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Cardiac Rhythm Detection and Classification by WOLA Filterbank Analysis of EGM Signals

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***Abstract*—A method of cardiac rhythm detection based on time-frequency analysis provided by a weighted overlap-add (WOLA) oversampled filterbank is proposed. Cardiac rhythms obtained from intracardiac electrogram signals are decomposed into the time-frequency domain and analyzed by parallel peak detectors in selected frequency subbands. Based on the coherence (synchrony) of the subband peaks, an optimal peak sequence representing the beat locations is obtained. By analyzing the synchrony of the subband beats and the periodicity and regularity of the optimal beat, the electrogram segment is classified into various possible classes including fibrillation, flutter, and tachycardia. This multi-tier method is evaluated using Ann Arbor Electrogram library in clean and in additive noise. The presented results show that in clean and in 15 dB SNR noise, the method never misses fibrillation or flutter. Other misclassification errors were within the acceptable limits.**

I. Introduction

This paper proposes new time-frequency analysis methods for detection of heartbeat and cardiac events using intracardiac electrogram (EGM) signals. These methods are targeted for real-time, implantable devices on an ultra-low power weighted overlap-add (WOLA) filterbank platform [1].

Although time-frequency analysis methods as applied to electrocardiogram (ECG) and QRS detection have precedence [2], the proposed methods are not well suited for ultra-low power implementation on implantable devices since they are either A) too complex or unsuitable for real-time applications or B) specifically designed for (and evaluated on) ECG signals and do not provide the robust and reliable performance essential for EGM signal processing. Possibly the most relevant to our research is the research by Afonso *et. al.* on ECG beat detection in real-time [3]. They employ a critically-sampled polyphase filterbank and extract up to six features based on accumulated energy (or absolute value) of groups of subbands. Peaks of individual features are detected by comparing their moving averages to thresholds that are tuned based on the estimated background noise. Peaks are then combined in a cascade of five stages (levels). In one stage, peaks of the same feature are detected with two different thresholds and combined in parallel. The method is evaluated on a standard ECG database, performing as expected.

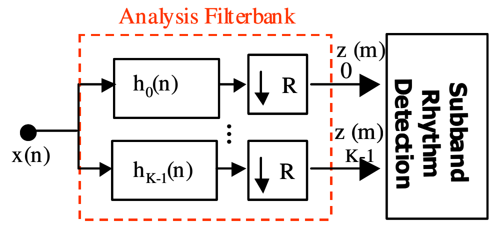

Figure 1: WOLA oversampled filterbank analysis for subband rhythm detection.

Our objective is to present a real-time detection method for beat and event detection of intracardiac EGM signals. Rather than using critically sampled polyphase filterbanks as in [3], we employ a very efficient WOLA oversampled filterbank [1] for time-frequency analysis of the EGM signals. Peak detection is done directly on the subband absolute value signals using recursive averages with no absolute thresholds. Novel methods are proposed to exploit the synchrony of the subband signals at the beat-time. Furthermore, from the narrowband subbands, wideband (complex) subband signals are obtained and used for wideband beat and event detection. Wideband detection results are then combined with the narrowband ones. This combination is needed to cope with the wide range of possible beat-rates and morphologies of the EGM signal. As we desire to describe the basis for the detection method, we limit our attention to single-electrode analysis, noting that extension to multiple-electrode analysis is straightforward. Also, since we are targeting low-power, real-time and implantable applications such as cardiac rhythm management devices, the algorithm simplicity has been a major focus in this research.

This paper is organized as follows: Section II discusses details of the detection algorithm, Section III presents evaluation of the methods using the EGM signals in clean and in additive noise, and Section IV presents research conclusions.

II. The Proposed Method

A. Overview

As depicted in Fig. 1, the time-domain EGM signal $x(n)$ is continuously analyzed by an oversampled filterbank. The filterbank is efficiently implemented using a WOLA structure [1] with $K=32$ subbands, analysis window length of $L=256$, subband decimation of $R=4$, and oversampling factor of $OS=K/R=8$.

The result of WOLA analysis is K complex-valued subband signals $Z_k(m)$, $k= 0, 1,\ldots, K-1$, where m is the subband time-index. For real input signals, only half of the subbands are needed due to Hermitian symmetry. Subband signals are then framed with a frame-length of 3 seconds and a frame-shift of 2 seconds. Since the cardiac beat generates a sharp pulse, the magnitudes of subband signals ($|Z_k(m)|$) exhibit mainly coherent peaks at the time of cardiac depolarization. One basis of the proposed method is to properly exploit this subband coherence (termed "synchrony" here) in selected subbands. While various methods are possible, we chose a robust method based on simple binary operations to quantify the synchrony.

As a result of synchrony analysis, an optimal beat sequence is detected every two seconds. Then the periodicity and the regularity of the optimal beat together with the synchrony measure are considered for event detection.

B. Subband Peak and Synchrony Detection

The first step is to find peaks in selected subbands. In each subband, we tracked the maximum with a two-time-constant first-order recursive filter. Given the subband magnitude signal $|Z_k(m)|$, $0.9<\alpha_{m1}<1$ and $0.1<\alpha_{m2}<0.5$, the following pseudo-code describes how the maximum signal ($M_k(m)$) is obtained:

$\alpha=\alpha_{m1}$

If $|Z_k(m)| > M_k(m-1)$, $\alpha= \alpha_{m2}$

$M_k(m) = M_k(m-1).\alpha + |Z_k(m)|.(1-\alpha)$

A similar average tracking with a two-time-constant recursive filter is used to track the average ($A_k(m)$) with $0.7<\alpha_{a1}<1$ and $0.5<\alpha_{a2}<0.7$. A peak ($P_k(m)$) is detected by comparing the instantaneous value ($|Z_k(m)|$) to the average and maximum values as described in the following pseudo-code.

$P_k(m)=0$

If $\{|Z_k(m)| > A_k(m-1)$ & $|Z_k(m)|> 0.5\, M_k(m-1)\}$ & $\{A_k(m-1)< 0.9\, M_k(m-1)\}$,

$P_k(m)= |Z_k(m)|$

In absence of EGM activity, $P_k(m)$ and $M_k(m)$ converge to each other. In this situation, the last term in the condition prevents peak detection. Currently peak detection is limited to subbands 2-9, ignoring the first subband as it captures noise and baseline wander. Fig. 2 depicts a typical segment of atrial EGM signal (top graph), and four WOLA subband energies with maximum, average, peak and instantaneous values. After peak detection, to simplify further operations, we convert each subband peak signal $P_k(m)$ to a binary (0/1 for peak/no-peak) signal $B_k(m)$. Once a pattern of consecutive peaks followed by zeros (eg. {1 1 1 0 0}) is found, the falling edge of the peak is registered as a valid peak. The rest of the peak signal is reset to zero. This avoids detecting short-term spurious peaks. All further operations are applied to the binary peak signals $B_k(m)$. Next, the degree of synchrony between various subband peaks is measured by simple AND operations of binary peak signals. Given a pair of signals $B_k(m)$ and $B_l(m)$, synchrony of the pair $S_{k,l}$ (in percentage) is measured as:

$$S_{k,l}= 100\, NP(B_k(m) \,\&\, B_l(m)) / \max\{NP(B_k (m)), NP(B_l(m)) \}$$

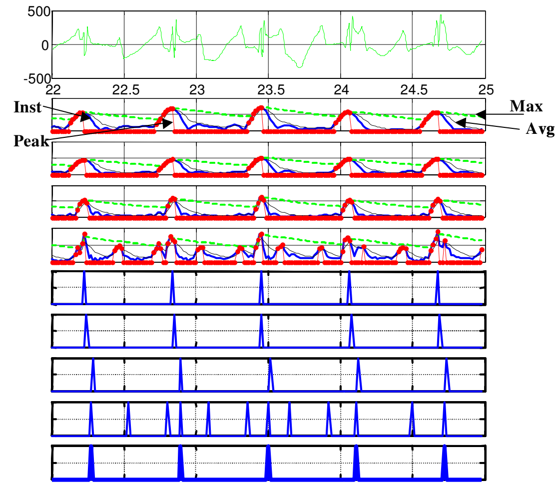

Figure 2: From top to bottom, A segment of Atrial EGM signal, four WOLA subband energies with their average, maximum, instantaneous, and peak signals, their corresponding binary pulses $B_k(m)$ (rows 6-9), and the optimal detected pulse (bottom row).

where function $NP()$ denotes the number of peaks in a frame of peak signal. The synchrony of all non-identical pairs is evaluated (for 8 subbands this involves 28 AND operations on frame pairs). To avoid the influence of noise and interference, only the top 3 synchrony scores are kept as measures of the frame synchrony. Based on the top 3 scores, using fixed synchrony thresholds, the algorithm classifies the subband beats as perfectly synchronous ($Syn=4$), as borderline synchronous ($Syn=2$), or asynchronous ($Syn=0$).

The top 3 binary pulse pairs also provide a robust method for detecting optimal beat times. We apply a majority voting rule (2 out of 3) to detect beats using the 3 pairs after the logical AND operation within each pair. This proved to be very robust in noise and especially when the signal quality was compromised in flutter and fibrillation. The result of beat detection is an optimal beat sequence $OB(m)$ per frame. Fig. 2 (rows 6-9) depicts binary subband pulses for the EGM segment together with the optimal detected beat (last row).

C. Periodicity and Regularity Analysis

The detected optimal beat signal $OB(m)$ is further analyzed to find its period histogram, its mean period ($\overline{T}$), and the mode of the histogram (T_m). Also, the standard-deviation-to-mean ratio of the detected periods (σ/μ) is calculated. σ/μ values more than 40% indicate very irregular beats, values less than 20% show very regular beat patterns, and values in between indicate moderate regularity. Also if unusual lack of EGM activity is detected within a frame, the irregularity flag is set ($Ireg=1$).

D. Cardiac Even Detection

Based on the synchrony score (Syn), periodicity and regularity of the optimal beat ($\overline{T}$, T_m, σ/μ, and $Ireg$), cardiac events are classified as one of the following 8 events:

1. Stable Sinus Rhythm (SR)
2. Transitional SR (T-SR)
3. Stable Tachycardia (VT or AT)

4. Transitional Tachycardia (T-VT or T-AT)
5. Flutter (VFLUT or AFLUT)
6. Fibrillation (VFIB or AFIB)
7. Synchronous but Irregular rhythm (Syn-Irg)
8. Unclassified

We have represented by VT, VFLUT, and VFIB ventricular events of tachycardia, flutter, and fibrillation respectively, and similarly by AT, AFLUT, and AFIB the corresponding atrial events. A transitional event of T-SR is detected when the mean period is within the range for sinus rhythm but the rhythm is irregular. A similar criterion is used in detection of T-VT or T-AT. Event 7 is detected when there is perfect synchrony but the periods are too irregular or insufficient in number to be considered for other classes. Finally, event 8 is reserved for unclassified rhythms.

Fig. 3 depicts a flowchart of the event detection algorithm using three features of synchrony, rate, and regularity of periods. The algorithm operates by "setting traps" for various events. As shown, it first tries to identify fibrillation or flutter (classes {5,6}). In absence of either (state A in the figure), it searches for fast beats (classes {3,4,7}) and then sinus rhythms (classes {1,2,7}). If none of the traps succeed in detection, the beat remains unclassified (class 8).

E. Wideband WOLA Analysis

The time-frequency representation obtained by the narrowband WOLA analysis (*K=32*) is not suitable for fast rhythms that occur during flutter or fibrillation. As expected from the classic time-frequency resolution trade-off, the time resolution is insufficient to separate two closely spaced beats. This is especially problematic when the signal quality is further compromised as it likely is during these events.

An effective remedy is to use a wider band filterbank analysis. In the WOLA filterbank, it is possible to combine, for example, every neighboring pair of complex subband signals to obtain a wideband analysis, *doubling* the time resolution. Notice that all the subband signals are centered around base-band after WOLA analysis. So, to combine subbands one needs to modulate the bands to line up sequentially. For example, to combine two subbands, one needs to apply a complex modulation to the higher-frequency subband and add the results to the other subband.

We combined the low-frequency subbands in pairs (subbands *2-7*) and in a group of four (subbands *2-5*). As a result four new wider subband signals are obtained. The limiting factor in grouping is the filterbank oversampling factor (*OS=K/R*). For wider bands, the effective number of bands (*K*) decreases, and therefore the potential for aliasing increases. With our proposed WOLA setup (*K=32, OS=8*), aliasing is minimal when grouping in pairs (equivalent to *K=16* bands) or in fours (effective *K* of *8*) since the combined bands are still oversampled by at least *OS=2*. Aliasing is also greatly affected by proper prototype filter design but we refrain from discussion here for brevity.

Using the four wider subbands, we applied a wideband peak detection, synchrony, periodicity and regularity analysis. Then the results of the two (narrowband and wideband)

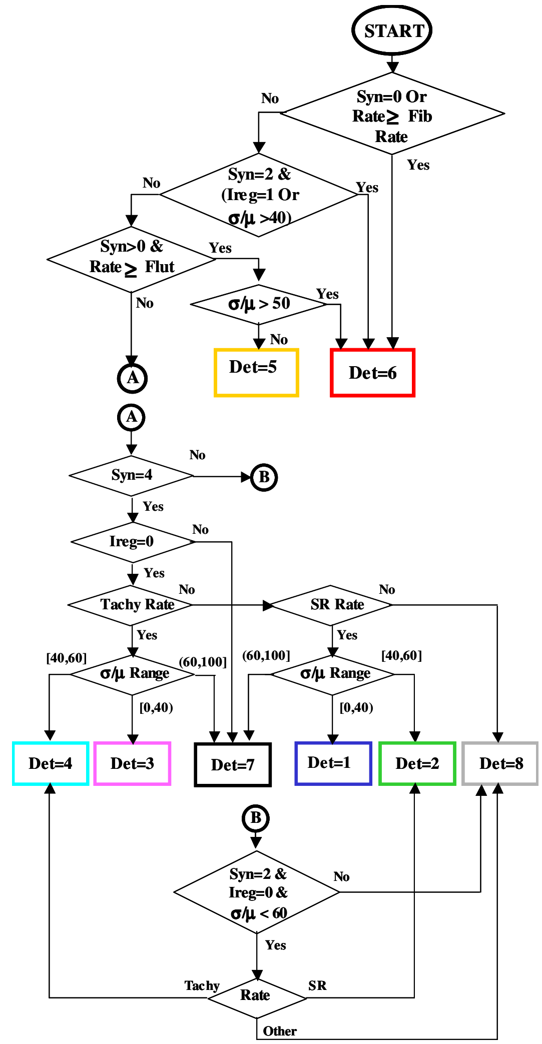

Figure 3: Flowchart of the event detection algorithm.

detections were combined together as follows. The narrowband detection was taken as the default. The switch to the wideband detection occurs when it detects perfect synchrony and when its period σ/μ ratio is either less than σ/μ of the narrowband system or it is less than 40%.

III. System Evaluation

We employed all the EGM data from vol. I of the Ann Arbor Electrogram Libraries (AAEL) [4] for system evaluation. Only the two EGM signals recorded with bipolar electrodes were utilized. These signals offer the best quality and are recorded from Right Ventricular Apex and High Right Atrium, called RVAb and HRAb in the AAEL documentation, respectively. The EGM signal was digitally decimated from the original sampling frequency of *1000* Hz down to *Fs=250* Hz since our analysis and simulations revealed that it suffices. For every case in the library, we employed the detection algorithm and compared the results to the AAEL annotation. The system parameters were tuned until there were no missed events and the frame-by-frame classification was as accurate as possible for all types of rhythms. A typical output summary of the detection system

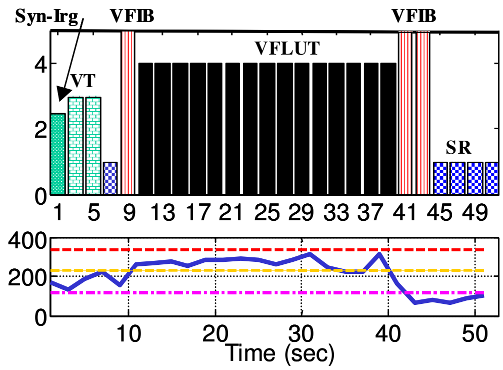

Figure 4: Algorithm performance for RVAb EGM signal (AAEL file: SET1, A177A26.SIG), top view: detected events in time, bottom view: detected rate in beats per minute (solid line) in time, and VFIB, VFLUT, and VT rate thresholds (dashed line, from top to bottom respectively).

Table 1: Number of TP, FP, TN, and FN frames for 15 dB SNR white noise.

		ACTUAL	
		FIB/FLUT	SR/VT
DETECTED	FIB/FLUT	True Positives: **1005** frames	False Positives: **43** frames
	SR/VT	False Negatives: **38** frames	True Negatives: **8777** frames

Table 2: Positive and Negative Predictivity for five noise types of 1-white, 2- lowpass, 3- bandpass, 4- highpass, and 5- 60 Hz.

Noise Type	+P %	-P %
1, 15 dB SNR	95.9	99.6
2, 15 dB SNR	95.2	99.7
3, 15 dB SNR	97.4	99.5
4, 0 dB SNR	99.2	99.8
5, 0 dB SNR	98.1	99.7

depicting various detected events and the beat-rate is shown in Fig. 5.

A. *Detection in Noise*

Once the detection system was optimized and tuned, it was employed for detecting in noise to examine the robustness of the method in noise. In reality, noise robustness is an important feature of an EGM processing system. Five different types of noise were added to the EGM signals: 1-white noise, filtered white noise (2-lowpass, 3-bandpass, 4-highpass), and 5-tonal (60 Hz) noise. Noises 2-4 each had a 3-dB bandwidth of a quarter of the full-band. Since the EGM signal rapidly changes in magnitude and polarity, and the morphology varies from very sharp pulses to wide waves, measurement of the noise level by signal-to-noise ratio (SNR) based on long-term power is inadequate. Instead we measured the SNR based on tracking the short-term (4 second) signal envelope (rather than power) of EGM and noise signals.

Event detection was performed for the whole EGM database, excluding frames representing cardioversion, lead failure and lead dislodgement. Then the output summaries (similar to that of Fig. 4) were carefully compared to the output summaries for the clean EGM signals to ensure that no block of event is lost. To further evaluate the performance, we compared the detection results in noise with the benchmark results (in clean). Grouping events in two separate groups, {1-4} (SR/Tachy) and {5-6} (Fib/Flut), we measured the detection performance using frame counts of *TP, TN, FP,* and *FN* defined as:

1. *TP*, True Positive: Correct detection of {5-6}
2. *TP*, True Negative: Correctly not detecting {5,6}
3. *FP*, False Positive: Falsely detecting {5,6}
4. *FN*, False Negative: Falsely not detecting {5,6}

Then the Fib/Flut Positive Predictivity (+*P*) and Negative Predictivity (-*P*) were calculated as:

$$+P = TP/(TP+FP), \qquad -P = TN/(TN+FN).$$

Table 1 depicts the total frame counts of *TP,FP,TN,* and *FN* for 15 dB SNR white noise. Also, the +*P* and –*P* measures for the five noises types are summarized in Table 2. As expected, white noise has the worst effect on subband detection as it affects all the bands equally. On the other hand, 60 Hz noise and highpass noise have the least effect on the performance. Overall, no block-event was missed or mis-recognized with five noise types in Table 2. Rather, recognition errors in noise were sparse and mostly before or after fibrillation or flutter events when the quality of EGM signal was already compromised.

IV. Conclusions

The proposed WOLA-based EGM processing methods perform reliably due to the novel subband synchronous beat detection. Extensive testing with the AAEL database has shown excellent performance in terms of correct event detection and beat-rate measurement even in fibrillation or flutter when the signal quality is compromised. Evaluation in noise and in the presence of far-field R-waves (not reported here) has also demonstrated significant robustness to noise and interference. This method is simple enough for implementation on an ultra-low power WOLA filterbank platform and requires only simple operations as a result of using binary peak signals.

For future work, we intend to use subband features for morphology analysis and pattern matching. This could outperform time-domain analysis since the WOLA subband features reveal the signal spectral signature and are less susceptible to noise and interference.

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