Ultra Low-Power Biomedical Signal Processing

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An Analog Wavelet Filter Approach for Pacemakers

Springer

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Foreword

As microelectronics has matured in human controlled tools like computers, another era of ubiquitous microelectronics is well underway. Compact, robust and dedicated microelectronic systems are combined with actuators and sensors in an increasing number of life-critical controls. Familiar questions from computer like: “Are you sure you want to do this? (Press OK to proceed)”, are not possible in these self-contained, autonomous control systems. These embedded control systems must make immediate decisions based on whatever information is available from the provided sensors.

The most challenging of these embedded control system are the devices implanted in humans. Not only do they control life-critical functions, but they have to do so under severe power and size constraints. In addition, the sensed signals are often noisy and weak, demanding complicated and computationally intensive signal processing. In spite of these challenges, cardiac pacemakers are implanted in hundreds of thousand humans every year. Some reports indicate battery lives exceeding twenty years of operation.

The implantable pacemaker was first introduced in the late 1950s and has been refined and improved in a number of ways since then. This new book “Ultra Low-Power Biomedical Signal Processing – An Analog Wavelet Filter Approach for Pacemakers” by SANDRO A. P. HADDAD and WOUTER A. SERDIJN is addressing the core problems of efficient linear and nonlinear, signal processing in biomedical devices in general, with special emphasis on pacemaker electronics. The proposed analog wavelet filter approach is demonstrated to be a power efficient and flexible method for integrated pacemaker electronics.

This book should be appreciated by anybody in need of power-efficient, linear and non-linear signal processing suitable for microelectronics. A balanced and understandable discussion of trade-offs towards the more traditional Fourier analysis exposes the benefits of wavelet filters. For pacemakers typical time-domain information like the QRS complex of the ECG signal is sought. Another important insight is how to use the log-domain (dynamic translinear) circuit technique for power efficient electronics. Convincing results are provided.

Although the primary device addressed in this book is the implantable pacemaker, the authors indicate the general properties and usefulness of wavelet filters in general, not only for biomedical applications. The completeness of wavelet filter theory combined with the transition to practical circuits make this book mandatory for everybody aiming at power efficient embedded control systems.

Oslo, November 2008

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Contents

Chapter 1

Introduction

Around 40% of all human deaths are attributed to cardiovascular diseases. A practical way to decrease the overall cardiac mortality and morbidity is to supply patients at risk with an implantable device, known as artificial pacemaker, that is designed to monitor the cardiac status and to regulate the beating of the heart. Cardiac pacing has become a therapeutic tool used worldwide with over 250,000 pacemaker implants every year.

Cardiac pacemakers include real-time sensing capacities reflecting the state of the heart. Current pacemaker detection circuitry can be interpreted as a cardiac electrical signal compression algorithm squeezing the time signal information into a single event representing the cardiac activity. Future cardiac pacing algorithms, however, are believed to take advantage of the morphological aspects of the sensed cardiac signal, improving the analysis and the recording of relevant cardiac activity data via implantable sensors. This will provide, for instance, a new opportunity for monitoring and managing infarct-threatened patients and post-infarction patients outside the hospital.

In implantable medical devices, such as pacemakers, power consumption is critical, due to the limited power density and the longevity of currently available portable batteries. This implies that the design of such devices has to be optimized for very low power dissipation.

The purpose of this book is to detail the significant advances in cardiac pacing systems and to develop novel signal processing methodologies and analog integrated circuit techniques for low-power biomedical systems.

1.1 Biomedical signal processing

Biomedical signal processing centers on the acquisition of vital signals extracted from biologic and physiologic systems. These signals permit us to obtain information about the state of living systems, and therefore, their monitoring and interpretation have significant diagnostic value for clinicians and researchers to obtain information related to human health and diseases.

The processing of biomedical signals strongly depends on the knowledge about the origin and the nature of the signal and poses many special properties, which usually presents some unique problems. The reason for this is mainly due to the complexity of the underlying biologic structures and their signals, and the need to perform indirect, non-invasive measurements. In addition, the detected signals are commonly corrupted with noise, and thus, the relevant information is not "visible" and cannot be readily extracted from the raw signal. For such reasons, advanced signal processing is usually required.

Another important aspect of biomedical signals is that the information of interest is often a combination of features that are well localized temporally (e.g., spikes) and others that are more diffuse (e.g., small oscillations) [1]. This requires the use of analysis methods sufficiently versatile to handle events that can be at opposite extremes in terms of their time–frequency localization. In this book, we will investigate the ability of the wavelet analysis to extract information from a biomedical signal.

1.2 Biomedical applications of the wavelet transform

Physiological signals are mostly non-stationary, such as the electrocardiogram (ECG), the electroencephalogram (EEG) and the electromyogram (EMG). Those signals represent the electrical activity of the heart, the brain and the muscles, respectively. The main difficulty in dealing with biomedical signal processing is the extreme variability of the signals and the necessity to operate on a case by case basis [1]. The Wavelet transform (WT) has been extensively used in biomedical signal processing, mainly due to the versatility of the wavelet tools. It has been shown to be a very efficient tool for local analysis of non-stationary and fast transient signals due to its good estimation of time and frequency (scale) localizations [2], [3]. The wavelet transform is a linear operation that decomposes a signal into components that appear at different scales (or resolutions). The transform is based on the convolution of the signal with a dilated filter, thereby mapping the signal onto a two-dimensional function of time and frequency.

The uses of the WT in biomedical applications are extremely diverse. Signal analysis methods derived from wavelet analysis [2] carry large potential to support a wide range of biomedical signal processing applications including noise reduction [4], feature recognition [1] and signal compression [5]. The discussion here shall deal with wavelet techniques for cardiac signals analysis. It is, however, believed that these techniques can also successfully contribute to the analysis of other types of non-stationary signals, like those present in electroencephalograms (EEGs), i.e., electrical potentials associated with the brain; electrocorticograms (ECoGs), i.e., electrical potentials associated with the cerebral cortex; electromyograms (EMGs), i.e., electrical potentials associated with muscles and electroretinograms (ERGs), i.e., electrical potentials associated with retinas.

Cardiac signal analysis

In the past few years, many new approaches to cardiac signal analysis have been proposed [6], e.g., algorithms based on filter banks [5], artificial neural networks [8], non-linear transformations [9] and the wavelet transform [10]. In Fig. 1.1, one can compare the numbers of publications in the IEEE online database related to electrocardiogram (ECG) signal detection for three different types of algorithms, being filter-based, wavelet transform and neural networks. Besides the fact that wavelet analysis is still relatively new, the wavelet-based signal processing methods have been evolving very rapidly and the rate of publication keeps increasing steadily.

There are several reasons for the growing number of algorithms using wavelets. Since usually cardiac signal and noise components share the same spectral bands, the scope of linear signal processing methods (linear filtering) is rather limited. Therefore, signal analysis methods improving discrimination of signals from noise and interference are of great importance. Several approaches [6] have demonstrated the potential of wavelet-based feature extraction for discriminating between normal and abnormal cardiac patterns.

Being a multiscale analysis technique, wavelets allow analysis of the electrogram focusing on the signal at various levels of detail, in analogy with

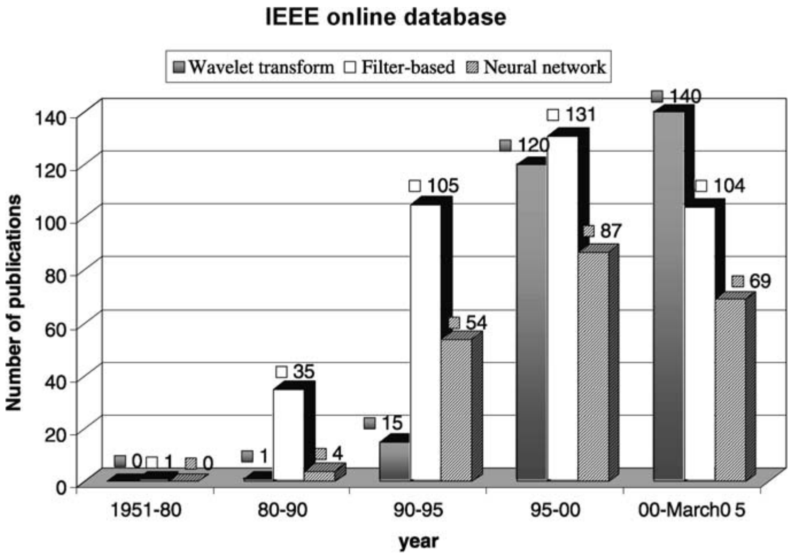

Fig. 1.1. IEEE online database publications of cardiac signal detection for different types of algorithms

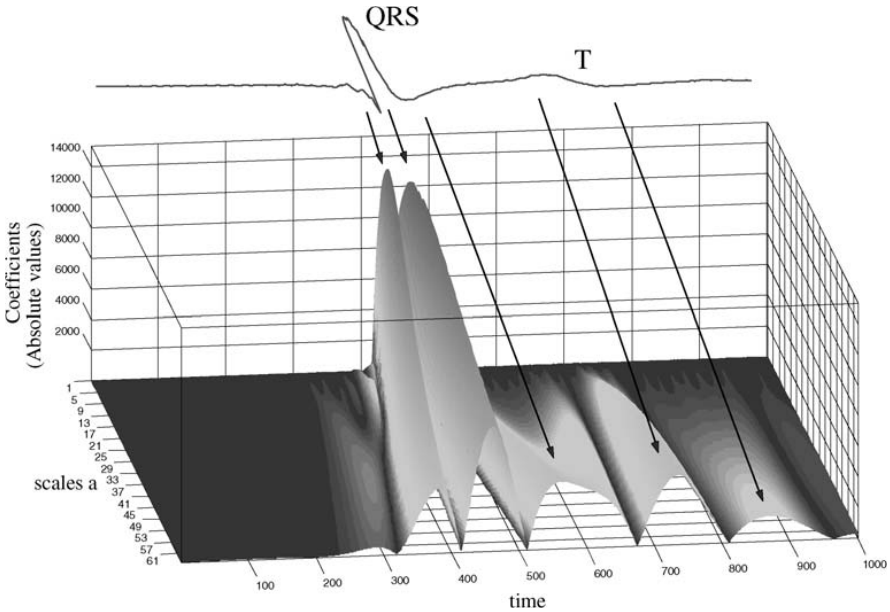

Fig. 1.2. Wavelet analysis of an intra-cardiac signal (IECG). For small values of scale a, the QRS-complex information is dominant, whereas for large values of a both QRS and T waves are well localized

inspection of a sample with a microscope at various levels of magnification. As one can see in Fig. 1.2, at very fine scales (smaller values of scale a), details of the electrogram, e.g., the QRS-complex (most striking waveform within the ECG), are revealed while unimpaired by the overall structure of the signal. At coarse scale (larger values of the scale factor a), the overall structure of the electrogram can be studied while overlooking the details. Note that by this global view, both the QRS-complex and the T-wave can be detected.

1.3 Analog versus digital circuitry – a power consumption challenge for biomedical front-ends

A modern pacemaker consists of a telemetry system to receive and transmit data, a sense amplifier (analog or digital) consisting of passive/active filters, an amplifier and a comparator, analog output circuitry (also known as pulse generator) which stimulates the heart, and a microprocessor acting as a controller for all the settings of the pacemaker system. Moreover, an algorithm in the microprocessor determines whether pacing is needed or not. Nevertheless, the longevity of a pacemaker must not be shortened by new improved features,

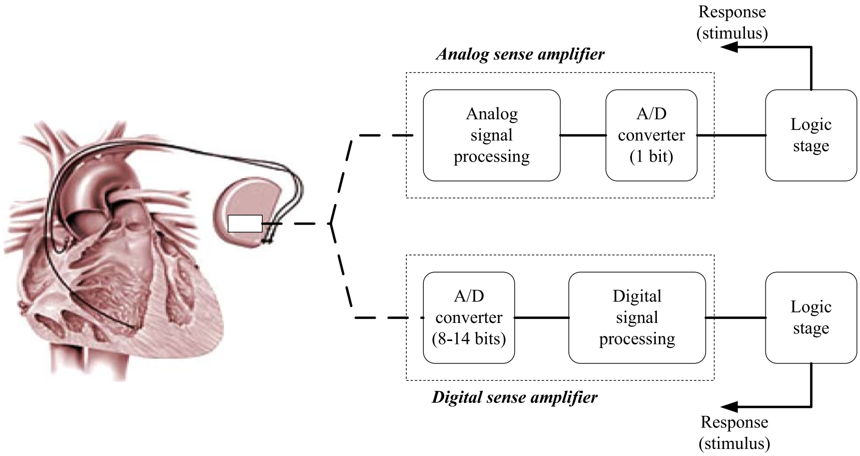

Fig. 1.3. Analog and digital sense amplifiers for pacemakers

so, reliable detection performance as well low power consumption is one of the most challenging design constraints.

The sense amplifier plays a fundamental role in providing information about the current state of the heart. State of the art implantable pulse generators or cardiac pacemakers include real-time sensing capabilities that are designed to detect and monitor intra-cardiac signal events (e.g., R-waves in the ventricle). A sense amplifier and its subsequent detection circuitry, together called the front-end, are shown in the block diagram in Fig. 1.3. As one can see in Fig. 1.3, the signal processing block of the front-end can be implemented with analog or digital circuitry and in the subsections that follow we will compare the minimum power required for both analog and digital implementations.

1.3.1 Power consumption in analog sense amplifiers

Generally, the detection of the electrical activity of the heart requires filtering, where there is a discrimination between cardiac signals and noise based on differences in energy spectra, and comparison to determine if a heart beat has occurred. Therefore, an analog sense amplifier derives only a single event (characterized by a binary pulse from the 1-bit A/D converter) and feeds this to a micro-controller (logic stage) that decides upon the appropriate pacing therapy to be delivered by the stimulator. The system consists of an analog signal processing unit, usually a bandpass filter, and a 1-bit comparator circuit. The bandpass filter is used to specifically select intra-cardiac signals and to minimize the effect of the noise and interference. Normally, an integrated continuous-time filter is realized as a network of integrators and this integration is exclusively performed by capacitive elements. The power per pole figure of merit [11] gives an indication of the power dissipation associated with the elementary signal processing operation of integration (filtering).

Power per pole for analog filters

From this figure of merit, the minimum power dissipation (P_{an}) of an integrator, connected as a first-order low-pass filter and driven by a sinusoidal input signal, can be expressed in terms of the dynamic range (DR)

$$P_{an} = 8fkT\xi \, \mathrm{DR} \tag{1.1}$$

where f is the cut-off frequency, kT is the thermal energy and ξ is the excess noise factor of the (trans)conductance element [12]. ξ is fundamentally greater equal than $\frac{1}{2}$. Thus, a large value for the noise factor translates directly to a proportionate disadvantage in terms of power dissipation. For a linearized transconductor, as found, e.g., in a G_m−C structure, the excess noise factor can be significantly larger, with common values of $\xi_{lin} \approx 3$–8 [13]. Whereas, for log-domain integrators, the noise factor can be approximated as $\xi_{log} \approx \frac{3}{2}$ [13]. This means that log-domain filter allows a substantial power saving compared to more traditional continuous-time filters. This can be partially explained by the fact that log-domain filters do not require any local linearization as traditional filters do [12].

1.3.2 Power consumption in digital sense amplifiers

Digital information is different from its continuous counterpart in two important respects: it is sampled, and it is quantized. In order to interface digital circuitry with the physical world, analog-to-digital converters (ADCs) are required, which convert the continuous-time signals to discrete-time, binary-coded form.

Power consumption in A/D converters

The resolution of the converter indicates the number of discrete values it can produce. The signal-to-noise ratio (SNR) of an ideal ADC is given by

$$\mathrm{SNR_{dB}} = 6.02N - 1.25 + 10 \cdot \log \frac{f_s}{f_{sig}} \tag{1.2}$$

where N is the stated number of bits, f_s is the sampling frequency and f_{sig} is the highest frequency of the input signal. It can be noticed that for a Nyquist converter, where sampling frequency is defined as $f_s = 2f_{sig}$, the $\mathrm{SNR_{dB}}$ is now given by

$$\mathrm{SNR_{dB}} = 6.02N + 1.76 \tag{1.3}$$

In [14], a figure of merit (F) has been defined that emphasizes efficiency with respect to power dissipation and signal-to-noise-and-distortion ratio SNDR

$$F = \frac{2^N f_s}{P} \tag{1.4}$$

where P is the power dissipation. Here we will consider an optimistic case where SNDR is equal to the Dynamic Range (DR). By this, one can quantify the ADC power consumption performance (P_{ADC}), which can be related to the correspondent DR by

$$P_{\mathrm{ADC}} = \frac{2^{\mathrm{ENOB}} f_s}{F} = \frac{2^{\frac{\mathrm{DR_{dB}}-1.76}{6.02}} f_s}{F} \tag{1.5}$$

ENOB being the "effective number of bits" of the ADC.

In this analysis, we will consider F equal to $1.2 \cdot 10^{12}$, which represents the present-day state-of-the-art A/D according to Walden in [14]. Another figure of merit known as the quantization energy (E_Q) per conversion step [15], is based on the effective resolution bandwidth (F_{BW}) instead of the sampling rate. This is defined as

$$E_Q = \frac{P_{\mathrm{ADC}}}{2^N 2 F_{\mathrm{BW}}} \tag{1.6}$$

where for a Nyquist ADC, F_{BW} is equal to f_s. As one can see, this quantity is nearly the inverse of the figure of merit suggested by Walden. Again, the analysis for minimal power consumption will be based on recently published papers, where the lowest reported number for E_Q is 2.8 pJ [16].

Finally, the fundamental limit for the quantization energy can be calculated based on the minimum thermal noise per pole (single capacitor) and the quantization noise [17]. This absolute lower bound on the quantization energy E_Q for an ADC of a given resolution N at any speed is given by [17]

$$E_{Qmin} > 48kT2^N \tag{1.7}$$

Thus, the absolute minimum power per cycle for an analog-to-digital converter can be defined from Eq. 1.6 and Eq. 1.7, resulting in

$$P_{min,\mathrm{ADC}} > 48kT2^{2N} \tag{1.8}$$

The following analysis relates consumed power to the function of the number of bits (N) representing the filtered information inside the digital filter. In the case of pacemakers, for instance, proper cardiac signal characterization would require at least 8–12 bits A/D conversion, at a sample rate of 1 kHz [18].

Power consumption in digital filters

To have a fair comparison of the minimal power needed in analog and digital filters, we will assume that the only noise source presented in the circuit is the thermal noise integrated on the capacitor, which presents a Gaussian distribution. Note that in a digital filter, the signal is represented by a sequence of bits, rather than a voltage or current. Hence, for digital signals, we can consider the associated noise in terms of probability that a bit-error will occur.

The bit-error function $P_{bit,error}$ is defined by the probability of having an instantaneous noise amplitude exceeding a certain threshold, so that a wrong decision about the logic level will be made. It is known that the power consumed by a digital filter and its corresponding dynamic range depend on the probability of the error we can allow in the logic gates [19], [20]. Hence, the function $P_{bit,error}$ can defined as [19]

$$P_{bit,error} = \frac{1}{4}\left(\frac{1}{DR} - \frac{1}{2^{2N-1}}\right) = \frac{1}{2}\mathrm{Erfc}\left(\frac{1}{2}\sqrt{\frac{P_{dig}}{fkTN}}\right) \tag{1.9}$$

where Erfc represents the error function given by $\mathrm{Erfc}(x) = 1 - \frac{2}{\sqrt{(\pi)}}\int_0^x e^{-t^2}$. Note that from Eq. 1.9, we can relate the dynamic range (DR) with the corresponding power dissipation (P_{dig}) in a digital filter.

Figure 1.4 shows minimal power consumption per cycle, $(\frac{P_{an}}{f})$, $(\frac{P_{\mathrm{ADC}}}{f})$, $(\frac{P_{dig}}{f})$, for the analog (analog filter) and digital (digital filter plus A/D converter) sense amplifiers, respectively, as a function of the DR achieved in the system. One can see that a digital filter presents lower power consumption than the equivalent analog filter. Nevertheless, due to the huge amount of power required for the analog-to-digital conversion, application of a fully digital signal processing in implantable devices like pacemakers is not feasible yet.

As a prediction of the power consumption related to A/D converters over the years, we can use the E_Q figure of merit described before. Figure 1.4 also shows how much the lowest reported quantization energy, and the corresponding $\frac{P_{\mathrm{ADC}}}{f}$, decrease yearly [17]. One can see that E_Q decays almost linearly, from 29.3 pJ in 1995 [17] to 2.8 pJ in 2004 [16], with only a factor of ten improvement over nine years.

Thus, we can conclude that the power efficiency of A/D converters needs to improve considerably in order to have the power dissipation of the digital sense amplifier comparable to the analog signal processing and, due to its power constrains, implantable devices will still be implemented using analog signal processing for many years to come.

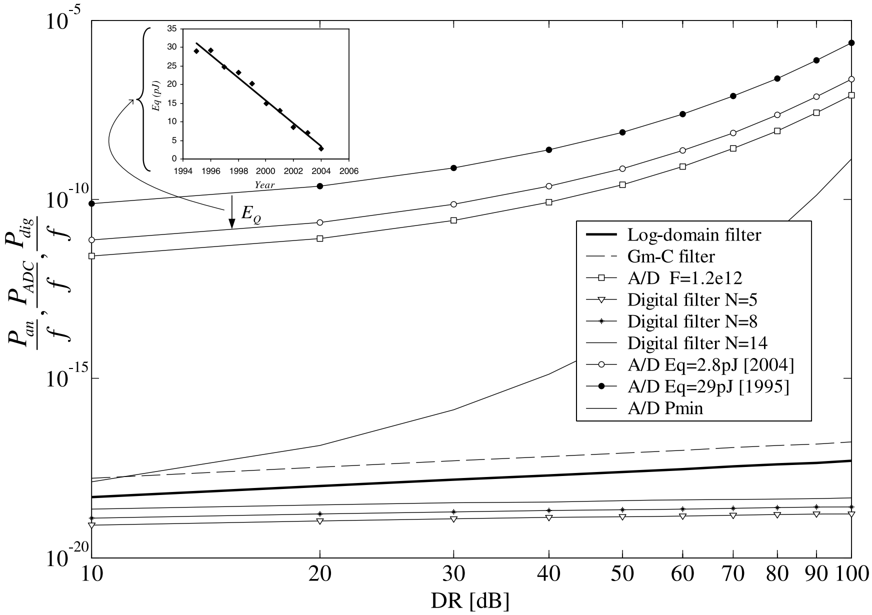

Fig. 1.4. Comparison of the analog and digital sense amplifiers' power consumption

1.4 Objective and scope of this book

The main objective of this book is the design of a novel signal processing system for ultra low-power real-time sensing of cardiac signals in pacemakers. Given the advantages in previous sections, the system will be based on wavelet transform using continuous-time analog circuitry.

The Wavelet Transform (WT) has been shown to be a very efficient tool for analysis of non-stationary signals, like cardiac signals. Being a multiscale analysis technique, it offers the possibility of selective noise filtering and reliable parameter estimation.

Low-power analog realization of the wavelet transform enables its application *in vivo*, e.g., pacemakers. In this application, the wavelet transform provides a means to extremely reliable cardiac signal detection. A promising technique for the design of ultra low-power analog integrated circuits is by means of Dynamic Translinear (DTL) circuits. The DTL principle can be applied to the implementation of functions described by linear and non-linear polynomial differential equations. Another suitable technique for low-power filters design is based on CMOS triode nA/V transconductors for linear G_m−C filters.

In this book, we propose a method for implementing the novel signal processing based on WT in an analog way. The methodology will focus then on the development of ultra low-power analog integrated circuits that implement the required signal processing, taking into account the limitations imposed by an implantable device.

1.5 Outline

A brief overview of the history and development of circuit designs applied in pacemakers is presented in Chapter 2. The advances in integrated circuit designs have resulted in increasingly sophisticated pacing circuitry, providing, for instance, diagnostic analysis, adaptive rate response and programmability. Also, based on future trends for pacemakers, some features and improvements for modern cardiac sensing systems are described.

Chapter 3 deals with the properties of the WT as well as the definition of some wavelet bases. In addition, an example is given to illustrate the advantages and limitations of the frequency (Fourier transform), time (windowing function) and time–frequency (wavelet transform) representations.

From the wavelet definition, we can state that implementation of the WT is based on a bandpass filter design which presents an impulse response equal to a wavelet base. In order to obtain a suitable transfer function of such a "wavelet filter", mathematical approximation techniques are required. Some of these approximation methods, i.e., Complex first-order system (CFOS), Padé and least mean square (L_2) approximations, will be presented in Chapter 4.

In Chapter 5, we will see that there are many possible state space descriptions, and, of course, different filter topologies that implement a particular transfer function. By choosing an appropriate state-space description and thus corresponding wavelet filter topology, we are able to achieve the required low power consumption, dynamic range, insensitivity to component variations and sparsity.

The trend towards lower power consumption, lower supply voltage and higher frequency operation has increased interest in new design techniques for analog integrated filters. The class of translinear (TL) filters, also known as log-domain filters, has emerged in recent years as a promising approach to face these challenges and will be presented in Chapter 6. In addition, new class-A log-domain and class-AB *sinh* integrator designs will be presented. In the field of medical electronics, active filters with large time constants are often required to design low cutoff-frequency filters (in the Hz and sub-Hz range), necessitating the use of large capacitors or very low transconductances. To limit capacitors to practical values, a transconductor with an extremely small transconductance G_m (typically a few nA/V) is needed. Ultra low-power CMOS triode nano-A/V and pico-A/V transconductors for low-frequency $G_m{-}$C filters are also introduced in this chapter.

In Chapter 7, the methodology presented in the previous chapter will be employed in the design of several ultra low-power biomedical systems. First, a benchmark cardiac sense amplifier, i.e., a standard pacemaker front-end, based on the Dynamic Translinear (DTL) circuit technique is presented. Then, an analog QRS complex detection circuit, based on the Wavelet Transform (WT) is described. The system uses an CFOS structure to approximate the Gaussian wavelet base and the decision stage detects the wavelet modulus maxima of the QRS complex. Two convenient methods to provide the transfer function of the wavelet filter are given by the Padé and L_2 approximations and, thus, some designs based on these approaches, for Gaussian and Morlet wavelet bases, will also be presented. In addition, a complex wavelet filter design, based on the combination of the real and the imaginary state-space descriptions is described. To fulfill the low-power requirement, the filter's state space description will be optimized. Simulations and measurement results of the various systems are also presented in this chapter.

Finally, Chapter 8 presents the conclusions and suggestions for further research in this area.

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