complex. Once classified, these complexes along with other parameters of the ECG signal form a basis for further analysis and interpretation.

2.4.7 Classification of ECG Signals

The classification of ECG signals boils down to the discrimination of P-QRS-T complexes as belonging to one of the existing classes (de Chazal et al. 2004; Evans et al. 1994; Hu et al. 1997; Osowski and Linh 2001; de Chazal and Reilly 2006). The discrimination is mostly based on an analysis of the shape of the QRS complex itself. At the same time considered is also a location of the waves P and T relative to the QRS complex and a location of the successive QRS complexes. In classification, the following features come with significant discriminatory properties.

Shape of the QRS complex expressed in terms of its width, shape, and a slope of the R wave

Lengths of intervals within the P-QRS-T complex

Length of the RR interval

At this level, we distinguish between the following main classes of P-QRS-T complexes

- Ventricular complexes VC,
- Supraventricular complexes SVC,
- Premature ventricular complexes PVC,
- Premature supraventricular complexes PSVC,
- Myocardial infarct complexes MIC, wide QRS complexes with the elevation of the ST segment, and upside down T wave,
- WPW complexes, characteristic of Wolf Parkinson White syndrome – wide QRS complex with the characteristic deviation from the increasing slope – so-called delta wave.

The P-QRS-T identified in the classification of ECG signals form a basis for analysis of the heart rhythm disturbances, which is the next phase of ECG signal processing.

2.4.8 An Analysis of Rhythm Disturbances

The objective of the ECG testing is an identification of heart dysfunctions and an identification of their causes. The essence of these testing relies on the assessment of the functioning of the heart. During such testing carried out is an analysis of the changes of some essential cardiac parameters of diagnostic nature. The most generic is the analysis of the heart rhythm disturbances. The rhythm disturbances are associated with abnormalities of action of the stimuli generation system of the heart or with abnormal conduction of these stimuli. In the first case, there are the heart rhythm disturbances, and in the second one we are concerned with the heart conduction disturbances. (Dubin 2000; Hampton 2003).

These abnormalities can be classified as follows:

- Irregular rhythms,
- Substitute rhythms,
- Premature stimulations,
- Tachyarhytmies.

These deviations in the conductance of electrical impulses in the heart muscle manifest in so-called heart blocks (Hampton 2003) which block conductance of a depolarization wave. These blocks could concern sinus node, atrioventricular, or main branches of the electrical conduction system of the ventricles. Here we distinguish the following main categories of conduction disturbance (Dubin 2000):

- Sinus blocks,
- Atrio blocks,
- His bundle branch blocks,
- Hemiblocks (infarct blocks).

In this analysis, an important role is played by the changes in the Heart Rate Variability (HRV) (Acharya et al. 2007; Almeida et al. 2006). Here one analyzes the changes of the time intervals between successive R waves (RR interval). During normal human activities, the length of distances RR varies. The rhythm frequency and the variability of changes in successive heart evolution to a significant extent is reflective of the influence of the autonomic system on electrical activity of the sinus node. The quantitative assessment of the heart rhythm variability is an indirect indicator of the activity of the autonomic system (T.F. of the ESC/ASPE 1996).

In recent years one can note an increasing interest in the development of methods of analysis of heart rhythm disturbances (Almeida et al. 2006; Mateo and Laguna 2000).

2.4.9 Interpretation of ECG Signals

Interpretation constitutes a final stage of the overall process of signal processing of ECG signals realized in electrocardiographic systems. The objective is to understand the results of the ECG testing and offer an interpretation in order to provide diagnosis and consider further testing. The final interpretation is always realized by the specialist so the computer system provides a decision-support environment. The currently available systems embrace this phase of the overall analysis by focusing on data understanding (Boudreau Conover 2002; Gertsch 2003; Kowalak and Turkington 2007; Lippincott Williams & Wilkins 2005), quite often exploiting the technology of Computational Intelligence. In this phase of interpretation (Alesanco and García 2008; Skillmasters 2006; Lippincott Williams & Wilkins 2005) not only the results of ECG tests are considered but they are augmented by results of other tests as well as personal data of the patient.

Processing of ECG data associated with the interpretation process is often realized in the setting of expert systems. In this case, formulated is a certain diagnostic hypothesis concerning a heart status. This hypothesis must be verified by a cardiologist. In spite of this, to a significant extent the automatic interpretation of ECG signals can support medical diagnosis. The level of the improvement associated with this depends upon the effectiveness of the processing methods applied to ECG signals.

2.5 Categories of ECG Tests

ECG tests are the generic tests used to assess functioning of the heart muscle reflected by the ECG signal measured at different points of the body. Depending on the location area, we distinguish among the main ECG tests:

– Invasive – recording of ECG inside or on heart surface,
– Semi-invasive – recording of ECG in oesophagus,
– Nonivasive – recording of ECG on the body, mainly on the chest.

Likewise, ECG tests can be also classified as routine ones and those of specialized nature. The routine ECG tests could be further classified depending upon a way in which the tests were administered. We have the following categories:

– Rest ECG examination – multi-lead ECG recording in rest state,
– Exercise ECG examination – multi-lead ECG recording in exercise state (patient is loaded by means of cycloergometer or treadmill),
– Holter ECG recording and monitoring – several-lead ECG recording in normal life conditions,
– Spatial ECG recording – vectocardiography – orthogonal-lead ECG recording,
– Mapping of heart – multi-channel ECG recording on the heart muscle or on the Chest.

Similarly, in case of the specialized ECG tests we can offer a classification depending upon a leading electrocardiographic parameter, which is subject to analysis in order to detect some irregularities in heart functioning. In this case we identify the following categories of tests:

- Heart micropotentials analysis – high resolution electrocardiography,
- Sinus rhythm variability analysis – HRV analysis,
- Heart rhythm disturbances analysis – arrhythmia analysis,
- Baroreflex examination –.BRS (Baroreflex Sensitivity),
- Repolarization analysis – analysis of QT segment duration and dispersion,
- Microvolt T wave variability analysis – alternation of T wave (T-wave afternans TWA).

The specialized ECG tests come with their own specificity which means that the diagnostic information is conveyed in quite limited changes of parameters, either specified in time or frequency domain. The detection of changes in these parameters in a noisy ECG signal becomes a difficult task. Practically, its direct identification realized by a cardiologist is impossible; it can be done based on the registered ECG signal.

The required diagnostic information in case of such specialized ECG tests is obtained through running advanced algorithms. In particular, this concerns problems dealing with noise suppression and a precise determination of the basis points.

In what follows, we discuss some specific tests in detail.

2.5.1 Analysis of Heart Micropotentials LVP

This is a high-resolution analysis of ECG signals. This test is aimed at the assessment of potential threat of occurrence of ventricle frequent contraction. In this case, of particular interest are late heart potentials LVP (Narayanaswamy 2002). By LVP one means irregular (up to 25 mV) meshed waves of the extended QRS complex obtained as a result of averaging hundreds of correlated QRS complexes. These complexes are registered at high sampling frequency (2,000–4,000) Hz and at high amplification (5,000–40,000). The occurrence of late potentials in patients after heart attack forms an independent indicator of a danger of permanent frequent ventricle contraction, which leads to the sudden heart arrest. In this case, an analysis of an average QRS complex can be realized in a time domain (Simpson method), frequency domain (Fourier analysis), or in time–frequency domain (say, through autoregressive time series modeling or through a generalized Wigner transformation).

In the analysis of the late ventricle potentials, the Simpson method is the standard one. It is based on the analysis of a vector S formed on a basis of the three orthogonal leads X, Y, Z.

$$S = \sqrt{X^2 + Y^2 + Z^2}$$

referred to as a filtered QRS complex or a Simpson vector (Simson 1981).

2.5.2 Microvolt Variability of T Wave (T-Wave Alternans TWA)

The analysis of the microvolt variability of the T wave (Monasterio et al. 2009) is a non-invasive diagnostic test done to detect threats of the sudden heart arrest. These tests are realized for patients after heart attack and other serious damages of heart muscle or for which there is a danger of serious disturbances of heart rhythm. The testing of the microvolt variability of the T wave (repolarization variability) is based on the testing of the changes of the vector and amplitude of the T wave present in the ECG signal. The changes alternate and its magnitude is low (expressed in mV). This test is of high resolution and like the analysis of heart microptentials it calls for highly specialized methods of signal analysis.

2.5.3 Analysis of Variability of Sinus Rhythm HRV

This testing is concerned about an analysis of the changes of heart rhythm. This analysis helps us evaluate the quality of the autonomic heart control system. The autonomic nervous system controlling functioning of the heart consists of sympathetic and parasympathetic systems. These two systems work in two opposite directions with regard to the frequency of heart action, controlling it depending upon the existing situation. The heart rhythm is increased when there is an increasing activity of the sympathetic system. When the activity of the parasympathetic system increases, the heart rhythm decreases. In a healthy individual, there exist some fluctuations of the rhythm within the bounds of the adaptation. However under certain stimulus (say, alcohol, nicotine, some medications) and as a consequence of some diseases (for instance, infarct of myocardium, diabetes second type, failure of kidneys), the adjustment of the heart rhythm is made difficult and the variability is significantly reduced (Acharya et al. 2006; Almeida et al. 2004; T.F. of the ESC/ASPE 1996).

The analysis of the variability of heart rhythm reduces to the analysis of changes of the length of RR distances for QRS complexes of sinus origin. An essential component of the analysis is a precise localization of the peaks of the R waves.

The analysis of RR distances (RR periods) is done in a time domain, frequency domain by utilizing methods of time–frequency analysis or other nonlinear methods (Acharya et al. 2006; Sornmo and Laguna 2005; T.F. of the ESC/ASPE 1996).

2.6 Conclusions

ECG signals are electrical signals generated and conducted by cells of the heart muscle. They offer valuable diagnostic information about the functioning of the heart and, indirectly, other organs. The nature and properties of ECG signals have been a subject of intensive study for over 100 years. The ECG signals, even though they are the most recognized biomedical signals, are still a subject of intensive research both in the realm of cardiology as well as biomedical engineering. Cardiologists are interested in the diagnostic properties of ECG signal while at the engineering end the interest lies in the processing and analysis of such signals. As a result, there is an emergence of new medical technology exploiting ECG signals. The specific properties of these signals, as discussed in the chapter, give rise to a number of challenges in the signal acquisition, processing, analysis, which definitely exacerbate a way in which the diagnostic information becomes obtained.

ECG signals are nonstationary, susceptible to noise, and exhibit a high variability. They are a source of imprecise information. All of these imply that the processing and analysis of ECG signals calls for the use of effective methods of signal processing that can function given all the limitations outlined above. In particular, this concerns techniques of noise suppression, efficient signal representation, and feature extraction.

There is no doubt that in this area in the recent years the technology of Computational Intelligence has played a visible role. We can envision that it will be even more instrumental in the future.

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