Idle Tone Detection in Biomedical Signals Using Time-Frequency Techniques

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Abstract. Sigma Delta based biomedical acquisition systems are popular amongst the possible hardware architectures developed for this purpose. It allows for the creation of high-resolution low power and cost-effective universal systems, where oversampling is used with the advantage of the associated simplified anti-alias filter design. However, spurious idle tone generation is commonly present, whose location in frequency and amplitude are not predictable. Despite their amplitude being typically low, in some applications it may tamper with the signal processing parameters. In the ECG, EMG and EEG processing, idle tones may degrade frequency energy content. Given the non-stationary nature of biomedical signals, time-frequency analysis is the adequate tool for idle tone detection due to its dual representation which includes time localization. The spectrogram along with other quadratic time-frequency representations (QTFR) are applied for idle tone analysis where QTFR's show to have appealing frequency resolution capabilities under low cross terms amplitude conditions.

Keywords: Time-Frequency Analysis, Wavelets, Idle Tones.

1 Introduction

Time-frequency representations (TFR) are widely used in the analysis of biomedical signals, since they are useful to understand the frequency content variations of non-stationary signals with time. The TFR concept was introduced by Ville [1], Blanc-Lapierre et al. [2], and Claasen et al. [3]. Nowadays several algorithms are available and are applied to the biomedical signals, such as the Continuous Wavelet Transform [4] and the Choi–Williams distribution [5]. Some biomedical signals are collected through acquisition systems based on Sigma Delta modulators, which are broadly used due to its high performance, low power consumption and design versatility [6]. However, idle tones are still a common phenomenon in Sigma Delta systems namely for modulators order below 3 [7], and their presence translates as a narrowband, low amplitude component, added to the original signal, that may vanish or increase during the acquisition session in a unpredictable way. The most common causes for idle tone presence are voltage-reference modulation, the DC signal level input and modulators orders below 3 [7]. To the best of the authors knowledge, no report was written describing idle tones detection and visualization in biomedical signals. The aim of this work is to show how the TFR can be a useful tool in the detection of idle tones in biomedical signals. The Choi-Williams distribution will be used as the best compromise involving the following factors: frequency resolution and computational cost.

2 Contribution to Life Improvement

Diagnostic techniques in health care include a wide range of vital signals acquisition, such as the Electrocardiogram (ECG), Electroencephalogram (EEG) and the Electromyogram (EMG). Medical decision regarding diagnostic and treatment typically rely upon on the information obtained from these signals. Artifacts and interference should be kept at levels compatible with the ability for the downstream algorithms or the human expert evaluation reliability. Idle tones interference in sigma delta-based biomedical acquisition systems may introduce interference components not related do the electrophysiological processes under scrutiny. This may pose an array of signal interpretation problems, if the frequency band of interest overlaps with the tone's frequency. Unfortunately, this subject is often overlooked in biomedical signal processing. So, the adequate time-frequency analysis tool for idle tone detection in Sigma Delta based biomedical acquisition systems play an important role in medical decision and diagnosis.

3 Methods

Time-frequency representations (TFR) are the suitable tool for non-stationary signal analysis which include most of the bio-signals. Furthermore, for interference detection, whose frequency and time location have an unpredictable nature, this method outperforms the classic spectral analysis. However, one must take in account that a suitable time-frequency method should be selected. A key factor to have in consideration is the narrowband nature of the idle tones which prompts the use of TFR with an optimal time-frequency resolution such as the Wigner-Ville Transform (WVT). However, the WVT is also notorious by its high level of cross terms, which renders the tones identification a difficult task. Relatively to the WVT, the Choi-Williams transform (CWT) is a compromise between cross terms level reduction and frequency resolution. The CWT, which along the Spectrogram belongs to the Quadratic Time-Frequency Representations (QTFR), and uses a kernel function (Φ) given by:

$$\Phi(\theta,\tau) = e^{-\theta^2\tau^2/\sigma}. \tag{1}$$

where θ and σ are positive kernel parameters, being τ is the time lag. Substituting the kernel in the general Cohen [8] class expression, we obtain the QTFR:

$$P_{CW}(t,\omega) = \frac{1}{4\pi^{3/2}} \iint \frac{1}{\sqrt{\tau^2/\sigma}} exp\left[-\frac{(u-t)^2}{4\tau^2/\sigma} - j\tau\omega\right] s^*\left(u-\frac{1}{2}\tau\right) s\left(u+\frac{1}{2}\tau\right) du\, d\tau. \tag{2}$$

where t is the time and ω is the angular frequency. For $\sigma \to \infty$ the CWT becomes the WVT, so that this parameter may be used as a control factor for cross-terms reduction, at expense of frequency resolution. The CWT is thus chosen for the idle tone detection task, upon on the selection of a suitable σ parameter. For this application, the wavelet based scalogram non-uniform time-frequency plan tilling is an obstacle, since the idles tones may fall in a low-resolution frequency cell. This can be overcome by changing the mother wavelet length, but this would require a possible fastidious trial and error procedure. A test signal was implemented with a duration of 1800 seconds and a frequency sampling of 4 Hz, containing two linear chirps, and four sinusoidal segments, with different frequencies, two of them asymmetrical to test appropriate transform alignment. Signal overlap corners were also created to assess the transform resolution. A Dirac function was added at 400 seconds. There is a silence zone between 800 and 1000 seconds to test for transform compact support. Regarding real signals, idle tones were evaluated in the EMG, EEG and the ECG signals. All data was analyzed with MATLAB®.

4 Results

Figure 1 represents the effort in order to demonstrate that the CWT is the adequate tool for idle tone detection, for which, as mentioned, a reasonably good frequency resolution is required. The synthetic signal is plotted in the top plot. Considering that the spectrogram, represented in the second plot, is a widely used TFR with average computational cost, where the chirps and tones are clearly visible and cross terms are virtually nonexistent. Frequency resolution is around 0.05 Hz (Arrow A). The third plot shows the CWT using a σ = 100. The frequency resolution dropped to approximately 0.0175 Hz (Arrow A). However, an unacceptable level of cross terms is patent between tones and chirps (Arrow C). The fourth plot shows the same CWT with a σ= 0.1, where an acceptable cross terms level is present and with a frequency resolution of 0.025 Hz (Arrow A), approximately. It becomes also patent that signal overlap corners (Arrow B) are better defined in the CWT. In view of this results, the CWT with a σ= 0.1 is selected for idle tone detection in real signals. Figure 2 shows (top) an EEG signal [9] which includes a seizure occurring from 100 to 150 seconds. Idle tones are present at 16, 32 and 48 Hz. Compared to the higher power component, a reference 0 dB plateau, the idle tones amplitude is higher in the pos-ictal area relatively to the pre-ictal area, as shown in Table 1. This could be explained by the shifting input conditions in the sigma delta modulator imposed by the ictal signal higher energy burst. Figure 3 is a comparison of the marginal power density of the EEG signal between the spectrogram and the CWT. In both methods peaks were found at 16, 32 and 48 Hz. Their amplitude does not stand out and could be easily taken as a bio-signal feature. However, in the TFR (Figure 2) it is possible to determine that these peaks represent idle tones and not a physiological feature of the signal. Moreover, the 12 Hz peak is due to the EEG spindles as it can be observed in the TFR representation. As expected these frequency peaks are sharper in the CWT. Figure 4 shows the CWT for a hand movements EMG signal [10]. In order to enhance the idle tones, the selected analysis frequency band was between 55 and 145 Hz. Three idle tones are visible at frequencies 70, 100 and 140 Hz. There is a frequency feature at 80 Hz that could be a candidate to idle tone classification, but preventively is ruled out, since the frequency structure fades between 1.5 and 2.5 seconds. Table 2 shows the average relative amplitude of the idle tones compared to the peak plateau power reference. The acquisition systems used in both previous cases are not referred by the respective data holders. In the third case is presented an ECG (Figure 5) where no idle tones are present, whose acquisition system is frequently used among the biomedical research and teaching community. The sigma delta modulator order is 3. No idle tones are identified using the CWT with the same σ parameter as above.

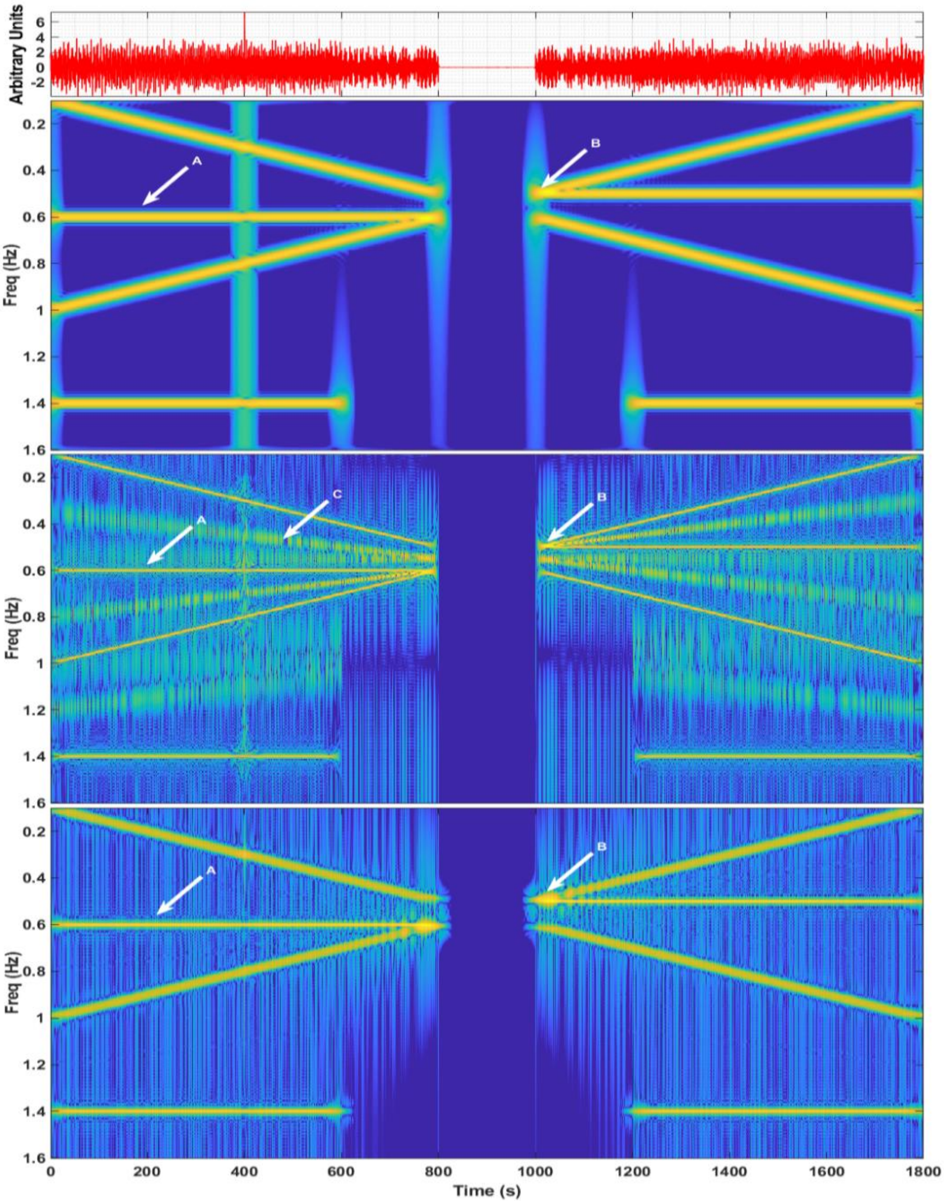

Fig. 1. From up to down: Test signal, Scalogram, Choi-Williams with σ =100 and Choi-Williams with σ =0.1. Refer to the text for explanations.

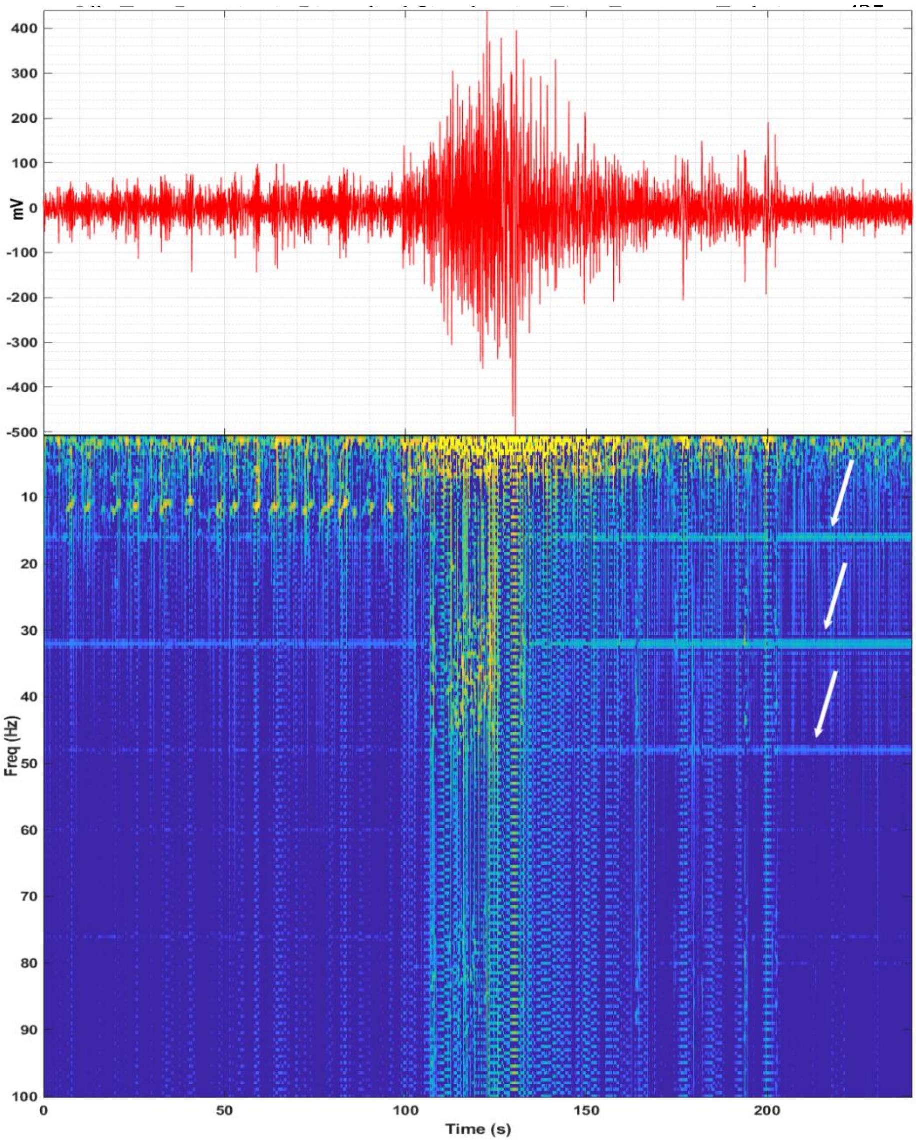

Fig. 2. Top: EEG seizure signal (onset at 100 s). Bottom: CWT with σ =0.1 and time window=1 s Refer to the text for explanations.

Table 1. Idle tones compare table for the EEG epileptic seizure case. Power peak plateau reference of 0 dB is considered.

Tone Frequency (Hz)	Before Seizure (dBW)	After Seizure (dBW)
16	- 33	- 26
32	- 36	- 28
48	- 42	- 39

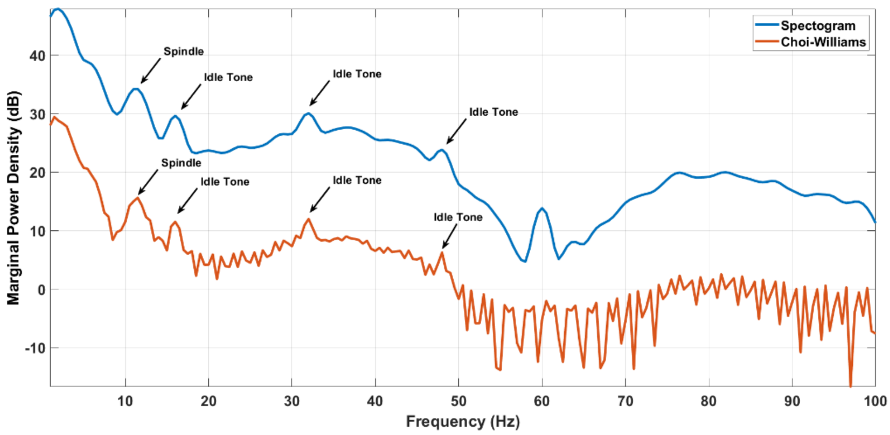

Fig. 3. Marginal Power Density of EEG signal in Figure 2. Refer to the text for explanations.

Table 2. Idle tones compare table for EMG case for a power peak plateau reference of 0 db.

Tone Frequency (Hz)	(dBW)
70	- 20
100	- 33
140	- 24

5 Discussion and Conclusion

A method of detection of idle tones in biomedical signals is herein presented, using TFR techniques. Figure 3, that has been mentioned earlier, is crucial to understand the importance of TFR, since it allows the identification of distinct peaks in the Marginal Power Density spectrum which might be idle tones or physiological signal features. TFR will allow to sort out the real nature of these frequency peaks through their time shape variation, thus conducting to its correct classification. TFR is an essential tool to identify idle tones in biomedical signals where a balance between time-frequency resolution and cross-terms must be found in order to reach valid interpretations. The Wigner-Ville TFR features the higher time-frequency resolution cells, however the high cross terms level restricts the use of this method in this application. The CWT with a $\sigma = 0.1$ was selected as a compromise. Other TFR kernels may be explored for optimal time-frequency resolution in idle tones detection and this would require exhaustive experimentation using the numerous available kernels. Some other kernels have been, for this work, tested with similar time-frequency resolutions, relatively to the CWT, however its computational cost and execution times hamper their application in mundane biomedical signal analysis platforms. Idle tones presence is systematically overlooked in biomedical signal processing with the associated analysis bias, namely if sigma delta modulators with an order below 3 are used. As shown in Table 1 and Table 2, the idle tones power lies in an interval between -20 dB and -42 dB below the reference power plateau, which, despite being a low level interference, becomes a substantially higher if the bandwidth of the application happens to be restricted to the tones vicinity. This information is commonly not available in the systems technical specifications and stands out that a mandatory action should make this compulsory in biomedical acquisition systems technical documentation, having in mind that the obtained signals might be used for medical diagnostics and healthcare algorithm development.

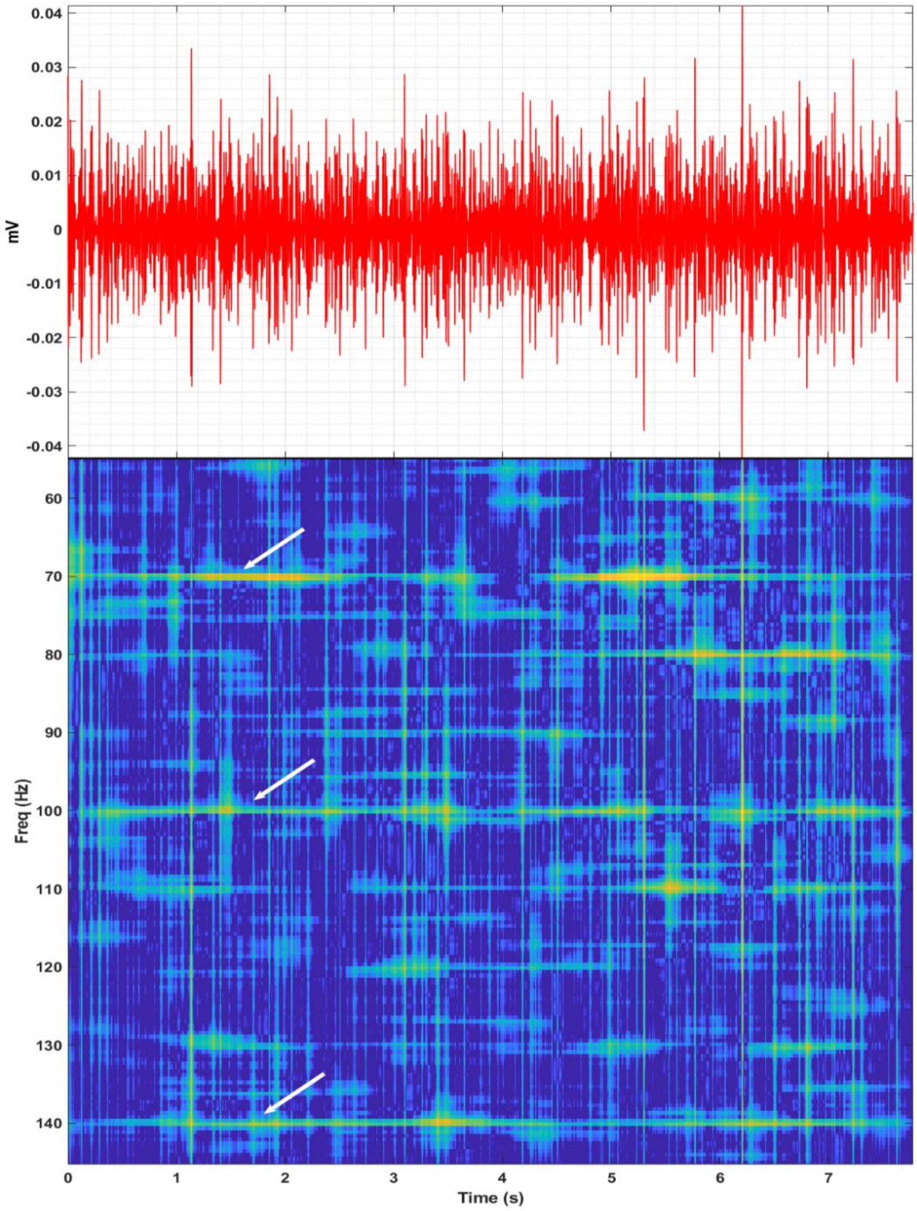

Fig. 4. Top: EMG signal. Bottom: CWT with σ =0.1 and time window=1 s Refer to the text for explanations.

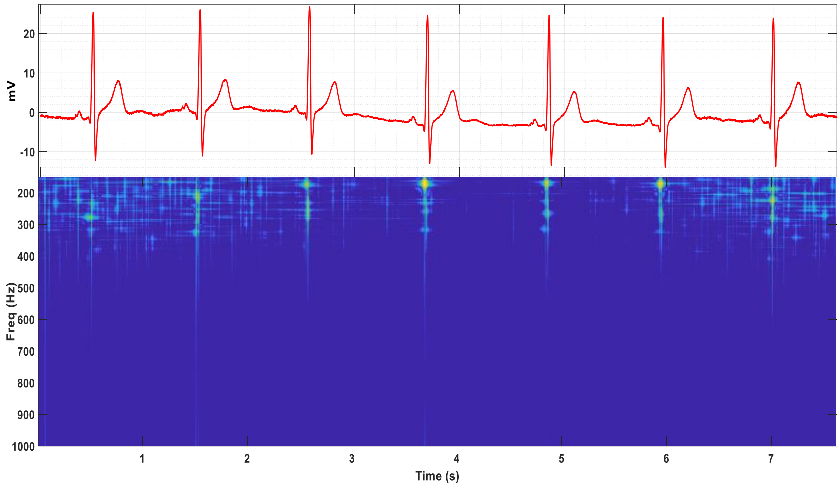

Fig. 5 Top: ECG signal. Bottom: CWT with σ =0.1 and time window=1 s. Refer to the text for explanations.

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