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Abstract

Short overview about Biological Signal Processing methods and biological system identification approaches. Report contains references to basic related literature

Keywords
Biological, signal processing, biosignal, system identification

1 Introduction

Biological signals (sometimes called biosignals) are in common-sense records of parameters measured on living organisms. We can see them for example on any hospital as ECG, EEG, EMG or in research laboratories. This time series enables us better to understand functionality (or disfunctionality) of observed biological systems. Biological systems can be defined on wide range of living objects (from single living cell to global ecological systems). Similarly as dynamics in physics is in biology developing specific mathematical methodology enabling formal description of biological processes and biological systems identification.

2 Biological signals

2.1 Characteristics

As is biological signal defined as an evolution of measured parameter in time, the measured parameters are values gathered as output from some measuring system, connected to observed organism. The frequency of measurements (sampling frequency) depends on dynamical characteristics of biological systems and on technical possibilities of measuring technology used. This limitation leads from theoretical continual parameter evolution in time to sampled time series. Biosignals can be classified in groups by:

type of observed living organism

- single cell (for example single neurone electrical activity)
- biological preparat (for example neural fibber electrical reactivity)
- living animal (for example temperature)
- human (for example ECG, Blood pressure, EEG)

methods of parameter measurement

- invasive methods (for example electrocorticogram)
- non-invasive methods (for example skin impedance)

type of sampling

- events (for example biochemical measurements, heart beats)
- time series with regular sampling frequency (e.g. A/D sampled ECG)

sampling frequency

- longitudinal data (for example biochemical)
- intraday variability (for example heart beat variability (tachograms))
- seconds time scale (for example ECG, BP, spontal EEG)
- milisec. scale (for example EEG evoked potentials (EP))

experimental conditions type

- spontal activity
- event response activity

However the signal sources and time scale of observed processes are different, there exist from mathematical point of view lot of similarities.

2.2 Typical biological signals

ECG

Electrocardiogram (ECG) is record of heart electrical activity measured on skin. There is about 12 standard electrode positions and 6 standard electrical connections (I II III, aVRLF, V1 V2 V3, V4 V5 V6, X YZ, MULTI).

Measurement method

Changes of electrical potentials (cca 100uV) on skin are amplified and recorded.

Signal characteristics

For ECG is typical heart beat periodicity of signal consisting from specific components (waves). We can recognise P, Q, R, S, T, U waves by defined characteristics. For standard ECG records there are used 12 bit A/D converters using 200 Hz sampling frequency. For recognition of some specific high frequency components are used 500 or 1000 Hz sampling frequencies.

EEG

Electroencephalogram is record of brain electrical activity measured on the scalp. There is defined standard of 21 electrode positions (system 10-20).

Measurement method

Changes of electrical potentials (cca 10uV) on scalp are amplified and recorded.

Signal characteristics

For EEG is typical spontal oscillating characteristic in 4-20Hz frequency range. There are recognised types of signals which can be observed in EEG. This types are defined by typical frequency band: Delta (0.1-4Hz), Theta (4-7Hz) Alpha (7-12Hz) Beta (12-18Hz) waves. For spontal EEG analysis are usually used 12 bit A/D converters and 200 Hz sampling frequency.

EOG

Electrooculogram is record of eye movements.

Measurement method

Eye electrical dipole potecial changes (cca 10uV) on scalp are amplified and recorded.

Signal characteristics

For EOG are typical relatively slow changes of potential related to eye movements.

EMG

Electromyogram is record of muscle fibbers activity measured using electrodes.

Measurement method

Changes of electrical potentials (cca 50uV) are amplified and recorded.

Signal characteristics

For EMG are typical high frequency electrical spikes (10khz). Integrated EMG is closely related to muscle activity.

Blood pressure (BP)

Noninvasively continually measured blood pressure is measured by special finger probe.

Measurement method

Pressure feedback loop enables to estimate blood pressure changes.

Signal characteristics

For BP signal is typical heart rate periodicity. On each period can be recognised Systolic blood pressure (BPS), Diastolic blood pressure (BPD) and uncizura. there can be estimated also Cardiac output (CO) wih parallel analysed ECG signal.

3 Biological signal processing methods

3.1 Artefacts rejection

However examination or experimental conditions can reduce artefacts in measured signals there are still artefacts which can not be simply rejected by measuring system. That is why there were developed sophisticated signal processing methods which enable to reject some artefacts in biosignals.

Power line (AC noise)

Probably most known artefact in electrophysiology is power line artefact. This artefact has origin in induction power line on electrodes and wire connections to observed organism. The result is mixed biosignal with power line harmonic signal. There was different methods rejecting this artefact evolved.

The simplest method is so called notch or band reject filter. This filter rejects from signal all components in defined frequency band. This frequency band is selected around powerline frequency. This solution can be relatively simply realised in analogue electrical circuits or simple digital filters. One has to be careful with the application of these filters, since they may have considerable transients. The trailing edge of the QRS complex serves as an impulse for the filter and transient will be superimposed on the ST segment.

Better solution are different adaptive filtering methods. The adaptive noise cancelling technique (e.g. ADALINE (adaptive linear neurone)) seems quite appropriate

for suppression of the interference but a reference signal is required. This limits its application to on-line analysis of the ECGs, where a line signal is available as reference signal.

Mortara [13] described a non-linear technique for the estimation of the line interference component in the ECG. This filter introduse less distortion than the notch filter and needs not reference signal. Besides this positive properties, also the computational simplicity of the Mortara filter favours its application

Baseline wandering

So called base line wandering artefact is characterised by slowly changes of biolsignal baseline. This artefact has origin in slowly changes of electrical field. Typically this effects can be observed on ECG or EEG signal during slow patient movements. Four different algorithms for the correection of baseline wandering in ECG are described in literature.

The algorithm described by Riedl [17] utilises every 20 sample of the original data (with sampling freq. 250 Hz). A number of these samples will originate from the QRS complexes. These samples are corrected by special designed correction algorithm. One basic difficulty occurs in this algorithm. The samples, adjacent to the one under test need not to represent the baseline.

Meyer and Keiser [12] have described a baseline estimation and corredction algorithm based upon a cubic spline approximation. Before each QRS complex a baseline level is determined (PR knot). A third order estimator (cubic spline) has to connect these PR knots.

Macfarlane et al. [10] described a baseline correction procedure that utilises a linear interpolation between the onsets of two consecutive QRS complexes. This routine is only used when the maximal baseline shift between any two consecutive complexes in a recording is between 0.2 mV and 0.5 mV.

Muscle artefacts, spikes sudden baseline shifts and signal saturation

No substantial literature cold be found dealing with the detection and/or correction of muscule artefacts, spikes and sudden baseline shifts. In some of references, in which the various processing systems are described, a statement is made that a couple of artefacts is searched for, but in only one a brief description of the algorithm is given.

Wolf et al. [20] describe a procedure for the detection of muscle artefacts in ECG. For each lead, a 300 ms signal segment following the first QRS complex is analysed. The power spectrum is determined and the energy of the 50 and 60 Hz components as well as the energy in a frequency band between 30 and 120 Hz is measured. These three energies are compared with the total energy in the 300 ms signal segment to determine whether the noise is mainly due to line interference or due to muscle artefacts.

3.2 Data compression

Using digital measuring systems and digital signal processing methods has big impact on data storage units capacity. Furthermore requirements of clinical data exchange

and telemedicine brings problems with the huge biosignal data transmitting. That reasons lead to developing special highly sophisticated biological signal data compression methods. Deterministic character of biological signals enables do develop much better compression methods than standardly used "data compressors".

The most of methods are based on first or second difference coding. Relatively small differences between following samples enables to use shorter codes. Another approach is based on data parametrisation. Relatively small number of estimated signal parameters enables signal reconstruction.

3.3 Signal preprocessing

The most of applications digital signal processing methods are in biosignal preprocessing. Preprocessing of biological signal means extraction of physiologically interpretable information from raw signal data. Typical applications are on-line ECG parameters estimation or on-line EEG spectral parameters calculations.

Cardiological parameters estimation

Estimation of cardiological parameters means each heart beat period evaluation of standard ECG and/or BP parameters.

To select heart beat period must be first in ECG signal detected QRS complexes. There exist a lot of QRS complex detecting methods, but mostly used method is based on first derivation energy or spatial velocity calculation and adaptive threshold estimation. Detected QRS complexes enables to find R wave and consequently Q and S point, isoline part, P and T wave using characteristics definition and simply pattern recognition algorithms. The VCG amplitude signal must be used for ECG waves amplitude estimation.

From continual blood pressure signal can be extracted systolic and diastolic pressure, uncizura position and estimated cardiac output for each heart beat period.

EEG parameters estimation

For spectral power in defined frequency bands (Delta (0.1-4Hz), Theta (4-7Hz) Alpha (7-12Hz) Beta (12-18Hz)) is usually used fast Furrier transformation (FFT) which transforms EEG signal from time to the frequency domain. This method is using moving overlapped time window and from Furrier coefficient are estimated power spectra. Spectral power is evaluated as power integral in defined bands.

Another approach is using bandpass digital filters and integrators. The absolute power in specified frequency band can be calculated from a raw EEG signal using Chebyshew bandpass filter (e.g. Alpha: lower cut-off 7.5 Hz, upper cut-off 13.0 Hz, pass band ripple 0.056) and then squared and averaged by exponential window.

3.4 Stage recognition

Analysis of dynamics in syndrome space enables use of classification methods which can be used for different physiological stages recognition. Typical application in this

area are sleep stage recognition systems. This systems usually use preprocessed EEG parameters (Alpha, Theta power) from selected electrodes, Integrated EMG, EOG and respiration activity. This syndromes are used as input to classifier based on classical linear classification methods or some non-linear algorithms (e.g. Kohonen maps) .

4 System identification methods

There exist a lot of approaches to biological system identification. We can recognise two main groups. Statistical (probabilistic) and deterministic approach. Typical representants of this groups are characterised as following.

4.1 Bayesian approach

Bayessian system identification approach seems to be natural for biological systems identification. One of the assumptions in Bayessian modelling is that every variable of unknown true value represents a random variable (see [8] for basics of the Bayessian approach). This can be both the order of the autoregressive model and its coefficients. Apriori information about the system status can be involved. Then aposteriori distribution of probabilities of the investigated parameters is computed meaning a transformation of the apriori information on aposteriori one on the basis of real data. Probability in this sense means a degree of confidence in the validity of assumptions, and system identification means estimation of the order and model coefficients with certain likelihood ([5], [15]).

4.2 Artificial neural network based approach

Artificial neuronal networks ([2]), can be applied for predictions and classifications of the biological system behaviour. Neuronal networks can describe the dynamics of the system without apriori knowledge about the structure of the system. For system identification is usually used Multilayer Perceptron. Furthermore, Kohonenen self-organizing nets can be applied for system classification.

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