

# Cardiac Arrhythmia Spectral Analysis of Electrogram Signals Using Fourier Organization Analysis

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## Abstract

*Implantable Cardioverter Defibrillator (ICD) are devices which give relevant information about tachyarrhythmias in patients. The classical spectral approaches to assess cardiac electrograms (EGM) from ICD, Dominant Frequency Analysis (DFA) and Organization Analysis (OA) have often discarded relevant information in the spectrum, such as the harmonic structure. We propose a description, called Fourier Organization Analysis (FOA), for characterizing the spectral and organization features of EGM. FOA includes two stages, a first step involving fundamental frequency estimation, and a second organization analysis step, using Least Squares projection onto a signal space of sinusoids possibly containing fluctuations. The algorithm was first tested on synthetic EGM from a simple model simulation. Then, a data base was analyzed which included 14 episodes, namely, 5 Sinus Rhythm, 8 Supraventricular Tachycardia, 8 Ventricular Tachycardia, and 7 Ventricular Fibrillation records. Each episode had two EGM recordings, monopolar and bipolar. FOA showed high accuracy when estimating fundamental frequency for all rhythms, and also allowed to establish a coherent comparison between them. We conclude that FOA yields a more compact and adequate framework for analyzing ICD stored EGM.*

## 1. Introduction

Spectral analysis of intracardiac electrograms (EGM) has been recently pay wide attention in the clinical environment, and specifically in the detection of clinical targets for atrial fibrillation (AF). These targets aim to give a regular description on the frequency domain for a visually irregular waveform in the time domain, in terms of low cycle length (CL) and or high regularity regions [1]. Such spectral features have been used both in electrical and in optical mapping sequences, during AF and ventricular fibrillation (VF) [2].

Two complementary approaches have been mainly followed in spectral analysis: Dominant Frequency analysis (DFA) and Organization Analysis (OA) [2, 3]. The former aims to estimate the averaged CL of the EGM by means of the dominant frequency  $f_d$ , defined as the frequency for which the maximal absolute value of the EGM spectrum,  $P(f)$  occurs. There exists some procedures that compute  $f_d$  on an auxiliary signal obtained by filtering and rectifying the original EGM, as automatic procedures for averaged CL estimation [4]. The OA approach aims to measure the relative contribution of the near-periodic component of the EGM, characterized by  $f_d$ , in terms of signal power. Two parameters have been mainly used, namely, the Regularity Index,  $ri$ , defined as the ratio of the power contributed by dominant peak and the total power in the band of interest, and the Organization Index,  $oi$ , defined as the ratio of the power contributed by the fundamental frequency and up to four harmonic peaks, and the power in the band of interest, this one last defined as being relative to the last harmonic [3, 5].

Though highly informative, the parameters yielded by DFA and OA do not give a complete spectral description, and they often can discard relevant information, as the harmonic structure or the spectral envelope. Sometimes, parameters from DFA and OA can become inaccurate, given that  $f_d$  will not always be a proper estimation of the averaged CL. This risk holds even when using the automatic algorithm in [4].

Therefore, our aim was to give a unified and simple signal analysis, which not only contains the information from DFA and OA, but also it gives additional parameters based on the spectral structure of the EGM. The proposed method, called Fourier Organization Analysis (FOA), consists first on the estimation of the fundamental frequency  $f_0$ , defined as an estimation of the inverse of the averaged CL. Then, the signal model, fitted by a Least Squares projection onto a signal space of sinusoids possibly containing fluctuations, is analyzed by using a set of spectral parameters.

The scheme of the paper is as follows. Section 2 describes the simulated and real data sets used in this paper. In Section 3, the algorithm for FOA is presented. In Section 4, the results are presented. Finally, Section 5 contains the conclusions of the work.

## 2. Data Sets

*Simulated Signals.* A computer model [6] was used to simulate examples of monopolar and bipolar EGM signals in different and simple electrophysiological conditions. A rectangular grid of  $1 \times 2$  cm (80 cell groups per cm) was made for discretizing a 2-dimensional tissue. A EGM recorded model was also programmed. A monopolar electrode was placed at  $x = 1.5$  cm,  $y = 0.5$  cm, and at 0.2 cm height. The bipolar electrode configuration consisted of this monopolar electrode at the positive pole, and the negative electrode at  $x = 1.52$  cm,  $y = 0.52$  cm, and at 0.2 cm height. Simulated EGM were recorded at 1600 samples per second during 2 seconds. The following electrophysiological conditions were simulated: Sustained line stimulation from the left border (pacing rate of 400 ms), yielding a plane wavefront; and Fibrillatory activity, generated by using a standard  $S1 - S2$  stimulation protocol.

*Real Signals.* We used a data base with EGM recordings stored in ICD from patients with a Medtronic (TM) device, in Hospital Universitario Virgen de la Arrixaca of Murcia and in Hospital General Universitario Gregorio Marañón of Madrid, Spain. For each analyzed episode, two EGM were simultaneously recorded, with pseudomonopolar (from can to coil) and bipolar (from tip to ring) configurations, at 128 samples per second. Recordings included in this work were revised and classified by an specialist. The data base consisted of EGM during four different rhythms, namely, 5 sinus rhythm (SR), 8 supraventricular tachycardia (SVT), 8 ventricular tachycardia (VT), and 7 (VF).

## 3. Methods

In this section, we propose the method FOA using well-known principles of spectral analysis and signal approximation.

Be  $EGM(t)$  a continuous time EGM signal. If it was a purely periodic signal with fundamental period  $t_0$ , its Fourier Series representation would be given by the following expression,

$$EGM(t) = \sum_{k=1}^K A_k \cos(2\pi(kf_0)t + \phi_k) \quad (1)$$

where  $f_0 = 1/t_0$  is the fundamental frequency, that corresponds to the inverse of the averaged CL, and  $A_k, \phi_k$  are the amplitude and phase for each harmonic component,

with  $K$  the number of harmonics. We start by assuming that  $f_0$  is known, and will address its estimation later.

Three additional elements can be introduced into the signal model (1). First, additive noise can be present, denoted by  $e(t)$ . Second, we work with a digitized version of  $EGM(t)$ , which yields  $N$  samples acquired at  $f_s$  samples per second. The spectral resolution of a nonparametric Fourier-based spectral analysis procedure is  $\Delta = f_s/N$  Hz. Third,  $EGM(t)$  will not be purely periodic in real recordings, but at most it will be near-to-periodic. This characteristic can be observed by the presence of narrow-band structure in the signal spectrum. In order to quantify this signal irregularity, we included in our model two additional sinusoidal components for each harmonic component, whose frequencies were the harmonic components  $\pm\Delta$  Hz. Adding these three elements, our signal model for  $EGM(t)$  is now given by,

$$\begin{aligned} EGM(t) = & \sum_{k=1}^K A_k \cos(2\pi(kf_0)t + \phi_k) + \\ & + \sum_{k=1}^K A_k^+ \cos(2\pi(kf_0 + \Delta)t + \phi_k^+) + \\ & + \sum_{k=1}^K A_k^- \cos(2\pi(kf_0 - \Delta)t + \phi_k^-) + e(t) \end{aligned} \quad (2)$$

where  $A_k^+, A_k^-, \phi_k^+, \phi_k^-$ , are the amplitudes and phases accounting for near-to-periodicity related to the harmonics. The previous signal model can be expressed in abbreviated form,  $EGM(t) = s_{f_0}(t) + e(t)$ , where  $s_{f_0}(t)$  denotes the organized or periodic component of  $EGM(t)$  that is explained by  $f_0$ .

In order to obtain model parameters  $\{A_k, A_k^+, A_k^-, \phi_k, \phi_k^+, \phi_k^-\}$  using the  $N$  samples from  $EGM[n] = EGM(n/f_s)$ , we propose a Least Squares projection onto a Hilbert signal space of sinusoids containing fluctuations components that accounts for the near-to-periodic behavior of the original signal.

We presented our signal model assuming that  $f_0$  is known, but in practice  $f_0$  is also an unknown parameter and must be estimated as a previous step. We proposed an automatic  $f_0$  estimation algorithm using the FOA signal model. The estimation is achieved by minimizing the *mean square error (MSE)* between the original signal,  $EGM[n]$  and the fitted signal model,  $\hat{s}_{f_0}[n]$  for a adequate frequency range, i.e.,  $f_0 \in [f_l, f_h]$  Hz., this is,

$$MSE(f_0) = \|EGM[n] - \hat{s}_{f_0}[n]\|^2 \quad (3)$$

Finally, the fundamental frequency is estimated as the argument that minimizes  $MSE(f_0)$ ,

$$f_0^* = \min_{f_0} MSE(f_0), \quad f_0 \in [f_l, f_h] \text{ Hz.} \quad (4)$$

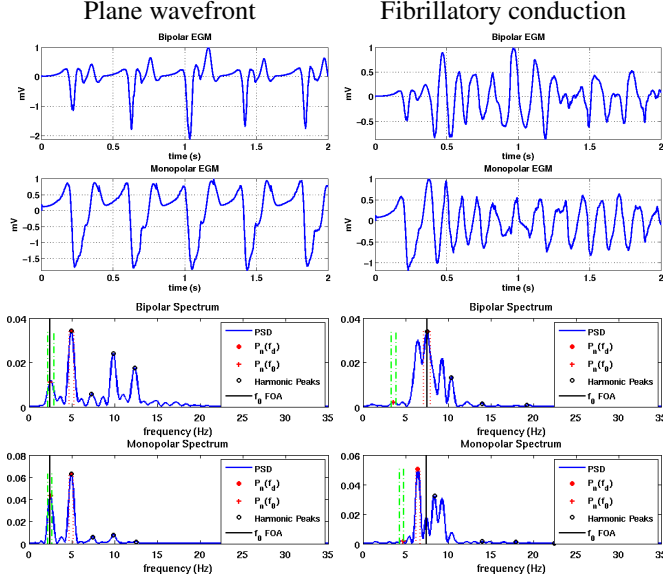


Figure 1. Simulation results: EGM and spectra, for bipolar (top) and monopolar (bottom) recordings in each simulated electrophysiological condition. Vertical lines in the spectra denote  $bw(f_0)$  (dash-dot) and  $bw(f_d)$  (dot).

where  $f_0^*$  is the optimum value to be used as a fundamental frequency for the FOA signal model. The number of harmonics ( $K$ ) to be used in the model is also a practical issue, and it has to be previously fixed, for example dividing the signal bandwidth to the value of  $f_0^*$ .

We defined two parameters from FOA signal model to quantify the regularity and spectral characteristics of the original EMG recording, defined as,

$$p_1 = \frac{\|\hat{s}_{f_0^*}[n]\|^2}{\|EGM[n]\|^2}; \quad p_e = \frac{\|e[n]\|^2}{\|EGM[n]\|^2} \quad (5)$$

Parameter  $p_1$  accounts for the organized component related to  $f_0^*$ , whereas  $p_e$  accounts for the part of the signal unexplained by  $f_0^*$ . Note that  $p_e$  accounts not only for the noise, but also for any additional component different than  $f_0^*$ .

## 4. Results

**Simulation Results.** Figure 1 shows the simulated EGM and their spectra. Table 1 contains the measured spectral parameters using DFA-OA and FOA procedures, namely:  $f_0$  estimated by the automatic procedure proposed in [4], dominant frequency ( $f_d$ ),  $ri$ ,  $oi$ , and power at frequencies  $f_0$  and  $f_d$  (denoted by  $P_n(f_0)$  and  $P_n(f_d)$ ). The parameters obtained with FOA procedure were: fundamental frequency  $f_0$ , and organization coefficients  $p_1$  and  $p_e$ .

The averaged CL was also obtained in time domain by an expert counting the EGM relevant peaks. For further

		Plane		Fibrillatory	
		M	B	M	B
Time	$CL$ (ms)	400	400	143	125
	$CL^{-1}$ (Hz)	2.5	2.5	6.9	8
DFA and OA	$f_0$ (Hz)	2.54	2.44	4.69	3.61
	$f_d$ (Hz)	4.98	4.98	6.45	7.52
	$P_n(f_d)$	63	34	50	34
	$P_n(f_0)$	43	11	2	2
	$oi$	0.99	0.80	0.53	0.47
	$ri$	0.45	0.26	0.32	0.30
	$p_1$	0.88	0.90	0.23	0.52
	$p_e$	0.12	0.10	0.75	0.48
FOA	$f_0$ (Hz)	2.47	2.43	7.49	7.53
	$p_1$	0.98	0.90	0.59	0.52
	$p_e$	0.02	0.10	0.41	0.48

Table 1. Results of DFA, OA, and FOA, in simulated EGM. Parameters from  $P_n(f)$  are reported as its value  $\times 10^3$ .

comparison with FOA procedure, we also obtained coefficients  $p_1$  and  $p_e$  for DFA, by just fitting the model in (2) using as  $f_0$  the value estimated automatically by DFA.

In the plane wavefront, a narrow-line spectral and harmonic structure was present. There was a high agreement between  $f_0$  estimated by DFA and by FOA, and with the inverse CL, whereas  $f_d$  was higher, in fact it corresponded with the 2nd harmonic of  $f_0$ . Parameter  $p_1$  was high for both methods, which indicates the goodness of LS fit for the  $f_0$  estimation, with slightly higher values for FOA method.

In Fibrillatory Conduction, it was not observed a clear harmonic structure. The inverse CL was more related to  $f_d$  and  $f_0$  estimated by FOA than to  $f_0$  estimated by DFA. The automatic algorithm for estimating  $f_0$  using DFA was checked to fail here. The values obtained for  $f_0$  using FOA were very similar for both monopolar and bipolar recordings, as it was expected.

Organization parameters  $oi$  and  $p_1$  were higher for plane than for fibrillatory, as expected due to the fact that fibrillation is more irregular. Both parameters were higher for monopolar than for bipolar recordings. However, since  $oi$  is computed from the estimation of  $f_0$ , it is necessary to be sure that  $f_0$  is correctly estimated.

**Real Signals.** Table 2 shows the measured spectral parameters computed with both DFA-OA and FOA procedures. There was a high disagreement between  $f_0$  computed by DFA and computed by FOA in SR recordings. FOA method gave higher  $p_1$  values, indicating that  $f_0$  was better estimated using this procedure. Both methods (DFA and FOA) gave slightly different  $f_0$  estimations in recordings from the remaining rhythms. Parameter  $p_1$  obtained using  $f_0$  estimated by DFA was lower than  $p_1$  in FOA, except for bipolar VF recordings, indicating that in some cases DFA failed when estimating  $f_0$ . Note also the agreement between  $f_0$  estimated by FOA in monopolar and bipolar recordings.

Organization parameters,  $oi$ ,  $ri$  (OA) and  $p_1$ ,  $p_e$  from FOA are showed also in Table 2. As it was stated, OA

		Sinus Rhythm		Supraventricular Tachycardia		Ventricular Tachycardia		Ventricular Fibrillation	
		Monopolar	Bipolar	Monopolar	Bipolar	Monopolar	Bipolar	Monopolar	Bipolar
DFA and OA	$f_0$	2.94 ± 0.76	3.66 ± 0.33	2.58 ± 0.16	3.51 ± 1.20	3.25 ± 0.67	3.25 ± 0.66	5.10 ± 0.87	5.25 ± 0.82
	$f_d$	3.94 ± 0.90	4.03 ± 2.67	6.62 ± 3.78	9.36 ± 11.68	5.36 ± 2.58	5.34 ± 4.62	5.24 ± 0.87	5.26 ± 0.85
	$ri$	0.15 ± 0.01	0.21 ± 0.25	0.26 ± 0.11	0.15 ± 0.04	0.35 ± 0.19	0.51 ± 0.70	0.71 ± 0.09	0.49 ± 0.11
	$oi$	0.47 ± 0.04	0.48 ± 0.19	0.92 ± 0.02	0.64 ± 0.02	0.84 ± 0.21	0.81 ± 0.28	0.81 ± 0.06	0.74 ± 0.08
	$p_1$	0.35 ± 0.10	0.19 ± 0.02	0.84 ± 0.12	0.51 ± 0.25	0.60 ± 0.25	0.49 ± 0.28	0.47 ± 0.27	0.52 ± 0.13
	$p_e$	0.66 ± 0.10	0.81 ± 0.02	0.16 ± 0.12	0.49 ± 0.25	0.40 ± 0.25	0.52 ± 0.28	0.53 ± 0.27	0.48 ± 0.13
FOA	$f_0$	1.15 ± 0.17	1.22 ± 0.11	2.58 ± 0.16	2.58 ± 0.16	2.74 ± 0.46	2.70 ± 0.52	5.26 ± 0.89	5.27 ± 0.87
	$p_1$	0.82 ± 0.12	0.68 ± 0.13	0.91 ± 0.08	0.70 ± 0.23	0.74 ± 0.21	0.64 ± 0.27	0.66 ± 0.15	0.51 ± 0.09
	$p_e$	0.18 ± 0.12	0.32 ± 0.13	0.09 ± 0.08	0.30 ± 0.23	0.26 ± 0.21	0.36 ± 0.27	0.34 ± 0.15	0.49 ± 0.09

Table 2. Results of DFA, OA, and FOA parameters (mean ± standard deviation) in clinical EGM signals from the different rhythms data base.

parameters has to be taken cautiously, since they are based on  $f_0$  estimation using DFA, which was checked to fail in several cases. Actually,  $p_1$  from FOA allowed to establish more coherent comparisons than  $oi$ . According to  $p_1$ , VF was the most irregular rhythm, as expected, whereas SVT was the most organized, even more than SR, which can be explained by the well-known heart rate variability.

## 5. Conclusions

A new method has been presented as a generalization of conventional DFA-OA, so-called FOA, which allow to study the spectral structure in EGM recordings. The use of simulations allowed to analyze the relationship between the underlying electrophysiological processes and the EGM spectral parameters. Also, a data base with different rhythms was assembled to evaluate the performance of the two different approaches, DFA-OA and the proposed FOA, in real EGM recordings with different electrophysiological and well-known situations.

Due to a number of factors,  $f_0$  and  $f_d$  can be different, and in that case, the use of  $f_d$  as a surrogate for the CL is not granted, since it might be just a harmonic of  $f_0$ . Also, the use of DFA automatic procedure was checked to fail sometimes when estimating  $f_0$ . FOA procedure was, in general, more accurate estimating  $f_0$ , since it is implicitly based in the harmonic structure in the signal to model it.

Acquisition configuration has a important role when estimating the periodicity of EGM recordings, since spectral envelope is simultaneously determined by the underlying physiological process and by the characteristics of the acquisition system. In general,  $f_d$  and  $f_0$  are more likely to be coincident in monopolar than in bipolar recordings.

Organization parameters  $oi$  and  $ri$  should be interpreted cautiously, since they are based on the  $f_0$  estimation. FOA in our simulation and real data studies show that regularity measurements have to account for the harmonics in its definition, otherwise, misleading low values of organization can be obtained from organized EGM recordings.

Eventhough, the mathematical model that has been presented is approximated and highly simplified. Accordingly, extrapolation of the results to the clinical environ-

ment should be made cautiously.

In conclusion, our results show that the proposed FOA yields a more compact and realible organization description of cardiac EGM than DFA and OA alone in ICD stored EGM signals.

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