

# Time–Frequency Analysis for EGM Rhythm Classification

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## INTRODUCTION

In this article, we study the problem of rhythm classification and event detection based on intracardiac electrogram (EGM) signals. At present, only a very limited scope of signal processing is possible in implantable cardioverter defibrillators (ICDs), due to the scarcity of available resources. As a result, relatively simple beat-by-beat time-domain analysis of the EGM signal(s) is employed for rhythm detection. Recently, researchers have attempted to exploit more sophisticated signal processing methods, such as wavelet transforms and template matching (Astrom, Olmos, & Sornmo, 2006; Brown, Christensen, & Gillberg, 2002; Koyrakh, Gillberg, & Wood, 1999). However, the new methods have rarely been employed in practical systems because of their computational and power demands.

Modern implantable cardiac rhythm management (CRM) systems such as ICDs face many challenges, some of which are summarized here:

1. Quick and reliable detection of serious cardiac events is yet to be achieved by CRM devices. Errors in event detection occur, due to many reasons, such as quick morphology, rate, and polarity changes of the EGM signal, abnormally wide R-waves and P-waves, and external noise (Astrom et al., 2006).
2. Modern CRM devices are challenged by a considerable rate of inappropriate device therapy (IDT) (between 10 to 30%) (Rojo-Alvarez, 2002). Major causes of IDTs include: poor EGM signal quality, sinus tachycardia, supraventricular tachycardia (SVT), myopotential interference, external interference, and T-wave oversensing (Schaer, 2000). In addition to being painful for the patient, IDT's deplete valuable device battery

power, and potentially place the patient at serious risk (Rojo-Alvarez, 2002; Schaer, 2000).

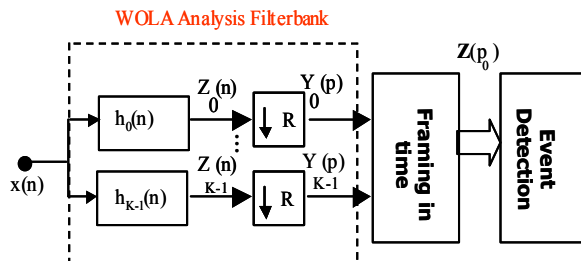
3. Rapid redetection of the EGM rhythm after device therapy (low-energy pacing or high-energy cardioversion) is problematic for CRM devices. This is particularly difficult when utilizing time-domain methods, due to their sensitivity to polarization of the EGM electrodes or baseline variations of the EGM signal following device therapy.
4. Modern CRM devices offer increasingly sophisticated multichamber detection and control, offering the physicians more potential therapies. In absence of powerful signal processing methods, however, the physicians are unable to fully exploit the multichannel information for effective programming of the device. The multichamber detection systems also require increased immunity to crosschannel interference.

In view of these challenges, we propose a multitiered detection method offering improved rhythm detection accuracy for CRM devices. This method, based on time-frequency analysis of the EGM signals, is targeted for implantable devices operating with extremely low-power budgets. It operates in real-time, and the processing delay is in the acceptable range for these applications. Although the method employs a specific filterbank implementation, it is not limited to this specific filterbank. Instead, the point is to prove that parallel processing of subband signals, resulting from a time-frequency analysis, offers more reliable detection in compromised situations.

## BACKGROUND

Time-frequency analysis has already been exploited to extract features for electrocardiogram (ECG) rate and QRS detection (Kohler, 2002).

Figure 1. WOLA oversampled filterbank analysis for subband rhythm detection



After surveying the literature, the contribution by Afonso et al. (1999) on ECG beat detection in real-time is most relevant to our research. Afonso analyzes the ECG signal by a critically sampled polyphase filterbank to extract six features that are all based on the energy (or absolute value) of groups of subbands to obtain six time-frequency signals. Each of these signals is then passed through a peak detector that compares the signal moving average to a threshold that is determined based on an estimation of the background noise. Next, in a cascade of five stages (levels), peaks are further refined. This method was evaluated on a standard ECG database with satisfactory performance.

Afonso's method and similar methods proposed for ECG analysis are, unfortunately, not applicable to ultra-low power implantable CRM devices using EGM signals for the following reasons:

1. The sensed EGM signals and ECG signals differ in many aspects.
  - a. ECG signals provide a composite signal after propagation of various electric waves to the body surface. In contrast, EGM signals provide direct access to individual heart chambers at the signal source.
  - b. Relative timing of various EGM signals is crucial in discrimination of various cardiac events. For ECG signals however, such timing information is not available.
  - c. Unlike ECG signals, sensed EGM signals are prone to cross-talk.
2. The ECG methods are too complex or unsuitable for real-time applications, are specifically designed for (and evaluated on) ECG signals, and do not provide the robust and reliable performance essential for EGM signal processing.

Among various time-frequency analysis methods, oversampled filterbanks have been implemented by a Weighted Overlap-Add (WOLA) structure in ultra-low resource devices (Brennan & Schneider, 1998). We, therefore, propose a cardiac event detection based on the WOLA analysis of the EGM signals, and demonstrate its capabilities in various signal conditions. As the intention here is to describe the basis for the detection method, we limit our attention to single-electrode analysis; an extension to multiple-electrode analysis is straightforward.

## SUBBAND-BASED CARDIAC EVENT DETECTION

### Overview

A time-domain digital EGM signal  $x(n)$  is analyzed by an oversampled filterbank (depicted in Figure 1) with  $K$  subbands. For efficiency, a WOLA structure is adapted that can be implemented with ultra-low resources (Brennan & Schneider, 1998, 2003). The filterbank parameters are:  $K=32$  subbands, analysis filters  $h_k(n)$ ,  $k=0, 1, \dots, K-1$ , each of length of  $L=256$ , subband decimation of  $R=4$ , and oversampling factor of  $OS=K/R=8$ . These parameters were optimally selected for the EGM signal analysis through experimentation. As depicted in Figure 1, the subband signals are decimated with respect to the EGM signal. Figure 1 only depicts a schematic representation of the WOLA analysis. The actual WOLA implementation based on Brennan and Schneider (1998, 2003) is involved, and not described here. The WOLA time-frequency analysis stage produces  $K$  complex-valued subband signals  $Y_k(p)$ ,  $k=0, 1, \dots, K-1$ , where  $Y_k(p) = Z_k(n.R)$ , and  $k$  is the subband time-index. Due to Hermitian symmetry, half of the subbands are unique for real signals, because the other half are complex conjugates. For the next stage, subband signals are framed with blocks of  $M$  samples (in time) for further analysis. For a subband time-index of  $p_0$ , this generates a  $K/2$ -by- $M$  matrix  $Z(p_0)$  including subband signals  $Y_k(p)$ ,  $k=0, 1, \dots, K/2-1$ ,  $p=p_0-M+1, (p_0-M+2), \dots, p_0$ . The frame-length  $M$  and the frame-shift  $p_0$  were selected to be three and two seconds, respectively. The frame-length should be long enough to cover more than one beat for slow beats (around 60 beats per minute (bpm)) for statistical analysis. At the same time, the frame should be as short as possible

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