VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ
BRNO UNIVERSITY OF TECHNOLOGY

FAKULTA INFORMAČNÍCH TECHNOLOGIÍ
ÚSTAV INTELIGENTNÍCH SYSTÉMŮ

FACULTY OF INFORMATION TECHNOLOGY
DEPARTMENT OF INTELLIGENT SYSTEMS

EEG SIGNAL PROCESSING AND ANALYSIS

BAKALÁŘSKÁ PRÁCE
BACHELOR'S THESIS

AUTOR PRÁCE MICHAL UHLIARIK
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SUPERVISOR

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Abstrakt

Tato práce se zabývá oblastí elektroencefalografie, zpracováním EEG signálů a jejich analýzou. Jsou vysvětleny základní principy vzniku biologických signálů v mozku, charakteristické mozkové vlny a jejich klasifikace. Dále práce ilustruje základní metodologie měření a záznamu těchto signálů, chyby měření, vliv a zdroje signálových artefaktů. Následně je rozebrána problematika předzpracování signálu, nejrozšířenější metodologie, jejich primární určení a teoretické podklady. Zároveň je obsažen i přehled metod pro analýzu EEG signálu v časové, frekvenční a časově-frekvenční oblasti. Jádrem práce jsou metody analýzy EEG signálu v časové oblasti, jsou uvedeny jejich teoretické podklady, omezení, odchylky a zaměření, jako i vhodné matematické aparáty pro kompenzaci uvedených nedostatků. Praktická část popisuje architekturu a implementaci aplikace Easy EEG Player, která vznikla jako součást téhle práce. Jsou popsány metody reprezentace, zpracováni a analýzy EEG dat za použití zvolených metodologií.

Abstract

This thesis covers topic of electroencephalography, EEG signal processing and analysis. It explains fundamental concepts of biological signal genesis in brain, characteristic brain waves and their classification. Then it illustrates basic methodologies of EEG signal recording, measurement errors, impact and sources of signal artifacts. Thesis provides overview of the most common methodologies for EEG preprocessing and analysis with special focus on methods for spectral analysis. Practical part of this thesis describes architecture and implementation of Easy EEG Player application created as a part of this thesis.

Klíčová slova

Elektroencefalogram, elektroencefalograf, EEG, zpracování signálu, neurónová síť, automatická analýza.

Keywords

Electroencephalogram, electroencephalograph, EEG, signal processing, neuron network, automatic analysis.

Citace

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EEG Signal Processing and Analysis

Prohlášení

Prohlašuji, že jsem tuto bakalářskou práci vypracoval samostatně pod vedením paní Ing. Karolíny Lankašové a uvedl jsem všechny literární zdroje, ze kterých jsem čerpal.

....
Michal Uhliarik
May 21, 2014

Poděkování

Zde bych chtěl poděkovat své vedoucí paní Ing. Karolíně Lankašové za cenné rady a odborné vedení při tvorbě této práce.

Contents

Chapter 1

Preface

Since the dawn of time, human kind was looking for a new ways how to prolong life, discover, monitor and treat abnormalities and diseases. In these days, more than ever is this trend eminent. Modern medicine is still looking for new, more affordable, effective, precise and non-invasive methods.

Electroencephalography is one of the most widely spread and successful clinical methods for analysis and monitoring of cerebral diseases, activities and abnormalities. For over a century, it has been priceless source of knowledge about nervous system, and is commonly used up to this date.

Main goal of this thesis is to introduce basic principles of electroencephalography, genesis of bioelectrical signals in human brain, their properties, basic classification of main EEG components and introduction to EEG signal processing and analysis. Practical part of this thesis covers implementation of software Easy EEG Player, which can be used for analysis of EEG recording with special regard to spectral analysis methods.

Chapter 2 provides theoretical introduction to electroencephalography, describes bioelectrical signals genesis and methods of their recording. Chapter 3 contains information about EEG artifacts, their classification and identification. Afterwards, chapter 4 covers the topic of EEG signal preprocessing, filtering and cleansing. Chapter 5 provides comprehensive overview of EEG signal analysis methods and their comparison. Key part of this thesis is chapter 6 covering topic of Frequency domain analysis, providing theoretical foundations for of EEG signal analysis implemented as a part of practical part of this thesis. Chapters 7 and 8 describe architecture and implementation of Easy EEG Player with the focus on individual architectural layers and used technologies.

Chapter 2

Electroencephalography

2.1 Introduction

Electroencephalogram (abbreviated EEG) is recording of time-dependent fluctuation of electrical charge, originating in brain activity [14].

Electroencephalography is important non-invasive, clinical analytic method, based on observation of biological signals emitted by brain. It is used for wide range of medical areas and studies like metabolic disorders, various consciousness states, phases of sleep, effect of psychoactive substances and toxins, brain diseases and tumors.

Electroencephalographic examinations are performed in case of nearly all brain disorders in neurology and also often in psychology. From amplitude and frequency of depicted signals, it is possible to identify certain emotional conditions of subject and thus EEG can be used as part of polygraph machine commonly known as lie detector. Biological signal observed by EEG is stochastic electric signal generated by living organism, more precisely it is generated by neural activity of nervous system resulting from ionic current flows within neurons of the brain. The neural activity in the brain of human fetus starts between the 17^{th} and 23^{rd} week of prenatal development stage and ceases when human being dies. Fluctuations of electrical charge are being recorded between two measuring points and one referential point with stable electrical potential. The output of the measurement is curve, depicting changes in electrical potential in the time.

2.2 History

Electroencephalography is one of the basic brain diagnostic methods. The history of EEG is dated back to the year 1875 when Richard Canton (1842-1926) physician and scientist from Liverpool, England first recorded brain activity in the form of electric signal, using galvanometer and two electrodes. In 1890, Polish scientist and physiologist Adolf Beck presented paper about electrical activity peaks in the exposed brains of rabbits and dogs induced by external stimulus, when testing subjects were exposed to bright light and sounds. Discovered peaks had character of rhythmic oscillations. In 1914 Napoleon Cybulski had successfully induced epileptic seizure in a dog by electrical stimulation and provided the first EEG photography of epileptic seizure. After this discovery, the very first idea of correlation between epileptic attacks and abnormal electrical activity has been proposed.

True breakthrough in clinical neurology was made by German physiologist and psychiatrist Hans Berger in 1924 when he expanded the work conducted by Richard

Canton and others on animals and recorded the first human EEG. Hans Berger's most notable contribution to the neurology was invention of actual electroencephalograph machine. Findings and inventions of Hans Berger were confirmed in 1934 by British scientists Edgar Douglas Adrian and B. H. C. Andrews. By 1938, electroencephalography had gained widespread recognition by leading authorities and researchers in the field of neurology, leading to its usage in diagnostic, monitoring and observations in United States, England and France. In 1950s EEG technology has been used as foundation for electroencephalogram topography, methodology of mapping electrical activity across the surface of the brain [21].

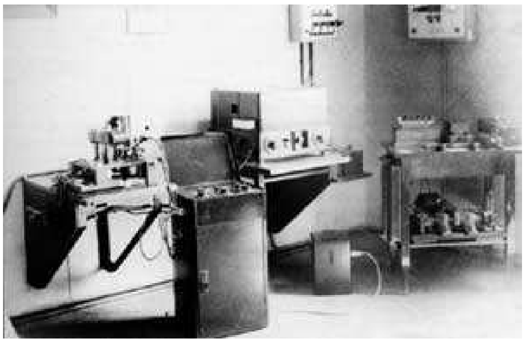

Figure 2.1: Equipment for EEG Recording (1926).

2.3 EEG signal source

The central nervous system mainly consists of billions of nerve cells, or neurons, and glia cells separating neurons. Neuron is chemically or physically excitable cell that collects, processes and transmits information by chemical and electrical signals. Discoverer of neurons J. E. Purkyně in 1835 differentiated two basic parts of neuron - neuron's body (cell body) and nerve fibers. There are two basic types of nerve fibers. First basic type of nerve fibers is afferent fibers or dendrites, which are short and highly branched fibers that transmit stimuli to the cell body, sum of their area greatly exceeds size of the cell body they belong to. Dendrites usually branch profusely, getting thinner and thinner with each branching. Main objective of dendrites is to respond to chemical and physical stimuli from the cell's vicinity and transform them as coherent signals to the cell's body. The second type of nerve fibers is efferent fibers or axons (neurites), neuron has typically only one axon, which can be long up to one meter, leading from neuron to executive organ.

Nerve fibers transmit stimuli by chemical and electrical impulses, changing electrical charge of neuron. Neurons are electrically charged by membrane transport proteins exchanging ions of potassium and chlorine. Due to different concentration of ions at the both sides of neuron's membrane, neurons continually exchange ions through their membranes with the space outside of the cell body, also known as extracellular milieu. This process is known as potassium-chlorine pump. Ions of same electrical charge repel each other causing chain reactions in the extracellular milieu. The electric potential generated by potassium-chlorine pump of single neuron is too small to be detected by EEG, but when enough neurons simultaneously cast out ions with same charge to the same direction, they can create wave of chain reactions. This process is known as volume conduction. Produced fluctuation of electrical charge in the wave can be strong enough to reach scalp of the head and electrodes of electroencephalograph. Recording of these fluctuations over time gives us electroencephalogram [20].

2.4 Electroencephalograph description and methodology

Electroencephalograph contains two basic parts: electrodes detecting voltage fluctuations on the scalp of subject's head and EEG machine responsible for preprocessing, storing and analysis of signals detected by scalp electrodes. Electrodes are essential part of EEG, their quality, location and conductivity have immense influence on depicted signal. Electrodes are usually made of well-conducting metal that cannot be polarized and is suitable for fast signal transfer with minimal information loss. Contact area of electrode is typically made from thin layer of Silver Chloride (AgCl) or Precious metals due to their low chemical reactivity.

Locations and names of individual electrodes are standardized by International 10-20 system. This system is being used by most clinical and research applications and ensures that the name and characteristics of electrodes are consistent. System is named after schema of electrodes distribution on the surface of scalp where mutual distance between individual electrodes is 10 or 20 percent of the overall length of scalp. This system ensures equal distribution of electrodes on the surface of scalp.

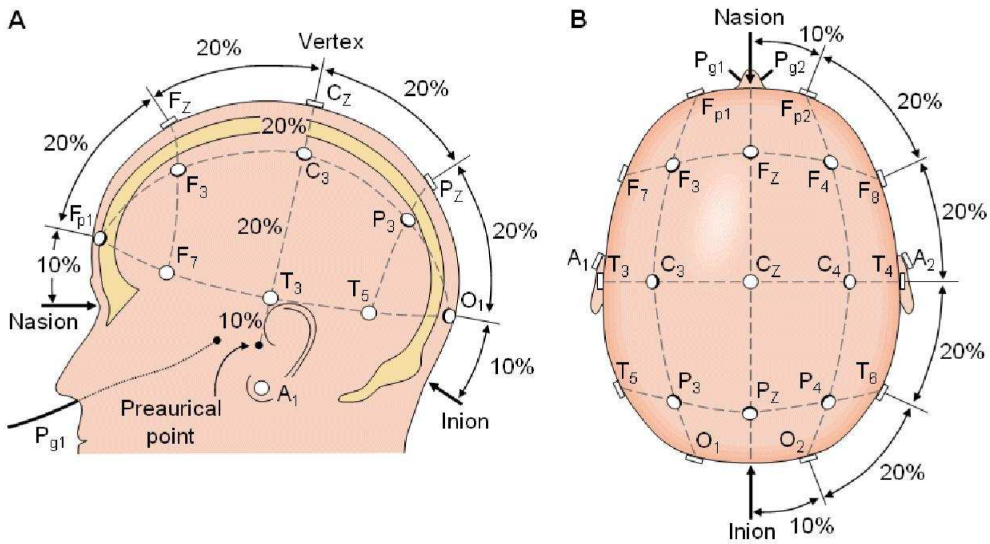

Figure 2.2: Distribution of electrodes according to International 10-20 System [19].

2.5 EEG recording characteristics

Graphical recording of voltage fluctuation curves resulting from ionic exchange is called electroencephalogram. Depicted curves highly depend on numerous of factors - health of the tested subject, age, mood, stress level, state of consciousness, gender, lifestyle etc. EEG curve is very complex and nondeterministic, it varies over the time and contains a lot of redundant information, noise, with origin outside of the brain.

Some typical EEG elements are well observed and documented and their source has been proven by numerous tests performed on various test subjects. These well documented elements called graphoelements are important marker for EEG analysis and predictions. Basic graphoelement is wave - graphical recording of single neural electrical oscillation. Neural oscillations also known as brain rhythms are very sensitive and subtle pointers of brain functions. Neural oscillation is rhythmic, repetitive neural activity in central nervous system, usually generated by large numbers of neurons. Neural oscillations have been linked to many cognitive functions such as memory, perception, data processing, creativity, information transfer, motor control, generation of rhythmic activity like heartbeat and the neural binding of sensory features in perception, such as the shape and color of an object. In general, these oscillations can be characterized by their phase, frequency and amplitude.

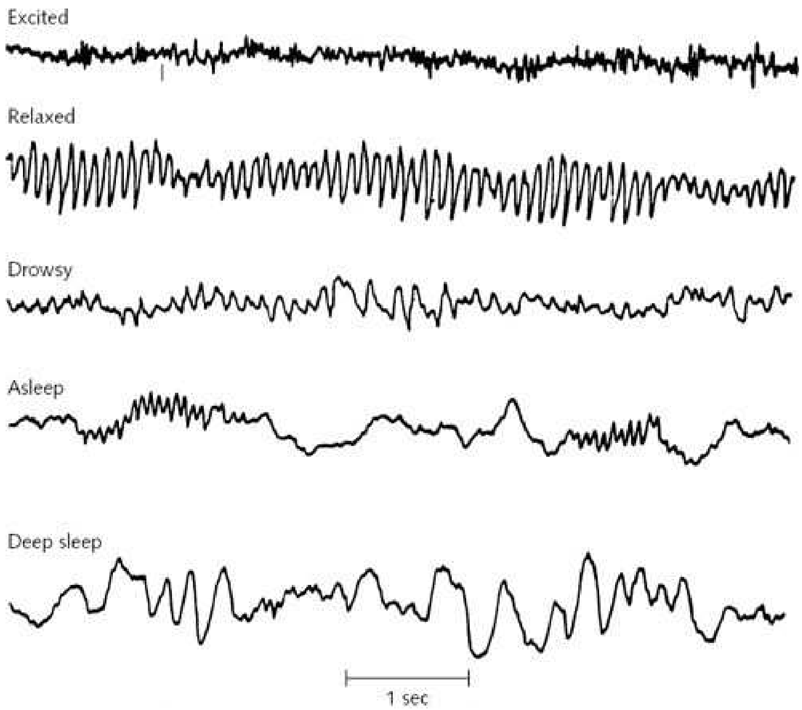

Figure 2.3: Effect of subject's mood on depicted EEG recording.

2.6 Basic EEG waves

EEG signal consists of periodic sinusoidal waves. The clinical experts in the field are familiar with manifestation of brain rhythms in the EEG signals. For healthy adults, the amplitudes and frequencies of respective brain waves change, depending on the state of human consciousness, such as wakefulness and sleep, characteristics of these waves also greatly depends on age.

There are five major brain waves distinguished by their different frequency ranges. These frequency bands are identified by letters of Greek alphabet ascending from lowest frequencies to highest as follows: delta – δ (0.5-4 Hz), theta – θ (4-7Hz), alpha – α (7-14 Hz), beta – β (15-30 Hz), and gamma – γ (30 – 100+ Hz). Basic frequency range is from 7 to 14Hz, most common frequency range is 9.5-10.5Hz, in the sleepy state common frequency is 7-8Hz. Frequency is consistent in both brain hemispheres. Alpha frequency band changes through human life. In the first year of life typical alpha frequency is only 5Hz, in fifth year it is 7Hz and it reaches its stabilized level at the age of eight. Children signal's amplitude is higher than adult's. For example, amplitude of alpha waves of child reaches 50-60 μV, for adults, amplitude typically reaches 15-50 μV [19] [11].

Frequency band	**Frequency (Hz)**	**State of consciousness typically associated with band**	**Affected cognitive functions**
Delta (δ)	0.5-4	Deep sleep, trance, ecstasy	Unknown, none clinically confirmed
Theta (θ)	4-7	Falling asleep, hypnosis, lucid dreaming, deep relaxation	Enhanced memory, concentration, subconscious learning, creativity
Alpha (α)	7-14	Relaxed/reflecting, self-calming, idling, coma	Enhanced memory and observation skills, state of high attention
Beta (β)	15-30	Vigilance, alertness, high concentration	High perception and acuteness
Gamma (γ)	30-100+	Rush, stress, anger, hyperactivity, information over flooding	Decreased attention, concentration, perception, increased irrationality and alertness

Table 2.1: Comparison table of EEG frequency bands.

Chapter 3

EEG artifacts

Electrical signals detected along the scalp by an EEG may not always origin from the brain activity. Such signals are considered as misguiding and unfavorable. These signals, originating from non-cerebral origin are called artifacts or noise. EEG recording is almost always polluted by such artifacts. Artifacts can be easily mistaken for spike activity. EEG artifacts are divided to two basic groups, depending on their origin and nature they are endogenous and exogenous [11].

3.0.1 Endogenous EEG artifacts

Endogenous or internal artifacts have their origin inside the subject's body. These artifacts are of biological origin and are very common. Amount of biological artifacts present in EEG depends on tested subject and precision of measurement. Most significant biological artifacts are:

- Eye-induced artifacts
- Cardiac artifacts
- Artifacts of muscular system
- Glossokinetic artifacts

Eye-induced artifacts

Most significant eye-induced artifact is caused by significant potential difference between the retina and cornea of the eye bulb. This potential is significantly greater compared to electric potentials caused by cerebral activities. When there is no movement of eye bulb, this potential doesn't affect EEG. However, even fully closed eyes do move, willingly or unwillingly. Vertical and horizontal movements of eyelid caused by reflective movements of eye muscles cause fluctuations of potential between retina and cornea. Eye muscle movements also generate transient electromyographic potential, known as saccadic spike potentials, which further contribute to eye induced EEG noise. Another typical eye induced artifact is so called Kappa (κ) rhythm, which is an anterior temporal alpha-like rhythm. It can be typically found in the outputs of pre-frontal EEG electrodes on human forehead. In the past scientist were convinced that kappa rhythm new typical frequency band, that has its origin in cerebral functions of frontal brain lobe, due to its periodicity and vicinity of the frontal lobe. Later clinical studies discovered that origin of this artifact is fast trembling of eyelid [25] [11].

Cardiac artifacts

Cardiac artifacts are artifacts produced by cardiovascular system. The heart produces two types of EEG artifacts: electrical and mechanical. Both of these artifacts are closely related to cardiac contractions - rhythmic oscillations of heart pumping blood throughout body in veins and body tissues. These artifacts are usually easily identified by their similarities with electrocardiograph (ECG) recordings, thus to eliminate cardiac artifacts, EEG and ECG are typically recorded simultaneously. After the recording of EEG and ECG, recordings are compared and artifacts matching activities detected by ECG are considered to be noise and removed from EEG [11].

Artifacts of muscular system

Artifacts of muscular system are the most common artifacts. Source of these artifacts can be found in muscle contractions. Main source of these artifacts are so called frontalis and temporalis muscles. Frontalis muscles are muscles which cover parts of scull and mainly serve for facial expressions and jaw movements. Temporalis, also known as temporal muscle, is one of muscles of mastication. It is a broad fan-shaped muscle on both sides of head covering temporal bone. Its main action is to elevate the mandible and perform movements of the lower jaw. Activity of these muscles is very common and can be induced willingly and unwillingly. Due to high vicinity of EEG electrodes located on the scalp of the head, noise generated by these muscles is very common and unavoidable [11].

Glossokinetic artifacts

Glossokinetic artifacts originate in tongue. Tongue functions as dipole the tip of tongue has negative charge with respect to the base of the tongue. Tip of tongue is most important in sense of potential fluctuations because it is mobile compared to tongue base, which is basically still. Minor tongue movements can contaminate the EEG, especially if subject suffers from parkinsonian or tremor disorder [25].

3.0.2 Exogenous artifacts

Exogenous artifacts or technical artifacts have their origin outside of the subject's body. These artifacts have their origin in technical sources of electrical and magnetic noise and defects in EEG machine itself. Almost every electronics can alter EEG measurement, this is why clinical EEG is usually performed in specialized rooms shielded from electro-magnetic interference with minimum of other electronic devices. Most common and significant exogenous artifacts sources are 50/60Hz power supply inferences, cable and EEG defects, electrical noise from the electronic components, impedance fluctuations and unbalanced impedances of the electrodes. Exogenous artifacts impose a high chance of EEG pollution and thus many sophisticated methodologies have been devised to eliminate them [25] [11].

Chapter 4

EEG signal preprocessing

Unprocessed EEG recording is not suitable for clinical use or analysis, it contains many artifacts or noises that may cause recording to be practically impossible to analyze. In order to make EEG recording suitable for analysis and clinical usage, recording undergoes through the stage of preprocessing. Main goal of EEG preprocessing methodologies is to eliminate or significantly reduce number of unwanted patterns polluting EEG recording. There are various methodologies of voice reduction, some are applied in the time of actual EEG recording - like Faraday cage shading the walls of room where recording is being performed, or application of well conductive gel on the scalp. However, most noise reducing methodologies are applied after the recording has been finished.

Fast advancements in information technologies are gaining ever increasing significance in preprocessing of EEG recording. Digital preprocessing has greatly increased quality and informative value of EEG recordings, as can be seen on Figure 4.1, and greatly decreased time and financial expenses related to the process. In this section, I would like to provide quick overview of some of the most significant methodologies used for EEG recording preprocessing and cleansing.

4.1 Filtering

The raw EEG signals have amplitudes of the order of μvolts and contain frequency bands up to hundreds of Hz. To retain the effective information the signals often have to be amplified before they are suitable for further processing. Filtering is very efficient method that can eliminate huge quantities of irrelevant or redundant data. Filtering can be performed either by hardware means or digitally. Filters are typically designed and used to erase unidirectional signal elements, noise created by power supply inference and artifacts with wavelengths over 70Hz. The filters are designed in such a way not to introduce any change or distortion into the signals. This feat can be done by hardware analog filters or their digital equivalents. Hardware analog filters are commonly part of EEG to perform filtering of received signal in the time of recording. Most commonly used filters for such filtering are: high-pass filter, low-pass filter and notch filter.

4.1.1 High-pass filter

High-pass filters are intended to filter-out unidirectional signal artifacts and very low frequency components such as those of breathing. This ensures stability of main signal components. Typical cut-off frequency of high-pass filters is usually from 0.1 to 0.5 Hz.

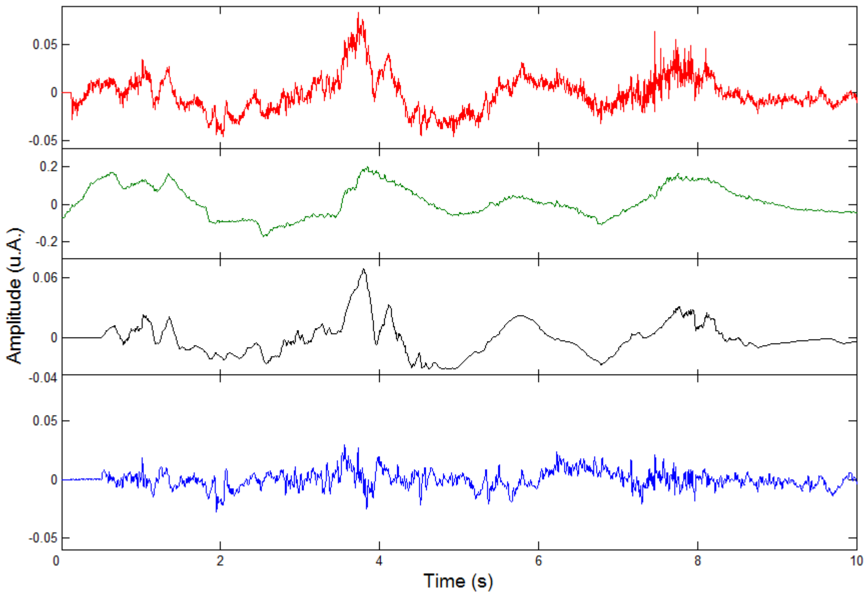

Figure 4.1: Example of EEG recording preprocessing. Red signal – Unprocessed EEG recording, green – EOG artifact, black – ECG artifact, blue – EEG recording after preprocessing.

4.1.2 Low-pass filter

Low-pass filters are typically used to filter-out high-frequency artifacts, such as electromagnetic inferences or signals produced by skeletal muscles – so called electromyographic signals. These artifacts may present significant amount of collected data. Typical cut-off frequency of low-pass filters is from 50 to 70 Hz.

4.1.3 Notch filters

Main responsibility of Notch filters is to filter-out strong periodic harmonic signals generated by power supply inference. Frequency of such signals differs from country to country, for example in Europe, typical frequency of power supply signals is 50Hz, while in the USA 60Hz. Notch filters of precise null frequency are necessary to ensure perfect rejection of strong power supply signals while imposing minimal impact on high frequency signal elements.

4.2 EEG signal segmentation

EEG is a complex mix of various signals overlapping each other. Such a mixture may present quite a challenge to be analyzed so it is often necessary to divide EEG signals to segments of similar characteristics that are easier to analyze, isolated from other unrelated segments and provide maximal informative value about particular depicted signal segment. Within each segment, signals are considered to be statistically related, usually having similar time and frequency statistics. Segmentation may be divided to two basic groups:

- segmentation with constant length of segment
- segmentation with adaptive length of segment

4.2.1 Segmentation with constant length of segments

Constant segmentation has segments of fixed length thus all segments contain same amount of samples and have same length. Typical length of segments is in tens of seconds to several minutes. Constant segmentation algorithms are easy to implement but they may hide correlation between signals of different frequencies or length.

4.2.2 Segmentation with adaptive length of segments

Adaptive segmentation has segments of variable length. Length of the segment depends on its actual position, time and frequency properties. Lengths of segments are chosen to illustrate correlations between individual signals and segments. Transformation of individual segment from time-domain to frequency-domain representation may be used to determine total number of signal waves of the EEG recording in individual wave bands, and identify dominant frequency of the recording. Adaptive segmentation may be performed using linear transforms such as the discrete Fourier transform (DFT), fast Fourier transform (FFT) or discrete cosine transform (DCT).

Adaptive segmentation by the means of discrete Fourier transform

DFT is one of oldest and most widely spread methodologies of adaptive segmentation. Continuous periodic signal $f(t)$ can be replaced by time-dependent sequence of N samples $f(nT)$ and if it complies with sampling theorem then:

$$DF(\frac{k}{NT_0}) = T_0 \sum_{n=0}^{N-1} f(nT_0) e^{-j\frac{2\pi kn}{N}}, k = 0, 1, 2, 3..., N-1 \tag{4.1}$$

where T_0 is period of sampling frequency and k represents degree of harmonic frequency spectrum, n is ordinal number of the sample and N is number of samples.

Adaptive segmentation by the means of fast Fourier transform

Fast Fourier transform provides same numeric results as discrete Fourier transformation, the only difference is that FFT requires less arithmetic operations than DFT and thus time spent calculating it is shorter. Basic wave bands (delta, theta, alpha, beta, gamma) and their respective typical frequency ranges may be used to differentiate 5 characteristic frequency bands. Segments borders are defined by partial differences in characteristic frequency bands. We can take frequency borders as input for segmentation and transform them to frequency-domain by:

$$X[k] = \frac{1}{N} \sum_{n=0}^{N-1} x[n] e^{-jkn\frac{2\pi}{N}}, k = 0, 1, 2, 3..., N-1 \tag{4.2}$$

where k represents degree of harmonic frequency spectrum, n is ordinal number of the sample and N is number of samples.

Chapter 5

EEG signal analysis methods overview

Electroencephalography is one of the most successful, time-proven and widely spread methods of monitoring and analyzing brain activity. Throughout the last century, various methods and algorithms have been developed to perform EEG signal analysis. Used methodologies include, but are not limited to, time-domain analysis, frequency-domain analysis, spatial-domain analysis, several algorithms have been developed to visualize brain activity by processing images reconstructed from depicted EEG activity. Fast growth of computational power and increasing usage of informatics technologies cast ever increasing significance to machine processing of EEG, sophisticated methodologies of computer science are being used to aid in this cause such as artificial intelligence, artificial neural networks, data mining, pattern matching etc.

Depicted signal can be analyzed in two basic domains frequency domain and time domain by their combination we can observe EEG recording in third domain which is time-frequency domain. Fore-mentioned signal domains have their specifics and different analysis methods, although many of them have different basic concepts, approaches and methodologies, they all have one common goal: valid processing and presentation of EEG data in order to provide maximal informative value [19].

5.1 Time domain signal analysis

Time domain analysis observes and analyses depicted EEG signal in dependence upon time. Signal is being observed without the use of time or frequency transformations, as a whole unaltered recording or individual frequencies filtered by frequency filters. Significant information can be extracted by analysis of signal in time domain, for instance neural activity through course of time, neural activity in individual emotional states or phases of day, neural response for pharmaceuticals or external stimuli. Time domain signal analysis is very significant part of clinical EEG usage [19] [14].

5.1.1 Processing of long term EEG recordings

Processing of long term EEG recording, also known as Holter monitoring is a clinical method of monitoring neural activity and activity of cardiovascular system using Holter monitor – portable monitoring device, recording activity through longer time periods. It is used to prove epilepsy and localize source of epilepsy in subject's neural system, monitor individual sleep stages, monitor influence of mental and psychological states of subject and their influence on neural activity. Holter monitor continuously record neural activity and stores it on portable memory device for further clinical processing. Monitoring is usually performed for the period of 24 to 72 hours, to provide relevant data. Analysis of such a long recording may be very complex and time consuming operation, because of this various subsequent analysis methodologies are applied to depicted signal to identify and extract significant parts of recording or to filter out insignificant data. Automatic systems are typically used to identify specific graphoelements or classify specific parts of recordings [14].

Long EEG with video recording

Special alternative to long term EEG recording processing may be its combination with video and audio recordings, recorded video and audio is subsequently synced with EEG to provide additional information. Such approach allows experts to link recorded EEG patterns and abnormalities with particular actions that observed subject performed during recording. These combined recordings may be invaluable for better understanding of neural activities in brain and for better identification of potential sources of pathogenic neural activities.

5.2 Frequency domain analysis

Frequency domain analysis, also known as spectral analysis, is one of the most significant diagnostic methods for clinical EEG analysis, it enables analysis of separate frequency components. Frequency domain analysis allows determination of spectrum of the signal or Power Spectral Density (PSD). Frequency domain analysis methods are cornerstone of this thesis and will be covered at greater detail in Chapter 6.

5.3 Time-frequency domain analysis

EEG recording depicts voltage fluctuations, some fluctuations are eminent only if specific stimuli is provided or in specific phases of day. Sometimes it is desirable to analyze specific frequency band through time. Time-frequency domain analysis assigns time to specific frequency bands, which enables effectively observe changes in individual frequency bands through time.

5.3.1 Spectrogram

Spectrogram is a graphical, time dependent representation of spectrum of frequencies in signal. A common format of EEG spectrogram is a two-dimensional graph where horizontal axis represents time and vertical axis represents frequency. Intensity of signal in two dimensional spectrograms is typically illustrated by different colors, with corresponding legend explaining meaning of individual colors used. Three-dimensional spectrograms, also known as Compressed Spectral Arrays, may be used to provide information about amplitude (intensity) of depicted signals. Significant problem in creation of spectrogram is to choose correct time kernel, also known as time window. Chosen length of time window has significant impact on informative value provided by spectrogram, too long window may hide necessary details about the signal due to small time scale for high frequency signals as their graphical representations may overlap. Too short window may clutter important information about signal changes or periodically appearing signals. Selection of correct time window length is typically compromise. In clinical practice, spectrograms with various time windows are usually used to represent single EEG recording [19] [14].

5.3.2 Wavelet transform

Wavelet transform is currently one of the most widely-spread method of time-frequency transform, it has been introduced in 1980's. The fundamental idea incorporated in wavelet transform is that transform should perform only modifications of time representation but should not affect shape. It can be viewed as a tool for decoleration of data, decomposition of signal to basic components. Most common application of wavelet transform is detection of desired graphoelement and determination of its duration. Term wavelet transform denotes group of transforms with common properties, differing only in the base function or wavelet. In contrary to spectrogram, which provides information about amplitude of all frequencies in specific time, wavelet transform provides information about separate frequencies, about their first appearence in time and amplitude, thus modifications of time kernel do not cause loss of information for high frequencies [11].

5.4 Topographical brain mapping

Topographical brain mapping is set of techniques and methodologies based on mapping specific neural activities onto spatial representation of their source, brain mapping attempts to relate the brain's structure to its function. Result of such mapping is a brain map depicting topographical representation of brain activity in human brain and scalp. Brain maps also depict density of recorded activity in individual brain regions. This methodology has its foundations in late 1980s in the USA and have registered massive boom thanks to increasing computing power of computers and their general availability. Brain mapping techniques are perpetually evolving as they heavily rely on other EEG signal processing methods used to process depicted data for visualization and interpretation. Most commonly used method to preprocess data for brain mapping is Fast Fourier Transform. Pitfall of this methodology is that it heavily relies on used referential electrode, usage of different referential electrodes may provide different results, which may be misleading and confusing.

5.5 Artificial neural networks

Application of Artificial Neural Networks (ANN) is one of advanced methodologies for analysis of EEG recording. ANN are practical application of concepts of Artificial intelligence, from the perspective of EEG analysis, most importantly their ability to „learn" through time. Thanks to ability to learn, they may represent a very power tool for automatic analysis and processing of EEG data, they are typically used for detection of graphoelements, technical and biological artifacts, markers of neural diseases and identification of correlation between seemingly unrelated brain activities. Though learning, they can be used to emulate cognitive process of intelligent being. In clinical and scientific practice, ANN are used to emulate analytical approach and reasoning of domain specialist, trained neurologist or scientist, in the process of EEG analysis. Artificial intelligence may be used to unveil new knowledge about observed system, in this case brain, or quickly process and represent data.

Chapter 6

Spectral analysis

Mathematical foundations for spectral analysis are orthogonal transformations that assign signal spectrum to time-domain and vice versa. Transformation of selected part or region of EEG recording to frequency domain allows identification and quantification of individual frequency bands or identification of dominant frequency. Methods of spectral analysis can be divided into two basic groups:

- Nonparametric methods
- Parametric methods

6.1 Nonparametric analysis

Nonparametric methods are group of versatile generic methods for signal processing, they are not specifically designated for analysis of EEG signals, but may rather be used to analyze any signal. Nonparametric methods process signal directly. Most commonly used nonparametric methods are based on filtering, Discrete Fourier Transform and Fast Fourier Transform.

6.1.1 Periodogram

Periodogram or power spectra density estimate is a non-parametric method that can be used to illustrate effective power spectrum of depicted signal, it is a representation of variable quantity corresponding to spectrum of signal. It is usually computed from final-length digital sequence using Fast Fourier Transform. One of the drawbacks of periodogram method is that variance of power spectra density estimation doesn't lower with increasing number of samples used to compute it. In other words, as we take more sampled points from the original function (either by sampling a longer period of time at the same sampling rate, or else by resampling the same length of recording with a higher sampling rate), periodogram estimates do not become more accurate, this is the reason why new methods based on periodogram were introduced. Spectrum depicted in periodogram can be formally described as follows:

Following text has been adopted from [17]:

If we take an N-point sample of the function $c(t)$ at equal intervals and use the FFT to compute its discrete Fourier transform

$$C_k = \sum_{j=0}^{N-1} c_j e^{\frac{2\pi ijk}{N}} \qquad k \ = 0, \dots, N-1 \tag{6.1}$$

then the periodogram estimate of the power spectrum is defined at $\frac{N}{2}+1$ frequencies as

$$P(0) = P(f_0) = \frac{1}{N^2}|C_0|^2 \tag{6.2}$$

$$P(f_k) = \frac{1}{N^2}\left[|C_k|^2 + |C_{N-k}|^2\right] \qquad k \ = 1, 2, \dots, (\frac{N}{2}-1) \tag{6.3}$$

$$P(f_c) = P(f_{\frac{N}{2}}) = \frac{1}{N^2}|C_{\frac{N}{2}}|^2 \tag{6.4}$$

where f_k is defined only for the zero and positive frequencies

$$f_k = \frac{k}{N\Delta} = 2F_c\frac{k}{N} \qquad k = 0, 1, \dots, \frac{N}{2} \tag{6.5}$$

By Parseval's theorem, is normalized so that the sum of the $\frac{N}{2}+1$ values of P is equal to the mean squared amplitude of the function c_j .

6.1.2 Bartlett's method

Bartlett's method of power spectrum density estimation, also known as the method of averaged periodograms, is named after English statistician M. S. Bartlett who proposed it in 1948. Bartlett's method is based on usage of multiple periodograms. Main goal of this method is reduction of the variance of the periodogram estimates because the periodogram method does not give zero variances as the data length approaches infinity. Bartlett's method accomplishes this in exchange for a reduction of resolution using statistical methods. The Bartlett's method divides the signal length N into K segments, with each segment having the length of $L = \frac{N}{K}$. Periodogram is then computed for every segment, resulting periodograms are then averaged and the resulting estimated power spectra density is taken as a result of Bartlett's method. A final estimate of the spectrum at a given frequency is obtained by averaging the estimates from multiple periodograms at the same frequency, derived from a non-overlapping portions of the original series [18].

According to [17] Bartlett's method can be formally described as:

$$\hat{P}_{Bartlett}(e^{j\omega}) = \frac{1}{K}\sum_{i=0}^{K-1}\frac{1}{L}\left|\sum_{n=0}^{L-1} x(n+iL)e^{-jn\omega}\right|^2 \tag{6.6}$$

6.1.3 Welch's method

Welch's method is method of spectral density estimation, used for estimating the power of signal at various frequencies with reduction of signal noise in exchange for reducing the frequency resolution. It's founded on the concept of periodogram. Welch's method may be viewed as improvement of Bartlett's method on which it lays its foundations. The Welch's method eliminates tradeoff between variance reduction and resolution reduction present in the Bartlett's method. Original signal is split up into overlapping segments, which are then divided into the windows. The Welch's method imposes higher significance to the data, or parts of signal, located in the middle of the window, than to the data present at the edges of the window, which represents the loss of the information due to the signal noise. Importance of data is continuously decreasing from center of the window to its edge representing zero significance. This approach reduces statistical dependence caused by overlapping. Modified signal windows are then converted into periodograms and time-averaged. Result of such transform is that individual signal peaks in spectrum are wider and signal noise is minimized [24].

Mathematically, the estimated power spectrum $P_{Welch}(e^{j\omega})$ resulting from the use of the Welch's method can be described as [24]:

$$\hat{P}_{Welch}(e^{j\omega}) = \frac{1}{KLU} \sum_{i=0}^{K-1} \left| \sum_{n=0}^{L-1} w(n) x(n+iD) e^{-jn\omega} \right|^2 \tag{6.7}$$

K is the number of segments, L is the length of each segment, $U = \frac{1}{L} \sum\limits_{n=0}^{L-1} |w(n^2|$, D is the offset of two consecutive segments, $L - D$ is the number of overlapped points.

6.2 Parametric analysis

Parametric methods of analysis require set of parameters to be provided to conform to special mathematical model of processed signal. Main goal of signal analysis is to estimate these parameters from obtained data. Parametric methods are used for modelling, denoising or prediction. Most common models of data are:

- Autoregressive model (AR)
- Moving average model (MA)
- Autoregressive-moving average model (ARMA)

6.3 Window function

Analytical methods based on the use of Fast Fourier Transform (FFT) are subject to errors and deviations caused by effect known as spectral leakage. FFT itself theoretically is not the source of spectral leakage, the actual source is that the measured signals are limited in time and the FFT calculates the frequency transform over a certain number of discreet frequencies called bins. The power spectrum represents the average distribution of power of a time series as a set of components harmonically related to (integer multiples of) the fundamental frequency. When all the power of the time series occurs at frequencies that are integer multiples of the fundamental frequency, then it can be adequately represented by the Fourier series. However, a problem arises when there is power in the time series at frequency components that are not harmonic. When this happens, the power of these components is misrepresented. Spectral leakage refers to the misrepresentation of components other than integer multiples of the fundamental frequency. The effect occurs when the finite duration of the signal does not result in a sequence that contains a whole number of periods. This is especially true when FFT is used for signal detection or estimation - that is, for detecting weak signals in the presence of strong signals or resolving a cluster of equal strength frequencies [18] [10] [23].

In FFT analysis, „windows“ are frequency weighting functions applied to the time domain data to reduce the spectral leakage associated with finite-duration time signals. Windows are smoothing functions that peak in the middle frequencies and decrease to zero at the edges, thus reducing the effects of the discontinuities as a result of finite duration [10].

6.3.1 Rectangular window

Rectangular window, also known as Dirichlet window, is the simplest window function. This function assigns constant positive weight to all samples within it and zero weight to all samples outside of it, this weighting creates discontinuities in the endpoints of signal. These discontinuities may have deteriorative effect on signal analysis using Fourier Transform [23].

Rectangular window can be characterized as:

$$\omega(n) = 1 \tag{6.8}$$

6.3.2 Hann Window

The Hann or Hanning window named after its inventor Julius von Hann, has the shape of one cycle of a cosine wave with 1 added to it so it is always positive. Window functions with the shape of cosine wave with some constant addition are often referred to as „raised cosine“ windows. The sampled signal values are multiplied by the Hanning function, and corresponding weights are assigned to them. Hann window minimizes discontinuities at the endpoints of signal by decreasing weight of signal samples as they are closer to the end of window, but it also adds distortion to the wave form being analyzed in the form of amplitude modulation [18] [23].

According to [22] Hann window can be formally described as:

$$\omega(n) = 0.5\left(1 - \cos(\frac{2\pi n}{N-1})\right) \tag{6.9}$$

6.3.3 Hamming Window

The Hamming window belongs to the group of „raised cosine“ windows. It is named after Richard W. Hamming, who proposed particular coefficients for this raised cosine window. Hamming window is optimized to minimize nearest maximum side lobe, greatly reducing its height [23].

Generally, Hamming window can be defined as [6]:

$$\omega(n) = \alpha - \beta\cos(\frac{2\pi n}{N-1}) \tag{6.10}$$

Hamming proposed that $\alpha = 0.54$ and $\beta = 1 - \alpha = 0.46$.

6.3.4 Bartlett Window

Bartlett window is special kind of „triangular window“, group of windows with the shape of triangle. Window is named after M. S. Bartlett (also known for Bartlett's method). Bartlett's window can be viewed as a convolution of two rectangular windows of the length $\frac{N-1}{2}$. Main lobe of Bartlett's window has twice the width of rectangular as main lobe of rectangular window of length M [23].

Mathematical definition of this window is [23]:

$$\omega(n) = 1 - \left| \frac{n - \frac{N-1}{2}}{\frac{N-1}{2}} \right| \tag{6.11}$$

6.3.5 Blackman window

Blackman window is named after its inventor Ralph Beebe Blackman. It is similar to Hann and Hamming window, but it has one additional cosine term, thanks to this it approaches zero more smoothly and creates very low side lobe. It is suitable for windowing by convolution in frequency domain [10] [2].

Formally Blackman window is defined as:

$$\omega(n) = a_0 - a_1 \cos(\frac{2\pi n}{N-1}) + a_2 \cos(\frac{4\pi n}{N-1}) \tag{6.12}$$

Where:

$$a_0 = \frac{1-\alpha}{2} \tag{6.13}$$

$$a_1 = \frac{1}{2} \tag{6.14}$$

$$a_2 = \frac{\alpha}{2} \tag{6.15}$$

Chapter 7

Easy EEG Player

One of the most important tools for EEG analysis nowadays are specialized computer programs providing means for EEG signal visualization, processing and analysis. Application Easy EEG Player was implemented as part of this thesis, to provide simple, portable and out-of-the box solution for EEG signal processing and analysis.

7.1 Technology overview

One of the key architectural decisions taken in early phases of Easy EEG player development was to choose suitable programming language for implementation. Java programming language was chosen. This decision was influenced by number of key properties which make Java one of the most widely-spread and commercially successful programming languages, namely:

- Portability
- General purpose language
- Object-oriented
- Robustness
- Large, active community

Java is interpreted, architecture neutral programming language. Source codes of Java application are compiled to java byte code and can be run on any architecture implementing Java Virtual Language. This key concept makes Easy EEG Player portable and it has been successfully tested on 3 major operating systems (Windows, Linux and IOS).

7.1.1 Java glossary

Java is multi-paradigm programming language with strong Object oriented features. Java has sophisticated approach to organizing source code and namespace of individual source elements. For better understanding of some of the architectural and design decisions made in Easy EEG Player code base, I would like to introduce several basic terms from the vast topic of Java programming language. Following terms have close relation to object-oriented programming paradigm:

Object – Object is entity encapsulating state information about itself and providing series of operations for manipulation with information it is encapsulating. In programming terms, an object is a self-contained component that contains properties and methods needed to make a certain type of data useful. An object's properties are what it knows and its methods are what it can do. In the object-oriented programming paradigm, „object," refers to a particular instance of a class where the object can be a combination of variables, functions, and data structures [5].

Class – In object-oriented programming, a class is an extensible template for creating objects, providing initial values for state (member variables) and implementations of behavior (member functions, methods) [8].

Interface – In the Java programming language, an interface is a reference type, similar to a class, that is used to specify an interface (in the generic sense of the term) that classes must implement. Interface can contain only constants, method signatures and nested types. Interfaces cannot be instantiated – they can only be implemented by classes or extended by other interfaces. Interfaces are used to encode similarities which the classes of various types share, but do not necessarily constitute a class relationship, interface merely defines common contract, the implementing class has comply to [16].

Package – A Java package is a mechanism for organizing related classes and interfaces into namespaces. Typically classes and interfaces organized in same package are closely related and share common characteristics or provide similar functionality. Packages can be used to hide implementation details of individual classes they contain [16].

7.2 Architecture overview

In order to provide reliable and extensible solution for EEG analysis tool, architecture of such tool has to be well-considered. Elaborate design and logical distribution of competencies can be very time-saving and greatly reduces error proneness of whole application. Well designed and documented software is easy to extend and maintain. From architectural point of view Easy EEG Player was designed to be multilayered. Its design has been influenced by „Layers" architectural pattern as described in [3]. Separation of architecture into logical layers addresses major concerns of the application like:

- Sustainability - by high modularity and low-coupling of individual modules
- Reusability - by separation of concerns
- Flexibility and expandability - implementation of individual layers can be modified without affecting other layers

Logical multilayered architecture of Easy EEG Player can be divided into following three layers as shown on diagram 7.1:

- Infrastructure layer (a.k.a. Data layer)
- Domain layer
- Presentation layer

Each layer has delineated competencies and hides its implementation details from the rest of the application. Functionalities provided by individual layers can be accessed through their public Application Programming Interface (further API). Individual layers, their organization, members and competencies will be described in more details in following chapters.

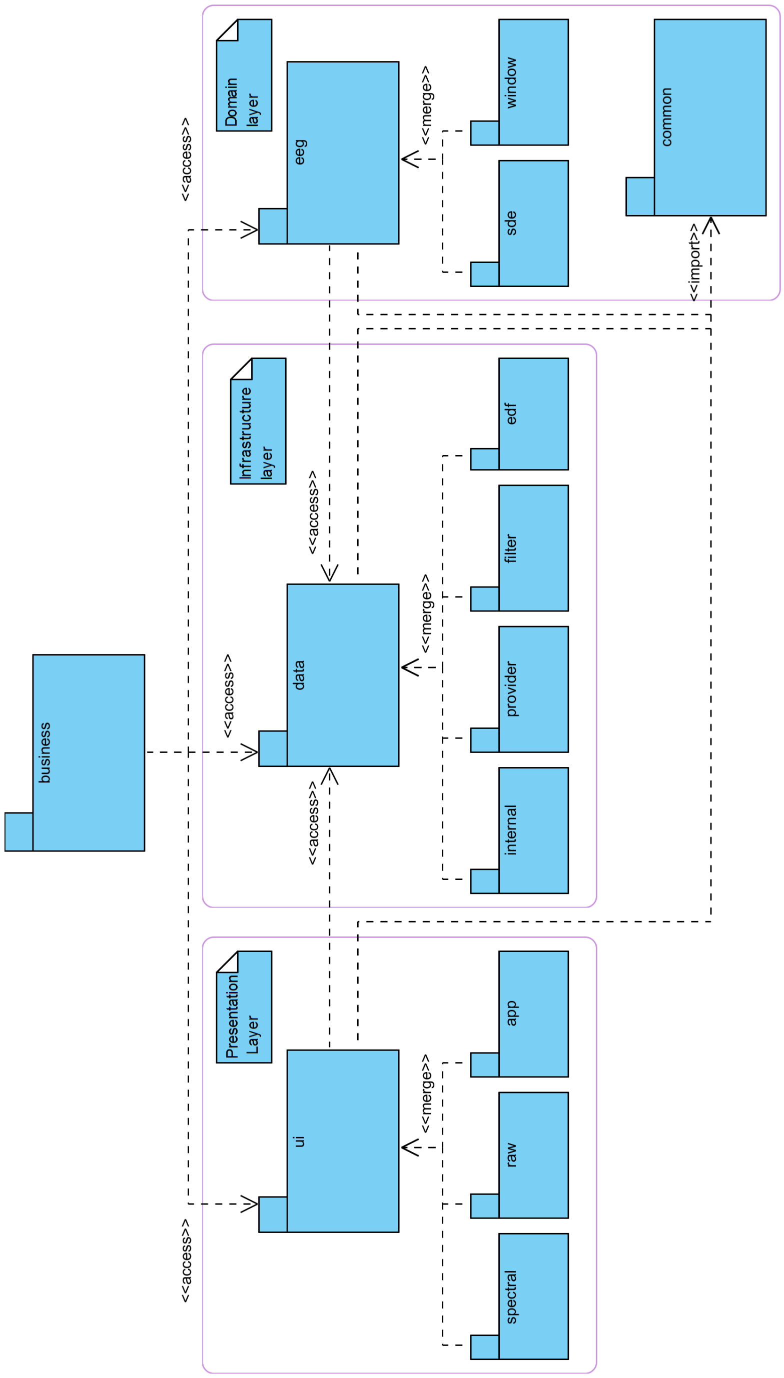

Figure 7.1: Package diagram of Easy EEG Player (diagram was rotated for better readability).

Chapter 8

Implementation

8.1 Infrastructure layer

Infrastructure layer of Easy EEG Player is intended to provide easy, uniform and reliable operations with EEG data and internal data structures. Individual classes and interfaces belonging to infrastructure of application can be found in top level package `cz.vutbr.fit.xuhlia01.bt.data` and its sub-packages as shown on diagram 8.1. Main responsibilities of Infrastructure layer can be divided to following four basic groups:

1. Input data decoding, parsing and conversion
2. Data representation
3. Data persistence
4. Data access

8.1.1 Input data decoding, parsing and conversion

In the process of development of Easy EEG Player, one of the most challenging tasks was to provide reliable and easy-to-use module for input data processing. EEG recordings are distributed in various proprietary file formats supported by vendors providing Electroencephalograph machine they are recorded on. Often these file formats are unknown and their specifications are business secrets of individual vendors. Some formats are supported by majority of EEG analysis tools because vendors providing EEG recordings in these particular formats hold significant share of the market. One of the few successful attempts to provide standard EEG data representation format is European Data Format or EDF introduced in 1992 [12]. Easy EEG Player currently supports two input data file formats EDF and internal data file format EEP with extension „.eep“. Java Interface `DataFileProcessor` has been defined to provide uniform access to data which is not specific for specific data format. As for now, `DataFileProcessor` has two implementations `InternalDataFileProcessor` and `EdfDataFileProcessor`. Implementation of `DataFileProcessor` corresponding with provided data file can be obtained via class `FileProcessorFactory` implementing Factory Design Pattern [8]. Support for new input data formats can be easily added to application by providing corresponding implementation of `DataFileProcessor`.

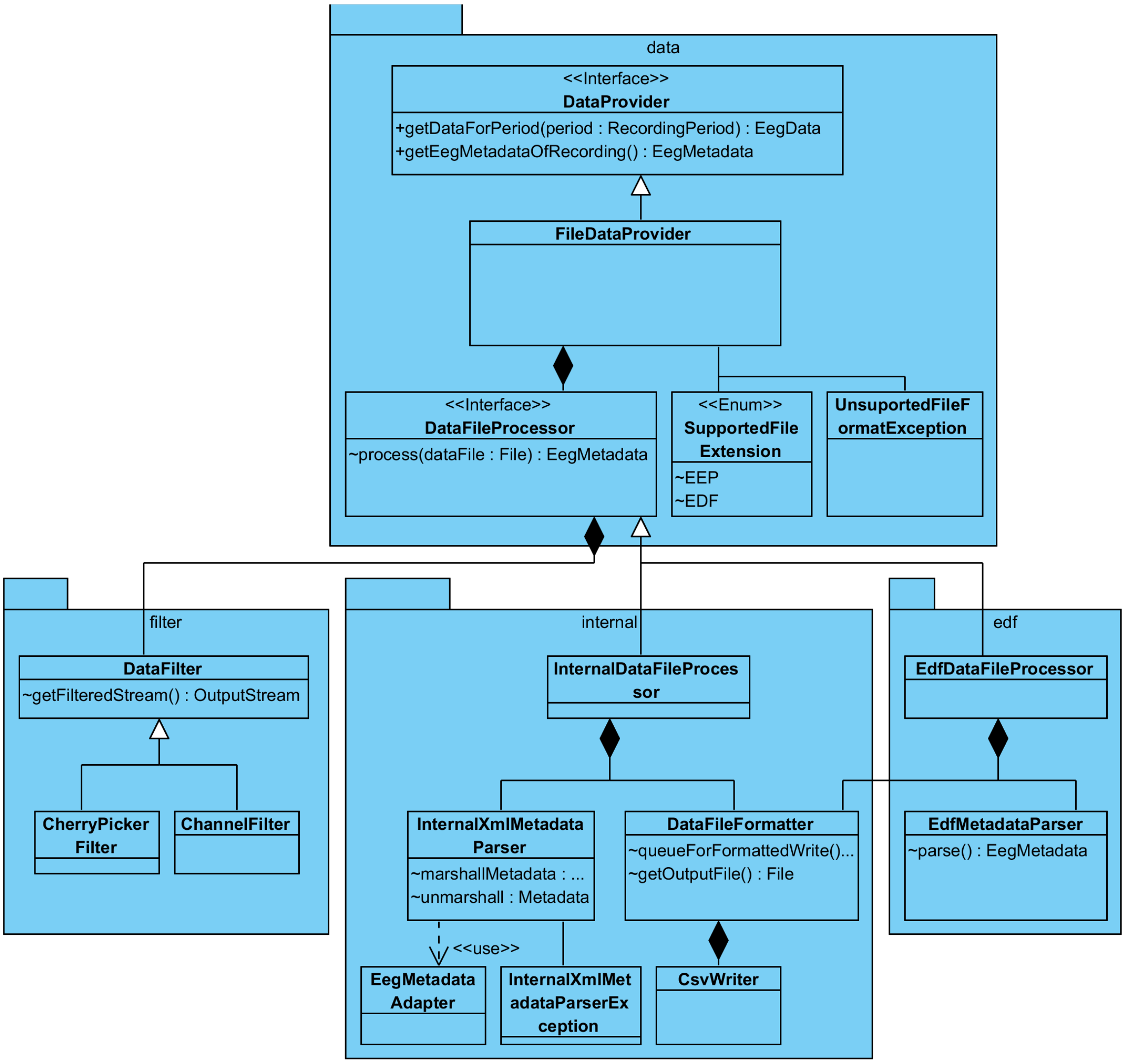

Figure 8.1: Infrastructure layer.

8.1.2 Data representation

For the needs of inter-application communication and data exchange custom internal data format EEP has been devised. EEP format has been influenced by European Data Format (EDF). EDF is multi-purpose data format, suitable not only for EEG but for most medical data working with time-series recordings and thus contain a huge amount of metadata. Internally it includes a header and one or more data records. The header contains some general information (patient identification, start time…) and technical specs of each signal (calibration, sampling rate, filtering etc.), coded as ASCII characters. Data records are stored as multichannel data, allowing different sample rates for each signal, mixed with meta-information about epochs of signal or events occurred during recording. The data records contain data samples as little-endian 16-bit integers [12].

EEP is simplified version of EDF, omitting most of the meta information present in EDF format, that are redundant for Easy EEG Player application, holding only minimal set of information needed, such as sampling rate, duration, number of channels etc. Raw recording data are stored as Comma Separated Values or CSV in strictly defined structure, where individual channels are organized in columns and signal samples are organized in rows. This organization is only logical, without the need to hold metadata about it in actual file. Organization of data in columns and rows, allows efficient orientation in file and retrieval of desired information without the necessity to process redundant data and metadata. All input data are converted to internal data format for further utilization in Easy EEG Player application.

8.1.3 Data persistence

Easy EEG Player often needs to store various data, whether it is several gigabyte long EEG recording in the process of data preprocessing or few kilobyte long snapshot of EEG that should be exported from analysis tool, this task should be simple and storage independent, with all implementation details separated from business logic of application. For this reason `DataStorage` interface has been introduced. Currently this interface has only one implementation and it is `FileDataStorage` which persist all information to data files in EEP format. This interface can be used to provide alternative means of data persistence, such as database or cloud, without affecting the rest of the system. All stored data are identified by unique numeric id by which they can be anytime retrieved again.

8.1.4 Data access

EEG recording typically consists of large quantities of data. Accessing, reading and processing large data sets can be very challenging and resource consuming. Data have to be loaded and processed in chunks, using minimum of memory and CPU resources. In order to achieve this, Easy EEG Player have specialized module for data accessing. This module can be accessed and harnessed through `DataProvider` interface. This interface has been designed to provide uniform access to source data and to hide implementation details of individual data sources. It provides means for easy orientation in the recording sources, retrieval of specific time periods from recording, individual channels or retrieval of metadata about the recording. Currently `DataProvider` has one implementation: `FileDataProvider` reading information from data file.

`DataProvider` interface is entry point to the whole data access layer. It takes raw data source as its initializer and using sub-modules for data conversion, representation and persistence converts external data source to representation usable in Easy EEG Player application. By the means of `DataProvider` interface it is possible to add alternative data sources, such as remote server or other application, without affecting the rest of the system, simply by providing corresponding implementation of `DataProvider` interface.

8.2 Domain layer

In software architecture the domain layer is a collection of entity objects and related business logic forming business model of the application. The main goal of this layer is to create a standardized, separated and consistent set of objects, which could be easily reused in various different projects, while maintaining their full information value. Domain entities should not be coupled to any process definition, so they are intrinsically agnostic and potentially reusable. While designing domain layer of application, special care needs to be put to maintain three basic principles:

1. Coherent, standardized design according to industry standards [26]
2. Design agnostic entities
3. Separation of technology details

Standardized design is the key to successful reusability, consistent style of design and source code as well as use of industrial standards, makes source code easily readable and comprehensible. Design agnostic entities are entities decoupled from any process definition. Such entities could and should be easily reusable in different application with only a little effort. These entities should hold full informational and functional value they represent even when separated from the rest of domain layer. Separation of technology details should ensure that domain layer entities are not coupled to any specific technology such as database, UI, communication channel etc. [8]

Domain layer of Easy EEG Player can be divided to two basic groups: First group are Common classes holding general information about EEG recording, individual channels and raw data, providing information value. These common classes aren't specifically tied to Easy EEG Player and can be reused in any EEG related application. Second distinct group are classes implementing Digital Signal Processing (DSP) operations, present in top-level package `cz.vutbr.fit.xuhlia01.bt.dsp` and its sub-packages. These classes represent general mathematical and physical apparatus, which can be reused in any DSP application. Diagram 8.2 illustrates class diagram of Domain Layer.

8.2.1 Common classes

For the needs of information transfer in application, package `cz.vutbr.fit.xuhlia01.bt.dsp.common` has been created. `Common` package contains classes encapsulating general information about EEG recording and its data. Entities present in this package are used throughout whole application from infrastructure layer to presentation layer. For internal use, all data samples of EEG recording are stored as instances of type `java.math.BigDecimal`, representing immutable, arbitrary precision signed decimal numbers. Class `BigDecimal` supports various formats of numerical value representation and scale. Permissible formats of numerical values are described by following grammar [2]:

BigDecimalString:
    Signopt Significand Exponentopt
Sign:
    +
    -
Significand:
    IntegerPart . FractionPartopt
    . FractionPart
    IntegerPart
IntegerPart:
    Digits

FractionPart:

Digits

Exponent:

ExponentIndicator SignedInteger

ExponentIndicator:

e

E

SignedInteger:

Signopt Digits

Digits:

Digit

Digits Digit

Digit:

any character for which Character.isDigit(char) returns true, including 0, 1, 2 ...

This variability of input value representation makes `BigDecimal` perfect tool for uniform representation of numerical values obtained from various sources, encapsulating implementation details about specific data representation.

Time series of individual samples are represented as instances of immutable class `RecordingPeriod`. This class is specifically designed to check and preserve time invariants and logical preconditions needed to correctly represent time series of EEG samples.

8.2.2 Spectral Density Estimation

Key set of features for EEG signal analysis implemented in Easy EEG Player are methods of Spectral Analysis which enables user to view Power Spectra Density (PSD) of EEG Recording. PSD of EEG recording is computed using methods of Spectral Density Estimation (SDE), implementation of these methods can be found in package `cz.vutbr.fit.xuhlia01.bt. dsp.sde`. Theoretical aspects of implemented SDE methods were introduced in greater detail in Chapter 6.1 Nonparametric methods. Easy EEG Player provides three basic implementations of SDE estimation Periodogram, Bartlett's method and Welch's method sharing common interface `SpectralDensityEstimationMethod` with corresponding implementations in following classes:

1. `Periodogram`
2. `BartlettMethod`
3. `WelchMethod`

8.2.3 Window functions

Easy EEG Player provides number of window functions applicable to EEG recording. Implementations of these functions can be found in package `window`. Theoretical aspects of window functions have been described in more detail in Chapter **??** Window Function. Window functions are represented by enumeration type `WindowType` and interface `WindowFunction` that has following 5 implementations:

1. `RectangularWindow`

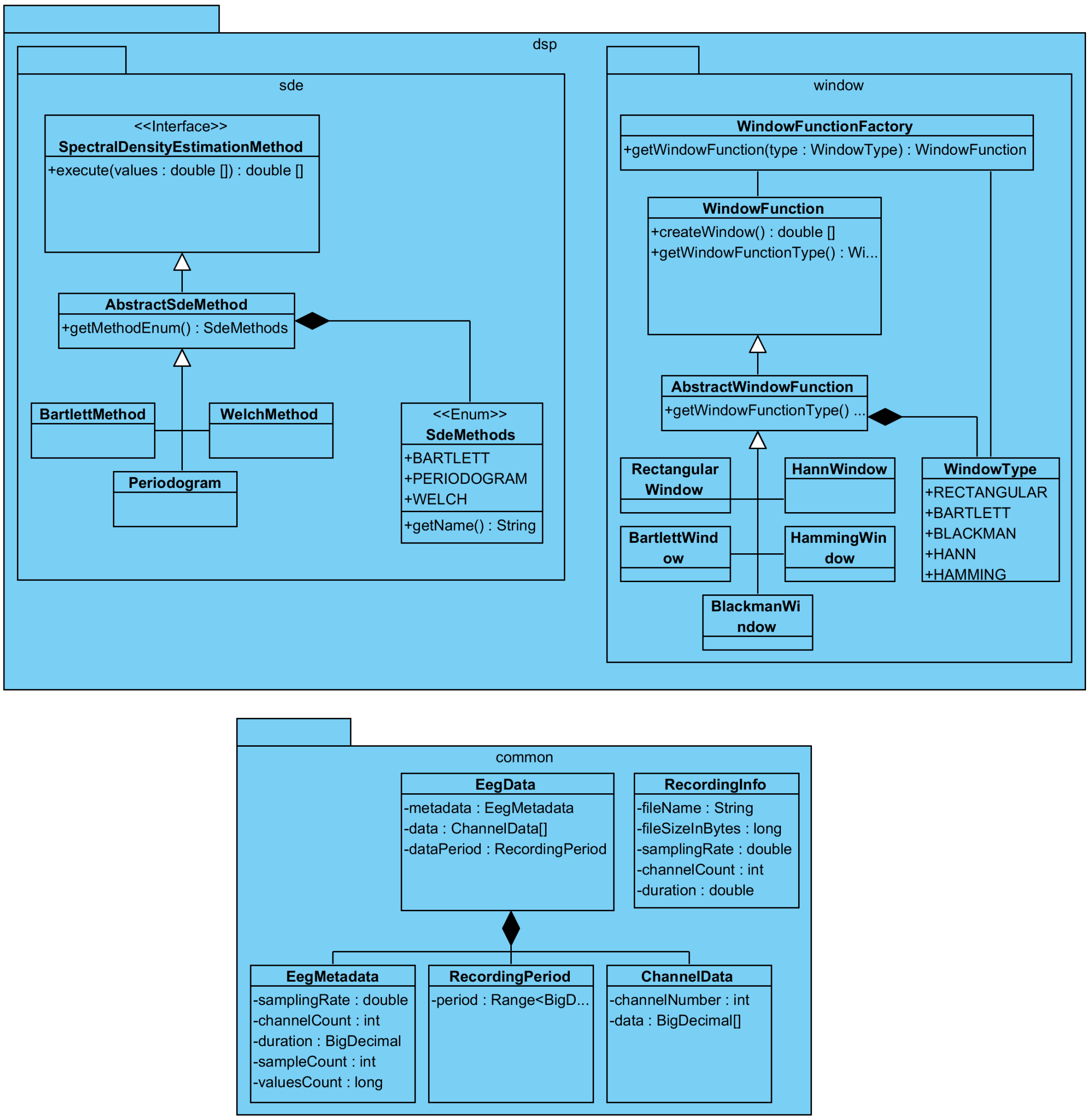

Figure 8.2: Class diagram of Domain Layer.

2. `BartlettWindow`
3. `BlackmanWindow`
4. `HammingWindow`
5. `HannWindow`

Instances of individual windows can be easily obtained by `WindowFunctionFactory` class. Addition of new window functions is possible simply by adding new implementation of `WindowFunction` interface.

8.3 Presentation layer

Last but not the least layer in Easy EEG Player is the Presentation Layer responsible for the interaction between user and application. Presentation layer of Easy EEG Player consists of Graphical User Interface, providing user means to directly visualize EEG recording and results of individual EEG processing and analysis methods in real time. Graphical representation of EEG signal is one of the most important tools in EEG signal analysis, providing lucid view of recorded data and easy way to inspect large quantities of information. Raw recorded signal consists of vast series of numerical data recorded from individual electrodes depicting voltage fluctuations, although reading these raw data is possible, it can be very challenging and inaccurate. On this account, graphical representation of EEG recording has been used as one of the first methods of EEG signal analysis.

Implementation of Easy EEG Player's presentation layer can be found in package `cz.vutbr.fit.xuhlia01.bt. ui` as illustrated on Diagram 8.3.

8.3.1 GUI technology overview

Graphical User Interface of Easy EEG Player was implemented using Java GUI widget toolkit - Swing. Swing was developed to provide a more sophisticated set of GUI components than the earlier Abstract Window Toolkit (AWT), on which it lays its foundations. Unlike AWT components, Swing components are not implemented by platform-specific code. Instead they are written entirely in Java and therefore are platform-independent, such components are typically described by term „lightweight" [13]. Swing provides a native look and feel , such as layout, shapes ,colors, typefaces and the behavior of dynamic elements, that emulates the look and feel of several most widely spread platforms, and also supports a pluggable look and feel that allows applications to have a look and feel unrelated to the underlying platform. Thanks to integrated support of various look and feel profiles, java swing provides intuitive and familiar graphical representation through different platforms.

Swing provides wide variety of standard, highly customizable graphical components, which can be easily used to build robust, user friendly GUIs. Swing directly incorporates most of the basic graphical components and controls such as buttons, menus, labels, frames, windows etc.

One of the key concepts of Java Swing is implementation of Model-View-Controller software design pattern, also known as MVC [8]. MVC conceptually decouples the data being viewed from the user interface controls through which it is viewed.

8.3.2 Chart plotting library

One of the most significant parts of Easy EEG Player's GUI is plotting of charts, thus choosing most suitable charting library was most crucial. There are many charting libraries available for Java available as both commercial and free products. After analyzing available products, as the most suitable candidate, JFreeChart [15] was chosen.

JFreeChart is widely used open source Java charting library distributed under the terms of GNU Lesser General Public License (LGPL) [7]. It supports wide range of charts including: X-Y charts, Pie charts, Bar graphs, Gantt charts, Pareto charts, combination charts, wafer map charts etc. It comes with consistent and well-documented API, flexible design that is easy to extend, and targets both server-side and client-side applications,

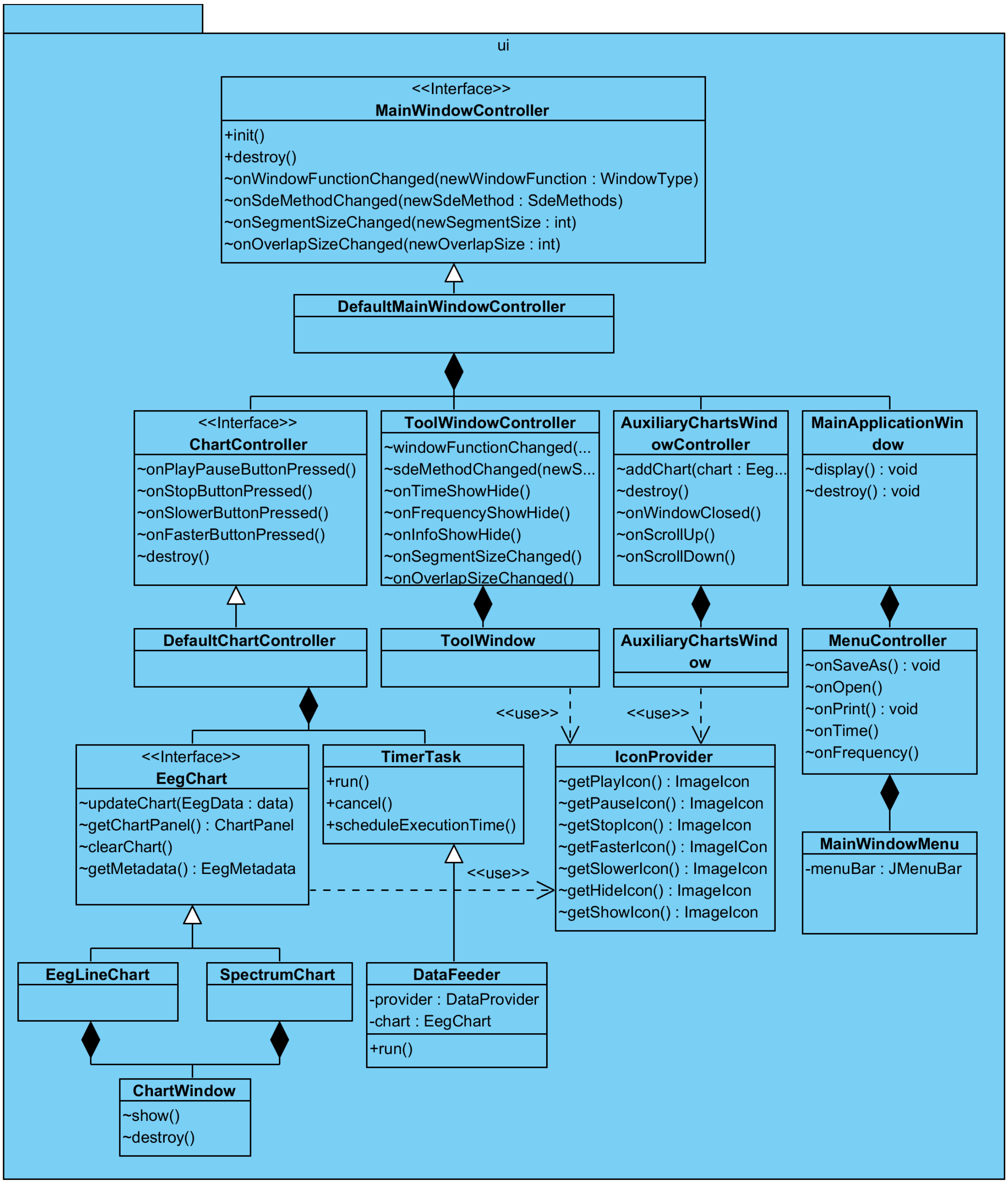

Figure 8.3: Class diagram of Easy EEG Player presentation layer.

support for many output types, including Swing components, image files (including PNG and JPEG), and vector graphics file formats (including PDF, EPS and SVG).

8.3.3 Application GUI

Individual graphical elements of application's GUI, were designed to be intuitive and easy to use, while preserving maximum information value about the signal. Application's GUI can be divided into four distinctive parts:

- Main application window
- Toolbox panel
- Chart panel

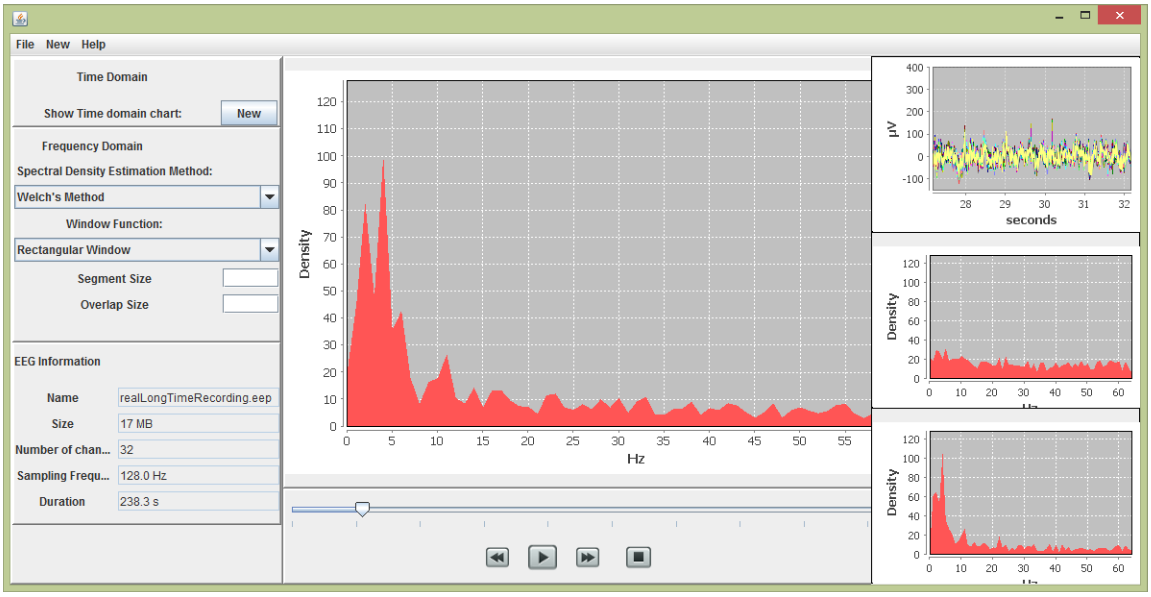

Figure 8.4: Graphical User Interface

Main Application window

Main application window encapsulates all GUI elements of Easy EEG Player, it is responsible for lifecycles of displayed elements and propagation of user events throughout whole GUI. It also serves as layout manager for whole application, responsible for correct (re)sizing and positioning of individual components. This window contains menu bar providing user with single point-of-command for various advanced aspects of this application like:

- Opening new EEG recording
- Saving (as Image file)
- Printing
- Plotting new chart in time/frequency domain

Visual part of Main application window is implemented in classes `MainWindow` and `MainWindowMenu` functional part of window is implemented in classes `MainWindowController` and `MenuController`.

Toolbox panel

Toolbox panel is located on the left side of Application window. Toolbox panel represents graphical representation for set of available EEG analytical tools. It provides simple and intuitive way for user to directly modify properties of used analytical tools, change perspectives or view additional information about currently loaded EEG recording. Toolbox panel has dynamical layout and content, intended to show only relevant information to the user, such as applicable tools or configuration properties directly related to selected analysis tool.

Chart panel

Chart panel can be viewed as a focal point of whole application's GUI. The concept and design of Chart panel is what gave Easy EEG Player its name. Chart panel provides option to view content of EEG recording and applied analysis methods in dynamic manner. Its graphical design has been inspired by the design of video players, providing comparable set of basic recoding manipulation operations. Chart panel enables direct manipulation with displayed EEG recording and its graphical representation enabling following operations:

- Playback of recoding
- Dynamic plotting in real time
- Play/Pause/Stop operation
- Ability to Increase/Decrease playback speed
- Slider for easy orientation in recording in both directions: backward and onward
- Rescaling of individual displayed chart axis
- Zooming in/out in particular regions

Chart panel is implemented using Model-View-Controller software design pattern [8].

Model component is represented by class `DataFeeder`, which notifies associated controller and view about new data, which should be reflected in their state, e.g. plotted on chart (view) or added to slider value (controller). View component is represented by interface `EegChart` with two implementations `EegLineChart` for time domain and `SpectrumChart` for frequency domain. View component is responsible for generating output representation of data obtained from model. Controller component is represented by `ChartController` interface and its implementation `DefaultChartController`. Controller handles user actions related to chart panel and invokes corresponding reactions on model and view.

8.4 Software testing

Software testing is very important part of development lifecycle of application. Concise and throughout tests are one of the basic preconditions of successful software, as they provide overall image about quality of software and may discover hidden bugs. One of the many approaches is test automation - the use of special software to execute and control series of automated tests. Automated tests are based on execution of predefined test cases and the comparison of actual outcomes with predicted results. Automated test can be used to test validity of individual application modules, their contract and error proneness, or simply preserve functionality and expected behavior of individual modules. Usage of automated tests is essential for quality assurance of application and identification of potential errors.

This is why Easy EEG Player application has number of automated tests which are executed as a part of every build of application. For testing of individual classes java unit testing framework TestNG [4] has been chosen. For acceptance tests written in a behavioral-driven development style java port of Cucumber [1] testing framework, Cucumber-JVM, is used.

Chapter 9

Conclusion

In my thesis, I explained fundamental principles of electroencephalography, genesis of biological signals and methodologies of EEG measurement and recording. I provided basic characteristics of EEG recording and EEG classification of well-known and documented brain rhythms and their correlation with various physical and psychological conditions. Besides that, I discussed problems related to recording of EEG, genesis of signal artifacts their sources and influence on recording quality and information value.

Topic of EEG signal preprocessing and analysis was covered in greater detail, considering various methodologies and approaches. After rigorous consideration and consultation with my supervisor, Spectral Analysis was chosen as a corner stone of this thesis. Based on the study of available literature concerning digital signal processing, I proposed and implemented 3 spectral density estimation methods and 5 window functions.

I designed and implemented application Easy EEG Player: standalone, multiplatform tool for EEG analysis and preprocessing, written in Java programming language. This application provides graphical user interface enabling analysis in time and frequency domain. Application is compatible with wide-spread standard EEG data format, which enables import of data from public EEG signal databases without the necessity of any preprocessing. Application was designed with special emphasis on architecture of application. Use of layers design pattern in the architecture has proved to be judicious, especially in final phases of development when individual modules of application were successfully composed together into one complex without significant complications. One of the problems discovered, while testing on real life data, was choice of plotting library JFreeChart. Although JFreeChart is highly sophisticated and widespread charting library, it is mainly designed to work with static charts. When JFreeChart is used for dynamic plotting of charts, it has poor performance and frequent problems. As a more suitable alternative, library Live Graph was chosen, especially for its direct support for real-time data visualization. In simple proof-of-concept application, Live Chart [34] library showed much better results than JFreeChart both in render time and overall stability. In future releases of Easy EEG Player, Live Chart library will be used as main chart plotting library.

During my work on this thesis I was consulting encountered problems with many field experts and hobbyists on various forums focused on digital signal processing and electroencephology. I received many priceless advices and directions. As my contribution to this community, I would like to maintain, develop and share Easy EEG Player as open-source project on web-based hosting service GitHub [9].

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