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A STUDY OF SIGNAL PROCESSING TECHNIQUES FOR MODERN NAVIGATION

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Abstract

Signal processing is an enabling technology that encompasses the fundamental theory, applications, algorithms, and implementations of processing or transferring information contained in many different physical, symbolic, or abstract formats broadly designated as *signals*. It uses mathematical, statistical, computational, heuristic, and linguistic representations, formalisms, and techniques for representation, modelling, analysis, synthesis, discovery, recovery, sensing, acquisition, extraction, learning, security, or forensics.

Keywords: Electrical Engineering, Power Engineering.

Introduction

Signal processing is an enabling technology that encompasses the fundamental theory, applications, algorithms, and implementations of processing or transferring information contained in many different physical, symbolic, or abstract formats broadly designated as *signals*. It uses mathematical, statistical, computational, heuristic, and linguistic representations, formalisms, and techniques for representation, modelling, analysis, synthesis, discovery, recovery, sensing, acquisition, extraction, learning, security, or forensics

Subsequently, broadcasting and recording media made electronics part of daily life. The invention of the transistor and, subsequently, the integrated circuit brought down the cost of electronics to the point where they can be used in almost any household object.

Electrical engineering has now subdivided into a wide range of subfields including electronics, digital computers, power engineering, telecommunications, control systems, RF engineering, signal processing, instrumentation, and microelectronics. The subject of electronic engineering is often treated as its own subfield but it intersects with all the other subfields, including the power electronics of power engineering.

Electrical engineers typically hold a degree in electrical engineering or electronic engineering. Practicing engineers may have professional certification and be members of a professional body. Such bodies include the Institute of Electrical and Electronic Engineers (IEEE) and the Institution of Engineering and Technology (IET).

Application fields of signal processing

- Audio signal processing – for electrical signals representing sound, such as speech or music
- Speech signal processing – for processing and interpreting spoken words
- Image processing – in digital cameras, computers and various imaging systems
- Video processing – for interpreting moving pictures
- Wireless communication - waveform generations, demodulation, filtering, equalization
- Control systems

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- Array processing – for processing signals from arrays of sensors
- Seismology
- Financial signal processing – analyzing financial data using signal processing techniques, especially for prediction purposes.
- Feature extraction, such as image understanding and speech recognition.
- Quality improvement, such as noise reduction, image enhancement, and echo cancellation.
- (Source coding), including audio compression, image compression, and video compression.

CATEGORIES OF SIGNAL PROCESSING

Analog signal processing

Analog signal processing is for signals that have not been digitized, as in legacy radio, telephone, radar, and television systems. This involves linear electronic circuits as well as non-linear ones. The former are, for instance, passive filters, active filters, additive mixers, integrators and delay lines. Non-linear circuits include compandors, multiplicators (frequency mixers and voltage-controlled amplifiers), voltage-controlled filters, voltage-controlled oscillators and phase-locked loops.

"Analog" indicates something that is mathematically represented by a set of continuous values; for example, the analog clock uses constantly moving hands on a physical clock face, where moving the hands directly alters the information that clock is providing. Thus, an analog signal is one represented by a continuous stream of data, in this case along an electrical circuit in the form of voltage, current or charge changes *(compare with digital signals below)*. Analog signal processing (ASP) then involves physically altering the continuous signal by changing the voltage or current or charge via various electrical means.

Historically, before the advent of widespread digital technology, ASP was the only method by which to manipulate a signal. Since that time, as computers and software became more advanced, digital signal processing has become the method of choice.

Discrete-time signal processing

Discrete-time signal processing is for sampled signals, defined only at discrete points in time, and as such are quantized in time, but not in magnitude.

Analog discrete-time signal processing is a technology based on electronic devices such as sample and hold circuits, analog time-division multiplexers, analog delay lines and analog feedback shift registers. This technology was a predecessor of digital signal processing (see below), and is still used in advanced processing of gigahertz signals.

The concept of discrete-time signal processing also refers to a theoretical discipline that establishes a mathematical basis for digital signal processing, without taking quantization error into consideration.

Digital signal processing

Digital signal processing is the processing of digitized discrete-time sampled signals. Processing is done by general-purpose computers or by digital circuits such as ASICs, field-programmable gate arrays or specialized digital signal processors (DSP chips). Typical arithmetical operations include fixed-point and floating-point, real-valued and complex-valued, multiplication and addition. Other typical operations supported by the hardware are circular buffers and look-up tables. Examples of algorithms are the Fast Fourier transform (FFT), finite impulse response (FIR) filter, Infinite impulse response (IIR) filter, and adaptive filters such as the Wiener and Kalman filters.

Literature Review

The neural network is the suggested classifier in this paper. The suggested method in (Ward2000) is based on the Short Time Fourier Transform (STFT) as features and Finite Impulse Response Neural Network (FIRNN) as classifier. For performance evaluation, the authors have utilized the recorded data by Defense Research Establishment Atlantic using underwater son buoys in the Bedford Basin off Nova Scotia, Canada. The authors of (Farrokhrooz 2005) represented the acoustic radiated noise of ships by an AR model with appropriate order and coefficients of this model are used for classification of ships. A Probabilistic Neural Network (PNN) (Duda 2000) is used as the classifier and the AR model coefficients are used as the feature vector to this classifier. The performance of this method is examined by using a bank of real data files. The authors of (Xi-ying 2010) have analyzed the advantages and disadvantages between discriminating features extracted from power spectral density and higher order spectrum, and then combined the power spectrum density estimation and higher order spectrum to extract the distinguishable characteristics synthetically. The proposed classifier is a kind of Back Propagation (BP) neural network (Duda 2000) with some modifications. Two sets of discriminating features proposed in (Farrokhrooz 2011). The first set of features is extracted from AR model of radiated noise and the other is directly extracted from power spectral density of radiated noise. The proposed classifier is the modified probabilistic neural network, which is referred to Multi-Spread PNN (MS-PNN) and a method for estimating the parameters of classifier. Advanced technologies in SONAR systems have been thoroughly presented in (Silva 2009),the underwater wireless telecommunication networks challenges, signal processing techniques and current studies have been discussed in (Stojanovic 2006, Stojanovic 2008),State-of-the-Art in underwater acoustic sensor networks have been studied in (Akyildiz2006) and a survey on underwater networks can be found in (Peterson 2006). In addition, hardware issues have been considered in (Benson 2008) as pioneer works of underwater acoustic networks researches and developments. A secure technique for underwater wireless networks has been recently introduced by (Peyvandi 2010).

Electrophysiological sources of control in current BCIs In BCI systems, electrophysiological sources refer to the neurological mechanisms or processes employed by a BCI user to generate control signals. Current BCIs fall into seven main categories, based on the neuro mechanisms and recording technology they use. In Wolpaw et al (2002) BCI systems are categorized as five major groups. These categories are sensor motor activity, P300, VEP, SCP and activity of neural cell (ANC). In this thesis, two other categories were added: ‘response to mental tasks’ and ‘multiple neuromechanisms’.

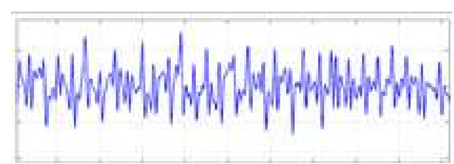
BCI systems that use non-movement mental tasks to control a BCI (e.g. Anderson et al (1995b) and Millan et al (1998)) assume that different mental tasks (e.g. solving amultiplication problem, imagining a 3D object, or mental counting) lead to distinct, task-specific EEG patterns and aim to detect the patterns associated with thesemental tasks from the EEG. BCI systems based on multiple neuromechanisms (e.g. Gysels et al (2005)) use a combination of two or more of the abovementioned Neuro mechanisms in a single design of a BCI system.

Note that although the designs that use direct cortical recordings are included as a separate group, direct cortical recording is a recording technology and not a neuromechanism. As shown in table 2, BCI designs that use sensor motor activity as the neural source of control can be further divided into three sub-categories: those based on changes in brain rhythms (e.g. the mu and beta rhythms), those based on movement-related potentials (MRPs) and those based on other sensor motor activity.

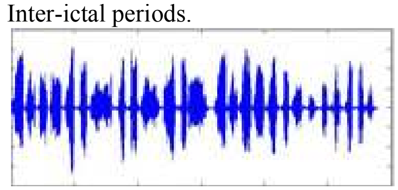
The research in the Signal Processing Laboratory at Tampere University of Technology comprises several areas of interest, including audio signal processing, but an analysis of musical signals had not been attempted before this project. Therefore, the first step in finding music transcription literature was to contact the Acoustic Laboratory of Helsinki University of Technology. The staff of that department provided us with initial references and a wider framework of the research topics that should be involved.

Signal Processing

The students and researchers working on various research areas are privileged to receive the mentorship of Dr. Jayachandran Nair, Distinguished Professor who has hands-on experience in various fields such as Computational Seismology, Communication, Biomedical Engineering, Wireless Sensor Networks and Signal Processing. The research areas of PhD scholars focus on areas such as Biomedical Signal Processing , Speech Signal Processing and Brain Computer Interface.



Research in Biomedical Signal Processing involves EEG (Electroencephalograph) signal analysis of patients using modern Signal Processing methods. The work currently in progress is Epileptic EEG analysis for Classification, Modeling and Estimation of Brain states in Ictal, Preictal and Inter-ictal periods.



The research work on Speech Signal Processing is focused on Speech Recognition, Feature Extraction & Classification of languages particularly-Malayalam phonemes and recognition of Malayalam speech. Even though the primary focus is on Malayalam, the work is intended to be extended to other languages also in future.

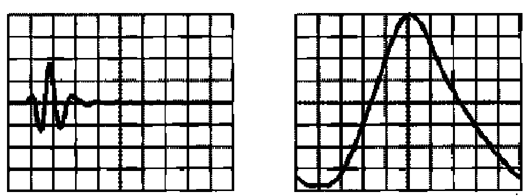
The research work on Brain Computer Interface focuses on the study of EEG signals, use of modern Signal Processing techniques and Machine

Learning Algorithms for Pre-Processing, Removal of Artifacts, Segmentation, Classification and Characterization. The research will also be dealing with classification of signals generated due to normal, event evoked and pathological conditions. The functional aspects of these classified signals are then studied using various Signal Processing Algorithms and Machine Learning Techniques. The effects of external stimulus on EEG will also be studied under supervised and unsupervised condition.

Signal Processing Techniques

Signal processing involves techniques that improve our understanding of information contained in received ultrasonic data. Normally, when a signal is measured with an oscilloscope, it is viewed in the time domain (vertical axis is amplitude or voltage and the horizontal axis is time). For many signals, this is the most logical and intuitive way to view them. Simple signal processing often involves the use of gates to isolate the signal of interest or frequency filters to smooth or reject unwanted frequencies.

When the frequency content of the signal is of interest, it makes sense to view the signal graph in the frequency domain. In the frequency domain, the vertical axis is still voltage but the horizontal axis is frequency.



------Time Domain ---Frequency Domain (Magnitude)

The frequency domain display shows how much of the signal's energy is present as a function of frequency. For a simple signal such as a sine wave, the frequency domain representation does not usually show us much additional information. However, with more complex signals, such as the response of a broad bandwidth transducer, the frequency domain gives a more useful view of the signal.

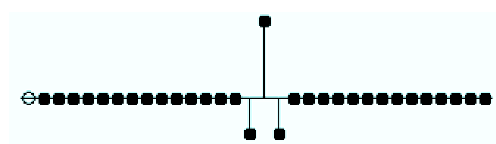
Fourier theory says that any complex periodic waveform can be decomposed into a set of sinusoids with different amplitudes, frequencies and phases. The process of doing this is called Fourier Analysis, and the result is a set of amplitudes, phases, and frequencies for each of the sinusoids that makes up the complex waveform. Adding these sinusoids together again will reproduce exactly the original waveform. A plot of the frequency or phase of a sinusoid against amplitude is called a spectrum.

The following Fourier Java applet, adapted with permission of Stanford University, allows the user to manipulate discrete time domain or frequency domain components and see the relationships between signals in time and frequency domains.

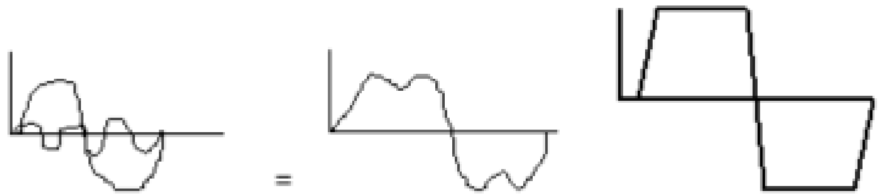
The top row (light blue color) represents the real and imaginary parts of the time domain. Normally the imaginary part of the time domain signal is identically zero.

The middle row (peach color) represents the the real and imaginary parts of the frequency domain.

The bottom row (light green color) represents the magnitude (amplitude) and phase of the frequency domain signal. Magnitude is the square root of the sum of the squares of the real and imaginary components. Phase is the angular relationship of the real and imaginary components. Ultrasonic transducer manufactures often provide plots of both time domain and frequency domain (magnitude) signals characteristic of each transducer. Use this applet to explore the relationship between time and frequency domains.



Baron Jean Baptiste Joseph Fourier was a French mathematician who in his Theorie analytique de la chaleur (Analytical Theory of Heat), developed the technique known as Fourier Analysis. This technique has proven to have application in many other unrelated disciplines including (in our case) the analysis of electromagnetic signals. Fourier's Theorem essentially states that the frequency content of any signal can be described as the sum of a specific set of sine waves. The sine wave is the only pure frequency and any distortion of this shape represents harmonics of some fundamental frequency. Thus any wave, no matter how oddly shaped, can be broken down into its component sine waves.



(a) (b) ©

For example: fig.a shows a fundamental frequency with its 3rd harmonic. Combining them, we get a composite wave form that looks something like fig.b. If we combine enough harmonics of increasing frequency and decreasing amplitude, we end up with a near perfect “square” wave (fig.c). There are two types of Fourier Analysis. The first is Fourier Series analysis for periodic signals (i.e. signals that have exactly the same pattern for each cycle, such as quasars, 60Hz wall current noise or regular heart beats -also referred to as “time invariant” signals). The second form of analysis is called the Fourier transform which deals with non periodic signals such as the human EEG which varies continuously over time. Thus the Fourier transform of a non- periodic signal produces a continuous transform. When the input signal is periodic (repeats itself exactly with each cycle) its frequency content can be represented by a discrete set of numbers called the Fourier series coefficients. They signify the “weight” given each frequency that is required to reconstruct the original signal. Furthermore, the frequencies that correspond to these different coefficients are harmonically related; each being an integer multiple of some fundamental frequency. This thesis will confine itself primarily to exploring the background and application of the Fourier transform since this is the signal processing technique utilized in neuro feedback (the EEG being intensely non-periodic).

The Fourier transform is one of the most commonly used methods of signal analysis. It is simply a mathematical transformation that changes a signal from a time domain representation to a frequency domain representation thereby allowing one to observe and analyze its frequency content. Plotting a Fourier transform gives us a visual representation of the relative proportion of different frequencies in an input signal. Some examples: the FT of single sine wave would appear as a single spike (see below), indicating that only one frequency was present. Similarly, the noise from florescent lights appears as a prominent peak at 60 Hz. Where as the processing of a periodic signal with the Fourier series produces a discrete set of coefficients, a non-periodic signal requires a mathematical tool that will produce a continuous transform (i.e. one that changes continuously over time instead of the “photo-like” transform of the periodic signal) . The Fourier transform therefore, requires something a bit more powerful. When moving from the time domain x(t) into the frequency domain X(f), the time function x(t) must be evaluated for all values of t (time). The following is the actual Fourier transform which illustrates the mathematical relationship between the time domain x(t) and the frequency domain X(f).

$$X(f) = \int x(t)[\cos(-2\pi\, ft) + j sin(-2\pi\, ft)]dt$$

The product of the time function x(t) and a [complex trigonometric expression] yield the frequency function X(f) when integrated over time t for a specific frequency f (Integration involves finding the area defined by a specific function over small increments, in this case dt.) Go over that last sentence slowly three more times and then please note: Although mathematical formulas will appear in this paper they are more for historical significance than anything else. The emphasis will be on developing an intuitive understanding of the concepts discussed.

Methods

Time-Frequency Methods The localization of a specific frequency at a particular time is the basic principle of time frequency analysis. The wavelet transform is a subclass of the general class of time-frequency domain analysis. It can be shown that the human ear is mathematically equivalent to a wavelet transformer. The wavelet transform is proving to be a highly useful tool in signal and image analysis, with hundreds of papers presented on the subject. The International Society for Optical Engineering (SPIE) has devoted four conferences on wavelet applications to date. Consider the continuous Fourier Transform,

$$'(\omega) = \int_{-\infty}^{\infty} f(t) e^{-j\omega t} c$$

is taken over all time. The details of exactly when certain events take place, and the effects of those events on the signal, are smeared over the duration of the signal. This is due to the infinite support, or time duration, of the exponential kernel $e^{-j\omega t}$C.

The continuous wavelet transform (CWT) is

$$ {}_{\psi}(b, a) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-b}{a}\right) $$

where the wavelet kernel $\frac{1}{\sqrt{|a|}} \Psi\left(\frac{t-b}{a}\right)$ has replaced the exponential kernel of the FT, and is specified to have finite support, or finite duration in time and bandwidth. Thus, by scaling and shifting the wavelet, selective portions of the time-frequency plane may be analyzed.

Several approaches may be applied in the analysis of the mine data with the purpose of developing a detection/classification scheme. One-Dimensional analysis may be applied to the he individual A-Scans or slices of the C-Scans. 1- or 2-D analysis may be applied to the B-Scans or C-Scans. This is clarified in the following examples.

Electromagnetic Resonance Methods

In 1971 Baum postulated that the solution for electromagnetic interaction of currents due to an incident field, and the resulting scattered fields, could be formulated in terms of the singularities (poles) of the current distribution in the complex plane (The Singularity Expansion Method, or SEM). A key result of this postulate is that the pole locations, and resulting summation of exponentially damped sinusoids in the time domain, would be invariant with target orientation relative to the radar. SEM parameters for conducting bodies of revolution (BOR) were determined, and a classification method was devised which permitted the discrimination between two classes of conducting BOR. Studies of SEM parameters applied to dielectric materials have been conducted, but, as shown, the SEM parameters of conducting BOR vary considerably with burial depth when the object is placed in a lossy dispersive medium such as the ground. Additional research is required to determine whether electromagnetic resonances are a viable means of detection/classification of buried objects.

RESULT & DECISSION

In the second case one realization of a Rayleigh fading process is generated. The statistics of the resulting process is estimated and compared with the analytical expected statistics. Finally, the last test case verifies that MC simulation gives the expected BER for transmission of π/4-DQPSK modulated symbols over a two-tap Rayleigh fading channel. Note that no equalizer is needed in these test cases since π/4-DQPSK modulation is used, where the information lies in the phase changes (relative phase) and not in the phase itself (absolute phase).

Case 1 - Simulation of an AWGN Channel

In the first test case we consider a system with a channel that is subject to AWGN only, and verify the simulation results by comparing them with the theoretical results of the chosen modulation scheme. We use a setting where we transmit 10000 π/4-DQPSK modulated symbols in each of the 10 Monte Carlo simulation runs at the rate of 24300 symbols/second. In Figure we show the BER curves for an over sampling factor of 13 employing SRRC filtering with roll-off factor 0.2. It is evident that the simulated and analytical BER are in good agreement. Consequently, we conclude that the simulator, with a high-degree of confidence, is correctly implemented.

Conclusion

The performance of wireless communications systems depends greatly on the propagation environment and the radio channel condition. An understanding of the wireless channel characteristics and the associated parameters is, therefore, an essential step in the simulation, analysis and design of wireless communication systems. This consequently allows the successful testing and evaluation of the performance of present and future wireless communication systems where the multimedia services and the advanced signal processing algorithms are expected to play a major role. This article presented physical, mathematical and statistical analysis of these systems. In addition, we have also presented an efficient and simple approach using Matlab for the simulation of digital wireless systems and compared its results with the theoretical analysis. The simulator can be easily adapted for the proper analysis and evaluation of the performance of emerging wireless technologies and services.

References

1. J. Alegre, M. Manzano, A. Pellacani, J. A. Lopez-Salcedo, E. Guerrero, G. Seco-Granados, “D2: Definition of the GNSS receiver module. Architecture and algorithms (155 pages)”, Funding source: ESA project Moon-GNSS: Weak Signal Navigation on the Moon, Jun 03 2013.
2. Y. Alaoui, E. Aguado, J. A. Lopez-Salcedo, G. Seco-Granados, E. Domínguez, “D22: EMSAU validation plan (73 pages)”, Funding source: EC project iGNSSrx, Jan 29 2013.
3. D. Lowe, Y. Alaoui, P. Vermaat, E. Domínguez, G. Seco-Granados, J. A. Lopez-Salcedo, E. Aguado, “D20: EMSAU

requirements document (62 pages)", Funding source: EC project iGNSSrx, Jan 24 2013.
4. J. A. Lopez-Salcedo, J. Vilà-Valls, G. Seco-Granados, F. Nunes, F. Sousa, R. Sarnadas, T. Ferreira, "TN2: Techniques definition and preliminary analysis (201 pages)", Funding source: ESA project ROCAT: Robust Carrier Tracking, Jan 16 2013.
5. E. Aguado, Y. Alaoui, G. Seco-Granados, J. A. Lopez-Salcedo, E. Domínguez, D. Lowe, "D21: EMSAU design justification (76 pages)", Funding source: EC project iGNSSrx, Nov 22 2012.