

# FREQUENCY DOMAIN ANALYSIS AS RISK PREDICTOR OF SUDDEN CARDIAC DEATH FROM LONG-TIME ECG RECORDINGS

Diego García, César Sánchez and Raúl Alcaraz

*Innovation in Bioengineering Research Group, University of Castilla-La Mancha, Cuenca, Spain*

**Keywords:** Sudden cardiac death, Signal processing, Electrocardiogram, Frequency analysis.

**Abstract:** Sudden Cardiac Death (SCD) is a disease that may not only affect patients with cardiovascular pathologies, but also to apparently healthy patients. Thereby, identification of patients with a high potential of suffering SCD is crucial for their treatment with adequate therapies. To this respect, in the present work, different signal processing tools were applied to surface electrocardiographic (ECG) recordings to develop markers which can clearly differentiate between subjects without cardiovascular pathologies and patients who died of SCD. Precisely, the proposed indexes were the Spectral Concentration (SC) around the main frequency peak, which reached a sensitivity of 100.00% and a specificity of 88.89%, and the Mean Frequency Distance (MFD) between the first spectral peaks, which provided a sensitivity of 95.00% and a specificity of 100.00%.

## 1 INTRODUCTION

Sudden cardiac death (SCD) is nowadays a surprising episode that causes death to 350,000 people per year only in the USA (Al-Khatib et al., 2007). According to recent statistics, it is one of the main causes of death for developed countries in apparently healthy population (Chugh et al., 2000). Moreover, 50% of deaths in patients with cardiovascular pathologies suffered SCD (Al-Khatib et al., 2007). Only 5% of patients who experienced SCD survived (Al-Khatib et al., 2007), but many of them could have been saved by cardioversion, especially those for which SCD was the first symptom.

Hence, risk stratification is a determining factor to reduce sudden cardiac mortality. To this respect, several medical diagnosis techniques are currently used. Thus, a low left ventricular ejection fraction ( $\leq 35\%$ ) is the gold standard, and subjects with NYHA class II and III symptoms are at higher risk for SCD (Al-Khatib et al., 2007). However, these methods have a low predictive capacity (Arya et al., 2006). Thereby, during the last years, many new lines of investigation have been developed to find effective markers which are able to predict SCD with anticipation. Most of the recently proposed predictors are based on the time domain analysis, such as QRS duration, QT dispersion,

ST abnormalities, T-wave alternans, late potentials, or heart rate variability complexity (Al-Khatib et al., 2007; Engel et al., 2004). Nevertheless, these indicators have also shown a low diagnostic accuracy (Durin et al., 2008). Overall, in this work, two promising indexes, developed from the frequency domain analysis of ECG signals, are proposed to detect subjects at high risk.

## 2 MATERIALS

For the study, two databases available from PhysioBank (Goldberger et al., 2000) were used: the MIT-BIH Normal Sinus Rhythm (NSRDB) and Sudden Cardiac Death Holter (SCDHDB). The first set includes ECG recordings, with a length between 20 and 24 hours, belonging to five men aged 26 to 45 and thirteen women aged 20 to 50. They are referred to the Arrhythmia Laboratory at Beth Israel Deaconess Medical Center, and were found not to have significant arrhythmias. This group of 18 ECG recordings of normal sinus rhythm was considered as reference. The second database contains 23 Holter signals associated to patients who suffered SCD during the 24-h monitoring. They were mainly obtained in the 1980's in Boston area hospitals. In the analysis, 20 recordings were only considered, given that paced patients were discarded.

### 3 METHODOLOGY

To predict SCD, the 60 minutes preceding ventricular fibrillation (VF) were taken from each SCDHDB recording. For the NSRDB signals, 60 minutes starting at an random instant were selected. In order to unify the sampling rates of the considered segments, the first lead was resampled at 1 kHz. Additionally, to improve later analysis, interferences present in the ECG were removed with four filters (Sörnmo and Laguna, 2005): an 8th-order Chebyshev low-pass filter ( $f_o = 100\text{Hz}$ ), a 3rd-order Butterworth high-pass filter ( $f_o = 0.50\text{Hz}$ ), a 2nd-order IIR notch filter ( $f_c = 60\text{Hz}$ ), and an envelope detector for baseline wander subtraction.

The power spectral density (PSD) of each chosen segment was computed over 4096 samples-length intervals, obtained with a Hamming window and overlapped 2048 samples, making use of an 8192-points Fast Fourier Transform (FFT). Finally, the Spectral Concentration (SC) around the main frequency peak and the mean frequency distance (MFD) between the  $N$  first were computed for each interval, thus obtaining two numerical series.

#### 3.1 SC Around the Main Frequency Peak

The Spectral Concentration,  $SC[x(t)]$ , around the main frequency peak,  $f_p$ , has been previously used as a performance indicator of the atrial activity extraction in atrial fibrillation and tachyarrhythmias episodes (Sánchez et al., 2004; Castells et al., 2005). It has been defined as:

$$SC[x(t)] = \frac{\sum_{f=0,82 \cdot f_p}^{1,17 \cdot f_p} x_P(f)}{\sum_{f=0}^{f_s/2} x_P(f)} \quad (1)$$

where  $f_s$  is the sampling rate of the analyzed segment,  $x(t)$  and  $x_P(f)$  is its PSD:  $x_P(f) = \Re^2\{DFT\{x(t)\}\}$ . This index relates present energy on the peak band to the rest of the distribution of interest. In this sense, an ideal sinus signal has a SC of 1, because all spectral content is on its own oscillation frequency. Similarly, ECG signal with a ventricular flutter presents a SC value very high, because this arrhythmic episode is highly regular (Castells et al., 2005). On the contrary, low SC values means that only a small part of the PSD is concentrated around main frequency peak, which suggests the existence of other notable peaks in the rest of the spectrum.

#### 3.2 MFD between the First Spectral Peaks

The  $MFD[x(t), N]$  is defined as the mean frequency distance between the  $N$  first peaks of the PSD. Its computation requires a smooth spectrum to determine with high accuracy the frequency peaks. Because of the PSD provided by Fast Fourier Transform (FFT) shows transitory peaks that may distort the index outcome, a smoothing spectrum technique consisting in a low-pass filter with a 40 samples-length Hamming window was applied (Proakis and Manolakis, 2007). This parameter can be used to estimate the PSD dispersion. Thus, a low value implies close frequency peaks and, therefore, an concentrated spectrum. On the contrary, a high value indicates a high dispersion and a PSD with considerable empty gaps between frequency peaks.

### 4 RESULTS

Table 1 shows the obtained SC and MFD values for all the recordings. To associate every ECG with an only value, the mean for the time series provided by each parameter was computed. The differences between the values obtained for the two groups, see Fig. 1, were statistically significant, given that the significance level, obtained by a  $t$  Student test, was  $p < 0.0001$  for both markers. Receiver Operating Characteristics (ROC) curve was used to obtain the discrimination threshold between healthy patients and those who died by SCD (Lasko et al., 2005). In addition, the predictive ability of both indicators was also obtained with this curve. Thus, sensitivity was considered as the number of healthy patients correctly classified, whereas specificity represented the percentage of patients who died by SCD correctly discerned. Fig 2 shows the ROC curves for the two makers, and Table 2 presents their values obtained of sensitivity and specificity.

As can be appreciated, the SC revealed only two falses positives (signals #19140 and #19093) with an area under ROC curve (AUC) of 0.9694 and an accuracy of 94.74% (36 out of 38). With regard to the MFD, only one false negative (signal #39), an AUC of 0.9944 and an accuracy of 97.37% (37 out of 38) were provided. Since the failures obtained with both tests were associated to different signals, a combining discriminator considering a positive result with  $SC > 16.25\%$  and  $MFD > 3.75\text{Hz}$ , would have an accuracy of 100% (38 out of 38).

Table 1: SC and MFD results for all the analyzed recordings.

| NSRDB    |        |          | SCDHDB   |        |          |
|----------|--------|----------|----------|--------|----------|
| Signal # | SC (%) | MFD (Hz) | Signal # | SC (%) | MFD (Hz) |
| 16265    | 11.9   | 2.704    | 30       | 26.1   | 5.848    |
| 16272    | 10.1   | 2.289    | 31       | 27.0   | 5.070    |
| 16273    | 12.2   | 3.404    | 32       | 49.4   | 5.747    |
| 16420    | 14.0   | 1.719    | 33       | 20.5   | 4.798    |
| 16483    | 11.5   | 2.423    | 34       | 16.3   | 5.960    |
| 16539    | 10.5   | 1.988    | 35       | 27.0   | 4.327    |
| 16773    | 12.7   | 3.070    | 36       | 19.1   | 5.514    |
| 16786    | 12.9   | 3.705    | 37       | 25.1   | 4.453    |
| 16795    | 14.9   | 2.917    | 38       | 67.7   | 4.523    |
| 17052    | 11.3   | 1.656    | 39       | 25.8   | 3.788    |
| 17453    | 16.1   | 3.340    | 41       | 34.5   | 5.154    |
| 18177    | 12.0   | 2.428    | 43       | 22.3   | 3.777    |
| 18184    | 12.1   | 1.729    | 44       | 16.3   | 5.022    |
| 19088    | 12.7   | 2.722    | 45       | 16.9   | 4.619    |
| 19090    | 10.9   | 2.228    | 46       | 16.4   | 3.952    |
| 19093    | 18.4   | 2.068    | 47       | 37.8   | 4.294    |
| 19140    | 22.2   | 3.661    | 48       | 24.0   | 4.428    |
| 19830    | 16.2   | 1.901    | 50       | 24.5   | 4.967    |
|          |        |          | 51       | 33.8   | 4.314    |
|          |        |          | 52       | 20.9   | 4.214    |
| Mean     | 13.5   | 2.553    | Mean     | 27.5   | 4.724    |
| Std      | 3.1    | 0.674    | Std      | 8.2    | 0.685    |

Table 2: Area Under ROC Curve (AUC), threshold, sensitivity and specificity for SC and MFD tests.

|     | AUC    | Threshold | Sensitivity | Specificity |
|-----|--------|-----------|-------------|-------------|
| SC  | 0.9694 | 16.25 %   | 100.00%     | 88.89%      |
| MFD | 0.9944 | 3.750 Hz  | 95.00%      | 100.00%     |

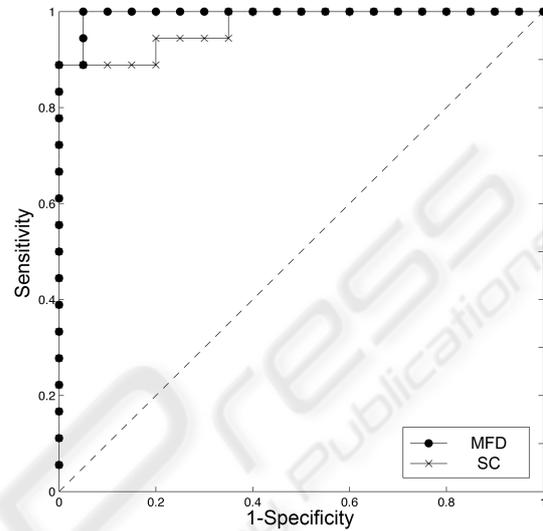


Figure 2: ROC Curves.

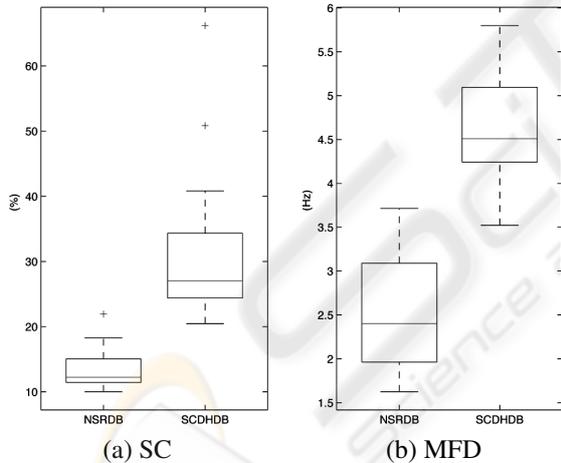


Figure 1: SC and MFD for NSRDB and SCDHDB ('box-and-whiskers' plot).

### 4.1 Numerical Evolution of Markers

Given that results showed that SCD could be successfully predicted with the SC and MFD, both parameters were computed for a longer time interval. Thus, the 300 minutes preceding VF from 13 SCDHDB were selected. In addition, for all the NSRDB signals, 300 minutes starting at a random instant were also chosen. For this case, the time course provided

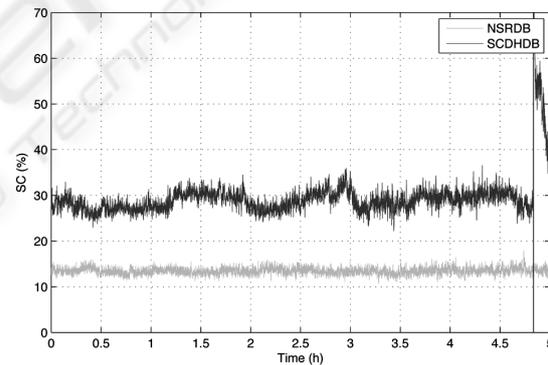


Figure 3: SC numerical evolution.

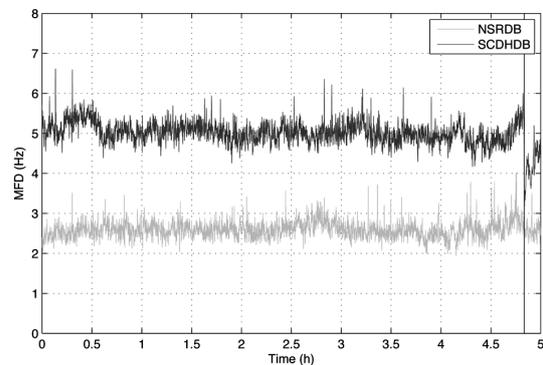


Figure 4: MFD numerical evolution.

by both markers is displayed in Figs. 3 and 4.

## 5 DISCUSSION AND CONCLUSIONS

In the present work spectral processing has been used to obtain two indexes that reveal statistically significant differences ( $p < 0.0001$ ) between patients who suffered SCD and a sample of completely healthy subjects.

Both parameters showed values substantially higher for patients who suffered SCD than for healthy subjects. This fact suggests that the ECG of healthy subjects is characterized by a higher harmonic content. Consequently, it could be considered that frequency peaks of relative high amplitude in the ECG of healthy patients are disappeared in subjects who suffered SCD, such as Fig. 5 shows.

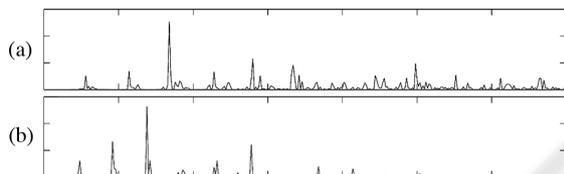


Figure 5: Typical PSD of an ECG for the (a) NSRDB and (b) SCDHDB.

On the other hand, the time course of the markers showed very constant values during the last 5 previous hours preceding the death of the patient. Therefore, SCD could be predicted with an anticipation above 5 hours, which suggests the problem that causes SCD, it can be congenital or acquired during subject's life.

Finally, given that the analyzed database are limited, the results should be considered with caution. Nevertheless, the work suggests that SC and MFD can initiate new lines of research as non-invasive predictors of SCD. In this sense, a wider data set allowing a more rigorous statistical analysis should be required in order to provide confidence in the robustness of the proposed parameters.

## ACKNOWLEDGEMENTS

This work was supported by the projects PII1C09-0036-3237 and PII2C09-0224-5983 from Junta de Comunidades de Castilla-La Mancha.

The authors would like to acknowledge the invaluable helpful support received from Dr. J.L. Bardají, Dr. M.L. López, Dr. F. Madero, and Eng. M.E. García.

## REFERENCES

- Al-Khatib, S. M., Sanders, G. D., Bigger, J. T., Buxton, A. E., and et al (2007). Preventing tomorrow's sudden cardiac death today: part i: Current data on risk stratification for sudden cardiac death. *Am Heart J*, 153(6):941–950.
- Arya, A., Haghjoo, M., and Sadr-Ameli, M. A. (2006). Risk stratification for arrhythmic death after myocardial infarction: current perspective and future direction. *Int J Cardiol*, 108(2):155–164.
- Castells, F., Rieta, J. J., Millet, J., Zarzoso, V., and Associate (2005). Spatiotemporal blind source separation approach to atrial activity estimation in atrial tachyarrhythmias. *IEEE Trans Biomed Eng*, 52(2):258–267.
- Chugh, S. S., Kelly, K. L., and Titus, J. L. (2000). Sudden cardiac death with apparently normal heart. *Circulation*, 102(6):649–654.
- Durin, O., Pedrinazzi, C., Donato, G., Pizzi, R., and Inama, G. (2008). Usefulness of nonlinear analysis of ecg signals for prediction of inducibility of sustained ventricular tachycardia by programmed ventricular stimulation in patients with complex spontaneous ventricular arrhythmias. *Ann Noninvasive Electrocardiol*, 13(3):219–227.
- Engel, G., Beckerman, J. G., Froelicher, V. F., Yamazaki, T., and et al (2004). Electrocardiographic arrhythmia risk testing. *Curr Probl Cardiol*, 29(7):365–432.
- Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., and et al (2000). Physiobank, physiotoolkit, and physionet: Components of a new research resource for complex physiologic signals. *Circulation*, 101(23):E215–E220.
- Lasko, T. A., Bhagwat, J. G., Zou, K. H., and Ohno-Machado, L. (2005). The use of receiver operating characteristic curves in biomedical informatics. *J Biomed Inform*, 38(5):404–415.
- Proakis, J. G. and Manolakis, D. K. (2007). *Digital Signal Processing. Principles, Algorithms and Applications*. Prentice Hall.
- Sánchez, C., Rieta, J. J., Castells, F., Alcaraz, R., and Millet, J. (2004). Wavelet domain blind signal separation to analyze supraventricular arrhythmias from Holter registers. *Conf Proc Independent Component Analysis and Blind Signal Separation*, 5:1111–1117.
- Sörnmo, L. and Laguna, P. (2005). *Bioelectrical Signal Processing in Cardiac and Neurological Applications*. Elsevier Academic Press.