# Generalized Hurst Exponents as a Tool to Estimate Atrial Fibrillation Organization from the Surface ECG

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## Abstract

*Atrial Fibrillation (AF) is the most common supraventricular arrhythmia found in clinical practice. The aim of the present work has been the application of the generalized Hurst Exponent of order 2, $H(2)$, to study AF organization from the surface ECG. $H(2)$ relates to the behavior of the autocorrelation function of a time series, thus measuring long-term statistical dependencies that could be used to estimate AF organization. Since the spontaneous termination of paroxysmal AF is related to the arrhythmia organization, the AF Termination Database available at Physionet has been analyzed to test the method's ability in the discrimination of organization-related events. The performance of $H(2)$ was compared with two non-invasive established AF organization metrics, the dominant atrial frequency (DAF) and Sample Entropy (SampEn). $H(2)$ yielded better classification accuracy results (95.0%) than DAF and SampEn (both 88.3%). Moreover, statistically significant differences were found between non-terminating and terminating groups and also between soon terminating and terminating groups. As conclusion, $H(2)$ can be considered as a promising tool for the non-invasive study of AF organization.*

## 1. Introduction

Atrial Fibrillation (AF) is the most common sustained cardiac arrhythmia and its prevalence increases with age [1]. However, the mechanisms causing its onset, maintenance and termination remain not fully explained [1]. AF organization can be defined as how repetitive is the atrial activity (AA) signal pattern [2], and it correlates with the therapy outcome and the likelihood of spontaneous termination in paroxysmal AF (PAF) [3]. Thereby, the noninvasive estimation of AF organization can provide valuable clinical information.

The two most widely used indices for estimating AF organization from the surface ECG are the Dominant Atrial Frequency (DAF) and Sample Entropy (SampEn) [3]. The DAF is related to the atrial cycle length, which depends on the atrial refractoriness [4]. On the other hand, SampEn provides an organization estimation based on the regularity of the signal [5] and it has been applied in different studies as a measurement of AF organization [3].

The Generalized Hurst Exponents $(H(q))$ [6] measure the existence of long-term self-dependencies in a time series and its estimation is based on the study of the statistical features of the signal. Hence, $H(q)$ could provide information about the regularity of the atrial activation patterns during AF and therefore it might provide an estimation of AF organization [7]. When $q = 2$, the exponent relates to the behavior of the autocorrelation function [8]. The aim of this work is to assess the performance of $H(2)$ in the study of AF organization-related events, like PAF spontaneous termination. To allow an easy comparison with previous works, a reference database [9] was analyzed. Classification results obtained using $H(2)$ have been compared with the two most established AF organization indices when surface ECGs are analyzed, DAF and SampEn.

## 2. Materials

The AF Termination Database available at Physionet [10] was analyzed to assess the metrics' performance in the estimation of AF organization. This database contains 80 two-lead, 1 minute long ECG recordings of PAF, which are classified into three groups: non-terminating (N) which lasted at least 1 hour in AF after the end of the recording, immediately-terminating (T), whose termination happened 1 second after the end of the recording and soon-terminating (S), which terminated 1 minute after the end of the recording. A more detailed description of this database can be found in [9].

Lead V1 was chosen for the analysis. In order to obtain better alignment in QRST subtraction the signals were upsampled to 1 kHz using a cubic spline interpolation method [11]. Then, the signals were preprocessed in order to improve the analysis. First, a bidirectional high-pass filtering with 0.5 Hz cut-off frequency was applied to remove baseline wander. Then, the signals were filtered using an eight order IIR Chebyshev low-pass filter with 70 Hz cut-off frequency to reduce high frequency noise. Finally, an adaptive notch filter, which preserves the ECG spectral information was used in order to remove powerline interference [12]. Finally, the AA was extracted through an adaptive QRST cancelation method described in [13].

## 3. Methods

### 3.1. Generalized Hurst Exponents

The Generalized Hurst Exponents ($H(q)$) [6] estimate the existence of long-term statistical self-dependencies in a time series from the $q$th order moments of its amplitude increments distribution [6]. This method was developed to analyze complex and inhomogeneous time series. The interpretation of $H(q)$ depends on the value of $q$ [8]. Due to the nonstationary and nonlinear nature of the physiological processes underlying AF, the study of this arrhythmia from the surface ECG making use of $H(q)$ seems appropriate.

For a stochastic variable $x(t)$ these $q$th moments can be represented by [6]

$$K_q(\tau) = \frac{\langle |x(t+\tau) - x(t)|^q \rangle}{\langle |x(t)|^q \rangle}. \quad (1)$$

Denoting the time between observations as $\nu$, $H(q)$ can be defined from $K_q(\tau)$ as [6]

$$K_q(\tau) \sim (\frac{\tau}{\nu})^{qH(q)}. \quad (2)$$

Furthermore, when $q = 2$, $H(2)$ describes the behavior of the autocorrelation function and therefore it relates to the power spectrum of the signal [8]. Thus, $H(2)$ might provide information about the coordination of the atrial activation during AF and therefore it could estimate AF organization. In the present work $H(2)$ is proposed as an AF organization estimator from surface ECG recordings.

### 3.2. Reference metrics

Two noninvasive AF organization metrics were computed as references. The Dominant Atrial Frequency (DAF) is defined as the frequency corresponding to the highest Power Spectral Density (PSD) amplitude in the 3–9 Hz band [4] and it is considered as an indirect estimator of AF organization [4]. The DAF was obtained computing the PSD of each AA using the Welch Periodogram with a Hamming window of 4096 points in length, 50% overlapping between adjacent sections and 8192-points Fast Fourier Transform.

On the other hand, Sample Entropy (SampEn) estimates the regularity of a time series, understood as the existence of similar patterns [3], yielding a non-negative number with larger values corresponding to more irregularity in the data. A detailed description of SampEn can be found in [3]. The computational parameter values chosen in the present work were $m = 2$ and $r = 0.35$ times the standard deviation of the signal as was recommended in previous works dealing with surface AF recordings [14].

### 3.3. Operation of the metrics

The performance of nonlinear metrics can be degraded due to the presence of noise and ventricular residua in the signal [15]. In order to reduce the effect of these nuisances, the Main Atrial Wave (MAW) [15] was extracted from the AA through selective filtering. To extract the MAW a linear phase band-pass FIR filter with 3 Hz bandwith centered on the DAF was applied to the signals [15]. This filter was designed with the Chebyshev approximation, a linear phase and a relative sidelobe attenuation of 40 dB.

In order to improve the regularity estimation, $H(2)$ and SampEn were computed on the MAW. $H(2)$ was calculated over the last 15 seconds of each recording as recommended in [16]. On the other hand, the DAF was obtained using the whole recording and SampEn was computed over all non-overlapping 10-second segments of the signal and then the average value for each recording was calculated [14].

Four different classification scenarios were studied: I) discrimination between groups N and T, II) classification between groups S and T, III) discrimination between groups N and S, and IV) identification of all terminating episodes (T and S).

### 3.4. Statistical analysis

First, the distributions were tested using the Kolmogorov-Smirnov and Levene tests. Since the distributions were not normal and homoscedastic, the Mann-Whitney U-test was applied in each of the analyzed scenarios. A two-tailed value of $p < 0.05$ was considered as statistically significant. Next, the classification thresholds, specificities and sensitivities were obtained from the receiver operating characteristic (ROC) curves. The closest point to 100% accuracy was chosen as optimum threshold. Finally, leave-one-out cross-validation was applied in order to improve the consistency of the classification results.

The signals were tested for stationarity using the runs test [17]. The signals were divided into non-overlapping 1 second segments and the average value and standard deviation of the signal amplitude was computed on each segment. Then, the runs test was applied to each sequence in order to check whether the process could be considered as stationary.

Since nonlinear indices have been applied to the signals, a study of surrogate data was performed in order to check the nonlinearity of the data. 40 surrogate data sets

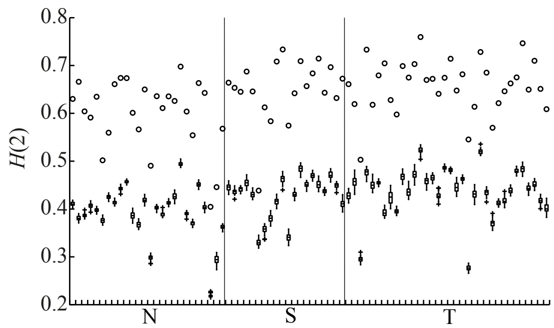


Figure 1. $H(2)$ values for each of the original signals (circles) and their corresponding surrogate data sets (boxplot).

were generated from each original signal using the Truncated Fourier Transform method [18] because the signals showed a nonstationary behavior. The cut-off frequency of 3 Hz was selected because the 3–9 Hz band contains most of the AA energy during AF [11]. Then, $H(2)$ was computed over each surrogate data set and compared with the values obtained from the corresponding original signals using the Wilcoxon T test.

## 4. Results

Regarding the surrogate data test, the results showed that the AA signals cannot be fully explained by a linear model. Thus, it can be concluded that the AA shows a nonlinear and nonstationary behavior. Figure 1 shows the values of $H(2)$ for the original signals in each group and its corresponding surrogate data sets.

On the other hand, the signals in groups S and T, which correspond to more organized AF, showed higher regularity than the ones in group N and their DAF values were also lower (Table 1). The metric $H(2)$ achieved better classification results than DAF and SampEn (Table 2). Moreover, the differences between non-terminating (group N) and terminating (groups S and T) AF found with all the metrics were statistically significant. Additionally, $H(2)$ showed statistically significant differences between groups S and T, while the differences between these groups found with the other metrics were not significant. Figure 2 displays the ROC curves obtained in the classification between non-terminating and immediately-terminating episodes and between non-terminating and soon-terminating groups. The optimum threshold and classification obtained in the identification of all terminating episodes are presented in Figure 3. Finally, Table 3 contains the cross-validation results.

## 5. Discussion

The use of the Generalized Hurst Exponents in the study of AF organization was proposed in [7]. In the present work the performance of $H(2)$ computed over 15 seconds of the MAW as is suggested in [16] has been evaluated.

Table 1. Average values and standard deviations of the metrics computed on each group.

| | Group N | Group S | Group T |
|---|---|---|---|
| DAF (Hz) | $6.46 \pm 0.69$ | $5.28 \pm 0.70$ | $5.04 \pm 0.69$ |
| SampEn x $10^3$ | $64.6 \pm 7.5$ | $49.5 \pm 6.7$ | $46.9 \pm 9.1$ |
| $H(2)$ x $10^3$ | $995.3 \pm 0.8$ | $997.0 \pm 0.7$ | $997.5 \pm 0.6$ |

Table 2. Results of classification accuracy for the different metrics in each of the studied scenarios.

| | N vs. T | N vs. S | T vs. S | N vs. (T & S) |
|---|---|---|---|---|
| DAF | 88.3% | 89.1% | 59.3% | 86.3% |
| SampEn-MAW | 88.3% | 89.1% | 61.1% | 91.3% |
| $H(2)$-MAW | 95.0% | 93.5% | 68.5% | 93.8% |

The accuracy in the discrimination between groups N and T has increased from 93.3% up to 95% analyzing only the last 15 seconds of each recording, as recommended in [16]. Moreover, in this work a statistically significant difference between groups S and T has been found, whereas in a previous study [7] no significant differences between those groups were reported through the use of different computational parameters. Therefore, the use of 15 seconds segments improves the performance of $H(2)$ in the prediction of AF termination.

Finally, only the last 15 seconds of each signal have been analyzed in this study. Therefore it would be interesting to evaluate in future works the classification capability of the method in different segments of the same length.

## 6. Conclusions

The Generalized Hurst Exponents discriminate between AF signals with different organization degrees with higher accuracy than DAF and SampEn and therefore this metric can be considered as a promising tool for the study of AF organization from the surface ECG.

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Table 3. Discrimination results between groups through the use of leave-one-out cross-validation.

| | N vs. T | N vs. S | T vs. S | N vs. (T & S) |
|---|---|---|---|---|
| DAF | 83.3% | 76.1% | 59.3% | 83.8% |
| SampEn-MAW | 86.7% | 84.8% | 59.3% | 85.0% |
| $H(2)$-MAW | 95.0% | 89.1% | 64.8% | 91.3% |

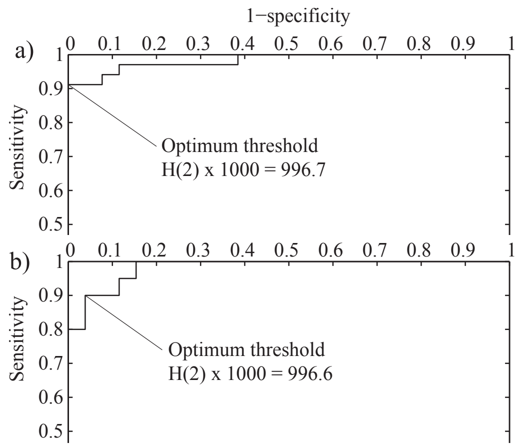


Figure 2. ROC curves obtained using $H(2)$. a) Classification between groups N and T. b) Discrimination between groups N and S.

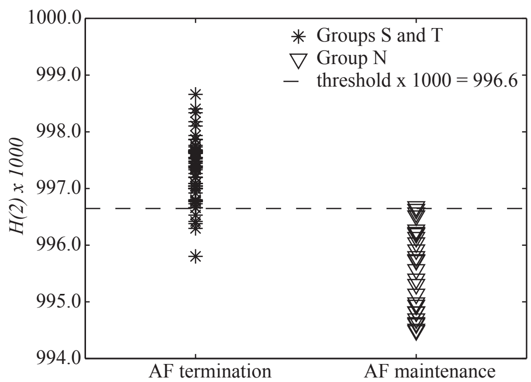


Figure 3. Identification of all terminating AF episodes (group N vs. groups S and T) using $H(2)$.

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