DE-NOISING METHOD FOR CONTINUOUS GLUCOSE MONITORING (CGM) SIGNAL WITH IMPROVED MORLET WAVELET FILTER

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

by
CEMAL KAVALCIOĞLU

In Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Electrical & Electronic Engineering

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

We certify this thesis is satisfactory for the award of the degree Doctor of Philosophy in Electrical and Electronic Engineering

Examining Committee in Charge:

Prof. Dr. Fahreddin Sadıkoğlu	Committee Chairman, Department of Computer Engineering, NEU
Prof. Dr. Bülent Bilgehan	Supervisor, Department of Electrical & Electronic Engineering, NEU
Prof. Dr. Sezai Dinçer	Department of Electrical & Electronic Engineering, NEU
Assoc. Prof. Dr. Ali Özyapıcı	Faculty of Arts and Sciences, Department of Common Courses, Cyprus International University
Assoc. Prof. Dr. Eser Gemikonaklı	Department of Electrical & Electronic Engineering, Girne Üniversitesi

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: Cemal Kavalcıoğlu

Signature:

Date:

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To my family…

ABSTRACT

Diabetes Mellitus (DM), a chronic, metabolic disorder, is a rapidly growing global problem with great social, health and economic consequences. In 2010, it is estimated that 285 million people (6.4% of the adult population) were exposed to this disease. This number is increased to 415 million in 2017. Without better control or recovery it is estimated that it will increase up to 642 million by 2040. Diabetes is the most important endocrine system disease. It is caused by impaired insulin levels in the blood. The insulin hormone is secreted from the pancreas. To avoid the negative effects of diabetes, human beings use continuous glucose monitoring systems to measure blood glucose concentrations in real-life conditions. In such patients, blood data are recorded within 24 hours to prove the accuracy of treatment. In practical applications, the data are known to be added to the noise due to various reasons. Minimizing the noise level in the data ensures the success of the treatment. For this purpose, the application was realized by providing an additional contribution to Morlet wavelet based on continuous wavelet transform. The continuous wavelet transform (Morlet Wavelet) is a powerful and formal tool for the analysis of signals that must be evaluated according to the time-frequency content, allowing a signal to be fully represented by allowing the translation and wavelet scale to change continuously. Undoubtedly, it is the coefficient values that make the wavelet the most effective one. Different methods are used in the calculation of coefficient values in the literature. The method foreseen in this research is provided by the method applied for the first time in the scaling matrix which increases the compatibility of the coefficients. The deviations in the calculation of the coefficient values in the classical method were minimized by the prescribed method. The proposed method is compared with the widely used Savitzky-Golay filter and the standard Morlet wavelet in the literature. The superiority of the new method is tabulated with PSNR and relative error values. The actual data obtained for this research was approved by the Near East University Hospital Ethics Committee.

Keywords: Continuous glucose monitoring(CGM); Savitzky-Golay Filter; Noise Effects; Noise Reduction; Continuous Wavelet Transform (CWT); Type 1 Diabetes; Fast Fourier Transformation; Morlet wavelet.

ÖZET

Diabetes Mellitus (DM), kronik, metabolik bir hastalık, büyük sosyal, sağlık ve ekonomik sonuçlarla birlikte hızla büyüyen bir küresel sorundur. 2010 yılında 285 milyon insanın (yetişkin nüfusun% 6,4'ü) bu hastalığa maruz kaldığı tahmin edilmektedir. Bu sayı 2017 yılında 415 milyona yükselmiştir. Daha iyi kontrol veya iyileşme olmadan 2040 yılına kadar 642 milyona çıkacağı tahmin edilmektedir. Diyabet en önemli endokrin sistem hastalığıdır. Kandaki bozulmuş insülin seviyelerinden kaynaklanır. İnsülin hormonu pankreastan salgılanır. Diyabetin olumsuz etkilerini önlemek için, insanlar gerçek yaşam koşullarında kan şekeri konsantrasyonlarını ölçmek için sürekli glikoz izleme sistemlerini kullanır. Bu tür hastalarda, tedavinin doğruluğunu kanıtlamak için 24 saat içinde kan verileri kaydedilir. Pratik uygulamalarda, verilerin çeşitli nedenlerden dolayı gürültüye ekleneceği bilinmektedir. Verilerdeki gürültü seviyesinin en aza indirilmesi, tedavinin başarısını garantiler. Bu amaçla, sürekli dalgacık dönüşümü temelinde Morlet dalgacıklarına ek bir katkı sağlayarak uygulama gerçekleştirilmiştir. Sürekli dalgacık dönüşümü (Morlet Dalgacık), zaman-frekans içeriğine göre değerlendirilmesi gereken sinyallerin analizi için güçlü ve resmi bir araçtır, çeviri ve dalgacık ölçeğinin sürekli değişmesine izin vererek bir sinyalin tam olarak temsil edilmesini sağlar. Kuşkusuz dalgayı en etkili kılan katsayı değerleridir. Literatürde katsayı değerlerinin hesaplanmasında farklı yöntemler kullanılmaktadır. Bu araştırmada öngörülen yöntem, katsayıların uyumluluğunu artıran, ölçeklendirme matrisinde ilk defa uygulanan yöntem ile sağlanmaktadır. Klasik yöntemde katsayı değerlerinin hesaplanmasındaki sapmalar öngörülen yöntemle en aza indirilmiştir. Önerilen yöntem literatürde yaygın olarak kullanılan Savitzky-Golay filtresi ve standart Morlet dalgacık ile karşılaştırılmıştır. Yeni yöntemin üstünlüğü, PSNR ve göreceli hata değerleri ile gösterilmiştir. Bu araştırma için elde edilen gerçek veriler, Yakın Doğu Üniversitesi Hastane Etik Kurulu tarafından onaylanmıştır.

Anahtar Kelimeler: Sürekli glikoz izlemesi (CGM); Savitzky-Golay Filtresi; Gürültü Etkileri; Gürültü Azaltma; Sürekli Dalgacık Dönüşümü (CWT); Tip 1 Diyabet; Hızlı Fourier Dönüşümü; Morlet dalgacık.

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LIST OF ABBREVIATIONS

AACE:	American Association of Clinical Endocrinologists
ADC:	Analog to Digital Converter
AGC:	Automatic Gain Control
AM:	Amplitude Modulation
AWGN:	Additive White Gaussian Noise
BG:	Blood glucose
CGM:	Continuous Glucose Monitoring
CGMS:	Continuous Glucose Monitoring Systems
CHO:	Carbohydrate
CWT:	Continuous wavelet transform
DC:	Direct Current
DM:	Diabetes Mellitus
DSP:	Digital Signal Processing
EQ:	Equalization
FFT:	Fast Fourier transform
FIR:	Finite Impulse Response
FM:	Frequency Modulation
HbA_{1C}:	Hemoglobin A1c
HCP:	Health professionals
IC:	Integrated Circuit
IIR:	Infinite Impulse Response
ISF:	Interstitial Fluid
ISIG:	Electrical output of the glucose sensor
LPF:	Low-pass filter
MATLAB:	Matrix Laboratory
MD:	Mean Difference
PC:	Personal Computer
PSNR:	Peak Signal Noise Ratio
RF:	Radio Frequency
SMBG:	Self Monitoring Blood Glucose
SNR:	Signal to Noise Ratio
STFT:	Short-time Fourier transform

SVD:	Singular Value Decomposition
SVR:	Support Vector Regression
USB:	Universal Serial Bus
WHO:	World Health Organization

CHAPTER 1

INTRODUCTION

Diabetes is an autoimmune system disease due to insufficient pancreatic secretion in insulin secretion. Insulin is a hormone secreted in beta cells in the pancreas that is found in the back of the stomach in our body, leaves the sugar in the blood to enter the cell, thus the level of sugar in the blood is reduced. The most important fuel for the human is blood glucose, by insulin and negative feedback system its level is controlled strictly. Solid glycemic control has been shown to significantly reduce short and long-term complications of diabetes and has been shown in studies of diabetes control and complications. The normal range of blood sugar should be between 70-120 mg/dL.

The decrease in the amount of glucose in the blood is called hypoglycemia, when the blood glucose level is between 50-70 mg/dl stimulation of the sympathetic nervous system, sweating, weakness, palpitations, paleness of color, tremors, feeling of faintness and acute hunger is seen. Hyperglycemia is a condition in which blood circulates excessively in the blood plasma. This is usually a blood sugar level of higher than 200 mg/dl, but even higher values such as (~250-300 mg/dl) may not be noticed, resulting in retinopathy, nephropathy, and diabetic neuropathy, leading to prolonged vascular complications.

Diabetes refers to a group of diseases that affect the body's blood glucose. Blood glucose is vital for our health because it is a significant source of energy for the cells that make up the muscles and tissues. It is also the main fuel source of the brain. The underlying cause of diabetes varies by species. However, regardless of the type of diabetes, blood can cause excess sugars. Too much sugar in the blood can cause serious health problems. In 2000, it was stated that 366 million people would be affected by the disease in 2030. In 2002, the number of people affected by the disease exceeded 200 million and in 2010, 285 million people, 6.4% of the adult population in the world were affected by this disease, which reached 415 million in 2017 and is expected to rise to 642 million by 2040 (Shi & Hu, 2014). Diabetes can lead to possible complications such as heart disease, vascular diseases, vision loss, renal failure, and nervous system diseases (Diabetes Fact sheet N.312.WHO, 2013). The most common diabetes types are as follows:

- Type 1 diabetes is a status in which the pancreas in our body is damaged as a result of autoimmune events and cannot produce insulin. Insulin therapy in type 1 diabetes is essential from the very beginning, and these patients cannot maintain their lives if they do not use insulin.
- Type 2 diabetes is more common in the community and accounts for about 90% of patients. Type 2 diabetes is a form of diabetes in which insulin resistance, predominantly genetic factors, is involved in a large proportion of patients, but also in which insulin secretion is involved.

As a result, monitoring is necessary to ensure proper glucose level control, thus improving life quality. At discrete time instances, blood glucometers are utilized to measurements. While continuous glucose monitoring (CGM) equipment supply invasive minimal mechanism to measure and record the status of the patient's current glycemic as often as each minute. Throughout the day diabetic patients provide maximum information about changes in blood glucose, leading to optimal treatment decisions. A variety of factors may contribute to hyperglycemia in individuals with diabetes mellitus, which include choices of food, and physical activity, including diseases, non-diabetic drugs, or not taking a sufficient amount of glucose-lowering drugs. Hyperglycemia therapy is important because, if not treated, hyperglycemia can be severe and lead to substantial complications, such as urgent care similar to diabetic coma. From the view of long-term, permanent hyperglycemia can cause complications that affect your nerves, your eyes, your kidneys, and your heart, even if they are not severe. By regular blood glucose monitoring and adjusting insulin dosage accordingly, intensive insulin therapy can decrease the risk of these complications by providing nearly normal levels of blood sugar levels. This dissertation focuses on the different types of errors in continuous glucose monitoring data and the solution that can be performed on continuous glucose monitoring. Because glucose is an important fuel for humans, the level, should be kept at a reliable range. CGM sensors are utilized to monitor the blood glucose level. The most significant error is the random audio component which is connected to sensor physics that affects continuous glucose monitoring devices. Continuous glucose monitoring signal is affected by high-frequency random fluctuations. Measurements have been unreliable, because of these noises at the sensor output. These noise components must be extracted before any signal processing application. DSP is committed to analyzing and modifying a signal to optimize or improve its effectiveness or performance. It involves applying different mathematical and computational algorithms to analog and digital signals to produce a signal to a higher standard than the original signal. Digital Signal Processing is mainly used to identify errors and filter and compress analog signals in transit.

Our body often reports data about our health. These data include heart rate, oxygen nerve conduction, saturation levels, blood glucose, blood pressure, brain movement, and so on, measured by physiological materials. Traditionally, such measurements are taken at specific times and marked on the patient's schedule. Biomedical signal processing includes the analysis of these measurements to provide useful information to these clinicians to decide. Engineers have discovered new techniques to manipulate these signals with various mathematical formulas and algorithms.

The turning point in the treatment of diabetes was the discovery of insulin and the introduction of insulin therapy (American Diabetes Association, 2014). Monitoring blood glucose is the cornerstone of diabetes management and monitoring blood glucose levels by patients significantly changes diabetes care (Boland et al., 2001; Karter et al., 2001; Uwadaira et al., 2015). Blood sugar test results are important in determining the diet of the diabetic patient, determining the amount and type of the drug, and maintaining the recommended exercise. Blood glucose self-monitoring is defined as coping with diabetes and regulating glycemic control. Healthy diabetics should keep blood glucose levels as close to normal as possible. This situation allows for the recognition and prevention of hypoglycemia and hyperglycemia and reducing the risk of long-term complications of diabetes plays an important role. To date, all the equipment for blood testing at home is divided into two parts as invasive and non-invasive. Invasive contact devices are based on taking blood, so you need to pierce your finger (Kasemsumran et al., 2006; Jin et al., 2014). If the non-contact glucometer takes the biological fluid for analysis from the patient's skin, the sweat secretions are often treated. Such an analysis is less informative than a blood test (Chuah et al., 2010). Type 1 diabetes patients should monitor levels of blood glucose continuously because they cannot produce insulin and if necessary may take insulin at doses specified by their physician (Cobelli et al., 2011). Although this process may seem simple, patients may forget to take insulin or use the wrong dose of insulin. An artificial pancreas designed to mimic the function of a pancreatic in a healthy individual; It consists of an insulin pump placed under the skin and a small system that continuously monitors blood sugar. An artificial pancreas, which is connected via Bluetooth to smartphones, shares the data of blood glucose in the smartphone and learn how much insulin should be pumped into the body with the specific application to the artificial pancreas on the phone. The artificial pancreas tries to keep the blood glucose levels at the levels predicted by the algorithms rather than directly. The most important components of an artificial pancreas are CGM devices and CGM devices are an important option for self-monitoring of conventional blood glucose (Klonoff, 2005; Zhao, 2015; Zhao, 2017; Mastrototaro, 2000). Continuous Glucose Monitoring (CGM) devices follow day and night glucose levels. Continuous Glucose Monitoring systems provide glucose measurements at regular intervals of 24 hours per day. Recorded values are converted to dynamic data and glucose direction and exchange rate reports are generated (Ward, 2004). Cobelli et al. (Facchinetti and Guerra, 2013; Facchinetti et al., 2013; Facchinetti et al., 2015) have been indicated that continuous noise monitoring sensors affected by random noise can significantly affect performance. Digital filtering can be utilized to minimize the random error noise content and improve the quality of the signal. It is necessary to extract random noise from the digital filter to improve continuous glucose monitoring signals quality. The purpose of digital filters can be used for various purposes, such as strengthening or attenuating certain frequencies of the signal, completely suppressing, isolating. Digital filters carry the general advantages of digital systems and are widely used, especially in that the filter characteristic is very simple to change. A low pass filter (LPF) transmits signals with a frequency less than a selected cut frequency and weakens signals with frequencies higher than the cut-off frequency. (Steil et al. 2010; Kaya &İnce, 2012). The precise frequency response of the filter depends on the filter design. LPF is one of the common methods used to remove noise from measured signals. (Panteleon et al., 2000). One of the main disadvantages of this filter is that it causes a large delay to distort actual signals. Delayed signals are unnecessary to stimulate abnormal glycemic events. To reduce random noise, Medtronic miniMed is an FIR (finite impulse response) filter, where filtered signals and z_k values are measured in the real-time continuous glucose monitoring system (Steil et al., 2010; Kaya & İnce, 2012) where $z_k = b_0 z_k + b_1 z_{k-1} + \cdots + b_M y z_{k-M}$is widely used (Panteleon et al.2003). In practice, a seventh stage filter was normally utilized (Knobbe & Buckingham, 2005). DexCom utilized an infinite impulse response filter (IIR), defined as in the data collection system $z_k = -b_1 z_{k-1} - \cdots - +b_N z_{k-N} + c_0 y_k + c_1 y_{k-1} + \cdots + c_M z_{k-M}$. (Knobbe & Buckingham, 2005). The Dexcom Seven Plus continuous glucose monitoring system is also used to elaborate this equation (Brauker et al., 2005). The most important problem with these methods is that no criterion determines how to define the appropriate parameters in the filtering of the measured signals. To improve filter performance, another method called Kalman filter is considered. To status forecast, the Kalman filter is known as a common approach that uses recursive maximum likelihood. Initially, Bequette (Bequette, 2004) utilized the Kalman filter to balance blood glucose with a delay in carrying subcutaneous glucose and predict future blood glucose. The Kalman filter was then utilized to address continuous glucose monitoring data by the subsequent development of the model developed by Knobbe and Buckingham (Knobbe & Buckingham, 2005). However, since the filter parameters are fixed after determining, they do not reflect the noise variability. Noise level may vary between variability between individuals (overtime for the same patient) and interpersonal variability (from patient to patient) (Facchinetti and Sparacino et al., 2013). The stabilizer module has been an important part of the "smart sensor" to develop the CGM sensor's accuracy. However, it constantly calculates the methods and updates the filter parameters, but it does not always change in the practical application, which increases the noise complexity and brings a heavy load. The most important problem here is to develop an appropriate evaluation rule to determine if the noise level has changed to adjust the filter parameters. In this dissertation, the suggested method with the real data is compared with the Savitzky-Golay filter and the standard Morlet wavelet to prove its superiority. In this research, an improved Morlet wavelet which is a powerful tool for analyzing according to time-frequency content has been proposed.

1.1 The contribution of the Thesis

The data used in the study are actual measurement values. The patient profile and details of the data are described in the section on obtaining the blood glucose concentration data of the dissertation. In such studies, the noise profile is known to be of Gaussian type. Thus, Gaussian, which is parallel to the real noise in the data analysis, was chosen. The standard application was used in the analysis of the results. However, the data were analyzed with values above the noise levels used in other articles and the validity of the applied method has been proven.

The major contributions to this dissertation are summarized as follows:

- The proposed method ensures that the parameters that make up the filter are more optimal so that the error at the filter output of the continuous glucose monitoring signal is minimized.
- Considering the simplicity of the proposed method and not increasing the processing time, it will make it more efficient and economical in real-time operations. Compared to other alternatives, it will stand out with this aspect.
- As a result of the proposed method, the noise level is reduced to the lowest level compared to the classical methods, which reduces the fluctuations, fast climbing, and sensitivity of the values which have negative effects on the signal and it has been proved its superiority with relative error calculations.
- Thus, continuous glucose monitoring signal analysis, which is closer to the real data free of noise, provides a high validity rate of treatment for the patient.

1.2 Thesis Overview

Other parts of the dissertation are as shown below:

- Chapter 2 relates to state-of-the-art literature on historical perspective and literature review about Diabetes Mellitus, Signal filtering, Fourier transform, and wavelet transform.
- Chapter 3 explains Continuous Glucose Monitoring Systems.
- Chapter 4 is about noise, noise types, additive white gaussian noise, and, filter design propertıes.
- Chapter 5 explains types, transforms of wavelet, Morlet wavelet filter, and calculation of Morlet wavelet parameters.
- Chapter 6 presents the most significant objective of this dissertation, the fundamental objective of this dissertation is to noise reduction methods, setting parameters and experimental outcomes for continuous glucose monitoring(CGM) signal using the MATLAB environment.
- Chapter 7 presents conclusions and suggestions.

CHAPTER 2

HISTORICAL PERSPECTIVE AND LITERATURE REVIEW

2.1 Overview

In this section, historical perspective and literature review about Diabetes Mellitus, Signal filtering, Fourier transform, and wavelet transform have been focused.

2.2 Diabetes Mellitus (DM)

Diabetes is known as a complex, chronic disease. In 1993, Black & Matasarin-Jacobs discovered diabetes as a metabolic disorder characterized by glucose intolerance. Systemic diseases caused by supply-demand imbalance are called insulin (Friderichsen and Maunsbach, 1997).

- 7.0 mmol/L or upward is the glucose of fasting plasma
- 11.1 mmol/L or upward is the glucose of causal plasma

were defined to be a metabolic criterion, in order to diabetes. (Baumann et al., 2002). Insulin is a hormone secreted by beta cells in the body organ called pancreas located under the stomach and behind our body. It allows the sugar in the blood to leave the blood and enter the cell. Thus, the level of sugar in the blood is not increased, adjusts blood glucose levels that regulate glucose storage and production. To reply to a reduction of insulin or insulin produced in the pancreas, metabolism of carbohydrates, proteins, and fats leads to anomalies and, is, therefore, leads to a reduction in the ability of the body. The result of hyperglycemia may lead to metabolic acute complications such as long-term ketoacidosis complications and chronic microvascular disease (Smeltzer & Bare, 1992). In 1987, Phipps et al. Described diabetes as a complex, chronic disorder characterized by macrovascular and neuropathic development over time, with regular carbohydrate destruction, fat and protein metabolism, and microvascular complications. Diabetes is a metabolic disease that is caused by an increase in the amount of glucose in the blood. It is a life-long disease caused by deficiency or ineffectiveness of insulin hormone. Glucose, which is normally obtained from foods or released from the blood in the liver from the stores, enters the cell with the help of the insulin hormone secreted by the pancreas and transforms it into energy there. As a result of the lack of insulin or insulin, the body cannot use glucose and the blood sugar increases. In diabetes, the organism cannot use carbohydrates, fats, and proteins sufficiently. Failure to control blood sugar can lead to death, long-term eye, kidney, nerve, heart, and vascular system disorders also impair the quality of life. Diabetes is one of the oldest known diseases in history. Diabetes mellitus is formed by the combination of the old Greek siphon and sugar. Increased blood sugar in the body increases the amount of urine and causes a lot of urine to be produced so that patients' urine production occurs. The presence of sugar in the urine called glucosuria occurs when the sugar in the blood called glycemia reaches very high values. There is another type of diabetes called diabetic insipid, which is accompanied by an intense feeling of thirst and an excessive amount of urine production, but it is caused by other mechanisms that have nothing to do with diabetes. World Health Organization defines that a fasting blood sugar level of 7.0 mmol/L (126 mg/dL) or higher indicates type 2 diabetes. Under normal conditions, fasting blood glucose should not exceed 110 mg/dl. Fasting blood glucose levels between 110-126 mg/dl are interpreted as a hidden sugar. Two Canadian scientists, Frederick Banting, and Charles Best discovered that the cells in a section called the Langerhans islets in the pancreas in 1921 produced hormone insulin started to be used as medication and the lives of the patients who have survived for an average of 22 months have changed. With the discovery of insulin, there has been a breakthrough in the treatment of diabetes.

2.3 Historical Perspective to Signal Filtration

Filters were initially seen as periodic selective behavioral circuits or systems. In electrical engineering, one of the most fundamental circuits is the series or parallel tuned circuit, and in the early crystal set a wave trap is a very significant component. In the IF band of most radio receivers; more sophisticated versions of this idea are available. Here, tuned circuits coupled with amplifiers and transducers are utilized to form a stop band in which amplified frequencies are characterized by a transition band and attenuation. Something more complex than tuned circuit collections is required for many applications and as a result, a wide set of filter design theory has been developed. Some places are fixed k and m derivative filters (Skilling, 1957) followed by Chebyshev filters, Butterworth filters and elliptic filters (Storer, 1957). In recent years, a comprehensive numerical algorithm for filter design has been developed. Amplitude and phase response characteristics are provided and a filter is designed to match these features with the help of computer-aided design packages that enable interactive operation. Normally, there are restrictions in the filter structure that must be met; These limits may include impedance levels, component types, component numbers, etc. For many years nonlinear filters have been utilized. The simplest is the AM envelope detector, a combination of diodes and a low-pass filter (Terman, 1955). Similarly, an AGC (Automatic Gain Control) circuit utilizes a nonlinear element and a low pass filter (Terman, 1955). The phase-locked loop utilized for Frequency Modulation reception is another nonlinear filter example (Viterbi, 1966) and has recently been used to increase the signal-to-noise ratio (SNR) of Dolby systems in voice recordings. The presence of the filter as an appliance that processes continuous-time signals and exhibits periodic selective behavior is further enhanced by two major improvements. The digital filtration which is the first development was made feasible by the latest innovations in integrated circuit technology (Gold & Rader, 1969; Rabiner and Gold, 1975; Oppenheim and Schafer, 1975). Circuit modules, which are completely different from those utilized in conventional filters, appear in digital filters such as analog-to-digital converters and digital-to-analog, digital recordings, read-only memories, and even microprocessors. Thus, although the final objectives of digital and conventional filtration are the same, the practical aspects of the digital filter structure are very little or not compared to the practical aspects of the m-derivative filter structure. In digital filtration, it is no longer possible to minimize the number of active elements, inductor length, termination impedance distortion, or distribution of reactive elements. Instead, it may want to minimize round-off error, word length, the number of wiring operations in structure, and process delay. In addition to the potential cost advantages, this new approach to filtering has other advantages. Perhaps most importantly, the filter parameters are set and maintained at a high sensitivity level, so that normal filtering can achieve filter properties that are not normally reliably achieved. The parameters can be easily reset or less adapted at an additional cost this is another advantage. Also, some microprocessor digital filters can be shared time, so that many concurrent tasks can be performed efficiently. The second important improvement came from the implementation of statistical ideas to filtration problems (Wiener, 1949, Kolmogorov, 1941, Wainstein and Zubakov, 1962; Kalman and Bucy, 1961; Kalman, 1960; Kalman, 1963; Kailath, 1974). Conventional approaches to filtering, at least explicitly, are these beneficial signals placed in a periodic band and are often unwanted signals which are called noise, spread elsewhere, but only overlap in some way. On the other hand, statistical approaches to filtration assume that full statistical features have beneficial unwanted noise and signal. The measurements consist of the sum of the signal and noise, and the tasks continue to make as much noise as feasible by processing the filter measurements in some ways. The oldest Wiener and

Kolmogorov statistical ideas (Wiener, 1949; Kolmogorov, 1941) are concerned with statistical features that do not change over time, that is, they change with continuous processes. It proved to be able to correlate useful signal and unwanted high statistical properties with periodic field properties for operations. Therefore, there is a notional connection with classical filtration. An important aspect of the statistical approach is to define the eligibility criterion or filter performance. Roughly, the best filter is, on average, the closest to the correct or useful signal output. A unique impulse response corresponding to the best performance value or suitability is given by the fact that the filter is linear and formulated in terms of performance and impulse response and signal and noise statistical features. As mentioned above, the supposition that basic signal and noise operations are constant and are very important for Wiener and Kolmogorov theory. Until the late 1950s and early 1960s, a theory that did not require this stagnation supposition was developed (Kalman and Bucy, 1961; Kalman, 1960; Kalman, 1963; the theory stems from the fact that Wiener and Kolmogorov's theory remains inadequate). the new theory soon acquired the Theory of Kalman Filter in order to cope with some applications where the stationary material is specific to the lumbar. however, there is still significant contact because, for another reason, a static process is a non-stationary type of process; Kalman noise reduction theory can now be easily realized As mentioned above, Kalman noise reduction theory was developed at the time the application was called, and the same interpretation was real, for the Wiener filtration theory. It is also important to note that the difficulties experienced in the application of Kalman filters and the time of application difficulties of the Wiener filter are compatible with the technology. Wiener filters can be applied with time-invariant network elements such as amplifiers, capacitors, and resistors, while Kalman filter can be applied with digitally integrated circuit modules. The point of contact between the last two streams, such as enhancement, statistical filtering, and digital filtering, occurs when you encounter a problem applying the discrete-time Kalman filter using digital hardware. In the future, it may be attractive to explicitly incorporate the practical limitations associated with digital filtering in the mathematical expression of the statistical filtration problem. However, this is not done today, and as a result, there is little contact between the two streams.

2.4 A Historical Perspective from Fourier Transform to Wavelet Transform:

Digital filtering techniques are used to improve signal quality and minimize random noise error component(Anderson&Moore, 2005). The signal from the Continuous Glucose Monitoring sensor can be defined as in the following formula.

$$y(t) = x(t) + \sigma . n(t) \tag{1}$$

Appropriate signal processing methods, to elicit the basic dynamics corresponding to the signals and to acquire information from such signals have been necessary. Typically, processing of the signal is to convert a time-domain signal to another area that is not easily observed in its original state to extract the characteristic information embedded in the time form. By representing a number of coefficients (Chui 1992; Qian 2002) based on the comparison among a number of known template functions $\{\psi_n(t)\}_{n \in z}$ and the x (t) signal as mathematically this time-domain signal can be obtained.

$$c_n = \int_{-\infty}^{+\infty} x(t)\psi^*{}_n(t)dt \tag{2}$$

$x(t)$ and $\psi_n(t)$ are the interior product between the two functions is described as the interior product between the two functions:

$$\langle x, \psi_n \rangle = \int x(t)\psi^*{}_n(t)dt \tag{3}$$

(·)*, it means the complex conjugate of the function of (·). Then the equation (2) can generally be expressed as follows:

$$c_n = \langle x, \psi_n \rangle \tag{4}$$

In essence, the inner product of (4), defines the similarity comparison process between the x (t) signal and the degree of proximity between two functions is known as the template function $\{\psi_n(t)\}_{n \in z}$. The more similar $x(t)$ is to $\psi_n(t)$, the larger the interior product c_n will be. The wavelet transform historical background is explained in this section. This is accomplished by observing differences in wavelet transform and other common techniques as well as in terms of selection of template functions $\{\psi_n(t)\}_{n \in z}$.

2.5 Fourier Transform

The most commonly used signal processing tool in engineering and science named The Fourier transform has been discovered by the French mathematician Joseph Fourier in 1807. Fourier has shown here that any periodic signal can be determined by converting the time domain from the frequency domain with a number of cosines and sinuses with a weighted sum. The frequency composition of the time series is represented as x (t).

2.6 Literature review on Wavelet Transform

Alfred Haar's Ph.D. thesis entitled The Theory of Orthogonal Function Systems at the University of Göttingen in 1909 was the first reference for wavelets in the history of science. Haar's research (Haar, 1910) on orthogonal function systems enabled the improvement of a series of rectangular basic functions. Then, the Haar wavelet had been the simplest wavelet family ever selected based on these functions in all applications of the wavelet family.

After Haar's work, little progress can be reported in the wavelet zone until the physicist Paul Levy's investigation of Brownian's movement in the 1930s.

The scale has discovered that the fundamental function of the changing function, i.e, Haar, is more appropriate to examine the fine details in the Brownian movement than the Fourier basic functions.

In addition, Norman H. Ricker (Ricker 1953) and Elias M. Stein (Jaffard et al. 2001), Richard Paley (Littlewood and Paley 1931), John Littlewood, conducted research on the wavelet from 1930 to 1970.

It was attributed to Jean Morlet in the mid-1970s, who implemented and applied a great advancement, scaling, and shift technique analysis in this field of research, which today is called wavelet (Mackenzie, 2001). When Morlet uses the STFT ***.** he determined that keeping the width of the function constant cannot be the solution. As a solution to the problem, Morlet (Mackenzie 2001) tried to keep the window constant while changing the window width by squeezing or expanding the window function. Morlet Wavelet was named after the waveform obtained and this wavelet was the beginning of the research process.

The theoretical wavelet transformation formation was first introduced by Jean Morlet and Alex Grossmann.

In this study(Grossmann and Morlet 1984), it has been suggested that a signal can be restored to its original state without any loss of information.

(*Short-term Fourier Transform (STFT): The short-term Fourier transform is a Fourier-related conversion used to determine the frequency of the signal and the phase content of the local portions of the signal as it changes over time to divide a time signal into short portions of equal length and then to calculate it Fourier transforms separately in each short section.. This reveals the Fourier spectrum in each short segment, one that usually draws varying spectra as a function of time.)

In the analysis of the different frequency components within a signal (Mallat 1998), it was shown that wavelet transformation enables variable window sizes, as opposed to the Short-Term Fourier Transformation technique, where the window size is constant.

This is accomplished by scaling the signal (i.e, contraction and dilatation) and searching for similarities by comparing it with a series of template functions obtained by shifting a base wave (i.e, rotating along the time axis) $\psi(t)$. It can also be expressed as the wavelet transform of a $x(t)$ signal using the display of the internal product:

$$wt(s,\tau) = \langle x, \psi_{s,\tau} \rangle = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t) \psi^{*}\left(\frac{t-\tau}{s}\right) dt \tag{5}$$

After Morlet and Grossmann's effective work, many researchers have made considerable efforts to further develop the wavelet transform theory. The following case studies include Strömberg's studies on 1983 intermittent fluctuations (Strömberg 1983). Examples include Grossmann, Morlet, and Paul scaling random signals as a scale and analyzing the single-base wavelet function translation (Grossmann et al., 1985, 1986), and in 1993 Newman's Harmonic Wavelet Transformation (Newland 1993).

Stephane Mallat Yves Meyer (Meyer 1989, 1993) and (Mallat 1989a, b, 1999) by the method of multi-analysis of the use of wavelets is seen as the most important step in facilitating the use. The present invention is presented by Meyer (Meyer 1989) in an article on orthogonal fluctuations named Orthonormal Wavelet. To design the scaling function of fluctuations to allow other researchers, to create their own basic wavelets in the simple mathematical way is key for multiple analyses. For example, Ingrid Daubechies formed her own wavelet family in 1988, based on the concept of multiple waves named as Daubechies wavelets (Daubechies 1988, 1992). This wavelet type is orthogonal and can be applied utilizing techniques of digital filtering that are not very difficult.

2.7 Summary

In this section, historical perspective and literature review of Diabetes Mellitus, Signal filtering, Fourier transform and wavelet transform are described.

CHAPTER 3
AN OVERVIEW ON MONITORING of CONTINUOUS GLUCOSE SYSTEMS

3.1 Overview

Since the 21st century early days, continuous glucose monitoring system has begun to be utilized in order to constant glucose levels with measuring concentrations of interstitial glucose. When carefully used to understand the properties of this system, it can potentially develop diabetes care. Although there is approximately 5-15 minutes delay among interstitial and blood levels of glucose, the system is regarded as the most appropriate appliance for precise control of glucose and prevention of hypoglycemia. Many studies have examined validity, clinical effectiveness, and reliability. WL Clarke who conceived analysis of continuous glucose-error grid assesses continuous glucose monitoring clinical trials. With analyzing the "temporal" features of the data and analyzing the reference pairs reading and the sensor as a timeline, they are represented by a "two-dimensional" time sequence and the natural physiological time delays are accounted for. Even if there are other methodologies for evaluation, the investment in the continuous glucose-error grid is clearly significant. Each method complementary utilize is the most effective proving way the correctness of apparatus. Devices have progressively developed and there is actual-time monitoring of continuous glucose commercially present that allows you to monitor the blood sugar level in real time. The use of actual-time monitoring of continuous glucose can potentially cause over or under treatment with insulin. Education of the patient is significant through the proper and effective use of new devices to develop diabetes care.

3.2 Historical views of CGM System

Diabetes management has seen changes in the lives of patients caught in the past 30 years. (Deeb, 2008). Development in the measurement of glucose was initiated at the end of the 1980s by self-monitoring of blood glucose, one of these significant changes. As the second appliance in order to measure glucose blood levels, the monitoring of continuous glucose system was introduced into the market at this century beginning. Local fluctuations supply the best information about decisions of optimal treatment in order to glucose levels and diabetes control throughout the day. (Klonoff, 2005). In 1999, in the United States, the glucose continuous monitoring device was approved by the Food and Drug Administration. Since then, the appliance has been dramatically developed and integrated into the actual-time monitoring of continuous glucose and insulin pump system has already been commercially launched in the US and Europe. In Japan, monitoring of continuous glucose history is relatively short. Health Ministry, Labor Ministry, and Social Security approved the monitoring of continuous glucose appliance in 2009 about 10 years after the US. What's more, the second generation blind monitoring of continuous glucose, Medtronic's MiniMed Gold, has become the only approved appliance in Japan under the government-sponsored insurance of health. New wireless but blind monitoring of continuous glucose will soon be on the Japanese market. CGM, which has a different background, has been extensively studied in Europe and the USA to date. At this stage, it is necessary to know that Japanese clinician has already called. Particularly, it is significant to know whether the monitoring of continuous glucose system is a correct, safe and clinically effective device (Golicki et al., 2008). The blood sugar of a person with a metabolic disease, whose body cannot produce any or sufficient insulin, leads to high levels of glucose in the blood, which constantly changes throughout the person's life every hour of the day. Patients can use glucose meters to check blood sugar, but it only gives blood glucose values at a specific time when tested. However, since a patient's blood sugar levels change from minute to minute, it may not be enough to check with blood glucose meters. In addition, 60% of glucose deficiencies may not occur by blood glucose self-monitoring alone (Pitzer et al., 2001). Another standard way of monitoring glucose of blood is the glycosated hemoglobin measurement, more commonly known as hemoglobin A_{1C} (HbA_{1C}). However, since HbA_{1C} can not monitor glycemic variability as long as it ensures information about glucose exposure, it does not tell the entire story. HbA_{1C} is a very beneficial test to determine how well the sugar of blood has been controlled during the previous 3 months. Nevertheless, since HbA_{1C} demonstrates the average blood sugar, how much fluctuation does not give a correct picture. Indeed, if a patient often has low blood sugar, low HbA_{1C} (HbA_{1C} indicates an average value) and a false sense of security for the patient and the doctor may result, even the blood sugar is usually high and in fact under control. Therefore, although SMBG (Self-monitoring of blood glucose) and HbA_{1C} are significant, they do not give us a complete picture, particularly about the patient variability of glycemic. Monitoring of continuous glucose can help formalize the patient glucose control. An effective way to understand how blood sugar changes throughout the day and monitor sugar levels to understand the course of the patient's glycemic tours is through the help of a technology named the CGM system. During the continuous glucose monitoring system study period, we read 288 readings per day and read sugar levels every 10 seconds and keep a record every 5 minutes. A small, sterile, flexible electrode measuring interstitial fluid (ISF) glucose is placed just below the skin. This data is then loaded into the computer and can be clearly seen in the graphic format that everyone understands. In many patients with high blood sugar during single hours of the day, you are unaware that blood and blood sugar cannot be detected by routine testing after fasting sugar (postprandial blood sugar), or that night blood sugar levels may be low. The CGMS use may ensure significant information for the physician to allow the physician to change his/her treatment appropriately to better control the sugar of blood throughout the day.

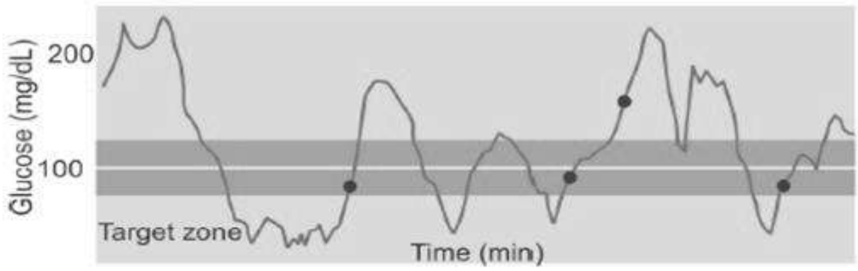


Figure 3.1: Fingersticks alone (CGMS) (Kannampilly, 2013)

3.2.1 What is the monitoring of continuous glucose

Diabetes helps people with the management of diabetes, disease and prevent related problems. To make decisions about food, physical activity, and medications, a person can utilize glucose monitoring. The most common way to control levels of glucose is to use a glucose meter to measure the level of glucose in the blood sample, then sewing a fingertip with an automatic fingertip to get a blood sample.

Figure 3.2: Diabetics typically use a tie-down tool to get a sample of blood and a glucose counter to measure the level of glucose in the sample
(National Diabetes Information Clearinghouse, 2008)

There are many glucose meters types present and they are accurate and reliable when used correctly. Some measuring devices use a blood sample, like the upper arm, forearm or thigh, which is less sensitive than the fingertip. Monitoring continuous glucose systems utilizes a small sensor placed deep under the tissue fluid to control levels of glucose. The sensor will remain in place in order to a few days and then replaced. A transmitter sends a pager-like wireless monitor with information about beak levels via radio waves from the sensor. The utilizer must check samples of blood with a meter of glucose to program the instruments. Monitoring of accepted glucose systems now utilizes a small sensor device; These devices are not as precise and secure as standard blood glucose meters, and utilizes should verify glucose levels with one meter before making any changes in the treatment.

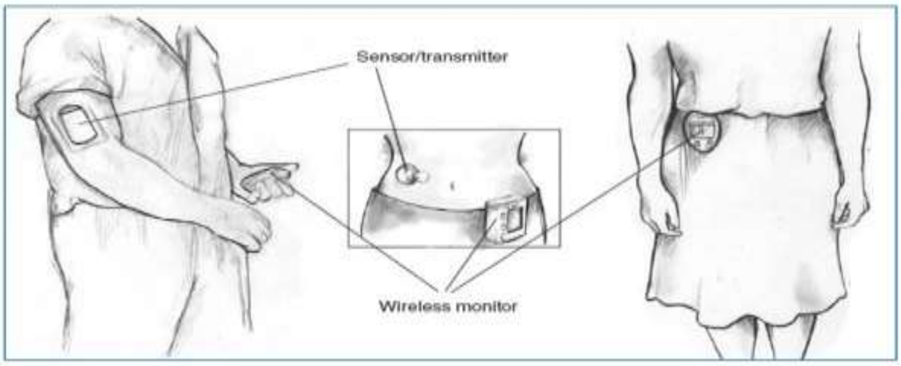


Figure 3.3: Continuous glucose monitoring systems frequently measures glucose once per minute. The meter is transmitted to a wireless monitor
(National Diabetes Information Clearinghouse, 2008)

Continuous glucose monitoring systems are more expensive than customary glucose monitoring but may provide preferable glucose control. Monitoring of continuous glucose appliances manufactured by Medtronic, Abbott, and DexCom have been approved and presented to the US Food and Drug Administration. These devices supply real-time glucose levels measurements displayed with glucose levels at 5 minutes or 1-minute intervals. Utilizers can set alarms to alert when levels of glucose are too low or too high. There is private software present in order to download data from devices to monitor and analyze trends from the models, and the systems may display trend graphics on the monitor screen.

Figure 3.4: Those who utilize monitoring of continuous glucose can download data to the computer to see patterns and trends in glucose levels.
(National Diabetes Information Clearinghouse, 2008)

What are the hopes in order to pancreas of artificial?

To come from the top of today's insulin limiting treatments, investigators have long been trying to link glucose monitoring and delivery of insulin with implementing artificial pancreas. An artificial pancreas is a system that mimics the way the healthy pancreas perceives changes in blood sugar levels and automatically responds to the suitable insulin secretion amount. Although there is no cure, an artificial pancreas has a significant potential to develop and monitor diabetes care and management and to lower blood sugar. An artificial pancreas based on mechanical instruments needs at least three components:

- A computer program that " closes the loop" by tuning insulin delivery based on changes in glucose levels.
- A system of insulin delivery
- Monitoring of continuous glucose system

Latest technological developments have taken the first steps towards the closing cycle. The first pairing of monitoring of continuous glucose system with an insulin pump is the first step in joining the glucose monitoring and insulin delivery systems utilizing the most improved technology present, not the artificial pancreas, the MiniMed Paradigm REAL-Time System. In the 1970s, blood glucose meters were available and self-monitoring of diabetes turned into self-monitoring. Nevertheless, glucose periodic blood measurements with blood glucose meters indicate blood glucose images at any time during the test. As you can see in the figure below, blood sugar measurement tests only ensure activity of glucose snapshots; Glucose periodic blood measurements may not really show the patient's profile control of glucose. CGM tells you that the story is just a "movie", just a snapshot of levels of glucose. It provides information on glucose trends among sugar of blood tests, develops knowledge and developed control of glucose.

3.2.2 Fundamentals of continuous glucose monitoring

The sensor is placed deep underneath and measures the glucose, named ISF, that is fluid among the veins and the cells. Blood sugar in blood counters is measured in blood capillaries. Glucose (primarily from carbohydrates) passes through cells into the blood vessels via the ISF. Thus, the glucose level saved in ISF decreases the registered glucose level.

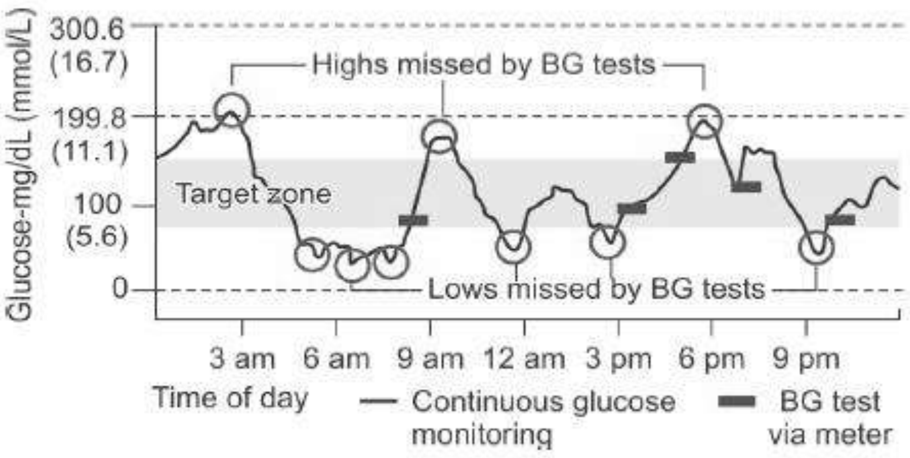


Figure 3.5: CGM system curve (Kannampilly, 2013)

Continuous glucose monitoring technology utilizes a glucose sensor replaced in the images in the ISF, penetrating the semi-permeable sensor membrane and reacting with the glucose oxidase present in the sensor. This reaction supplies the measured electrons as we call the input signal (ISIG) (the electron values indicate the value of the input signal captured by the sensor in the nanoamperes). This ISIG is then converted to the sensor glucose value utilizing the values of calibration blood glucose. Plasma (G1) and ISF (G2) glucose kinetic models are given below (Figure 3.3 A and B). Subcutaneous ISF glucose sensing accurately reflects levels of plasma glucose across a wide glucose profiles spectrum, changes regardless of plasma insulin.

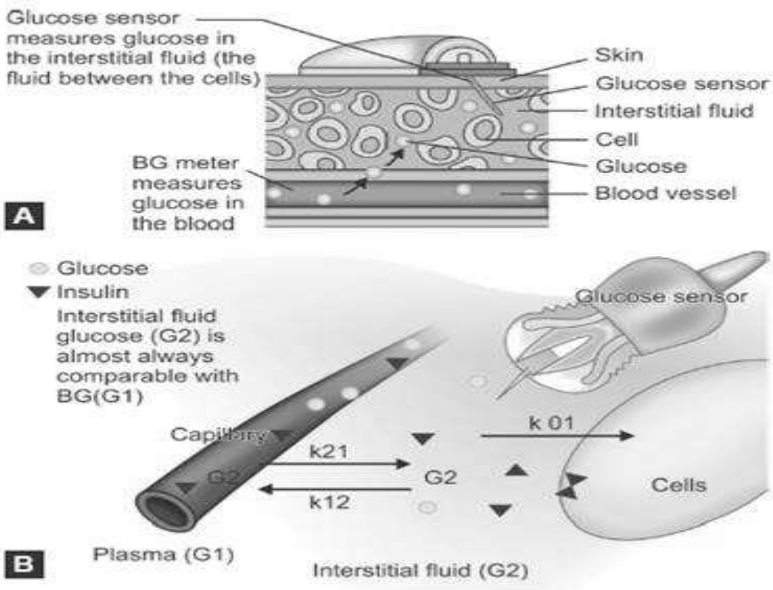


Figure 3.6: Model of a plasma (G1) and ISF (G2) glucose kinetics. (A) Glucose goes from vessels of blood to interstitial fluid and cells; (B) Interstitial glucose, plasma glucose (Kannampilly, 2013)

3.2.3 What kind of monitoring does continuous glucose systems have?

There are two types of CGMS:

- Individual (Real Time) monitoring of continuous glucose
- Professional monitoring of continuous glucose

Professional CGM *(in order to Health Care Providers)*

- No alarm
- Ideal for short-term blinded monitoring of continuous glucose assessment and retrospective analysis
- Can be utilized in all patients with diabetes to reveal patterns and patterns
- Minimal patient education
- Quick and easy installation

Personal (REAL-Time) CGM *(for Patients)*

- The motivation and training of the patient is the key to success.
- Glucose sensor readings are updated on the monitor every 5 minutes.
- Trend charts, arrows, and warnings help the patient to achieve the lowest and highest levels.

3.2.4 Who is a good candidate in order to CGM?

The information supplied by the IPro2 System can help you design personalized programs of diabetes care. The data is also beneficial as an educational tool to increase motivation and co-operation with patients. The system may be particularly beneficial in assessing the following situations and situations when it is effectively used with patients with diabetes:

- Elevated A_{1c} levels
- Patients who test infrequently
- Logbooks not reflecting A_{1c}
- Fluctuating levels of glucose
- Poor glycemic control (patients who desire better control)
- Nocturnal hypoglycemia (low glucose of blood) and hypoglycemic unawareness
- Pregnant women with diabetes
- Postprandial hyperglycemia(high glucose of blood)
- Children with diabetes

3.2.5 Monitoring of continuous glucose benefits

CGM not only indicates a glucose levels snapshot but also indicates the full picture of glucose activity. Utilizers and clinicians supply real-time information about glucose levels and developed insight by indicating glucose trends among the finger bars, thereby developing control of glucose. Monitoring of continuous glucose also supplies additional information beyond “averaging” the total glucose levels represented by HbA1c. A recent study indicated that patients who utilized continuous glucose monitoring in order to at least 6 days a week decreased Alc levels significantly without increasing hypoglycemia when compared to patients who utilized less (Pitzer et al., 2001; Tamborlane et al., 2008).
Readings of continuous glucose help to better manage disease diabetes by interfering with real-time to decrease the frequency and hypoglycaemic severity or hyperglycemic episodes. Patients can learn how diet, exercise, drug utilize, lifestyle, and illness periods affect levels of glucose. Moreover, historical analysis supplies information that can translate patients and health professionals (HCPs) into treatment regimens and optimization. Many studies have shown that A_{1C} results are a significant difference based on adjustments made to insulin regimens in response to CGM (Ludvigsson & Hanas, 2003; Tavris & Shoaibi, 2004; Kaufman et al., 2004). Hirsch, 2002 have shown that use of monitoring of continuous glucose in clinical practice may ensure necessary monitoring tool to decrease variability of glycemic and superoxide overdose, and may potentially decrease complications of diabetic (Hirsch, 2005).

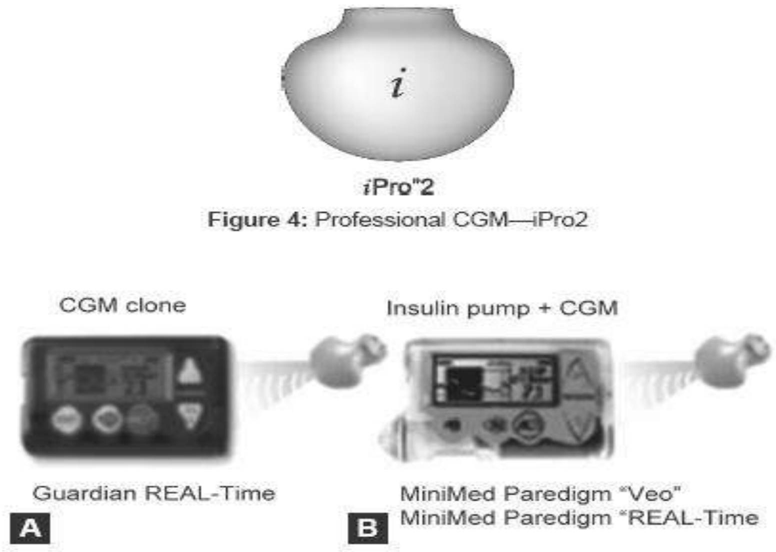


Figure 3.7: Individual monitoring of continuous glucose (A) Guardian Actual-Time; (B) MiniMed Paradigm ACTUAL-Time (Kannampilly, 2013)

3.3 CGM System Elements

The Diabetes Control and Complications Test confirm that patients treated intensively by insulin give preferable outcomes than those traditionally treated in diabetic microvascular complications prevention. Nevertheless, It is also known that intensive insulin therapy increases hypoglycemia risk. For detecting hypoglycemia, patients with a hypoglycemia history frequently heal various abnormalities and forfeit talent. This is called "hypoglycemia unconsciousness" and fulfills the "recurrent hypoglycemia vicious cycle". Nevertheless, there is strong evidence that hypoglycaemic attacks can be reversed in a more rigorous manner through glucose control, often counterproductive regulatory defects (Wolpert, 2007). For rigorous glucose control and hypoglycemia prevention, monitoring of continuous glucose is a beneficial appliance that provides maximum information about fluctuating levels of blood sugar throughout the day. (Sachedina& Pickup, 2003; De Block et al., 2006; Augstein et al., 2007; Rhee et al., 2007; Weinstein et al., 2007; Zhou et al., 2009; Foundation of Juvenile Diabetes Research CGM Study Group, 2010; Foundation of Juvenile Diabetes CGM Study Group et al., 2011). The fingertip test only provides information about the blood sugar at one point; So even if "hypoglycemia is unconscious" among the measurement points, we can not detect it. By monitoring continuous glucose, we can achieve both better control of intensive insulin treatment and avoiding "hypoglycemia unconsciousness". Monitoring of continuous glucose is a method that supplies continuous blood glucose control level by measuring concentrations of glucose in the interstitial fluid (Fogh-Andersen et al., 1995). At present, Medtronic's MiniMed Gold, which is utilized under government-based health insurance in Japan, has a sensor placed in subcutaneous tissue beneath the abdomen skin. The sensor includes a flexible, platinum-coated electrode that can be utilized in order to 72 hours, placed in a permeable membrane. By glucose oxidase method, level of subcutaneous glucose is measured and a monitor showing a mean blood glucose figure every 5 seconds, and every 10 seconds the interstitial glucose shows the measured level. Blood sugar values are computed utilizing the software. MiniMed Gold computes blood sugar values between 40-400 mg/dL. Although the owner can not reach actual-time glucose levels, the measured data can be downloaded as a spreadsheet (Corstjens et al., 2006). A significant procedure that needs to be repeated is calibration. At least four times a day this is done utilizing a finger bar test on MiniMed Gold. Self-monitoring of blood glucose means that at any point in time it is closer to true glucose levels, venous glucose levels. Care should be taken that the device is delayed among blood and interstitial levels of glucose.

3.4 Delay among interstitial and blood levels of glucose

In 2002 (Cheyne et al., 2002), CGM-related articles were published during controlled hypoglycemia in healthy volunteers. No information was present about the sensor performance during continuous hypoglycemia or during hypoglycemia recovery at that time. For this reason, they use hyperinsulinemic glucose clamps to prove interesting findings(Cheyne et al., 2002). Venous blood glucose levels dropped to 45 mg/dL for 60 minutes after 60 minutes of study at the end of the study, but eventually returned to diencephalon. Measurements of blood glucose are compared with the interstitial worths saved by the sensor. Profiles of the sensor decrease each glucose levels of three points with correlation coefficient 0.79 and 7% average absolute error. Reduce in blood glucose measured by drop sensor at a glucose level of the blood level, but the development in hypoglycemia was postponed by an average of 26 minutes (Cheyne et al., 2002). In 2003, the device was probably the first generation MiniMed of continuous glucose, that is less accurate than second-generation MiniMed Gold. (Boyne et al., 2003) the first generation tried to measure a time delay among MiniMed monitoring of continuous glucose and blood glucose, as well as among different sensors at the same time. In each of the 14 patients with type 1 diabetes, there were two sensors placed subcutaneously in their masts, taken every 5 minutes. Blood sugar was also sampled for 8 hours every 5 minutes. The results indicated that the time difference among blood and interstitial glucose levels varied between 4 and 10 minutes with interstitial glucose left behind by glucose of blood at 81% of cases. The difference of mean (± MD) among two sensors in each patient was 6.7±5.1 minutes The authors also found that

- (10.1±10.1 minutes, $P<0.001$) increase in delay times in glucose levels
- (6.9±8.5 minutes, $P=0.017$) falls
- (9.4±7.7 minutes, $P<0.001$) lowest

In both cases, the level of blood sugar was at the pre-interstitial glucose level (Boyne et al., 2003). Although there were some variations among different studies, the other groups reported similar results (Kulcu et al., 2003; Klonoff, 2004; Nielsen et al., 2005). Thus, the main results were a time lag among measured interstitial levels of glucose (Stout et al., 2004; Schrot, 2007) and because the true levels of blood and the different sensors have different sensitivities without measuring the interstitial levels of glucose (Boyne et al., 2003; Wentholt et al., 2005).

3.5 Summary

Diabetic patients control glucose, manage the direction of the disease and prevent related problems. The most common way to control glucose levels is to place a finger to pick up a blood sample and utilize a glucose counter to measure the level of glucose in the sample. Monitoring continuous glucose systems utilizes a small sensor placed deep under the tissue fluid to control levels of glucose. A transmitter sends measurements of glucose to the wireless monitor. An artificial pancreas based on mechanical devices includes a computer program in order to monitor the continuous glucose system, adjusting the insulin delivery system, and administering insulin according to changes in levels of glucose. It is crucial to understand glucose variability in a patient, and some research suggests that variable blood sugars may be more harmful than continuous high blood glucose, fluctuations in glucose levels may cause oxidative stress, and possibly increase risk in order to cell damage and complications. Microvascular and macrovascular. The utilize of continuous glucose monitoring in clinical practice may supply the necessary monitoring tools to decrease the variability of the glycemic and excess oxidant dose and potentially reduce diabetic complications. According to the American Clinical Endocrinologists (AACE), monitoring continuous glucose technology is not only new, but it can also develop patients' lives in a comprehensive diabetes management plan.

CHAPTER 4
NOISE, NOISE TYPES, ADDITIVE WHITE GAUSSIAN NOISE, AND, FILTER DESIGN PROPERTIES

4.1 Overview

Generally, the concept of noise in electronic circuits can be described as unwanted signal confusion. Particularly in electronic-communication technology and high-frequency RF (radio frequency) circuits, signals are transmitted using a conductor and electromagnetic waves. However, a continuous unwanted component is present on this transmitted signal. This component is sometimes too small to be noticed, and sometimes it can be annoyingly high. Such situations are also known as parasites among the public. Signal filtering is widely utilized in systems with various signal processing methods such as data communication biomedical implementations military and civil electronic systems industrial implementations. In general, it is described as separation of a signal into desired frequency components (such as noise) according to selected filter characteristic and improvement of the overall structure of signal (gain, amplitude, phase and group delay, etc.).

Digital de-noising is one of the powerful digital signal processing devices. Except for clear cleaning errors, passive component fluctuations, time and temperature, operational fluctuations (active filters), etc. Advantages associated with filtration are numerical filtration-capable performance explanations; this is achieved with an Analog implementation, even if performance is not feasible, if not feasible, at best. Also, digital filtrate features can easily be changed under software control. For this reason, they are commonly utilized in adaptive filtration implementations such as the cancellation of echoes in modems, voice recognition, and recognition of speech. In processing signals, the function of a filter is to remove unwanted signal parts such as random noise or to remove useful signal components such as components within a certain periodic interval.

4.2 Noise in processing of signal

A signal may be subject to noise during transmission, capture, storage, conversion, or processing, The general statement used for undesirable and often unknown changes in signal processing is called noise. (Tuzlukov, 2010). Occasionally word does not carry random (unpredictable) signals and helpful data; even if they do not interfere with other signals or are intentionally inserted as in comfort noise. De-noising is a widespread process used, in the design of signal processing systems. In particular, filters are a significant tool, to separate the original signal from the noisy signal. Nyquist-Shannon sampling theorem is mathematical limits for de-noising are determined by information theory.

4.2.1 Noise Types

Noise, in signal processing, can also be classified according to the statistical properties, occasionally named how it changes the intended signal and the "color" of noise.
Additional noises described below are added to the unwanted signal:

- Gaussian
- Contaminated Gaussian, whose probability density function is a linear mixture of Gaussian probability density functions
- White
- Pink or Flicker, with $1/f$ power spectrum
- Power-law
- Additive white Gaussian
- Black
- Brownian or brown, with $1/f^2$ power spectrum
- Cauchy
- Random time shifts in a signal known as phase noise
- Shot noise caused by static electricity discharge
- An error of quantization because of conversion from continuous values to discrete values
- Typical of signals that are rates of discrete events known as Poisson noise
- A short pulse followed by disruption of oscillations known as transient noise
- Multiplicative noise modulates or multiplies the intended signal
- Powerful but only during short intervals known burst noise

4.2.2 Noise in certain signal types

Often noise can be generated by signals that are of particular interest to technical and various scientific fields:

- **Noise (audio), such as "hum" or "hiss", in audio signals**
  - To fill silent Gaps comfort noise added to voice communications

- Audible noise due to electromagnetic vibrations, electromagnetically excited noise in systems containing electromagnetic fields
- Background noise caused by spurious sounds during signal capture
- **Noise (video), such as "snow"**
- **In radio transmissions, Noise (radio), such as "static"**

In signal processing, there is an absolute list of noise measures to measure noise based on some standard noise levels or desired signal levels. The most significant ones are given below.

- Dynamic range, frequently described by the inherent noise level
- The noise power ratio to signal power is named as SNR (Signal-to-noise ratio)
- In the system, PSNR (Peak signal-to-noise ratio) is the maximum signal-to-noise ratio

4.3 Additive white Gaussian noise(AWGN)

4.3.1 Gaussian Noise

Gaussian noise, also known as Gaussian distribution, named after Carl Friedrich Gauss, is A statistical noise equal to that of a probability density function normal distribution. In another saying, values that noise can take on are Gaussian-distributed. The density of function probability “p” of a Gaussian random variable ”z” is given in equation 4.1:

$$pG(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \tag{4.1}$$

where mean value μ, "z" represents a gray level and standard deviation σ. A special case is the white Gaussian noise, where the values in any pair are evenly distributed and are statistically independent (and therefore unrelated). Gaussian noise is used to generate additional white Gaussian noise in communication channel modeling and testing. To mimic the effects of many random processes occurring in nature additive white Gaussian noise is a basic noise model utilized in information theory. Modifiers denote certain characteristics:

- **Additive:** Because it is added to any noise that may be specific to information system.
- **White*:*** expresses idea that it is uniform to provide power in frequency band for information system. It is likened to white with uniform emissions at all frequencies in visible spectrum.

- **Gauss:** has a normal distribution because average time-domain value is zero in time domain.

Broadband noise, thermal vibrations of atoms (called Johnson Nyquist noise or thermal noise) in conductors, shot noise, blackbody radiation from earth and other hot objects, and Sun. Central limit theorem of probability theory, having a distribution called Gauss or Normal, indicates that many random processes are prone to summation. Additive white Gaussian noise is often used as a channel model in which only disturbance in communication is a linear addition of broadband or white noise with a fixed spectral density (bandwidth expressed in watts per hertz) and Gaussian amplitude distribution. Model not taken into account;

- frequency selectivity,
- nonlinearity
- fading,
- dispersion,
- or interference.

However, it produces simple and tractable mathematical models that are helpful to gain insight into underlying behavior of a system before these other phenomena are considered.

4.3.2 A Simple but Powerful Model: Additive White Gaussian Noise

A simple model of how noise affects a signal reception transmitted over a channel and processed by receiver. Noise in this model:

Additive: When a sample value Y[k] is taken at k^{th} sampling time, receiver interprets it as sum of two components: first is noiseless component $Y_0[k]$, i.e sample value taken is noiseless "k". at sampling time, as a result of passing input waveform only through channel distortion; second, noise component considered to be independent of input waveform is W [k]. So we can write;

$$Y[k] = Y_0[k] + W[k] \tag{4.2}$$

In absence of distortion, which is what we are assuming here, $Y_0[k]$ will be either V_0 or V_1.

Gaussian: W [k] noise component is random, but we suppose that each sample is taken from a constant Gaussian distribution at time; for concreteness, we consider this to be a Gaussian random variable distribution "W", so that each W [k] is distributed exactly like "W" reason why a Gauss makes sense is that noise frequently results of collection of several distinct and

independent factors that allow us to obtain a significant result from the probability and statistics, often named central limit theorem. This indicates that sum of individual random variables is well predicted by a Gaussian random variable (approximately improves when more variables are added). Gaussian distribution is better than a range of perspectives, not at least because it is characterized. with only two numbers: variance σ^2 and mean μ or standard deviation σ. In our noise model, average noise distribution will be assumed to be 0. This assumption is not a major concession: any consistent non-zero perturbation is easy to compensate. Zero average Gaussian noise fully characterizes noise as variance or equivalent for standard deviation. As a measure of expected "amplitude" of noise standard deviation σ can be considered and captures expected power of square. Distance between noiseless value of sample and digitization threshold must be sufficiently large than expected amplitude or standard deviation of noise so that noise does not disturb digitization of a bit detection model.
White: This feature relates to temporal change in individual noise samples that affect signal. If these Gaussian noise samples are independent from one sample to next, underlying noise process is called white Gaussian noise. "White" refers to frequency separation of group of noise samples and indicates that noise signal includes components with expected power at all frequencies. This noise model is often referred to as AWGN for additional white Gaussian noise.

4.4 Digital Noise Reduction Basic Concepts

Digital noise reduction has some features that you should pay particular attention to when analog signal input needs to meet specific needs. Also, when converting output digital signal to an analog form, signal must be further processed to obtain correct result. Digital de-noising process, block diagram was shown in figure 4.1

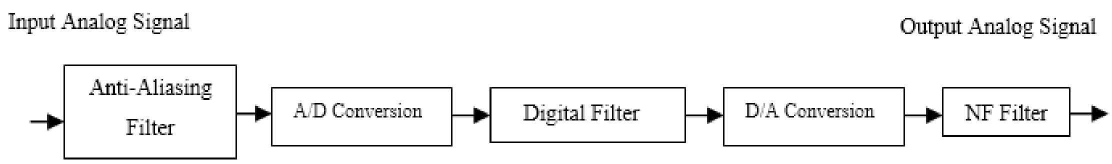


Figure 4.1: Digital noise reduction process

Transforming an analog signal to form of digital is performed by sampling with the "fs" frequency of end sampling. If an input signal includes frequency components higher than the "fs/2" (half-sampling frequency), it will distort original spectrum. This is first reason for implementing input signal filtering utilizing a low pass filter that cleans components of high frequency from input frequency spectrum. This filter is known for its aliasing in foreground anti-aliasing filter. After de-noising and sampling, a digital signal is available for filtering utilizing an appropriate digital filter. Output signal is, in some cases, a digital signal that must be converted analogously. After Digital-Analog Conversion, signal includes some frequency components higher than “fs/2”, which must be cleared.

4.5 Filters

The human mind can concentrate on only one point at a time. No matter how many stimuli around us, only one point can be observed. In electronic systems, although there is too much signal or input data in environment, systems are designed to operate with only one. This process of transmitting a single signal is called a filter. As with rectifier and filter circuit modules, filter circuits prevent unwanted signals. It only transmits signals that are appropriate for operation of system. These unwanted signals may be interference, noise, and other system signals. In its simplest definition, electronic filter is a circuit that passes and suppresses certain signals with similar frequencies. Theoretically, selected filter can filter specific frequency ranges. In practice, however, an applicable frequency selector circuit cannot perfectly and completely filter selected frequencies. Instead, filters attenuate any input signal having a frequency content other than specified frequency band. (Reduces or extinguishes the effect.)

4.5.1 Purpose of Use

Filter circuits, one of most significant elements of signal processing systems, are those which provide desired attenuation or delay feature in a given frequency domain. Filters in almost all signal processing systems allow a given frequency band to pass, while frequencies outside this band are attenuated and designed for this purpose.

4.5.2 Uses of Filters

Filters are often utilized to filter correct components, reduce noise, avoid resonance, or generate resonance, signal shaping, signal attenuation, and power factor correction. Filters, which are very important elements in electrical and electronic systems, are necessary circuits, especially for radio, television, audio, video, and data communication. Seismology, geophysics, medical electronics, brain waves, and distance measurement is also important in many types of scientific research.

4.5.3 Classification of Filters

Various types of filters are available for elimination of these signals in electrical-electronics, where signals are so diverse. There are dissimilar criteria for classification of filters. These:

- According to construction elements (passive filters, active filters)
- According to working principle (bandpass filter, high pass filter, low pass filter, bandstop filter)

Passive circuits are formed by basic circuit elements such as resistance, capacitor, and inductor. Active circuits are circuits that require a power supply to operate. These circuits have circuit elements such as transistors or microprocessors. However, in these circuits, filtering elements are passive elements. Low pass filter is called a low pass filter if it passes and weakens frequencies below specified frequency. Bandpass filter is called a band-stop filter if it exceeds frequencies in a given frequency range, or a band-stop filter if it weakens frequency range.

4.6 Design of filter

Signal processing design of filter is a process of designing a filter, some of which meet several conflicting requirements. Aim is to find that filter that meets each of needs is sufficiently applied to ensure that it is beneficial. A problem of optimization, where each necessity contributes to an error function that needs to be minimized, can be described as the filter design process. Parts specific to the design process can be automated, but an experienced electrical engineer is normally required to get a good outcome.

4.6.1 Requirements for typical design

In design process typical requirements considered for filters are:

- must be causal
- must be stable
- computational complexity must be below
- must have a certain phase shift or group delay
- must be localized (step or pulse inputs should cause infinite time output)
- must have a specific frequency response
- must be applied especially as hardware or software
- must have a specific impulse response

4.6.2 Function of frequency

A significant parameter is needed for frequency response. Particularly, the complexity and for filter order and feasibility steepness of response curve is a decisive factor. A first-order recursive filter will have only one frequency-dependent component. This is the meaning that the response of frequency slope is limited to 6 dB per octave. This is not enough for many aims. Higher grade filters are needed to achieve steeper slopes. Concerning the desired frequency function, there may also be a parity weighting function for each frequency that describes how significant it is for the desired frequency function to approach the desired function more weight, more obvious closest approach. Typical examples of frequency function have been given below:

- Proportional to frequency, a differentiator has an amplitude response.
- High frequencies pass quite well with a filter of the high pass; a filter of low-pass is utilized to cut signals of unwanted high-frequency is useful as a filter to cut unwanted low-frequency components.
- In frequency response, a peak EQ filter makes a peak or dip commonly utilized in parametric equalizers.
- By a specific amount a low shelf filter passes all frequencies but increases or decreases the frequencies below shelf frequency.
- A bandpass filter passes through a limited frequency range.
- The bandstop filter passes frequencies above and below a specific range. A very narrow bandstop filter is known as a notch filter.
- A high shelf filter passes all frequencies but increases or decreases frequencies above shelf frequency by a certain amount.

4.6.3 Phase and group delay

- The entire pass filter passes through all frequencies unchanged but changes the signal phase. To synchronize group delay of recursive filters such filters can be utilized. For phase effects, this filter is also utilized.
- A filter of fractional delay is an all-pass with a fixed group or phase delay that is specified for all frequencies.
- At unchanged amplitude, Hilbert transform is a certain full-pass filter that passes sinusoid but changes each sinusoid phase by $\pm 90^{o}$.

4.6.4 Response of impulse

Between the frequency function of the filter and the impulse response, there is a direct relationship. This is the meaning that any necessity of the frequency function is a necessity for the impulse response and vice versa. Nevertheless, in specific implementations, filter may have a clear impulse response and design process aims to produce a close response to desired impulse response as possible, given all other requirements. To take into account a frequency function and impulse response of independently selected filter in some cases, it may even be appropriate. For instance, we may want both filters to have a certain function of frequency and resulting filter to have an effective width as small as possible in signal field. By taking into account a very narrow function as the desired impulse response of filter second condition can be achieved but this function is not related to desired frequency function. To achieve a filter that tries to meet both of these contradictory design objectives as much as feasible is purpose of the design process.

4.6.5 Causality

Filters based on real-time run time should be causal: the response of filters is based only on the present and past inputs. A standard approach is to leave this obligation to the final stage. If the resulting filter is not causal, it can be causal by adding a convenient time shift or delay. If the filter is part of a larger system that is normal, such delays should be given carefully, as this affects the operation of the entire system.

4.6.6 Stability

To produce a limited filter response a stable filter allows each limited input signal. A filter that does not meet this necessity may not work or even be harmful in some cases. Some design approaches can only guarantee stability by utilizing circuits such as the finite impulse response filter. On the other hand, filters based on feedback circuits have other advantages, and consequently, even if there are unstable filters, this filter class can be preferred. In this instance, to avoid instability filters must be carefully designed.

4.6.7 Locality

In some embodiments, we need to address signals containing components that can be defined as local phenomena, such as beats or stages of a given time. One consequence of filtering a signal is to extend duration of local events to the width of the filter in heuristic terms. This is the meaning that it is occasionally significant to keep the response of impulse function width of the filter as short as feasible. According to the relation of Fourier transform uncertainty, the width of impulse response function of the filter and the width of the frequency function must exceed a specific constant of the product. This is the meaning that any necessity in position of the filter also depends on the width of the frequency function. As a result, it may not be possible to simultaneously meet impulse response function and frequency function requirements of the filter. This is a typical example of conflicting needs.

4.6.8 Computational complexity

The general demand in any design is that the number of operations (addition and multiplication) needed to calculate the filter response is as low as feasible. In some embodiments, this desire is a strict necessity, e.g., because of limited computing resources, limited power supplies, or limited time. The final limitation is typical for real-time implementations. There are several ways that a filter can have distinct computational complexities. e.g., the order of a filter is less or more proportional to the number of processes. This is the meaning that calculation time can be reduced by selecting a low-grade filter. For discrete filters, to the number of filter coefficients, computational complexity is more or less proportional. If filter has multiple coefficients, it may be appropriate to decrease coefficients number closer to zero in case of multidimensional signals such as tomography data. Number of coefficients in very fast filters to which input signal is sampled (e.g at critical frequency) and which takes advantage of bandwidth limits sampled after filtration. Another problem with computational complexity is separability, i.e whether and how a filter can be written as convolution of two or more simple filters. This problem is especially important for multidimensional filters. In this case, if filter can be divided into horizontal direction of a 1D filter and vertical direction of 1D filter, an important reduction in computational complexity can be achieved. One consequence of filter design process may be, for example, approaching the desired filter as a separable filter or as sum of separable filters.

4.7 Fundamentals of Filter

Digital filters are a very significant part of digital signal processing. Their outstanding performance is one of the main reasons why digital signal processing is so popular. Filters are used for two different purposes;

- When a signal is disturbed by noise, interference, or other signals, the signal must be separated from them.
- When a signal is somehow damaged, the signal needs restoration.

Analog or digital filters are attacking these problems. Which is better? Analog filters have a wide dynamic range in both amplitude and frequency, they are cheap and fast. In contrast, To the achievable level of performance digital filters are significantly superior. Analog filters are approximately thousands of times behind digital filters. When approaching filtration issues, this makes a dramatic difference. Limitations in the use of electronic components, in analog filters, such as the stability and accuracy of capacitors and resistors are emphasized.

In contrast, digital filters are so good that filter achievement is often overlooked. Emphasis is placed on theoretical issues related to the limitation and processing of signals. In digital signal processing, it is known that the input and output signals of a filter are in the time domain. This is because the signals are generally produced at regular intervals by sampling. However, this is not just a sampling way. Equal spacing in space is the second most widespread way of sampling. Nevertheless, time and space are the most widespread. In digital signal processing It should be noted that when the term time domain is seen, it may refer to samples taken overtime or a general reference to any area from which samples are received. As indicated in Figure 4.1, each linear filter response of the impulse contains the responses of the step and frequency. Each of these answers includes full data about the filter in a separate format. The other two are fixed, if one of the three is stated, and can be calculated directly. Because they define how the filter reacts under distinct conditions all three of these expressions are significant.

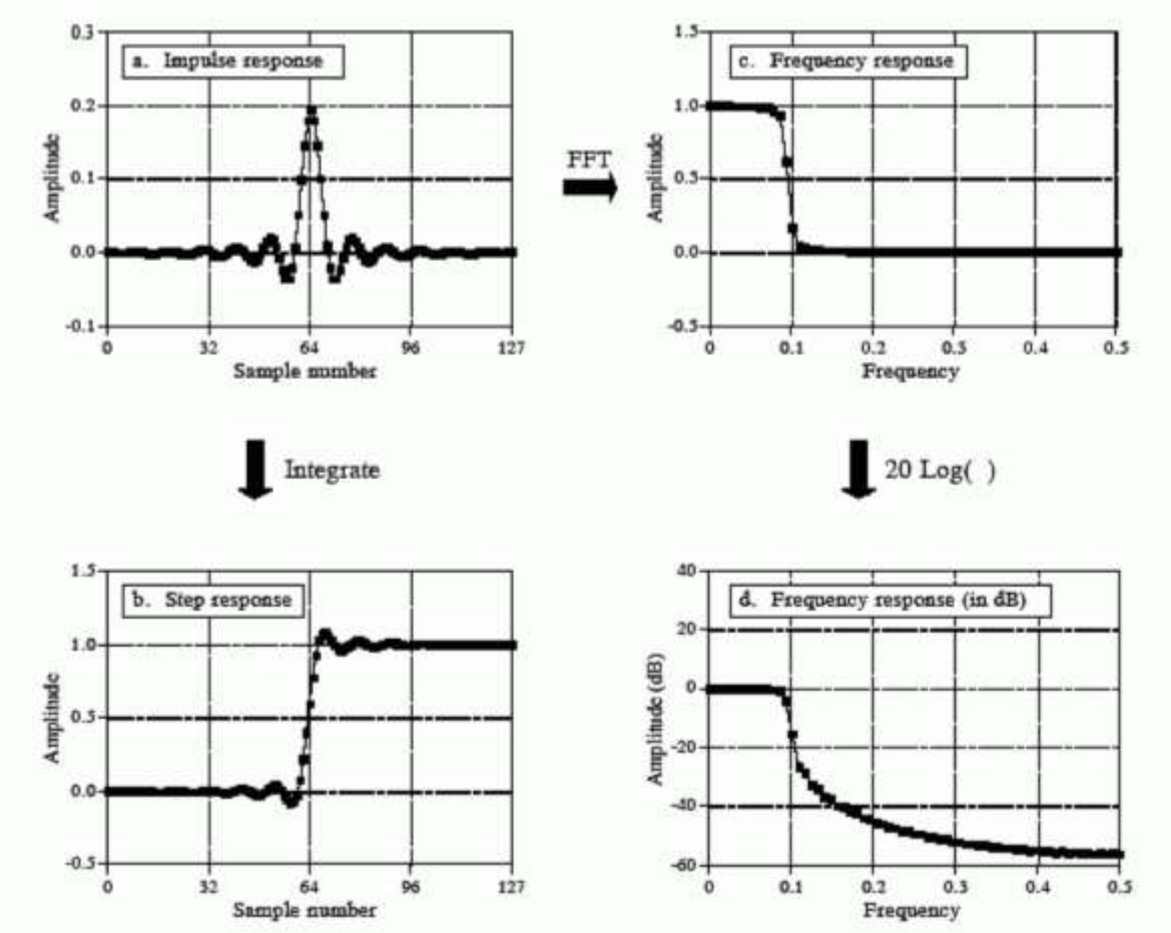


Figure 4.2: Filter parameters

Combining input signals with pulse response of digital filters is the simplest way to apply a digital filter. All suitable linear filters can be made in this way. When pulse response is utilized in this way, filter designers give a special name: filter core. There is another way to do digital filters named recursion. When a filter is applied by convolution, each sample in the output is calculated by weighting and pooling samples at inlet. Recursive filters are an extension of this, utilizing points in input and values previously calculated from output. Instead of utilizing a filter core, iterative filters are described by a series of iteration coefficients. What is important now is that all linear filters have impulse responses, even if you do not utilize them to apply filter. To find the recursive filter response of impulse, feed it with an impulse, and see what happens. Recursive filters response of impulses consists of exponentially disrupted sinusoids in amplitude. In principle, it prolongs the impulse response forever. However, at the end of the amplitude, it falls below the rolling noise of the system and the remaining samples can be ignored. Because of this feature, recursive filters are also called infinite impulse response filters. Unlike, convolution filters are named finite impulse response filters. As is known, when input is an impulse, the response of impulse is the output of a system. Similarly, step response is output when input is a step. Since step is integral of impulse, step response is integral of impulse response. This step provides two ways to find answer:

- It can be seen easily what comes out, by feeding a step waveform into the filter.
- Infinite impulse response. (To be mathematically correct: integration is utilized with continuous signals, while discrete integration, i.e. a sum that works with discrete signals) is used. By taking the discrete Fourier transform (utilizing fast Fourier transform) of the response of impulse frequency response can be found.

4.7.1 Information represented by signals

A most significant part of any digital signal processing task is to understand how data is incorporated into signals you are working on. To add data to a signal there are many ways. This is particularly true if signal is man-made. Fortunately, there are only two ways to represent data in naturally occurring signals. Data specified in the time and frequency domains will be searched. When something happened, and the amplitude of the event the data represented in the time domain explains.

Many things in the universe indicate periodic motion unlike the data specified in the frequency domain is more indirect. Step response defines how system changes data represented in the time domain. Unlike, frequency response indicates how the data represented in frequency domain changes. Since it is not feasible to optimize a filter for both implementations, this separation is critical in filter design. Good performance over time, low performance on frequency, or vice versa.

4.7.2 Time Domain Parameters

The step response can be very important when the field response is created. The reason why the pulse response is not an important parameter that can be explained as follows, it is the human mind's understanding and processing of data. It should be noted that all step, impulse, and frequency responses include the same data in similar regulations. The step response helps analyze time signals because it is related to how people show the data contained in the signals. The step function is the simplest way to represent the difference between two different regions. It can mark when an event started or ended. The human mind displays time-domain data as follows: a group of step functions that divide data into regions with similar properties. The step response is significant because it defines how to replace the dividing lines with the filter. In design of the filter, parameters of the step response that are significant are illustrated in figure 4.3. To allocate events from a signal, the step response time must be shorter than the range of the event. This indicates that the step response should be as fast as feasible.

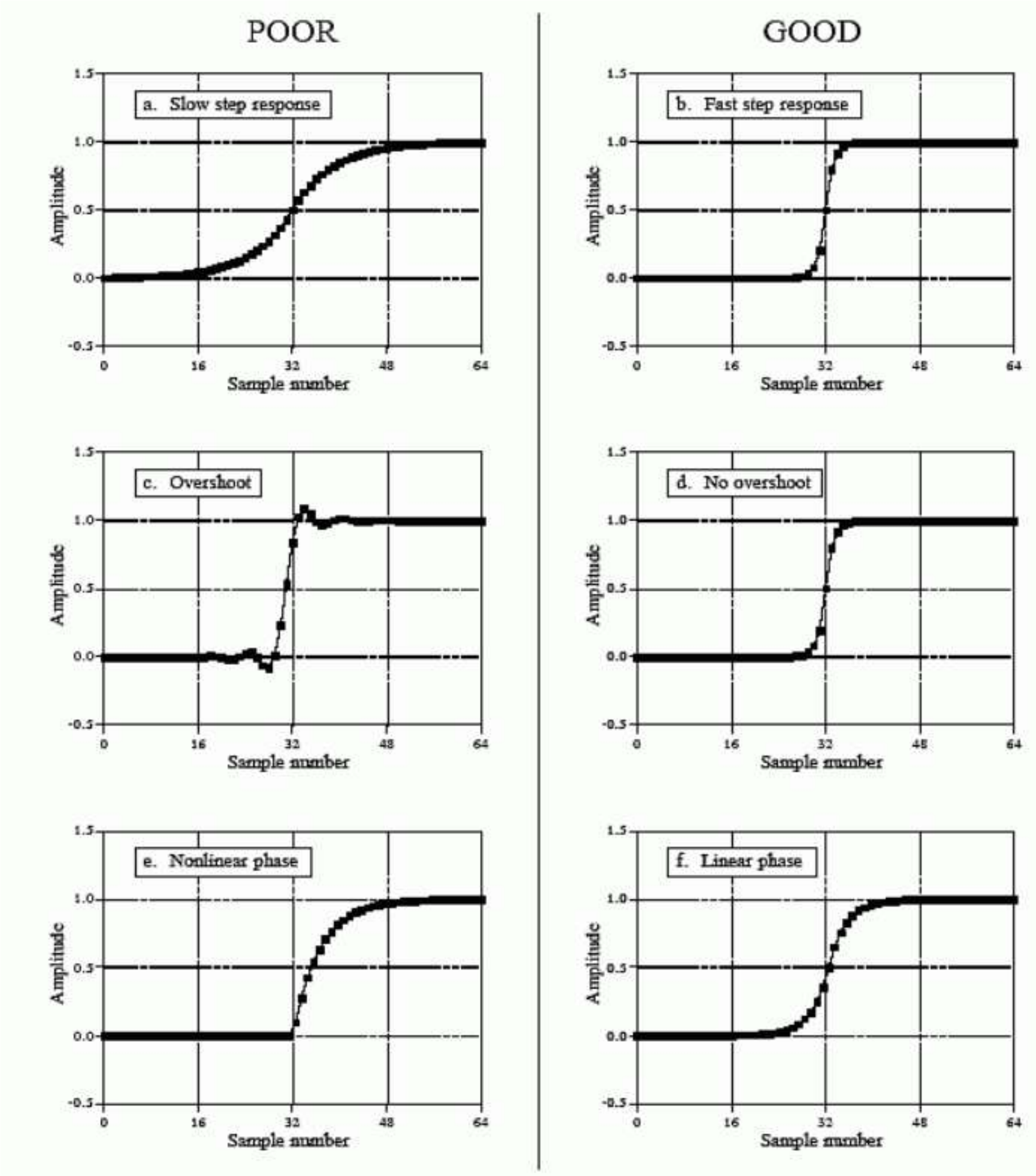


Figure 4.3: Parameters to evaluate time-domain performance

Generally, overvoltage must be extracted because in the signal it changes the samples amplitude, in the time domain this is fundamental data corruption. Finally, it is desirable to be symmetrical with lower half of upper half of step response. This symmetry is necessary for rising edges to look same as falling edges. This symmetry is named a linear phase because frequency response has a phase with a straight line. Make sure you understand these three parameters; it is key to evaluating time domain filters.

4.7.3 Parameters to frequency domain

Four basic frequency responses are shown in Figure 4.3. These filters aim to let some frequencies to pass unchanged while completely blocking other frequencies. Transition band includes frequencies blocked, while transition band refers to transmitted frequencies. Between transition band. Fast-rolling means that transition belt is too narrow. Section between transition band and transition band is named cut-off frequency**.**

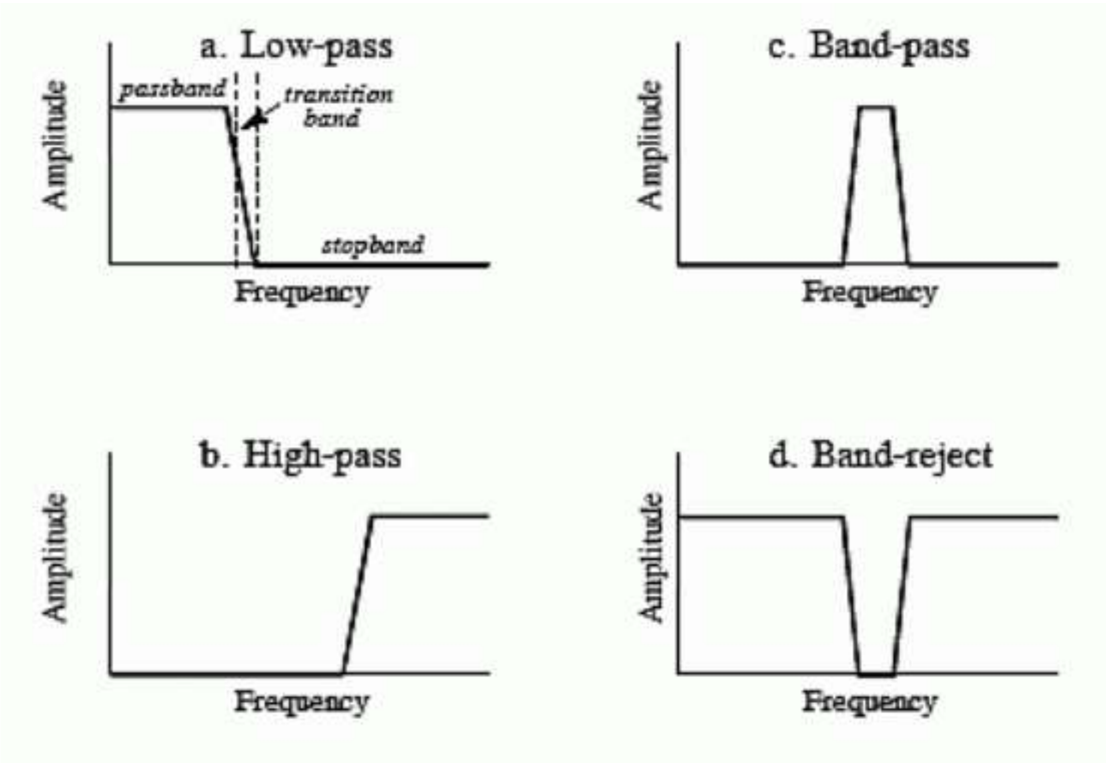


Figure 4.4: The four common frequency responses

in figure 4.5 three parameters that measure how well a filter carries out in the frequency domain have been illustrated.

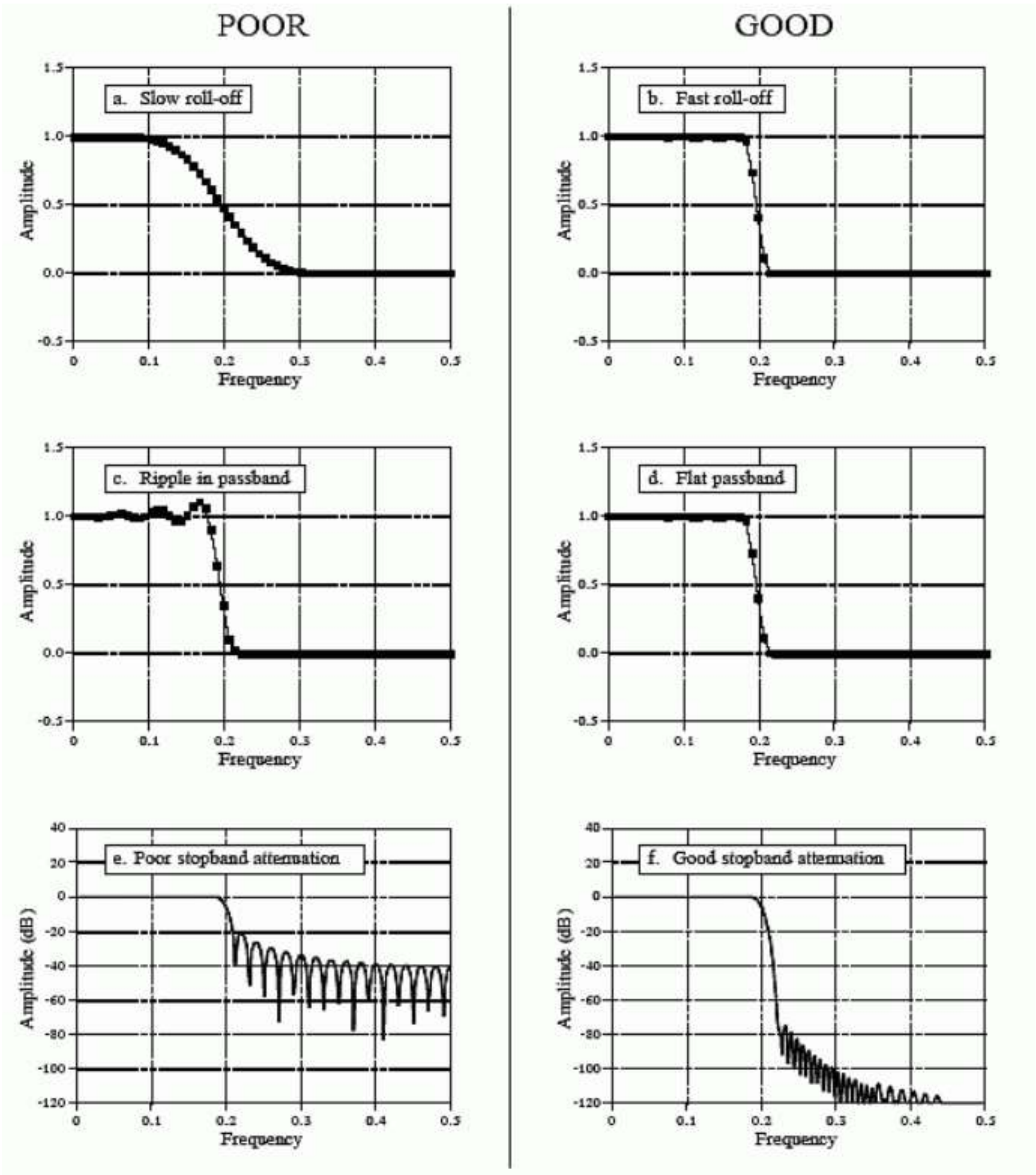


Figure 4.5: Parameters to evaluate frequency domain performance

Why is there nothing in-phase related to these parameters? First, phase is not substantial in most frequency-domain implementations. e.g., the audio signal phase is almost completely random and includes small beneficial data. Second, if the phase is substantial, with an excellent phase response, digital filters are very easy to design, that is, with zero phase shift, all frequencies pass through the filter.

4.7.4 Classification of filter

Digital filter classification by their utilization and their application has been summarized in Table 4.1. The use of digital filters can be divided as the time domain, custom, and frequency domain into three categories and given in table 4.1.

Table 4.1: Filter classification(Smith, 1999)

Filter Used For	Filter Implemented By	
	Convolution (FIR)	Recursion (IIR)
Time Domain (smoothing, DC removal)	Moving Average	Single pole
Frequency Domain (separating frequencies)	Windowed-sinc	Chebyshev
Custom (Deconvolution	FIR custom	Iterative design

Filters are utilized when the waveform of the data signal is encoded as a time domain. Time-domain filtration is utilized for such actions, these are:

- Waveform shaping,
- Elimination of DC
- Smoothing etc.

In contrast, filters of frequency-domain are utilized when data is added to the amplitude, frequency, and component sinusoids phase. To separate one frequency band from another is the purpose of these filters. When the filter requires special handling, which is more detailed than the four fundamental responses (high pass, low pass, bandpass, and band rejection) Special filters are utilized. In two ways as convolution and recursion, digital filters can be implemented. Convolution filters can perform much better than recursive filters, but run much slower.

4.8 Signals and Data

A signal is a quantity change that is delivered concerning a case, feature, composition, orbit, evolution, and behavior, or data source target. A signal is transmitting data about case(s) of variable. Data transmitted in a signal can be utilized by people or machines for communication, making of control, decision of geophysical, discovery, forecasting, forensic medicine, and medical diagnosis, etc. Signal types which signal processing deals with contain;

- Medical
- Ultrasonic
- Image
- Biological
- Audio
- Subsonic
- Financial
- Textual data
- Seismic signals
- Electromagnetic

4.9 Summary

Savitzky-Golay filter and wavelet transform are important de-noising methods used for demodulation of signal. However, with these methods, it is very difficult for them to be able to remove the weak signal from a noisy signal and identify early-stage defects. The signal purification issue has a powerful link with continuous glucose monitoring. Removing weak signals from noise is very significant for continuous glucose monitoring, so the features of the signal are frequently very weak and masked by noise. The standard approach to removing signals from a noisy background is to design a convenient filter that extracts the components of noise and also, to pass unchanged allows the desired signal. Depending on the reduction of noise and the type, noise must be applied and different filters must be designed. However, conventional design of filter can become a very difficult task, when the frequency range and noise type are unknown. For this reason, this research has been focused to find alternative methods. Wavelet transform is widely utilized in signal interference because of its ability to represent frequency of extraordinary time. Generally, most of the signal interference suppression approaches relate to detecting smooth curves of noisy raw signals. This unique property restricts the implementation of the traditional signal noise removal method. Noise removal method based on Morlet wavelet analysis has been recommended to clear continuous glucose monitoring signals from noise. This method is sought for optimal wavelet filters that give only the greatest kurtosis value for the converted signals, ignoring the periodicity of signal. In this dissertation, the success of wavelet decomposition and wavelet filter based noise removal methods are compared. Although the comparison outcomes show that the wavelet filter is more appropriate and dependable to determine weak and impulse-like signals of continuous glucose monitoring signals, the method of removing wavelet separation noise can achieve sufficient results in correct detection of the signal. Process of two-step optimization is recommended to choose the most suitable parameters for the Wavelet filter. Morlet wavelet is utilized as a criterion to optimize the shape factor of minimal Shannon entropy. Detection of periodicity method based on SVD (Single Value Discrimination) is utilized to select a scale for the wavelet transform. Noise reduction results from both experimental data and simulated signals are presented in this thesis and both supported the proposed method.

CHAPTER 5
TYPES, TRANSFORMS OF WAVELET, MORLET WAVELET FILTER, AND CALCULATION OF MORLET WAVELET PARAMETERS

5.1 Overview

Wavelets are widely used in a wide variety of technical fields. Generally, wavelets are indicated by mathematical formulas but can be understood for signals or correlations analyzed by simple comparisons. Wavelet filters, which allow us to actually utilize them in processing of digital signal, can be seen as a powerful tool in Morlet Wavelet Transform and Wavelet Transform time-frequency analysis, a kind of Wavelet transform. For the wavelet filter, two-stage optimization is recommended on top of all the tools in the time-frequency analysis, the Fourier transform is a well-known method to select the most appropriate parameters. Optimizing the shape factor of the Morlet wavelet, minimum entropy of Shannon is utilized.

5.2 Overview of wavelet

A wavelet is a limited time period waveform with an average value of zero. Theoretically, unlike minus to infinite sinusoids, wavelets have a beginning and an end. Figure 5.1 illustrates the continuous sinusoid representation and a putative "continuous" wave.

For identifying fixed frequency signals sinusoids are smooth and predictable. Wavelets are better at defining anomalies, pulses and other events that start and stop within the signal, they are irregular, limited duration and frequently not symmetrical.

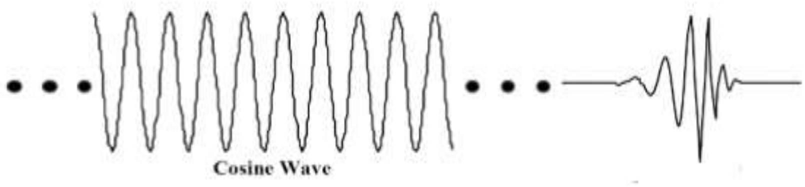


Figure 5.1: Representation of a continuous sinusoid and a supposed ”continuous” wavelet. (Chui, 1992)

5.2.1 Wavelets Types

In literature, Wavelets which are named as functions of mathematical, divide data into frequency different components and then to its scale investigate each component with an appropriate resolution. These basic functions are limited-time short waves, so the term “wavelet” is utilized. By frequency, basic wavelet transform functions are scaled. There are many distinct wavelets that can be utilized as a basic function are shown as ψ (t) basic function, also named as mother wavelet which is used as a transforming function. The main wavelet term is named for its two important wavelet properties. A small wave means, wavelet term. Smallness means the length of this (window) function is limited (supported compactly). The wave refers to the condition in which this function is released. The main wavelet is a prototype used to generate other window functions. In another saying, the term mother means that functions, which are a region support region, are utilized in the process of transformation derived from the main wavelet or the main function.

A wide wavelet function can be written as shown in equation 5.1. Usually, ψ(t) wavelet is a complex-valued function.

$$\psi_{s,\tau}(t) = |s|\tfrac{1}{2}\psi[(t-\tau)/s] \tag{5.1}$$

This τ shift parameter determines the window position over time, thus specifying which part of the $x(t)$ signal is analyzed. By frequency variable ω, scale variable s is replaced and the $t1$ variable of time-shift is replaced by τ in an analysis of wavelet transform. These functions of mother wavelet are used by Wavelet transform and perform signal decomposition $x(t)$ into a scaled weighted set $\psi(t)$ wavelet functions. Wavelets are localized in space this is main advantage of utilizing wavelets. Different kind of wavelets are demonstrated below:

- **dbN: Daubechies Wavelets**

N is order in Daubechies Wavelets. Some of Daubechies Wavelets are utilized as $2N$ in place of N. Daubechies wavelets have no clear statement other than db1, which is Haar wavelet. ψ and φ support length are $2N - 1$. The lost moments' number ψ is N. For some asymmetry, most dbNs are not symmetrical, very evident if order tidiness increases. When N gets very bigger, ψ and φ belong to $C^{\mu N}$ where μ equals about 0.2 pessimistic N for small order. It should be noted that at specific points than others and analysis is vertical functions are more regular.

- **symN: Symlet Wavelets**

N is order in Symlet Wavelets. Some of Symlet Wavelets are utilized, as $2N$ in place of N. Symlets are only near symmetric. Idea includes reusing function m_0 presented in dbN, considering $|m_0(w)|^2$ as a function w of, $z=e^w$. Then we can factor w in several distinct ways in $w(z)=U(z)U$ form because w roots with modulus not equal to 1 go in pairs. If one of roots is z1, then $z1$ is furthermore a root.

dbN Daubechies wavelets minimum phase filter which is U filter has been established by choice U such that modulus of all its roots is definitely less than 1.

- **db1: Wavelet of Haar**

Daubechies wavelets wavelet family written as dbl contains Haar wavelet, simplest wavelet imaginable and definitely earliest. Haar function of wavelet is demonstrated below:

$$\psi(x) = \begin{Bmatrix} 1 & 0 \leq x\frac{1}{2} \\ -1 & \frac{1}{2} \leq x < 1 \\ 0 & otherwise \end{Bmatrix} \tag{5.2}$$

- **coifN: Coiflet Wavelets**

N is order in Coiflet Wavelets. Some of Coiflet Wavelets are utilized $2N$ in place of N. ψ function has $2N$ moments equal to 0 and, what is more extraordinary, function φ has $2N-1$ moments equal to 0. Two functions have $6N-1$ support of length, coifN φ and ψ are much more symmetrical than dbNs. coifN has to be compared to sym3N or db3N according to support length. Regarding the lost moments' number of ψ, coifN has to be compared to sym2N or db2N. If s is enough orderly continuous-time signal, for large j coefficient $\langle {}^{s,\emptyset}{}_{-j,k} \rangle$ is estimated by $2^{-\frac{j}{2}} s(2^{-j}k)$. If s is a degree polynomial $d, d \leq N-1$, then estimation becomes equality. Connected with sampling problems this property is utilized, the difference between an expansion through $\emptyset_{j,k}$ of a specific signal and sampled version.

- **biorNr.Nd: Pairs of biorthogonal Wavelet**

New family is expanding the wavelet family. In the subband filtering assembly, if the same finite impulse response filters are utilized for restoration and separation it is well known that symmetry and complete reconstruction (except Haar wavelet) are incompatible. One, $\bar{\psi}$, is utilized in analysis, and a signal coefficients s are $\bar{C}_{j,k} = \int s(x)\bar{\psi}_{j,k}(x)dx$. Other, ψ, is used in synthesis, $s = \sum_{j,k}\bar{c}_{j,k}\psi_{j,k}$. Additionally, wavelets ψ and $\bar{\psi}$ are related by duality in following sense: $\int \bar{\psi}_{j,k}(x)\psi_{j,k}(x)dx = 0$. As soon as $j = j'$ or $k = k'$ and even, $\int \varphi_{0,k}(x)\varphi_{0,k}{}'(x)dx = 0$ as soon as $k = k'$. ψ,$\bar{\psi}$, φ and $\bar{\varphi}$ functions are zero outside of a segment.

- **Meyr: Wavelet of Meyer**

In frequency domain Wavelet of Meyer and function of scaling is described as follows:

Wavelet function

$$\psi(\omega)=\begin{cases}(2\pi)^{-1/2}e^{i\omega/2}\sin\left(\frac{\pi}{2}\upsilon\left(\frac{3}{2\pi}|\omega|-1\right)\right) & ;if\ \frac{2\pi}{3}\leq|\omega|\leq\frac{4\pi}{3}\\ (2\pi)^{-1/2}e^{i\omega/2}\cos\left(\frac{\pi}{2}\upsilon\left(\frac{3}{4\pi}|\omega|-1\right)\right) & ;if\ \frac{4\pi}{3}\leq|\omega|\leq\frac{8\pi}{3}\\ 0 & ;|\omega|\notin\left[\frac{2\pi}{3},\frac{8\pi}{3}\right]\end{cases}$$

where

$$v(a)=a^4(35-84a+70a^2-20a^3);\qquad a\in[0,1] \tag{5.3}$$

Scaling function

$$\varphi(\omega)=\begin{cases}(2\pi)^{-1/2} & :\quad if\quad |\omega|\leq\frac{2\pi}{3}\\ (2\pi)^{-1/2}\quad\cos\left(\frac{\pi}{2}v\left(\frac{3}{2\pi}|\omega|-1\right)\right) & ;\quad if\quad \frac{2\pi}{3}\leq|\omega|\leq\frac{4\pi}{3}\\ 0 & ;\quad if\quad |\omega|>\frac{4\pi}{3}\end{cases} \tag{5.4}$$

You get a different family of wavelets by changing auxiliary function. For necessary features of auxiliary function v. Wavelet is extremely different, this allows wavelet vertical analysis.

- **mexh: Wavelet of Mexican Hat**

Wavelet of Mexican Hat function is given as:

$$\psi(x)=\left(\frac{2}{\sqrt{3}}\pi^{-1/4}\right)*(1-x^2)*e^{-x^2/2} \tag{5.5}$$

This function is commensurate to the Gaussian probability density function second derivative. Analysis is not vertical since the function does not exist.

- **morl: Morlet Wavelet**

Morlet Wavelet function is given as:

$$\psi(x) = Ce^{-x^2/2} \ cos5x \tag{5.6}$$

Morlet wavelet does not fully meet requirement. For normalization, in reconstruction view, constant C is utilized.

5.3 Wavelet transform

From $\psi_{(a,b)}(t)$ that is a single function by translation and dilation methods wavelet is achieved:

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{5.7}$$

In the above expression "a" is supposed parameter of scaling, b is parameter of time localization and mother wavelet is named as $\psi(t)$. $b \in R$ translation parameters and $a > 0$ dilations, may be discrete or continuous. $x(t)$ wavelet transform that is a finite energy signal with wavelet analysis $\psi(t)$ is $x(t)$ convolution with a wavelet of scaled and conjugated that is given expression 5.8.

$$W(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \tag{5.8}$$

$\psi^*(t)$ is complex conjugation of $\psi(t)$, as translation functions b with each scale a wavelet transform $W(a,b)$ can be considered. Equation (5.8) demonstrates that the analysis of wavelet is an analysis of time-frequency or time-scaled. For a signal multi-scale analysis by dilatation and translation wavelet, transform can be utilized, unlike Short Term Fourier Transform, thereby effectively extracting time-frequency characteristics of a signal. This allows original signal to be reconstructed, wavelet transform can also be reversed. A classical reversing formula for wavelet transform has been given in equation 5.9.

$$x(t) = C^{-1}_{\psi} \iint W(a,b)\, \psi_{(a,b)}(t)\frac{da}{a^2}db \tag{5.9}$$

Where

$$C_{\psi} = \int_{-\infty}^{+\infty} \frac{|\bar{\psi}(w)|^2}{|w|} dw < \infty \tag{5.10}$$

$$\bar{\psi}(w) = \int \bar{\psi}(t) \exp(-jwt)\, dt \tag{5.11}$$

5.4. De-noising based on Wavelet decomposition

For noisy signal underlying model is fundamentally given as the following form:

$$x(n) = s(n) + \sigma w(n), n = 0,1 \ldots\ldots, N-1 \tag{5.12}$$

σ is noise level and $w(n)$ is standard Gaussian white noise in this simplest model, independent identically distributed indicated by $w(n) \sim N(0,1)$. It is a noise-generating object to extinguish the signal noise portion $x(n)$ and rescue $s(n)$. Thus, by reconstructing a signal from an average error between $s(n)$ and noisy data, this signal is minimized, theoretically obtainable. Method $s(n)$ can be seen as a non-parametric estimate and the model can also be used as a regression model using a vertical basis over time.

De-noising of Wavelet is based on a multi-resolution analysis principle (Donoho and Johnstone, 1995). A discrete detail coefficient and approximate coefficient can be achieved with multi-level wavelet dissociation. (Grossmann, 1988) showed that white noise details decrease regularly as the level of variance and amplitude increases at various levels; By modifying wavelet coefficients according to this feature noise can be reduced or even removed. Basic version of the general de-noising method can be divided into three parts, these are:

- **Reconstruction of signal**

  The reconstruction wave is calculated using original approximate coefficients at the N level and in this step, the detailed coefficients modified are from $1\ to\ N$.
- **Decomposition of signal**

  In this step, wavelet base and N level are selected, then at level N, the wavelet signal decomposition is computed.
- **Detail coefficients of Threshold**

  In this step, a threshold from $1\ to\ N$ for each level and application soft threshold according to detailed coefficients are selected.

In general, this method provides almost optimal de-noising while maintaining a signal and works very well on Gaussian noise. However, the problems that attract intensive research efforts were given below.

- How to choose optimal wavelet for a particular signal type. Fundamentally, if wavelet basis "resembles" signal under analysis, wavelet decomposition is better. Currently, there is still no common guide on how to choose optimal wavelet base or how to choose, corresponding scale level and shape parameter for a particular implementation.
- Concerns threshold choice and how to perform thresholding. (Donoho, 1995, Chang & Vetterli, 2000, Hansen & Yu, 2000, Donoho & Johnstone, 1994).
- Rarity of coefficients of wavelet.

Wavelet decomposition method is based on basic idea that signal energy will concentrate on several coefficients in field of wavelet. Therefore, the nonlinear threshold function will look to maintain several large coefficients representing the signal and will also tend to decrease noise coefficients to zero. if it is a smooth curve with small or no sudden change signal $s(n)$ works well. Nevertheless, it is very difficult to obtain a sparse wavelet representation, if signal $s(n)$ includes an impulse component plurality. This adds great difficulty in wavelet noise removal.

5.5 Optimal wavelet filter

5.5.1 Wavelet filter principle

Another method used to obtain useful data from a noisy signal is the wavelet filter. A Fourier transform significant feature is that convolution in one field corresponds to proliferation in others. Thus, equation 5.8 can take an alternate form in equation 5.13.

$$W(a,b) = \sqrt{a}F^{-1}\{X(f)\psi^*(af\} \qquad (5.13)$$

$x(t)$ Fourier transforms and ψ(t) is $X(f)$ and ψ(f), respectively, and inverse Fourier transform is indicated as F^{-1}. Equation 5.10 illustrates that transform of wavelet can also be considered as a special filtering process. By expanding analysis wavelet frequency segmentation is achieved. In another saying, in wavelet convolution process transformation is simply a filtration process if slide considered as a wavelet filter core. Wavelet filter response of frequency changes as basic scale changes and wavelet shape, so the wavy coefficients can be reconstructed at selected scales to form low pass, bandpass, high pass or even multi bandpass filters. Equation 5.8, $W(a,b)$ at a different resolution, levels to give $x(t)$ information and also $x(t)$ signal and measure similarity between wavelet function. This means that if wavelet utilized is similar to components hidden in signal, a wavelet can be used for element discovery. To some extent, daughter wavelet and this analyzed signal convolution process are look like to another notion of classical signal processing: matching filtering actually derived from the process of correlation. Therefore, the detection of weak signal purposes is to assign target signals rather than reconstruct signal.

5.6 Morlet Wavelet

In practice, the Morlet wavelet is the most popular complex wavelet utilized. Morlet wavelet has a very similar form to Gabor transformation. The significant difference is that the window function dose is also scaled by the scaling parameter, the window size in the Gabor transformation is fixed. Morlet wavelet is defined in equation 5.14.

$$\psi(w) = \exp(-2\pi^{2}(v - v_{0})^{2}) \tag{5.14}$$

The above statement is a complex wavelet and is divided into two parts, equation 5.15 illustrates real and equation 5.16 illustrates imaginary parts:

$$\psi_{r}(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\beta^{2} t^{2}}{2}\right) \cos(2\pi v_{0} t) \tag{5.15}$$

$$\psi_{i}(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\beta^{2} t^{2}}{2}\right) \cos(2\pi v_{0} t) \tag{5.16}$$

where β is shape parameter and v_{0} is constant that balances Morlet wavelet time and frequency resolutions. Usually, only Morlet wavelet real part is utilized. A distorted cosine signal folded both left and right, is the real part of the Morlet wavelet and its function is very close to an impulse. In continuous glucose monitoring signal implementations this similarity applies Morlet wavelet in a very attractive and widespread manner. By scale expansion and time translation from main wavelet a daughter Morlet wavelet is achieved;

$$\psi_{a,b}(t) = \psi\left(\frac{t-b}{a}\right) = e^{-\frac{\beta^{2}(t-b)^{2}}{2a^{2}}} cos\left[\frac{\pi(t-b)}{a}\right] \tag{5.17}$$

where“b” is for time translation and for dilation a is scale parameter. A wavelet of daughter Morlet that closely matches continuous glucose monitoring signals shape can be constructed as shown in (Chapter-6 figure 6.4) by carefully selecting parameters a and β, and if wavelet conversion is performed according to this filter core from the noisy signal should be able to sense similar components.

5.7 Shape factor *b* optimum selection based on Shannon entropy

To evaluate wavelet transforms efficiency scarcity of coefficients of wavelet is frequently utilized. Wavelet corresponding to dominant and a signal minimum wavelet conversion coefficients is ideal. The transform of optimal wavelet should be able to intensify the signal with several large coefficients. The simplest rarity description indicates that most elements are zero in a vector or sparse matrix. By various criteria, rarity of a series can be evaluated.

The simplest way was given in equation 5.18 and equation 5.19 as follows to measure sparseness is L_0 norm:

$$L_0 = \sum_i v_i; \qquad v_i \in \{0,1\} \tag{5.18}$$

$$\{x_i > Threshold \rightarrow v_i = 1; \quad x_i < Threshold \rightarrow v_i = 0 \} \tag{5.19}$$

vector "x" is completely sparse, if $L_0 = 0$, (i.e includes only zero). Quite clearly, L_0 norm, in order to measure noisy data rarity, is not very practical. Addition of a very small measurement noise makes the data fully rare. Therefore, L_p norm, kurtosis, Tanh-function, and so on. Various rarity measurement criteria such as are suggested. Among these, Shannon entropy is one of well-accepted infrequency criteria. In 1948, in connection with communication theory entropy of Shannon was first introduced by Shannon. (Shannon and Weaver, 1949, Kapur and Kesavan, 1992). Shannon entropy is defined as:

$$H(p) = -\sum_{i=1}^{n} p_i * \log\ p_i \quad , \quad \sum_{i=1}^{n} p_i = 1 \tag{5.20}$$

where p_i is observing probability "i^th^" feasible random variable value $X \in \left[x_1, x_{2,\ldots} x_n\right]$. As a measure of uncertainty entropy of Shannon is central role of theory of knowledge, occasionally referred. In distribution of probability terms and can be indicated to be a good randomness measure and rarity the random variable entropy is described. To appraise flexibility of coefficients of wavelet (Jin and Liangsheng, 2000) Shannon Entropy can thus be utilized. As last outcome coefficients of Wavelet transform with at least entropy of Shannon can be considered. Therefore, as optimal outcome, corresponding b shape factor can be adopted.

5.8 Scale based optimal selection on singular value decomposition

With minimal entropy of Shannon criterion next step is to select a suitable transformation scale of wavelet a, After shape factor β is determined, in another saying, wavelet filter frequency range so that noisy signal periodic pattern can be detected. The wavelet coefficients periodicity can be utilized as a criterion to choose the optimum scale a because the purpose of noise reduction is to assign components of weak periodic from a noisy signal. The a scale, which can find the strongest periodicity from the wavelet coefficients, will be chosen as the transformation of the optimum wavelet scale. Traditionally, signal detection periodicity is Fourier analysis, density of power spectral, periodogram, and so on. each component (Kanjilal, P., et al., 1999). Furthermore, impulse series poor dominance compared to background noise imposes another limitation on conventional methods. These constraints lead to a new detection of periodicity improvement method. To determine periodicity of time series, Single Value Separation (SVD) can be applied (Kanjilal and Palit, 1995). In information content terms and robustness, it is much stronger and more sensitive than existing tools based on Fourier decomposition (Kanjilal, P., et al., 1999). The mxn matrix SVD, D is defined as dissociation (Golub &Van Load, 1989).

$$D = UEV^{T} \tag{5.21}$$

where V is nxn square matrix with orthogonal columns and U is mxm square matrix so that;

$$U^{T}U = I,\ V^{T}V = I \tag{5.22}$$

Additionally, E is a mxn diagonal matrix, $E = diag(\sigma_{1,}\sigma_{2}, \dots, \sigma_{p})$, with $p = \min(m, n)$ and a matrix diagonal elements$[\sigma_{1,}\sigma_{2}, \dots, \sigma_{p}]$, E is matrix singular values D and nonnegative numbers $[\sigma_{1,}\sigma_{2}, \dots, \sigma_{p}]$ are traditionally ordered as $\sigma_{1} \geq \sigma_{2} \geq \cdots \geq \sigma_{n} \geq 0$. SVD power becomes evident as its connections with other linear algebra basic topics are explored. e.g., if $D\ r > 0$ and has rank r then D has exactly r strictly positive singular values so that all its singular values are nonzero $\sigma_{r} > 0$ and $\sigma_{r+1} = \cdots = \sigma_{p} = 0$ if D has full rank. Consider a periodic signal $X = [x_{1,}, \dots, x_{l}]$ with a period of length n. By dividing the series into periods and placing each period as the x sequence, an X matrix can be created in the 5.23 equation.

$$X = \begin{pmatrix} x(1) \dots \quad x(n) \\ x(n+1 \dots \quad x(2n) \\ . \\ . \\ . \\ x((m-1)n+1) \dots x(mn) \end{pmatrix} \tag{5.23}$$

X matrix has m recurred rows and is of rank 1. Consequently, X matrix should have only $m - 1$ zero singular values and 1 non-zero value of singular σ_{1}. Now if we take into account a periodic waveform case with amplitude of time-varying plus noise, suppose time series period length $X = [x_{1,}, \dots, x_{l}]$ is still n, a dissimilar size matrix $X(round(\frac{l}{i}), i)$,$2 \leq i \leq l/2$ can be created by dividing time series into segments with dissimilar lengths i. Due to noise X matrix may now be full rank, but $\sigma_{1,}$ would be very large compared to the rest of singular values when $i = n$ hence, by equation 5.24 below the ratio is indicated:

$$\delta_{i} = \left(\frac{\sigma_{1}}{\sigma_{2}}\right)^{2} \tag{5.24}$$

at $i = n$ will show its maximal value then to forecast periodicity of signal δ_{i} can be utilized. The algorithm of two-stage optimal parameter selection can be designed by connecting two optimization processes as shown in figure 5.2 below.

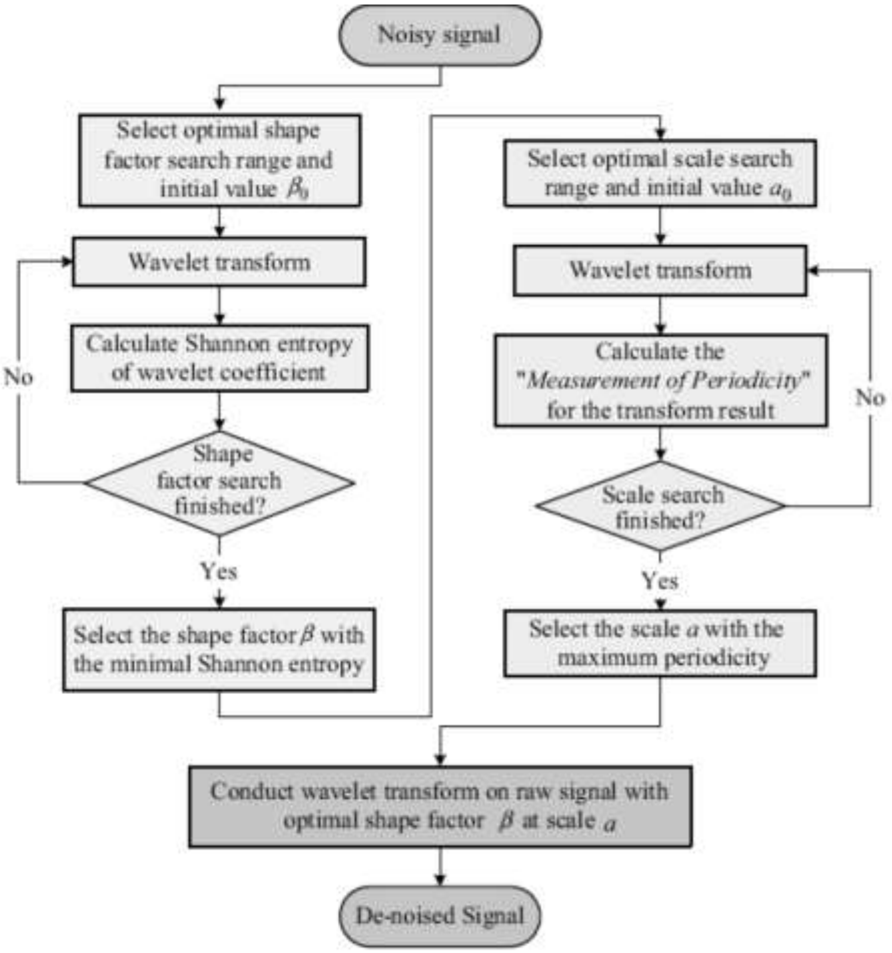


Figure 5.2: Flowchart to select optimum wavelet transform scale and shape factor

5.9 Continuous Wavelet Transform (CWT)

An analysis of wavelet function, a is position parameter of the wavelet and b is the scaling (dilatation) parameter of the wavelet where ψ * (t) is the mother wavelet complex conjugate ψ (t). It should be noted that a is any real number and b is any positive real number.

$$X_{w}(a,b) = \frac{1}{\sqrt{b}} \int_{-\infty}^{+\infty} x(t)\ \psi^{*}\left(\frac{t-a}{b}\right) dt, \begin{Bmatrix} a\ \in (-\infty,+\infty) \\ b \in [0,+\infty] \end{Bmatrix} \tag{5.9}$$

5.9.1 Wavelet Filter and how is it different from a Wavelet?

Wavelets are a child of digital age. Some wavelets are described in a mathematical expression and drawn continuously and infinitely. These are named as raw wavelets. However, to utilize them with our digital signal, they must first be converted to wavelet filters with a limited number of discrete points. In other words, we evaluate the raw wavelet equation at desired time (generally evenly spaced) to create filter values of that time.

5.10 Summary

From the noisy continuous glucose monitoring signal, de-noising, and weak signal extraction are very significant, in this case, its properties are frequently are masked by background noise and very weak. By signal coefficients, relative energy levels and white noise coefficients performance of de-noising based conventional methods on decomposition of wavelet is greatly influenced. When dealing with smooth signals, by manipulating threshold usually satisfactory outcomes can be obtained. The main reason for this is that few large coefficients can characterize the original signal with smooth signals. Nevertheless, where wavelet coefficients are not very intense, to obtain noise-canceling impulse series signals it is much more difficult. This method is based on the idea of identifying impulse-like components known as Morlet wavelet filter-based suppression of noise by designing a daughter Morlet from a noisy signal wavelet on a "b" scale "a" with a special shape factor "b". From a signal of continuous glucose monitoring where defect characteristics are impulse-like, this method is very appropriate in order to detect a weak signal. An optimum the shape factor of wavelet “b” with resolution of optimum time-frequency can be achieved by applying the lowest Shannon entropy criterion. For which results cannot be detected is Wavelet transform periodic separation-based periodicity evaluation with a single value optimal scale can be determined based on the assumption that the signal.

CHAPTER 6

NOISE REDUCTION METHODS, SETTING PARAMETERS AND EXPERIMENTAL OUTCOMES FOR CONTINUOUS GLUCOSE MONITORING(CGM) SIGNAL

6.1. Overview

Complex chronic disease is the inability of the body to produce one or sufficient insulin. This ensures an advantageous model for studying bio-behavioral processes in metabolic disease blood (diabetes), resulting in elevated glucose levels. However, an academic remotely is at the same time an increasing public health problem. Monitoring of continuous glucose, which aims to develop clinical care for diabetic patients, has led to the questions of research development that can be asked about diabetes. Most of the monitoring of continuous glucose studies were intended to demonstrate a clinical benefit for diabetes control and to describe patient satisfaction in the clinical setting. Continuous glucose monitoring systems gather and store data of glucose in a mode that lasts several days at a time. The main advantage of CGM is that it can help determine fluctuations and trends that will not be noticed by other glucose precautions.

The data used in the study are actual measurement values. In this, dissertation the patient profile and details of the data have been described in the section obtaining the blood glucose concentration data. In such studies, the noise profile is known to be of Gaussian type. Thus, Gaussian, which is parallel to the real noise in the data analysis, was chosen. The standard application was used in the analysis of the results. However, the data were analyzed with values above the noise levels used in other articles and the validity of the applied method has been proven.

6.2. Filtering of Continuous Glucose Monitoring Signal

Digital filtering techniques are utilized to minimize the random noise error component and improve signal quality. The formula described below shows the signal from the continuous glucose monitoring sensor;

$$y(t) = x(t) + n(t) \tag{6.1}$$

The glucose level (actual signal) indicated by x (t) has been measured at a time **t**. n (t) is the basic white Gaussian noise model that affects it. The signal from the continuous glucose monitoring sensor is indicated by y (t). One of the main problems for low-pass filtering is that it is very difficult to clean the White Gaussian noise, represented by n (t), without damaging the actual glucose level signal indicated by x (t). Because the signal and noise spectra have been normally overlapped. The purpose of the noise filtering is divided into two parts, the separation of the combined signals and the restoration of the distorted signals in some way. Noise filtering in continuous glucose monitoring is shown in figure 6.1.

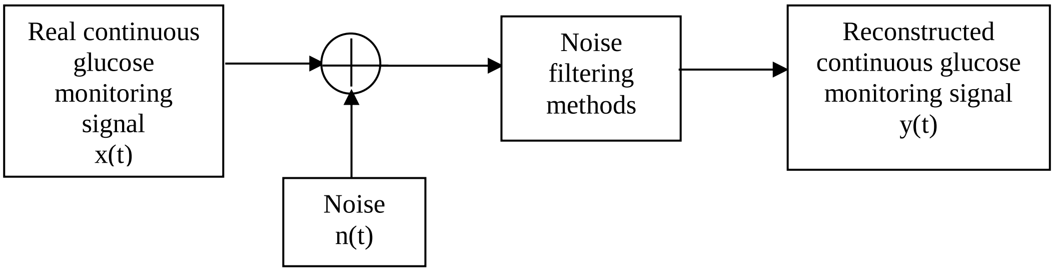


Figure 6.1: Block diagram of noise filtering from continuous glucose monitoring signal

Digital filtering is the process of decoding a signal from a signal. Both analog and digital signal processing devices have all the features that make them sensitive to noise. The noise may be random or white noise with an equal frequency distribution or the frequency-dependent noise generated by the mechanism of a device or signal processing algorithms. In order to minimize the noise contribution that may occur in the continuous glucose monitoring signal, an improved Morlet wavelet was proposed and compared with the current Savitzky-Golay filter and standard Morlet wavelet.

6.2.1. Savitzky-Golay Filter

The digital filter that can be applied to various digital data points to increase the accuracy of the data without disturbing the signal trend is known as the Savitzky-Golay filter. In 1964, Abraham Savitzky and Marcel Jules Edouard Golay published the tables of convolution coefficients for various polynomials and subset sizes in their original article. This is achieved by combining the lowest-squares method with a low-grade polynomial to concatenate the successive subsets of adjacent data points in a process known as convolution. When the data points are placed at equal intervals, an analytical solution can be found as a single "convolution coefficient" that can be applied to all data subgroups to give signal estimates.

It is a method based on mathematical operations created at the center of each subset:

$$Y = a_0 + a_1 z + a_2 z^2 + ... + a_k z^k \tag{6.2}$$

Savitzky-Golay, in their article entitled **Smoothing and Differentiation of Least Squares**

(Equation 6.3), showed that a moving polynomial alignment can be used in the same way as a numerically full weighted moving average (Jianwen and Jing, 2005; Savitzky and Golay). , 1964; Kavalcıoğlu and Dağman, 2016);

$$G = S(S^T S)^{-1} = [g_0, g_1, ..., g_n] \tag{6.3}$$

The matrix $G_{(2m)x(n+1)}$ includes the Savitzky-Golay filter convolution coefficients for distinct symmetry or distinct layout differentiation in the center of different origins. (i.e, the center of symmetry) given by correction and differentiation equations (Jianwen & Jing, 2005; Savitzky & Golay, 1964).

$$f_n(t) = \sum_{i=-m+1}^{m} h_{n,0,t,m,i} x_i \tag{6.4}$$

$$f_n^{(s)}(t) = \sum_{i=-m+1}^{m} h_{n,s,t,m,i} x_i \tag{6.5}$$

In Equations 6.4 and 6.5, “n” and “2m”, which are evaluated in the “t” position, smoothing by $(1 \le s \le n)$ using the equation $f_n(t)$ and $f_n{}^{(s)}(t)$ of the differentiation values at the moment of sampling.

6.2.2. Continuous Wavelet Transform (CWT)

CWT is utilized to divide a signal into fluctuations. The wavelet is a wave-like oscillation with an amplitude starting at zero and then increasing to zero (Aydın and Aslan, 2017). Although the Fourier transforms effectively transmit all-time localization information, the main functions of the continuous wavelet transform are scaled and shifted versions of localized wavelets, even when the signal is divided into infinite long sinuses and cosines. Continuous wavelet transform is utilized to produce a time-frequency representation of a signal that provides a very good frequency and time localization. continuous wavelet transform transformation is an ideal and perfect tool to determine whether a signal is globally constant to plan the changing properties of non-stationary signals. When a signal is evaluated as non-constant, the continuous wavelet transform can be used to identify the fixed parts of the data flow. Basic calculations in FlexPro's continuous wavelet transform procedures are usually followed by Torrence and Compo algorithms listed in the following references list. The terminology utilized in the following equations is also utilized in the Torrence and Compo article (Daubechies, 1990; Torrence & Compo, 1998).

The equations of continuous wavelet transform are as follows: (Chui, 1992; Qian, 2002; Meyer, 1993):

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right) dt \tag{6.6}$$

$$W_{n}(s) = \sum_{n'=0}^{N-1} x_{n'} \sqrt{\frac{\delta t}{s}}\, \Psi_{0}^{*} \left[\frac{(n'-n)\delta t}{s}\right] \tag{6.7}$$

$$W_{n}(s) = FFT^{-1} \left[\sum_{k=0}^{N-1} \hat{x}_{k} \left(\sqrt{\frac{2\pi s}{\delta t}}\, \hat{\Psi}_{0}^{*}(s\omega_{k}) e^{j\omega_{k} n\delta t}\right)\right] \tag{6.8}$$

$$\hat{x}_{k} = \frac{1}{N}\sum_{n=0}^{N-1} x_{n} e^{-2\pi ikn} \tag{6.9}$$

$$\omega_{k} = if(k) \leq \frac{N}{2}, \frac{2\pi k}{N\delta t}, -\frac{2\pi k}{N\delta t} \tag{6.10}$$

The continuous wavelet transform is a transformation of the data set with a scaled and translated version of the main wavelets of the main function. It should be noted that there is a continuous function except for continuous wavelet transform, discrete data sequence, and discrete Fourier transform. (Daubechies, 1988; Daubechies, 1992; Grossmann & Morlet, 1984; Jaffard et al., 2001; Mackenzie 2001). In these expressions, * denotes a complex conjugation, The length of the data sequence has been referred to as **N**, **s** wavelet scale, **δt** sampling interval, **n** localized time index, and ω angular frequency. Each expression includes normalization, so the wavelet function includes unit energy at any scale. For continuous wavelet transform, the correlation between the successive segments of the scaled wavelets and the data flow is calculated for each value of the scale used. Unless restructuring is required, there is no restriction in the continuous wavelet transform depending on the scale used or the distance between the scales. The continuous wavelet transformation spectrum can utilize logarithmic or linear scales with any desired density. If necessary, a high-resolution spectrum can be produced for a narrow frequency range. Shells can be made at any scale up to ”N” and all "N “ times should be done if using fast Fourier transform.

The continuous wavelet transform involves the "N" spectral values that require a reverse-speed Fourier transform for each scale. The calculation load and memory requirements of the continuous wavelet transform are therefore noteworthy. (Arslan & Ökdem, 2015; Karaboğa & Kamışlıoğlu, 2015; Üstündağ et al., 2014). Morlet wavelets are usually the wavelets used for time-frequency analysis of non-stationary time series data. In this study, improved Morlet wavelet has been compared with standard Morlet wavelet.

6.2.3. Morlet wavelet

The most important parameter of the Morlet wavelets is the width of Gaussian that touches the sine waves. This parameter selection plays an important role in time-frequency change. Morlet wavelet is defined by the following function.

$$\psi(\omega) = \exp(-2\pi^2(v - v_0)^2) \tag{6.11}$$

Morlet wavelet (Eq. 6.11) is expressed in complex function, it is possible to parse into real and virtual parts.

$$\psi_r(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\beta^2 t^2}{2}\right) \cos(2\pi v_0 t) \tag{6.12}$$

$$\psi_i(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\beta^2 t^2}{2}\right) \sin(2\pi v_0 t) \tag{6.13}$$

$$W(a,b) = \sqrt{a}\, F^{-1}\{X(f)\psi^*(af)\} \tag{6.14}$$

A constant value of " v_0" as defined in equations (6.12) and (6.13) refers to the formatting parameter that compensates for the resolution of the frequency of the ”β“ Morlet wavelet. In equation (6.14), $X(f)$ and $^*(f)$ are the Fourier transform of the x (t) signal, respectively, and the inverse Fourier transformation of $\psi^*(t). F^{-1}$. Usually, only the real part of the Morlet wavelet is utilized. The real part of the Morlet wave is an exponentially decreasing cosine signal on both the left and right sides and is alike to the impulse signal. All the basic functions that make up the Morlet wavelet are created by the translation of the time unit and scale expansion of the main wavelet (Grossmann & Morlet, 1984; Grossmann & Morlet, 1985; Grossmann et al., 1986).

$$\psi_{a,b}(t) = \psi\left(\frac{t-b}{a}\right) = e^{\frac{\beta^2 (t-b)^2}{2a^2}} cos\left[\frac{\pi(t-b)}{a}\right] \tag{6.15}$$

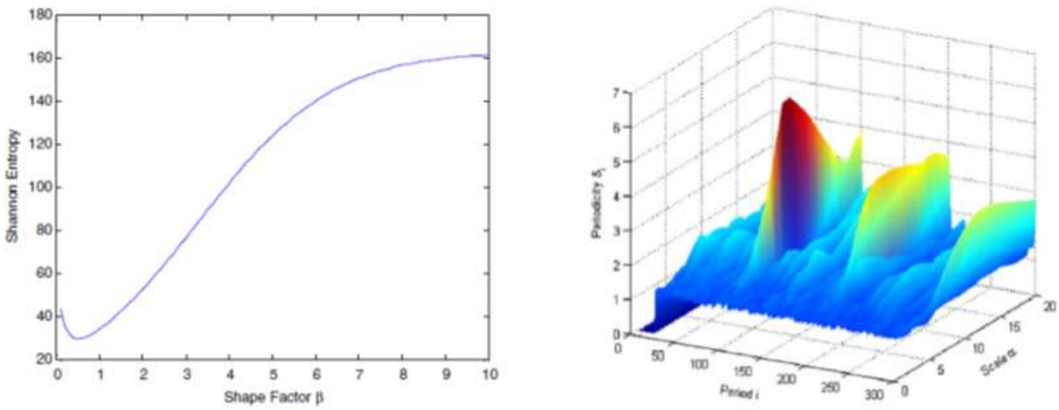
In equation (6.15), “a” refers to the scale parameter and “b“ time translation for expansion. The most important feature that makes the Morlet wavelet superior in noise cleaning is the flexibility of the basic function thanks to the appropriate parameters. This thesis succeeded to obtain the most appropriate parameters “a” and a “β ” for the first time. The parameters have completed the basic functions that can represent the noise inside the signal very well.

6.3. Methodology

Basically, the most appropriate Morlet wavelet is the one that represents the signal with the least coefficients. Generally, the wavelet forming parameters are evaluated with the following formula:

$$H(p) = -\sum_{i=1}^{n} p_i * \log p_i, \quad \sum_{i=1}^{n} p_i = 1 \tag{6.16}$$

Equation (6.16) in p_i, X∈ $[x_1, x_2, \dots, x_n]$ is the probability of observing the possible value of the random variable instantaneously. The coefficients with the lowest Shannon entropy are considered to be the clearest result. Therefore, figure 6.2 was drawn using Shannon entropy.



(a) (b)

Figure 6.2: (a) Determination of wavelet conversion coefficient β by Shannon entropy (b) Periodicity in different scales and stages.

It is necessary to explore the most suitable shape factor β to design the wavelet filter to produce periodic pulses from the noisy signal. In order to calculate the entropy of the coefficients by increasing the "β" value from 0.1 to 20, the most appropriate shape factor "β" value which provides the minimum Shannon entropy relationship is selected. As shown in figure 6.2 (a), the minimum value of entropy indicates β=0.54. Therefore, as the most suitable shape factor, β = 0.54 was chosen. The optimum "β" factor and the wavelet transform scale "a" have been determined with minimum Shannon entropy criterion. In this dissertation, it is essential to reveal the periodic particles in the signal, since the main purpose is to separate the noise from weak signals. For this purpose, periodic parameters that make up the wave are used. The parameters that changed periodically in the determination of "a" were used as a criterion. The "a" scale, which reveals the strongest periodicity of the wavelet coefficients, has been utilized as the most appropriate scale of the wavelet transform. Generally, signal periodic detection, Fourier analysis, power spectral density, periodogram, etc. are used as Spectral analysis methods. However, conventional Fourier-based methods, where only the sinusoidal model of the signal is allowed, it is assumed that each component may be separated into more than one component. In this thesis, the Single Value Decomposition (SVD) method has been implemented to define the time series continuity. The singular value decomposition is defined by a ”mxn“ matrix as follows.

$$A = UEV^{T} \tag{6.17}$$

In equation (6.17) "U" mxm square matrix and “V” matrix is considered to be the nxn square matrix with vertical columns;

$$U^{T}U = I, \quad V^{T}V = I, \tag{6.18}$$

In addition, 'E' is a mxn diagonal matrix; $E = diag(\sigma_1, \sigma_2, \dots \sigma_p)$, p = min (m, n) and diagonal elements $[\sigma_1, \sigma_2, \dots \sigma_p]$ The 'E' matrix is the singular value of the matrix “A” and non-negative numbers $[\sigma_1, \sigma_2, \dots \sigma_p]$ are generally arranged as $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n \geq 0$. The power of the Single Value Decomposition appears when the connections with other basic linear algebra issues are examined. For example, if “A” ‘r’and r> 0 has exactly the exact values so that $\sigma_r > 0$ and $\sigma_{r+1} = \cdots = \sigma_p$=0. If A has full degrees, all singular values are zero. When considering a periodic signal $X = [x_1, \dots x_l]$ with a length of “n”. an “X” matrix can be created by, dividing the series into sections and placing each period as the “X” line;

$$A = \begin{pmatrix} x(1) & \dots & x(M) \\ x(M+1) & \dots & x(2M) \\ x\big((N-1)M+1\big) & \dots & x(NM) \end{pmatrix} \tag{6.19}$$

Equation (6.19) is also defined by $2 \leq M \leq \frac{n}{2}, NM = n$. To assess the periodicity of the signals, the SVR spectrum (if any, the SVR spectrum, a method of determining the period length of the periodic components in any signal or data set) can lead to a limitation or even failure to evaluate the periodicity of the signals. This is due to the fact that the "$M\delta t$" assumption period and the actual period time “T” do not overlap. To solve this problem, an advanced matrix structure method has been proposed for the first time in this study.

In the proposed application it is possible to create the following new matrix when the complete periods of periodic particles are accepted as discrete signal $= [x(1), x(2) \ldots, x(n)], m(m \geq 2)$.

$$A = \begin{pmatrix} x(1) & x(2) & \ldots & x(M) \\ x(m_1 + 1) & x(m_1 + 2) & \ldots & x(m_1 + M) \\ x(m_{N-1} + 1) & x((m_{N-1} + 2) & \ldots & x(m_{N-1} + M) \end{pmatrix} \tag{6.20}$$

$M = round(m), m_k = round(km)(round(\,)$ is the nearest integer function, k = 1.2…)) is defined as $A \in R^{NxM}$. The initial error value in the "M" length is always less than half of the sampling time, in equal N lines, which is continuous in the matrix generated by the improved equation (6.20). With this method, in the previous application, errors are constantly collected and growth is eliminated. The following normalization equation has been defined in order to adapt to the theoretical SVD theorem.

$$\delta = \frac{\sigma_1 - \sigma_2}{\sigma_1} \tag{6.21}$$

Accordingly, each line in the wavelet coefficient matrix is the discrete signal as much as the "a" conversion scale. Thus, the coefficients in the wavelet matrix are determined by the newly developed equation (6.20) method. In equation (6.21), "δ " is calculated by the normal SVD method. The highest value in the wavelet matrix coefficients created was considered as the best representing the period. The scaling value "a" corresponding to the highest value selected is chosen as the most suitable conversion scale. In the newly proposed application instead of the standard SVD, the scaling calculations are performed according to the following procedure.

- Equation (6.8) is calculated with the new proposed version (Eq.6.20). In accordance, the wavelet coefficient matrix with the magnitude of mxn (**m** is the total number of scales, **n** is the signal-sampling number) has been acquired.
- In the matrix representing the continuous wavelet coefficients, the scale value corresponding to the largest value a_i $(1 \leq i \leq m)$ determines the discrete signal x_i values.
- In the calculation cycle, $i = i + 1 \in i \in [1, m]$ is increased and the second step is repeated until $i = m$ is achieved.
- In the completed calculation, the highest value from each line within the wavelet matrix coefficients provides the optimal scaling threshold value to be used for the conversion.

The Morlet wavelet filter was created according to equation (6.14) with the most appropriate transformation scale “a”.

6.4. Experimental Set-up

This section will describe the data collection method used for patients with diabetes.

6.4.1 Collection of blood glucose concentration data

With the approval of the Near East University Hospital Ethics Committee, the data were successfully obtained from 4 randomly selected patients from the 120 patients who were hospitalized in the Internal Medicine (Endocrinology and Metabolism) Department over a period of 2 months. The research ethics committee approved 100% of the children and adults participating in this study. Table 6.1 shows information from 4 patients randomly selected among 120 patients who were hospitalized in the internal medicine (endocrinology and metabolism section). There are 1440 measured values for each patient. (Diabetes glucose concentration data from different patients were taken at one-minute intervals for one day with a continuous glucose monitoring device). For this study, MATLAB (R2018a) software was used with different filters to filter continuous glucose monitoring data.

6.4.2 Monitoring of continuous glucose

Various glucose meter types are available for monitoring the blood glucose concentration and are reliable when used correctly. Some measuring devices, like the upper arm, use a blood sample less sensitive than the fingertip, such as the forearm or thigh. Monitoring continuous glucose systems uses a small sensor placed under the tissue fluid to control glucose levels. The sensor remains in place for several days and then needs to be replaced. The transmitter transmits information about the data levels via radio waves to a wireless monitor, such as a sensor-to-pager. The user must check the blood samples with one-meter glucose to program the instruments. It uses a small sensor device for monitoring accepted glucose systems; These devices are not as precise and safe as standard blood glucose meters, and users should verify their glucose levels with a precision meter before any changes in treatment are made. CGM systems are more expensive than conventional glucose monitoring but may provide preferred glucose control. Monitoring of continuous glucose devices produced by Medtronic, Abbott, and DexCom was approved and submitted to the US Food and Drug Administration. These devices provide real-time glucose level measurements with glucose levels at 5-minute or 1-minute intervals. Beneficiaries can be adjusted to alarm when their glucose levels are too low or too high. To monitor and analyze trends in models, special software is used to download data from devices and systems can display trend graphs on the monitor screen. Your interstitial glucose levels are measured 24 hours a day by Dexcom G4 PLATINUM continuous glucose monitoring system, revealing a complete picture of glucose peaks, failure, and daily change rates. Unlike finger bars that give a specific number for a single point, continuous glucose monitoring ensures information of dynamic glucose that indicates how your glucose develops every 1 or 5 minutes. Dexcom studio data manager software Dexcom is an easy-to-use software program that transfers glucose data stored in a CGM system to a personal computer (PC). The software can be utilized by the clinician or the end-user. By connecting the receiver to the computer, glucose values and other data available on the Dexcom system can be downloaded. Every time the software is started, it will automatically call the receiver every few seconds and is designed to start downloading data as soon as possible. Universal Serial Bus (USB-micro) cable is required to connect the receiver to the computer. Figure 6.3 shows the method of recording and transferring data to a computer with the Dexcom G4 PLATINUM CGM system.

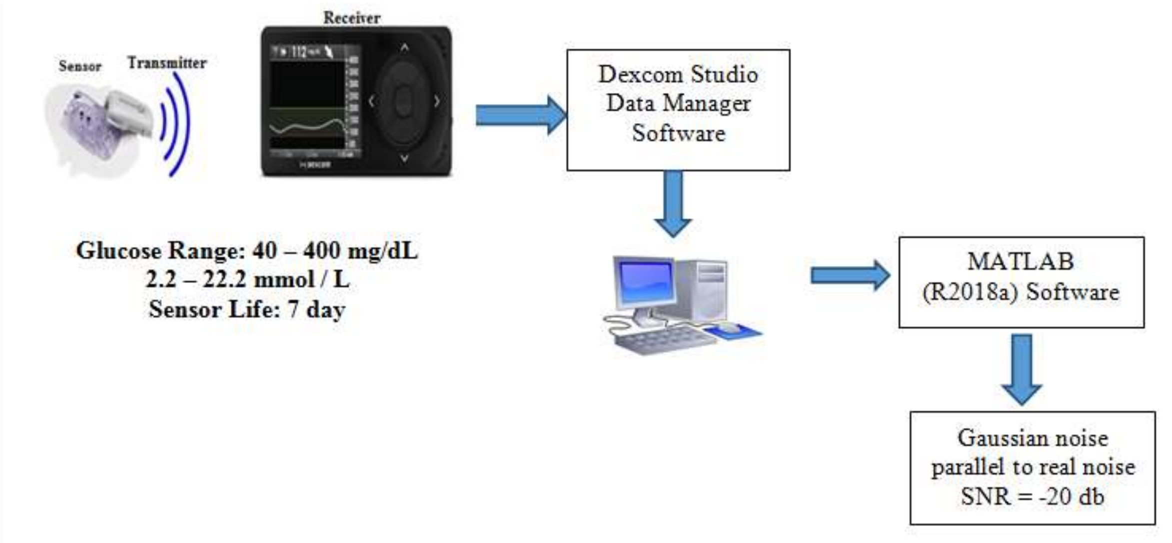


Figure 6.3: Continuous glucose monitoring (CGM) data record

CGM data related to body weight, carbohydrate content (CHO), mealtime and measurement time were measured. The input parameters applied to different patients are shown in Table 6.1.

Table 6.1: Input parameters of 4 randomly selected patients among 120 patients hospitalized in NEU Hospital Internal Medicine Department (Endocrinology and Metabolism) Hospital

Patient (1)						
The weight of the body (kg)=50 Simulation duration (Hrs.)=24	The Breakfast	The Snack	The Lunch	The Snack	The Dinner	The Snack
Time (hh:mm)	08:00	11:00	13:00	16:00	19:00	22:00
Carbohydrate content (mg/kg Weight of body)	25	0	56	23	38	0
Patient (2)						
The weight of the body (kg)=75 Simulation duration (Hrs.)=24	The Breakfast	The Snack	The Lunch	The Snack	The Dinner	The Snack
Time (hh:mm)	07:30	10:30	12:30	15:30	18:30	21:30
Carbohydrate content (mg/kg Weight of body)	50	10	40	10	40	10
Patient (3)						
The weight of the body (kg)=75 Simulation duration (Hrs.)=24	The Breakfast	The Snack	The Lunch	The Snack	The Dinner	The Snack
Time (hh:mm)	08:00	11:00	13:00	16:00	19:00	22:00
Carbohydrate content (mg/kg Weight of body)	25	0	56	23	38	0
Patient (4)						
The weight of the body (kg)=97 Simulation duration (Hrs.)=24	The Breakfast	The Snack	The Lunch	The Snack	The Dinner	The Snack
Time (hh:mm)	07:30	10:30	12:30	15:30	18:30	21:30
Carbohydrate content (mg/kg Weight of body)	25	0	56	23	38	0

For patient-1 blood glucose (mg / dL) measurement, the first 15 minutes of sample values are shown in Table 6.2.

Table 6.2: (Blood Glucose (Bl.gl. (mg / dL) measurement versus time over one minute (only 15 minutes for patient-1))

Time (Minute)	**Blood Glucose (mg / dl)**	**Time (Minute)**	**Blood Glucose (mg / dl)**
0	79	8	82
1	80	9	82
2	80	10	83
3	80	11	84
4	80	12	84
5	81	13	85
6	81	14	86
7	81		

6.5. Experimental results

In this kind of study, the continuous glucose monitoring time series has been formed by selecting the Gaussian type of noise used as the noise profile in the signal obtained from the continuous glucose monitoring device. First, the Savitzky-Golay filter was tested after adding Gaussian noise to the recorded values. The second trial was repeated for the continuous wavelet transformed standard Morlet wavelet. The noise-cleaning performances of the filters were performed by the relative error calculation method. Figure 6.4 shows the noiseless blood glucose signals used in this study.

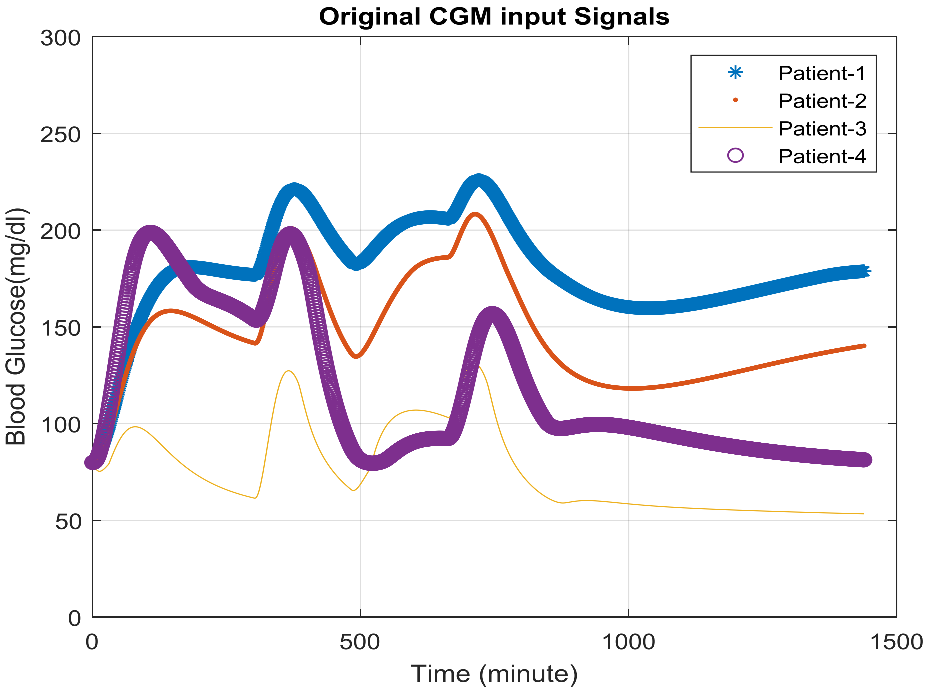


Figure 6.4: Noiseless blood glucose signal for patients

Figure 6.4 shows the graphical variation of 1440 data from four randomly selected patients. The aim here is to clear the noise on the signal. For these values, the Gaussian type of noise, which is likely to be -20 dB, has been added.

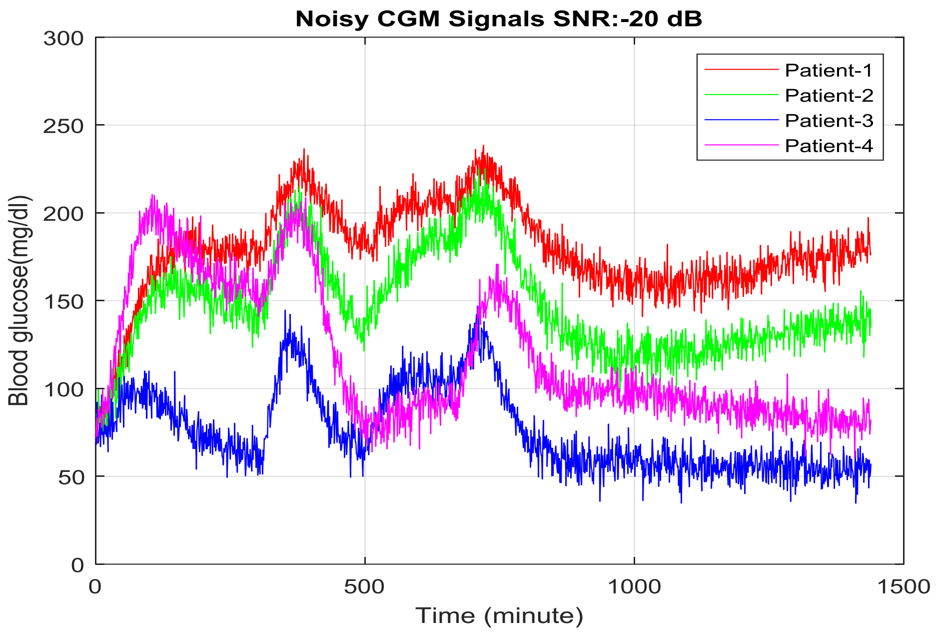


Figure 6.5: Noisy CGM signals for patients with noise value (SNR = -20 dB)

Figure 6.5 shows continuous glucose monitoring signals with noise addition. The aim of this study is to reduce the noise by reducing the original values in Figure 6.4 with the least error.

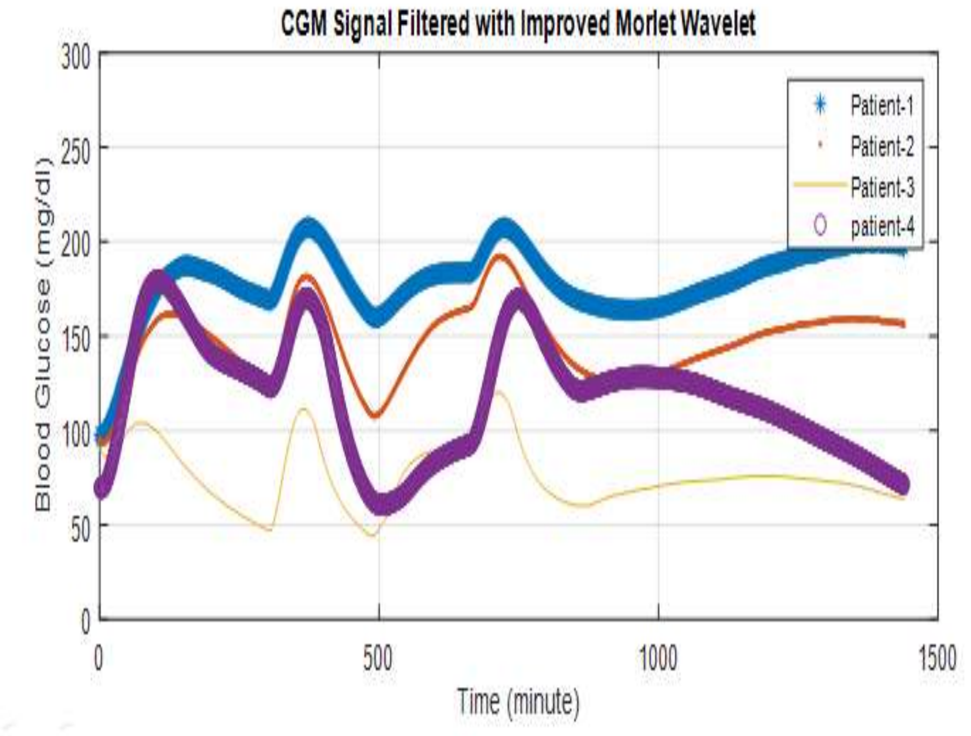


Figure 6.6: Filtering of patients noisy (SNR = -20 dB) continuous glucose monitoring signals via improved Morlet wavelet

Figure 6.6 shows that the reconstructed signals are very close to the original signals of continuous glucose monitoring. Improvement was achieved by the newly proposed method. After the continuous glucose monitoring signals were cleared by the new method, the difference was determined by the relative error analysis. Relative error analysis is considered to be the difference between the values measured after using the formula below and the noise clearance.

$$Relative\ Error = \left|\frac{Measured\ value - Value\ after\ noise\ filtering}{Measured\ Value}\right| x100\% \quad (7.22)$$

The results of this study are shown in Table 6.3, 6.4, 6.5. The Savitzky-Golay filter was applied to noisy continuous glucose monitoring signals in the standard Morlet wavelet and the additive Morlet wavelet conversion and compared to the noise-free continuous glucose monitoring signal. The related errors are calculated and tabulated for all three conditions. The relative errors calculated for filtering (%) are shown in table 6.3, table 6.4 and table 6.5, respectively.

Table 6.3: Savitzky-Golay Filter Relative Errors (%)

Patient No	**PSNR Values (dB)**	**Standard Morlet Wavelet Relative Error (%)**
Patient-1	+62,2166	21,13
Patient-2	+62,3484	20,97
Patient-3	+61,4041	22,16
Patient-4	+60,4294	23,40

In Table 6.3, the most successful relative error value of the Savitzky-Golay filter in the noisy four continuous glucose monitoring signals has been 20.97%. The same signal was carried out by noise reduction using the standard Morlet wavelet filter.

Table 6.4: Relative errors for filtering made with Standard Morlet Wavelet (%)

Patient No	**PSNR Values (dB)**	**Standard Morlet Wavelet Relative Error (%)**
Patient-1	+62,2629	21,076
Patient-2	+62,3277	20,994
Patient-3	+60,5412	23,258
Patient-4	+61,0266	22,643

In Table 6.4 the standard Morlet wavelet was applied to determine the most successful relative error value, in the four continuous glucose monitoring signals the most successful result has been 20,994%. The resulting values are very close to the performance obtained in the Savitzky-Golay filter. Improved Morlet wavelet filter results have been shown in Table 6.5.

Table 6.5: Improved Morlet Wavelet relative errors (%)

Patient number	**PSNR values (dB)**	**Improved Morlet Wavelet Relative Error (%)**
Patient-1	+70.504	10,63
Patient-2	+68,681	12,94
Patient-3	+66,181	16,11
Patient-4	+66,772	15,36

In Table 6.5, the most successful relative error rate was calculated as 10.63% in the application of the four CGM signals in the improved Morlet wavelet application. Table 6.3, 6.4, 6.5 shows that the improved Morlet wavelet has the best performance on a continuous glucose monitoring signal when compared. The improved Morlet wavelet filter performance was found to be about 50% better compared to current methods in the literature.

6.6 Summary

The application was implemented by providing an additional contribution to Morlet wavelets based on CWT. Morlet wavelet is a powerful and formal tool that allows a complete representation of a signal by allowing translation and wavelet scale to change continuously to analyze signals that need to be evaluated according to time-frequency content. Undoubtedly, the coefficient values that make the wave the most effective. Different methods are used in the calculation of coefficient values in the literature. The method envisaged in this research is provided by the method applied for the first time in the scaling matrix, which increases the compatibility of the coefficients. The deviations in the calculation of the coefficient values in the classical method are minimized by the prescribed method. The proposed method is compared with the Savitzky-Golay filter and standard Morlet wavelet, which are commonly used in the literature. The superiority of the new method is shown by PSNR and relative error values.

CHAPTER 7
CONCLUSION AND SUGGESTIONS

7.1 Conclusion

Excellent filtration of various noise signals in continuous glucose monitoring data allows further processing to detect hypo/hyperglycemic events. Unfortunately, continuous glucose monitoring data is affected by various error sources, such as deviation errors (erroneous / loss of calibration or sensor physics/chemistry) and random noise that manages the real signal at a high frequency. In diabetics, blood data are recorded within 24 hours to confirm the accuracy of treatment and treatment. In practical applications, data are known to be noisy for a variety of reasons. Minimizing the noise level in the data increases the success of the treatment.

The feasibility of the proposed method was approved by the Near East University Hospital Ethics Committee. In this study, the various types of errors in CGM data and the solution for CGM devices were analyzed by random noise and the above results were obtained. The results show that the Morlet waveform developed to filter continuous glucose monitoring (CGM) signals is appropriate. The proposed method is compared to the Savitzky-Golay filter and the standard Morlet wavelet to prove its superiority. The main goal in the entire system is to get clear, high-quality output signals for good consultations. The minimum relative error rate was found to be 10.63% in the noisy CGM data used in the proposed Morlet wavelet. The same procedure was calculated as 20,97% in the Savitzky-Golay filter and 20,994% in standard Morlet wavelet. Accordingly, the proposed contribution has been proven to be approximately 50% improvement in the CGM signal.

7.2 Suggestions

The major contributions of this dissertation are summarized as follows:

- The proposed method ensures that the parameters that make up the filter are more optimal so that the error at the filter output of the continuous glucose monitoring signal is minimized.
- Considering the simplicity of the proposed method and not increasing the processing time, it will make it more efficient and economical in real-time operations. Compared to other alternatives, it will stand out with this aspect.

- As a result of the proposed method, the noise level is reduced to the lowest level compared to the classical methods, which reduces the fluctuations, fast climbing, and sensitivity of the values which have negative effects on the signal and it has been proved its superiority with relative error calculations.
- Thus, continuous glucose monitoring signal analysis, which is closer to the real data free of noise, provides a high validity rate of treatment for the patient.

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APPENDICES

APPENDIX 1

NEAR EAST UNIVERSITY

SCIENTIFIC RESEARCH ETHICS COMMITTEE

13.09.2018

Mr. Cemal Kavalcıoğlu

The project proposal titled **“De-Noising Method for Continuous Glucose Monitoring (CGM) Signal with Improved Morlet Wavelet Filter”** of NEU / FB / 2018/35 of the Scientific Research Ethics Committee has been evaluated by our organization and found to be ethically appropriate. With this article, you can start your research by not leaving the information you specify on your application form.

Assoc. Prof. Dr. Direnç Kanol

Rapporteur of the Scientific Research Ethics Committee

Direnc Kanol

Note: If you wish to submit an official letter of acceptance to an institution, you can apply to the Near East University Scientific Research Ethics Committee with this letter and you can obtain an official letter signed by the chairman of the board.

APPENDIX 2

CURRICULUM VITAE

CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Kavalcıoğlu, Cemal

Nationality: Cyprus

Date and Place of Birth: 08 September 1977, Lefkoşa

Marital Status: Single

EDUCATION

Degree	Institution	Year of Graduation
M.Sc.	Near East University, Department of Electrical & Electronic Engineering	2002
B.Sc.	Near East University, Department of Electrical & Electronic Engineering	2000

WORK EXPERIENCE

Year	Place	Enrollment
2017 - Present	Department of Electrical & Electronic Engineering	Vice-Chairman
2016 - Present	School of Computing and Technology	Director
2014 - Present	Electronic Technologies Department (Vocational School)	3. Year Program Coordinator
2014 - Present	Electronic Technologies Department (Vocational School)	2-Year Program Coordinator
2004 - Present	Department of Electrical & Electronic Engineering	Lecturer
2000 - 2002	Department of Electrical & Electronic Engineering	Teaching Assistant

FOREIGN LANGUAGES

Fluent spoken and written English

HONORS AND AWARDS

- The first International Conference on Advances in Computing and Communications (ACC-2011), Kerela, India, **Best Paper AWARD.**
- DESAM 2016 Science Awards, **Scientific Publication Award.**
- Near East University 2017 Science Awards, **Young Researcher Award.**

DOCUMENTS OF THANKS FOR PARTICIPATION

- 2nd International Symposium on Electrical, Electronic, and Computer Engineering NEUCEE-2004.
- 3rd International Symposium and on Electrical, Electronic and Computer Engineering, ISEECE-2006.
- 11th WSEAS International Conference on Automatic Control, Modelling and Simulation (May 30 – June 1, 2009) İstanbul.
- 1st International Conference on Manufacturing Engineering Quality and Production Systems (MEQAPS'09) 24 - 26 September 2009, Romania, Brasov.
- Higher Education Planning, Evaluation, Accreditation and Coordination Council (01-03 March 2010).
- Değirmenlik Lisesi "Kariyer Günü" 11 Mart 2013.
- Yakın Doğu Koleji "2014 - 2015, 6. Kariyer Günü Etkinliği".
- International Biomedical Engineering Congress 2015 (IBMEC'15) 12-14 March 2015, NEU, Nicosia, North Cyprus.
- 12th International Conference on Application of Fuzzy Systems and Soft Computing, 29-30 August 2016 Vienna, Austria.
- 2015-2016 Öğretim Yılı Meslek Liseler Bilgi ve Beceri Yarışması Değerlendirme Komisyonu Üyeliği, KKTC Milli Eğitim ve Kültür Bakanlığı Mesleki Teknik Öğretim Dairesi Müdürlüğü.
- 2nd International Conference on Mathematics and Computer Science (MACOS 2016) 8-10 September 2016, Brasov, Romania.

- 2016-2017 Öğretim Yılı Meslek Liseler Bilgi ve Beceri Yarışması Değerlendirme Komisyonu Üyeliği, KKTC Milli Eğitim ve Kültür Bakanlığı Mesleki Teknik Öğretim Dairesi Müdürlüğü.
- 12-16 Haziran 2017 Eğiticinin Eğitimi Eğitim Programı, Yakın Doğu Üniversitesi.
- 9th International Conference on Theory and Application of Soft Computing with the Words and Perception. (ICSCCW-2017) 22-23 August 2017 Budapest, Hungary.
- International Biomedical Engineering Congress 2018 (IBMEC'18) 12-14 March 2015, NEU, Nicosia, North Cyprus.
- 13rd International Conference on Application of Fuzzy Systems and Soft Computing, 27-28 August 2018 Warsaw, Poland.

MEMBERSHIP OF PROFESSIONAL ORGANIZATIONS

- Chamber of Electrical Engineers (EMO)

SCIENTIFIC PUBLICATIONS

INTERNATIONAL SCI PUBLICATIONS

[1] Bilgehan, B , Kavalcıoğlu, C . (2019). Sürekli glikoz izleme (CGM) sinyalleri ile tip 1 diyabet tedavisi için sürekli dalgacık dönüşüm (CWT) tabanlı filtreleme yöntemi. **Journal of the Faculty of Engineering and Architecture of Gazi University**, 35 (2) , 581-594 . https://doi.org/10.17341/gazimmfd.492052 **SCI-Expanded.**

SCOPUS & WEB of SCIENCE (WoS)

[1] Kibarer G., Kavalcıoğlu C. **(2020)** An Intelligent Guide for Ranking the Hospitals in EU Countries Effective on Pancreatic Cancer Treatment via Fuzzy Logic. **Advances in Intelligent Systems and Computing, vol 1095. Springer, Cham https://doi.org/10.1007/978-3-030-35249-3_22**

[2] Yuvalı M., Kavalcıoğlu C., Kaba Ş., Işın A. **(2020)** Fuzzy Ordination of Breast Tissue with Electrical Impedance Spectroscopy Measurements. **Advances in Intelligent Systems and Computing, vol 1095. Springer, Cham https://doi.org/10.1007/978-3-030-35249-3_19**

[3] Kavalcıoğlu C., Bilgehan B. “A Fuzzy Based Gaussian Weighted Moving Windowing for Denoising Electrocardiogram (ECG) Signals”. **Advances in Intelligent Systems and Computing, vol 896. Springer, Cham.**,**DOI:10.1007/978-3-030-04164-9_18. 2019.**

[4] Alshahadat M., Bilgehan B., Kavalcıoğlu C. “An Effective Fuzzy Controlled Filter for Feature Extraction Method” **Advances in Intelligent Systems and Computing, vol 896. Springer, Cham., DOI: 10.1007/978-3-030-04164-9_15. 2019.**

[5]. Sadıkoğlu F., Kavalcıoğlu C., Dağman B., “Electromyogram (EMG) Signal Detection, Classification of EMG signals and diagnosis of Neuropathy muscle disease”. **Elsevier Procedia Computer Science, DOI: 10.1016/j.procs.2017.11.259. 2017.**

[6]. Kavalcıoğlu C., Dağman B., “Filtering Maternal and Fetal Electrocardiogram (ECG) Signals using Savitzky-Golay Filter and Adaptive Least Mean Square (LMS) Cancellation Technique”, **Bulletin of the Transilvania University of Braşov Vol 9(58), No. 2 – 2016 Series III: Mathematics, Informatics, Physics, 109-124**

[7]. Sadıkoğlu F., Kavalcıoğlu C., “Filtering Continuous Glucose Monitoring Signal using Savitzky-Golay Filter and Simple Multivariate Thresholding”, **Elsevier Procedia Computer Science, DOI: 10.1016/j.procs.2016.09.410. 2016.**

[8].Dimililer K., Kavalcioglu C., "Gaussian Noise and Discrete Cosine Transform Image Compression on Transmission of Dermatological Images**”, *In Abraham et al. (Eds.), Communications in Computer and Information Science(CCIS) 192, Part:III: Advances in Computing and Communications, Springer-Verlag Berlin Heidelberg, 2011.***

[9].Dimililer K., Kavalcioglu C., "Gaussian Noise and Haar Wavelet Transform Image Compression on Transmission of Dermatological Images” , **World Congress (DSA -2011) The Frontiers in Intelligent Data and Signal Analysis, The Sixth International Conference on Mass Data Analysis of Images and Signals in Medicine, Biotechnology, Chemistry and Food Industry (MDA 2011) New York, USA, 30 August - 3 September 2011. Communications in Computer and Information Science, Volume 192 CCIS, Issue PART 3, 2011, Pages 357-364.**

Books and Book Chapters

[1].Dimililer K., Kavalcioglu C., "Gaussian Noise and Discrete Cosine Transform Image Compression on Transmission of Dermatological Images**", *In Abraham et al. (Eds.), Communications in Computer and Information Science(CCIS) 192, Part:III: Advances in Computing and Communications, Springer-Verlag Berlin Heidelberg, 2011.***

Published Conference Proceedings

[1]. Yuvalı M., Kavalcıoğlu C., Kaba Ş., Işın A., "Fuzzy Ordination of Breast Tissue with Electrical Impedance Spectroscopy Measurements" **10th International Conference on Theory and Application of Soft Computing, Computing with Words and Perception, ICSCCW 2019, 27-28 August 2019, Prague, Czech Republic.**

[2]. Kibarer G., Kavalcıoğlu C., "An Intelligent Guide for Ranking the Hospitals in EU Countries Effective on Pancreatic Cancer Treatment via Fuzzy Logic" **10th International Conference on Theory and Application of Soft Computing, Computing with Words and Perception, ICSCCW 2019, 27-28 August 2019, Prague, Czech Republic.**

[3]. Bilgehan B., Kavalcioglu C., "A Fuzzy-Based Gaussian Weighted Moving Windowing for Denoising Electrocardiogram (ECG) Signals" **13th International Conference on Theory and Applications of Fuzzy Systems and Soft Computing, (ICAFS 2018), 27-28 August 2018, Warsaw, Poland.**

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[9].Kavalcioglu C., Dağman B. "Filtering of Noisy Continuous Glucose Monitoring (CGM) Signal with Savitzky-Golay Filter." **International Biomedical Engineering Congress 2015. (IBMEC'15). Nicosia, North Cyprus 12-14 March 2015.**

[10].Dimililer K., Kavalcioglu C., "Gaussian Noise and Haar Wavelet Transform Image Compression on Transmission of Dermatological Images" , **World Congress (DSA -2011) The Frontiers in Intelligent Data and Signal Analysis, The Sixth International Conference on Mass Data Analysis of Images and Signals in Medicine, Biotechnology, Chemistry and Food Industry (MDA 2011) New York, USA, 30 August - 3 September 2011.**

[11].Dimililer K., Kavalcioglu C., "Gaussian Noise and Discrete Cosine Transform Image Compression on Transmission of Dermatological Images", **The First International Conference on Advances in Computing and Communications (ACC-2011), Kerela, India, Springer-Verlag, 22-24 July 2011. (Best Paper Awarded)**

[12].Serener A., Kavalcioglu C., "Teledermatology based medical images with AWGN Channel in Wireless Telemedicine System." **Proceedings of the 1st WSEAS International Conference on Manufacturing Engineering, Quality and Production Systems (MEQAPS '09), Brasov, Romania, 24-26 Sep 2009.**

[13]. Serener A., Kavalcioglu C., "Wireless Telemedicine System in emergency medicine helicopter", **Proceedings of the 11th WSEAS International Conference on Automatic Control, Modelling, and Simulation (ACMOS '09), Istanbul, Turkey, 30 May - 1 June 2009.**

[14]. Kavalcioglu C., "General View to Electromagnetic Waves & Mobile Phones and Effects on Human Health **"Proceedings of the 3rd International Symposium on Electrical, Electronic, and Computer Engineering. (ISEECE 2006) Nicosia TRNC, 23 - 25 November 2006.**

Other Publications:

[1]. Kavalcioglu C., Dimililer K., " Kablosuz Teletıp Sisteminde Toplamsal Beyaz Gauss Gürültüsü(AWGN) Kanalı ile Teledermatolojik Tıbbi Görüntülerin İletilmesi ", **EMO Bilim Journal of the Chamber of Electrical Engineers, No. 34, North Cyprus, February 2012.**

[2].Kavalcioglu C., Dimililer K., Alaçam B., Fikretler H., " Enerji Kaynaklarının Kullanımı, Çevreye Etkileri ve Yenilenebilir Enerji Kaynakları", **EMO Bilim Journal of the Chamber of Electrical Engineers, No. 32, North Cyprus, July 2011.**

[3].Kavalcioglu C., Dimililer K., Alaçam B., Fikretler H., " Kompanzasyon Kavramı Temel Prensipleri ve Kompanzasyonun Gerekliliği ", **EMO Bilim Journal of the Chamber of Electrical Engineers, No. 31, North Cyprus, April 2011.**

[4].Canselen K., Kavalcioglu C., Ballı K., " Kompanzasyon Sistemleri Esasları ve Reaktif Güç Kompanzasyonu ", **EMO Bilim Journal of the Chamber of Electrical Engineers, No. 31, North Cyprus, April 2011.**

[5].Dimililer K., Kavalcioglu C., Alaçam B., Fikretler H., " Aydınlatma Kavramı, Aydınlatmanın Temel Prensipleri ve LED ile Aydınlatma", **EMO Bilim Journal of the Chamber of Electrical Engineers, No. 30, North Cyprus, January 2011.**

[6].Kavalcioglu C., Dimililer K., " E-Devlet Konusuna Genel Bir Bakış ", **EMO Bilim Journal of the Chamber of Electrical Engineers, No. 29, North Cyprus, October 2010.**

[7].Kavalcioglu C., Dimililer K., Alaçam B., “ Kuzey Kıbrıs Türk Cumhuriyeti ÜniversitelerindeMühendislik Eğitiminin Değerlendirilmesi”, **EMO Bilim Journal of the Chamber of Electrical Engineers, No. 28, North Cyprus, August 2010.**

[8].Kavalcioglu C., “ Acil Tıp Helikopterinde Kablosuz Teletıp Sistemi”, **EMO Bilim Journal of the Chamber of Electrical Engineers, No. 27, North Cyprus, June 2010.**

[9].Kavalcioglu C., “ Third Generation Wireless Communication Systems”, **EMO Bilim Journal of the Chamber of Electrical Engineers, Vol. 2, No. 5.**

THESISES

Master

- Kavalcıoğlu, C. (2002). *Analysis of Wireless Communication Systems and Traffic Modeling*. Master Thesis (M.Sc.), Near East University, Electrical & Electronic Engineering, Faculty of Engineering, Nicosia, Cyprus.

Undergraduate

- Kavalcıoğlu, C. (1999). *Pulse Width Modulation Techniques used in Power Electronics.* Undergraduate project (B.Sc.), Near East University, Electrical & Electronic Engineering, Faculty of Engineering, Nicosia, Cyprus.

COURSES GIVEN *(from 2004 to 2019)*

Undergraduate

English Program

- Introduction to Electrical & Electronic Engineering
- Circuit Theory I
- Computer Applications
- Electrical Measurements
- Electromagnetic Theory
- Electrical Materials
- Electronics I
- Electronics II
- Communication Systems
- Satellite Communication Systems
- Process Control &Instrumentation Technology
- Programmable Logic Controllers (PLC)

- Wireless and Personal Communication Systems
- Digital Signal Processing
- Intelligent Control Systems

Türkçe Program

- Elektrik & Elektronik Mühendisliğine Giriş
- Bilgisayar Uygulamaları
- Elektrik Malzemeleri
- Elektronik I
- Elektromanyetik teori
- Elektronik II
- Sinyaller ve Sistemler
- Kontrol Sistemleri
- Sayısal Sinyal İşleme
- Proses Kontrol & Enstrümantasyon Teknolojisi
- Aydınlatma Tekniği ve İç Tesisat
- Programlanabilir Mantık Kontrolerleri (PLC)
- Güç Elektroniği
- Elektrik Enerji Dağıtımı
- Güç Sistemi Koruması

Service Courses (English Program)

- Electrical Machinery
- Electrical Circuits
- Basic Electronics

Servis Dersleri (Türkçe Program)

- Elektrik Devreleri
- Temel Elektronik

Vocational School (2. Year & 3. Year Programs)

- Elektroteknoloji
- Matematik-1
- Elektrik Tesisatı-1
- Elektrik Tesisatı-3
- Elektrik Güvenliği
- Mantık Devreleri
- Bilgisayar Donanımı

- Haberleşme Teknolojisi
- Scada Sistemleri

HOBBIES

- Listening to music, watching TV
- Travel
- Dance
- Folk Dance,
- Learning new things
- Driving a car
- Playing and watching football, My favorite team is **BEŞİKTAŞ**
- Internet
- Educational and Technical Researches
- Playing chess
- Filling any type of puzzle

OTHER INTERESTS

- Wireless Communication
- Wireless Telemedicine Systems
- Intelligent Signal Processing
- Digital Signal Processing
- Biomedical Signal Processing

APPENDIX 3

SIMILARITY REPORT

DOKTORA TEZİM

GELEN KUTUSU | GÖRÜNTÜLENİYOR: YENİ ÖDEVLER ▼

Dosyayı Gönder

Çevrimiçi Derecelendirme Raporu | Ödev ayarlarını düzenle | E-posta bildirmeyenler

YAZAR	BAŞLIK	BENZERLİK	PUANLA	CEVAP	DOSYA	ÖDEV NUMARASI	TARİH
Cemal Kavalcioglu	ABSTRACT-ÖZET	%0	--	--		1239243389	04-Oca-2020
Cemal Kavalcioglu	CONCLUSION	%0	--	--		1239243842	04-Oca-2020
Cemal Kavalcioglu	CHAPTER 1 INTRODUCTION	%3	--	--		1239243442	04-Oca-2020
Cemal Kavalcioglu	CHAPTER 3	%3	--	--		1239243506	04-Oca-2020
Cemal Kavalcioglu	CHAPTER 2	%4	--	--		1239243476	04-Oca-2020
Cemal Kavalcioglu	CHAPTER 5	%5	--	--		1250930704	03-Şub-2020
Cemal Kavalcioglu	CHAPTER 6	%9	--	--		1246597652	26-Oca-2020
Cemal Kavalcioglu	CHAPTER 4	%11	--	--		1252104035	05-Şub-2020
Cemal Kavalcioglu	Ph.D. THESIS GENERAL	%15	--	--		1252444799	06-Şub-2020