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Detection of sudden cardiac death using the adaptive spectral method on the T wave: An experimental study on public databases

Detección de la muerte súbita cardíaca usando el método espectral adaptativo sobre la onda T: Estudio experimental sobre bases de datos públicas

Marco Flores-Calero[1,*,2] , Melisa Pilla-Barroso[3]

Abstract

T-wave alternans (TWA) analysis is one of the main techniques for determining whether an individual is at risk of sudden cardiac death (SCD). Among the existing methods for determining TWA is the adaptive spectral method (SM-Adaptive), which uses time-frequency distributions (TFD) for the analysis. The objective of the study is to apply the method on main public databases in order to detect the presence or absence of alternations, and to obtain quality parameters of the aforementioned method. The method was tested on synthetic signals, 90 signals without TWA and 450 with TWA; on the other hand, 10 signals from Physionet's TWADB database belonging to healthy patients and 26 signals from patients with risk factors associated to SCD were used. Tests with synthetic signals showed a sensitivity of 94.89%, specificity of 92.22% and accuracy of 94.44%. As for the tests in the database, the method exhibits an accuracy of 80.56%, which indicates that the SM-Adaptive method enables detecting TWA with an acceptable accuracy and, in addition, it shows greater robustness against noise and stationary data.

Keywords: ECG, sudden cardiac death, T-wave alternans, SM-Adaptive.

Resumen

El análisis de la alternancia de la onda T (TWA, T-wave alternants) constituye una de las principales técnicas para determinar la presencia del síndrome de muerte súbita cardíaca (MSC). Entre los métodos existentes para determinar TWA se encuentra el método espectral adaptativo (SM-Adaptativo), el cual utiliza distribuciones en tiempo-frecuencia (TFD, time-frecuency distribution) para el análisis. El objetivo del estudio es aplicar este método sobre las principales bases de datos públicas con el fin de detectar la presencia o ausencia de alternancias y obtener parámetros de calidad del método en mención. El método fue probado en señales sintéticas, 90 señales sin TWA y 450 con TWA; por otro lado, se utilizaron 10 señales de la base de datos TWADB de Physionet pertenecientes a pacientes sanos y 26 señales de pacientes con factores de riesgo asociados a la MSC. En las pruebas con señales sintéticas se obtuvo una sensibilidad de 94,89 %, especificidad de 92,22 % y exactitud de 94,44 %. En cuanto a las pruebas en la base de datos el método presenta una exactitud del 80,56 %, lo que indica que el método SM-Adaptativo permite detectar TWA con una exactitud aceptable, además, que presenta mayor robustez frente a ruido y a la estacionariedad de datos.

Palabras clave: ECG, muerte súbita cardíaca, alternancia de la onda T, SM-Adaptativo.

[1,*]Departamento de Eléctrica, Electrónica y Telecomunicaciones, Universidad de las Fuerzas Armadas, Sangolquí, Ecuador. Corresponding author ✉: mjflores@espe.edu.ec. http://orcid.org/0000-0001-7507-3325
[2]Departamento de Sistemas Inteligentes, Tecnología I&H, Latacunga, Cotopaxi, Ecuador.
[3]Profesional en libre ejercicio, Quito, Ecuador. http://orcid.org/0000-0002-1441-1236

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1. Introduction

The sudden cardiac death (SCD) is an event that causes the death in a fast and unexpected manner of an apparently healthy individual, or with a known cardiac disease but with low death probability. The SCD is produced by an electric instability of the heart, which prevents the occurrence of a heartbeat and, as a consequence, the heart stops pumping blood to the rest of the body. This produces a lack of blood flow to the brain, with causes the loss of oxygen; this gives rise to an abrupt loss of consciousness, and the death of the individual.

Among the main causes of the SCD are the cardiovascular problems [1]. The cardiac diseases that are more related to the SCD are the following: coronary artery disease, cardiomyopathies, electrophysiological anomalies, heart valve disease and congenital cardiac anomalies, among others [2].

Similarly, it is estimated that the SCD is responsible for 3 to 7 million of deaths worldwide every year [2, 3]. In Latin American countries there are no official records related to the SCD, which prevents knowing its incidence in a precise manner. The reports about this problem are not uniform, since the SCD constitutes a multifactorial problem and varies according to the age. In addition, there is the possibility that it continues to increase as a result of the increment of the coronary diseases (smoking, obesity, diabetes mellitus, high blood pressure, high cholesterol levels), thus becoming an important unresolved challenge.

At present, the therapies mostly used to prevent the SCD are the medication and the implantable cardioverter-defibrillator (ICD) [3], however, since they are invasive and high cost tests, it is evident the search for techniques that enable a fast detection of this type of phenomena of great interest in the social and technological areas.

The ECG is one of the tools mostly used for the study and diagnosis of heart diseases. It enables recording the electrical activity of the heart by placing electrodes on the body surface, such that it is obtained a sequence of heartbeats described in a set of waveforms (P, Q, R, S, T), segments and complexes [4, 5].

The existing mechanisms to measure the electrical instability of the heart in the ECG include the QT prolongation, QT dispersion, late potentials, T-wave alternans (TWA) and heart rate turbulence [6]. The TWA has been used for the analysis of the ventricular repolarization, which manifests in the ECG as periodic fluctuations of the T-wave amplitude [7].

The TWA estimation implies measuring, beat-to-beat, the variability of the amplitude, duration and shape of the ST-T segment of the ECG record [8]. The TWA signal is generally in the range of microvolts; therefore, it is necessary to use advanced digital signal processing techniques and computational algorithms for its detection.

In recent years, various TWA analysis procedures have been proposed. The techniques mostly used have been developed in time-domain, among which there is the moving average method (MAM), which calculates the TWA value using the difference of the mean value of even and odd beats [9]; another method is the correlation method (CM), which detects alternans using the cross-correlation [10]. The methods developed in frequency-domain include, among others, the spectral method (SM), which utilizes the discrete Fourier transform (DFT) to analyze the frequency component at 0.5 cycles per beat (cpb) [11]. A similar method is complex demodulation (CD), which fits a sinusoidal signal at the frequency of 0.5 cycles per beat of the aligned T-waves [12]. The main drawback of these methods is that they are very sensitive to signals with noise. Recently, artificial intelligence techniques are being used for SCD classification [5].

With the purpose of overcoming the limitations of the methods previously described, Ghoraani *et al.* [13] propose a method called Adaptive-SM for detection and quantification of TWA, which is based on the process of the SM method and carries out the analysis of TWA using time-frequency distributions; hence, it enables representing the spectral variations of TWA along time, and at the same has the capability of following nonstationary structures. On the other hand, it utilizes the non-negative matrices factorization (NMF) with the purpose of separating the noise from the TWA signal, so that the detection capability is improved.

The main objective in this work is evaluating the performance of the Adaptive-SM method in different scenarios. In order to achieve this objective, a set of synthetic signals (simulations) with and without added TWA of variable amplitudes, and with different levels of noise, have been utilized. The first group, i.e., the synthetic signals with added TWA were generated from five base signals to which alternans with different amplitudes have been added: $10\mu V$, $20\mu V$, $50\mu V$, $100\mu V$ and $200\mu V$. Therefore, there are 25 signals available; the alternans are generated from three wave shapes: Gaussian, triangular and rectangular, which results in 75 signals. At last, five different levels of Gaussian white noise were added to all ECG signals, with SNR: 10, 20, 30, 40 and 50. These signals together with the noise-free signals resulted in a total of 450 test signals. For the second group, constituted by synthetic signals with TWA, five signals were taken as base, with three different wave shapes (15 signals) and five noise levels. Therefore, together with the noise-free signals, 90 signals were obtained. Hence, between the two groups there is a total of 540 synthetic test signals. Then, the test on real signals was developed for which the Adaptive-SM method was applied to 36 signals of Physionet's TWADB database. The signals belong to healthy patients and to patients that have the risk of

SCD. The TWA magnitude was calculated with the purpose of determining the existence or absence of alternans of the test signal. This enabled to establish values of sensitivity, specificity and accuracy. In addition, a comparison of such parameters was carried out with the SM and MAM methods which are available in the TWAnalyser software [14].

2. Materials and methods

The present work is focused on the analysis of heart signals; 540 synthetic signals and 36 signals from the TWADB database, with the purpose of detecting TWA in the signals using the Adaptive-SM method, and then, obtaining the quality parameters of the algorithm, to evaluate its performance.

Initially, the method requires a preprocessing stage to filter the signals, and to detect and segment the characteristic points of the ECG signal.

Then, the Adaptive-SM method is applied followed by the NMF technique, with the purpose of detecting the presence or absence of alternans in the signal. This enables the classification of the signals with and without TWA. Figure 1 shows the stages of the proposed methodology.

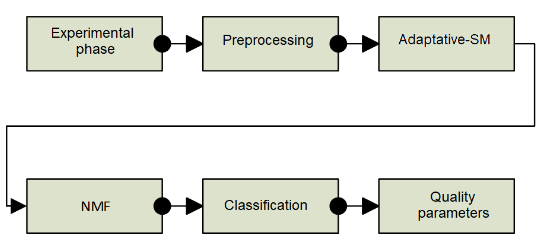

Figure 1. Proposed methodology for the detection of SCD.

This procedure enables obtaining the quality parameters of the model, namely sensitivity, specificity and accuracy.

2.1. Development of the experimental phase

First, it was tested the performance of the algorithm on 450 synthetic signals, which represent signals without TWA, with different noise levels and variable alternan amplitude. In addition, a second group of 90 signals without added TWA, i.e., with amplitude $0\mu V$ and different noise levels.

Then, 36 signals taken from the T-Wave Alternans Database (TWADB) presented in [15] were selected, which includes signals belonging to healthy patients and patients with risk factors associated to SCD. The ECG records have been sampled at 500 Hz with an approximate duration of two minutes.

The 36 signals are divided as follows, 10 signals corresponding to healthy patients, and the remaining 26 signals of patients with risk factors associated to SCD, these records have been obtained from patients with myocardial infarctions, transient ischemia, and ventricular tachyarrhythmias, among others.

2.2. Preprocessing

In general, heart signals have noise that disturbs and distorts the information contained in the signal. The noise is caused by external interferences, such as the body movement, breathing and muscle spasms, bad placement of the electrodes, etc. This is why a robust preprocessing stage is required, which includes the elimination of noise, the removal of interferences at different external frequencies and the correction of the baseline deviation [4].

The methods utilized should guarantee that an appropriate filtering is carried out, as well as that there is no loss of relevant information, since the alternans are often confused with noise components because they are in the level of microvolts. In this case, the aim is to maintain the alternans characteristics, and at the same time, eliminate noise.

On the other hand, as a prerequisite for the Adaptive-SM method, it is necessary to extract the ST-T segment from every beat. Therefore, a method for extracting the characteristics is required, and another for segmentation of the different waves, segments and complexes that constitute the ECG signal [5].

2.3. Description of Adaptive-SM

The Adaptive-SM method utilizes time-frequency distributions (TFD) to obtain a representation of the frequency components of the signal along time. It is constituted by two stages, (i) alignment and (ii) estimation of the adaptive TFD.

2.3.1. Alignment

With the aligned waves it is constructed a matrix A, as shown in Equation 1, of dimension M × N, where M is the number of beats, in this case 128, and N is the length of the segment ST-T.

$$A = \begin{bmatrix} T_1(1) & T_1(2) & \cdots & T_1(N) \\ T_2(1) & T_2(2) & \cdots & T_2(N) \\ T_3(1) & T_3(2) & \cdots & T_3(N) \\ \vdots & \vdots & \cdots & \vdots \\ T_M(1) & T_M(2) & \cdots & T_M(N) \end{bmatrix} = \begin{bmatrix} A_1 & A_2 & \cdots & A_N \end{bmatrix} \quad (1)$$

The rows represent the ST-T segments of each beat and the columns describe the beat-to-beat variations of the ST-T segment. The graphical representation of alignment matrix A is shown in Figure 2.

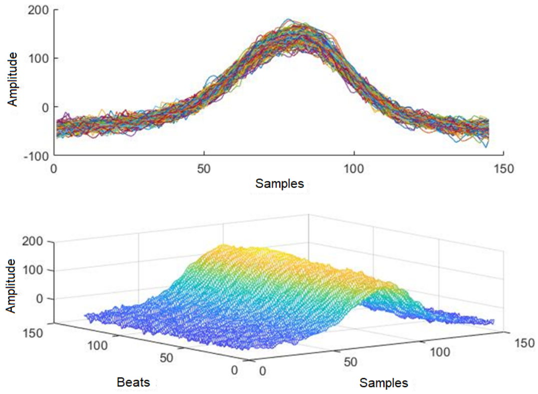

Figure 2. Aligned ST-T segments (128 segments) with a length of 132 samples, of the signal TWADB55.

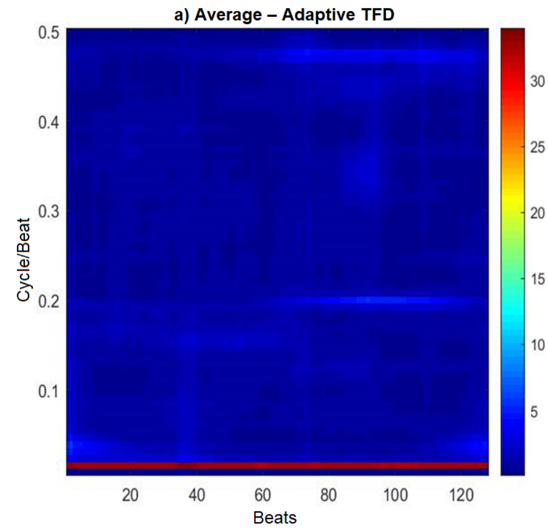

Figure 3. Average adaptive TFD of the TWADB55 signal corresponding to a healthy patient; it is observed low alternan values at 0.5 cpb.

2.3.2. Adaptive TFD

TFD is a two-dimensional representation of the signal energy in terms of time and frequency. The adaptive TFD method utilizes the Matching Pursuit algorithm to decompose a signal x in time-frequency atoms. Once the signal is decomposed, the Wigner-Ville distribution is used to obtain the energy distribution in the time-frequency domain, using Equation 2.

$$V(t,f)=\sum_{i=1}^{I}|\alpha_{\gamma i}|^{2}\,WVG_{\gamma i}(t,f) \qquad (2)$$

Matrix Vi is generated applying the Adaptive TFD method to matrix A, and then a matrix defined by Equation 3 is constructed calculating the average.

$$V_{\frac{M}{2}\times M}=\frac{1}{N}\sum_{i=1}^{N}V_i \qquad (3)$$

The TWA magnitude is calculated taking the energy values at 0.5 cycles per beat. The energy at 0.5 cycles per beat T(t) and the energy values of the noise present in the interval 0.36 to 0.49 cycles per beat, are required to estimate the TWA value.

Figures 3 and 4 show a graphical representation of the adaptive TFD on two heart signals of the TWADB database [15].

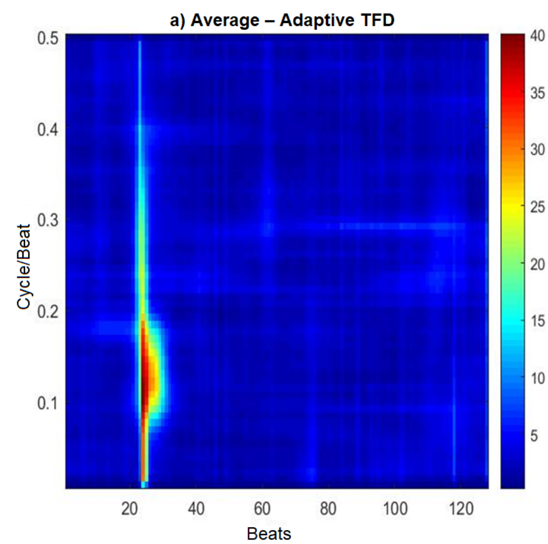

Figure 4. Average adaptive TFD of the TWADB12 signal corresponding to a patient with risk factors of SCD; it is observed low alternan values at 0.5 cpb, however, between samples 20 and 40 there is a possible alternan component.

2.4. Non-negative matrices factorization

A new matrix $V_{l\times M'}$ is constructed in this stage, where in this case $I = 16$ and M is equal to the length of the analysis window, 128 in this case. NMF factors the input matrix V in two matrices $W_{m\times r}$ and $H_{r\times n}$ of smaller size. Taking the value $r = 3$, three vectors W_1, W_2 and W_3 are determined. The representative components of the TWA magnitude are grouped in a single vector represented as W_t .

The TWA magnitude is expressed according to Equation 4, and thus it is possible to separate the alternans components of the noise.

$$TWA = w_t h_t \tag{4}$$

At last, the TWA value of vector w_t is calculated, which is the component with the greatest TWA magnitude, according to equation 5.

$$f = Real\sqrt{T - \mu_{noise}} \tag{5}$$

Figures 5 and 6 show the separation of the alternans components of the noise. The upper graph indicates the alternan components, and the lower part shows the noise extracted from the signal.

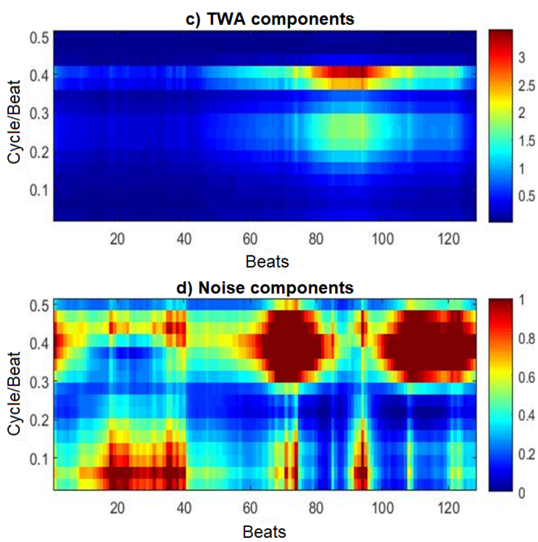

Figure 5. Decomposition of the TWADB55 signal in its alternan and noise components.

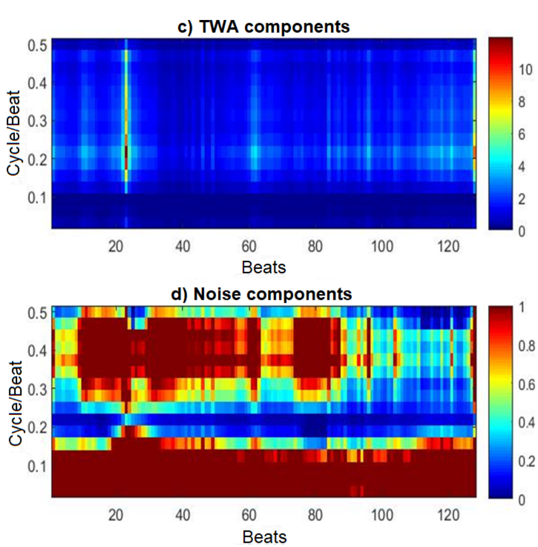

Figure 6. Decomposition of the TWADB12 signal in its alternan and noise components.

Figures 7 and 8 correspond to the signal factorized in three components; the component with the greatest TWA magnitude is indicated in the graph.

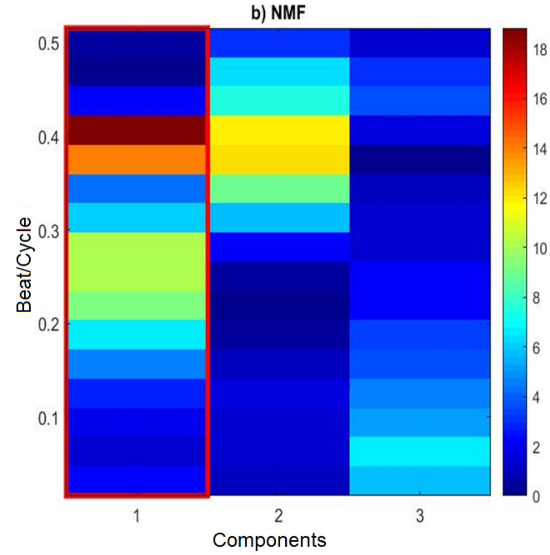

Figure 7. Component with the greatest TWA magnitude of the TWADB55 signal, the TWA is calculated at 0,5 bcpl.

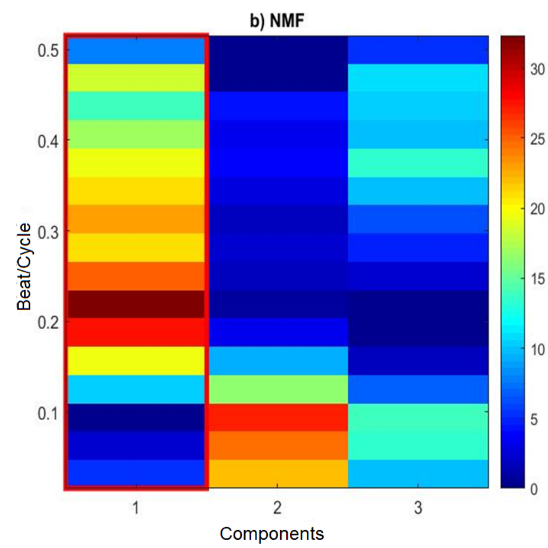

Figure 8. Component with the greatest TWA magnitude of the TWADB12 signal, the TWA is calculated at 0,5 bcpl.

2.5. Classification

Immediately after calculating the TWA magnitude, a threshold value (Th) of $1,5\ \mu V$ is established. Then, the signals are classified according to the hypothesis given by Equation 6.

$$\begin{array}{l} f > Th \Rightarrow H_0 \\ f < Th \Rightarrow H_1 \end{array} \tag{6}$$

Where H_0 indicates presence of TWA in the signal, and inversely, H_1 indicates absence of TWA.

3. Results and discussion

3.1. Tests with synthetic signals

This first test was carried out with the purpose of evaluating the performance of the Adaptive-SM method on synthetic signals, which simulate heart signals, to which artificial alternans and noise have been added, at different levels.

The scheme of Figure 9 shows the synthetic signals used, divided in two groups, and the process necessary to find the quality parameters.

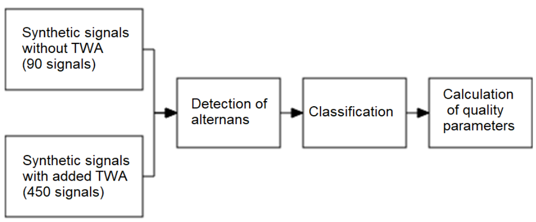

Figure 9. Process for obtaining the quality parameters using synthetic signals with and without added TWA.

Initially, the SM-Adaptive method was evaluated in 90 synthetic signals without TWA, i.e., signals that simulate heart signals without the presence of alternans, which correspond to healthy individuals. The results of the classification obtained applying the method to the 90 signals can be found in Table 1, the values are presented according to the different levels of noise.

Table 1. Classification of the synthetic signals without TWA according to the levels of added noise

SNR (dB)	VN	FP
Without noise	15 (100 %)	0 (0 %)
50	15 (100 %)	0 (0 %)
40	15 (100 %)	0 (0 %)
30	15 (100 %)	0 (0 %)
20	12 (80 %)	3 (20 %)
10	11 (73,33 %)	17 (26,67 %)
Total	**83 (92,22 %)**	**23 (7,78 %)**

As a result, 83 true negatives (TN) and 7 false positives (FP) were obtained. In this case, the true negatives indicate that a signal without TWA has been effectively classified as a signal without TWA; on the other hand, the false positives indicate that a signal without TWA has been classified as a signal with TWA.

Table 1 shows that the signals without the presence of any type of noise, which does not occur in real signals, have been correctly classified. It occurs similarly with the signals with high SNR values, 50, 40 and 30, which correspond to low noise levels (amplitude of the noise), since they are inversely proportional. The classification of the signals starts generating false results for lower values of SNR, it is seen that for SNR of 20 and 10 the number of false positives is 3 and 17, respectively, i.e., for these values of SNR the classification does not show a 100 % accuracy and in any case it has been reduced up to 73.33 % for the signals with the lowest SNR value. This indicates that the algorithm is sensitive to high levels of noise (low SNR), in particular for values of SNR smaller than 20.

However, when calculating the specificity of the method which was found to be 92.22 %, the Adaptive-SM method has been capable of appropriately classifying signals without TWA (healthy individuals), even with high noise levels.

Continuing with the tests on synthetic signals, 450 synthetic signals with TWA artificially added have been taken, which represent individuals with risk factors associated to the SCD.

The results of the classification are shown in Tables 2 and 3. In Table 2 the results are divided according to the noise level, while Table 3 shows the results according to the amplitude of the added alternans.

Table 2. Classification of the synthetic signals with TWA according to the added noise levels

SNR(dB)	VP	FN
Without noise	75 (100 %)	0 (0 %)
50	75 (100 %)	0 (0 %)
40	75 (100 %)	0 (0 %)
30	74 (98.66 %)	1 (1,34 %)
20	70 (93.33 %)	5 (6,67 %)
10	58 (77,33 %)	17 (22,67 %)
Total	**427 (94,89 %)**	**23 (7,78 %)**

Table 3. Classification of the synthetic signals with TWA according to the amplitude of the added alternans

Amplitude (µV)	VP	FN
10	76 (84,44 %)	14 (15,56 %)
20	85 (94,44 %)	5 (5,56 %)
50	87 (96,67 %)	3 (3,33 %)
100	89 (98,89 %)	1 (1,11 %)
200	90 (100 %)	0 (0 %)
Total	**427 (94,89%)**	**23 (5,11 %)**

As a result of the classification carried out by the Adaptive-SM method, there are 427 tests diagnosed as true positives and 23 as false negatives. The true positives indicate that a signal with TWA has been correctly classified, and on the contrary, the false negatives indicate that a signal with TWA has been classified as a signal without TWA.

Table 2 includes the responses of the method for signals with different noise levels. A noise-free signal is diagnosed with an accuracy of 100 %, and similar results are achieved for SNR values of 50 and 40, i.e., as the SNR value of the signal is greater, the method shows more accurate results. For SNR values of 30 dB, 20 dB and 10 dB, the classification starts to give wrong results; it is the case that for these values of SNR there are 1, 5 and 17 false negatives, respectively. Therefore, the method is more sensitive for values of SNR smaller than 30 dB, resulting in false detections.

Table 3 shows the resulting classification for different values of alternans. For an amplitude of 200 µV the detection is made with an accuracy of 100 %, which indicates that, as the alternans contained in the signal are greater, it is simpler for the algorithm to detect them. As the amplitude of the alternans decreases, also does the detection percentage, and for 10 µV it has decreased up to 84.44 %, i.e., the method shows difficulties in detecting a very small alternan wave, which could be due to the fact that such wave is being confused with noise or another type of interference.

From the known values of true positives and false negatives, the value of sensitivity was determined as 94.89 %, an acceptable value, which shows that the method has a high probability of correctly classifying a signal with TWA (individuals with risk of SCD). Therefore, the method has been capable of performing a correct classification with an accuracy of 94.44 %, which indicates that it has a high probability of diagnosing correctly signals with and without TWA, with different levels of noise and variable alternans.

3.2. Tests with signals from the TWADB database

A second way for evaluating the performance of the Adaptive-SM method was conducted utilizing real signals from the Physionet's TWADB database. The selected signals correspond both to healthy individuals and to individuals with risk of SCD, as shown in the scheme in Figure 10.

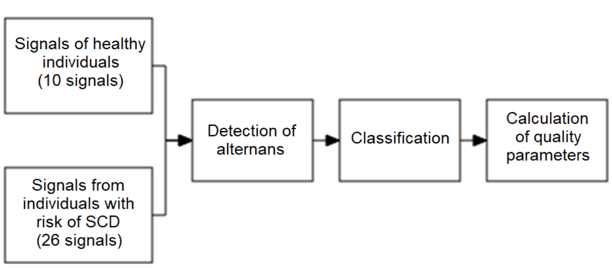

Figure 10. Process for obtaining the quality parameters using signals from the TWADB database.

The tests were carried in two groups of analysis, on one side, ten signals from healthy patients were taken, i.e., signals that do not contain alternans. Once the Adaptive-SM method is applied to these signals, the classification shown in Table 4 is obtained as a result, which has the following information: name of the signal chosen, calculated value of the detected alternan and the diagnosis generated, true negative or false positive.

Table 4. Results given by the Adaptive-SM method in signals of healthy individuals

Signal	TWA Value	Diagnosis
twa39	0	VN
twa46	8,3949	FP
twa55	0	VN
twa60	0	VN
twa10	0	VN
twa23	0	VN
twa61	0	VN
twa62	0	VN
twa71	0	VN
twa93	27,1057	FP

The method classified 8 of 10 signals as signals without TWA, i.e., there are 8 true negatives and 2 false positives. This indicates that the method is capable of correctly detecting a signal without TWA and, therefore, a healthy individual (specificity), with a probability of 80 %.

The other group of analysis is constituted by 26 signals corresponding to patients with risk of SCD. The results are shown in Table 5, which has the following information: name of the signals, calculated TWA value, in µV, and diagnosis of the detection.

In the case of signals with risk of SCD, of the 26 signals, 5 were classified as signals without TWA, i.e., there are 5 false negatives; on the other hand, the remaining 21 signals have been correctly classified, and thus there are 21 true negatives. With the number of true positives and false negatives, the sensitivity of the method has been calculated resulting in 80.76 %, i.e., it has a high probability of correctly detecting signals without TWA and, therefore, individuals with risk of SCD.

According to the data of Tables 4 and 5, there are 29 signals correctly classified of a total of 36 signals, among signals with and without TWA, which results in an accuracy of the method of 80.56 %, i.e., the method has a high probability of correctly detecting and classifying signals with and without TWA.

Table 5. Results given by the Adaptive-SM method in signals of patients with risk of SCD

Signal	TWA Value	Diagnosis
twa07	8,1842	VP
twa32	8,0292	VP
twa85	0	FN
twa92	3,6081	VP
twa00	0	FN
twa08	0	FN
twa45	40,2243	VP
twa63	1,8172	VP
twa68	4,1085	VP
twa95	6,5078	VP
twa12	0	FN
twa27	0	FN
twa03	24,1159	VP
twa11	9,8338	VP
twa18	6,7598	VP
twa19	6,1028	VP
twa20	0	FN
twa31	10,3374	VP
twa36	6,6947	VP
twa40	0	FN
twa41	5,6962	VP
twa48	8,1214	VP
twa49	4,0385	VP
twa53	2,6401	VP
twa54	53,9866	VP
twa83	9,1466	VP

Subsequently, in this work a comparison was made between the Adaptive-SM method and the SM and MMA methods; these latter are implemented in the TWAnalyser software [14]

The 36 signals previously described were taken for this experiment. The results of specificity, sensitivity and precision are shown in Table 6.

The MMA method is the one that exhibits more problems, since its sensitivity of 100 % and specificity of 0 % suggests that it classifies all signals as signals with TWA, although they do not have alternans. Then, this method considers any type of disturbance as an alternan, which is wrong, and this is the reason why the methods classifies incorrectly 50 % of the test signals. On the other hand, the SM method shows a more balanced performance, however, when compared to the Adaptive-SM the percentage of accuracy in the classification is considerably smaller, with a precision of only 63.89 %. The Adaptive-SM method results a more acceptable method with a balanced behavior in the detection of signals with and without TWA.

Table 6. Quality parameters of the Adaptive-SM, SM and MMA methods

Parameter	Adaptative-SM	SM	MMA
Sensitivity	80,76%	61,53%	100%
Specificity	80%	70%	0%
Precision	80,56%	63,89%	50%

From the results in both types of tests, i.e., on synthetic signals and records from the TWADB databases, these indicate a better performance of the Adaptive-SM method with respect to the other two methods, in all quality indices. Specifically, the Adaptive-SM algorithm is characterized by its robustness in the detection of alternans.

4. Conclusions

The extensive experiments showed that the Adaptive-SM method is capable of correctly detecting alternans and classifying the signals. In addition, it could be compared, by means of standard metrics, the performance of the algorithm when subject to different noise and alternans levels, exhibiting advantages with respect to the classical SM and MMA methods. This superiority is because the Adaptive-SM utilizes time-frequency distributions that enable a more detailed analysis of the signal, thus avoiding the loss of relevant information contained in the heart signal and, therefore, yielding better results in the detection of alternans.

In conclusion it could be indicated that the Adaptive-SM is a promising technique for the early and non-invasive detection of the SCD.

In a future work it will be studied the capability of the algorithm for long-term analysis, and its performance in mobile monitoring systems intended to eHealth; all this accompanied with the criterion of an expert cardiologist specialized in SCD.

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References

[1] M. Vargas Sanabria, J. C. Vega Chaves, G. Hern A¡ndez Romero, and G. Montero Solano, "Síndrome de brugada como casusa de muerte súbita de origen cardíaco," *Medicina Legal de Costa Rica*, vol. 34, pp. 157–164, 03 2017. [Online]. Available: https://bit.ly/2ZEI4Sf

[2] R. Devi, H. K. Tyagi, and D. Kumar, "Early stage prediction of sudden cardiac death," in *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, 2017, pp. 2005–2008. [Online]. Available: https://doi.org/10.1109/WiSPNET.2017.8300112

[3] J. T. Willerson, J. N. Cohn, H. J. J. Wellens, and D. R. Holmes, *Cardiovascular Medicine*, ser. SpringerLink : Bücher. Springer London, 2007. [Online]. Available: https://bit.ly/3eag8cD

[4] U. Satija, B. Ramkumar, and M. S. Manikandan, "Automated ecg noise detection and classification system for unsupervised healthcare monitoring," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 3, pp. 722–732, 2018. [Online]. Available: https://doi.org/10.1109/JBHI.2017.2686436

[5] F. Panjaitan, S. Nurmaini, M. Akbar, A. H. Mirza, H. Syaputra, T. B. Kurniawan, and R. Umi P, "Identification of classification method for sudden cardiac death: A review," in *2019 International Conference on Electrical Engineering and Computer Science (ICECOS)*, 2019, pp. 93–97. [Online]. Available: https://doi.org/10.1109/ICECOS47637.2019.8984465

[6] E. V. Garcia, C. A. Pastore, N. Samesima, and H. G. Pereira Filho, "T-wave alternans: desempenho clínico, limitações, metodologias de análise," *Arquivos Brasileiros de Cardiologia*, vol. 96, pp. e53–e61, 03 2011. [Online]. Available: http://dx.doi.org/10.1590/S0066-782X2011005000018

[7] Y. Karplyuk, K. Ivanko, and N. Ivanushkina, "Peculiarities of t wave alternans detection and evaluation," in *2015 IEEE 35th International Conference on Electronics and Nanotechnology (ELNANO)*, 2015, pp. 356–361. [Online]. Available: https://doi.org/10.1109/ELNANO.2015.7146909

[8] O. Karnaukh, Y. Karplyuk, and N. Nikitiuk, "Evaluation of machine learning techniques for ecg t-wave alternans," in *2018 IEEE 38th International Conference on Electronics and Nanotechnology (ELNANO)*, 2018, pp. 346–350. [Online]. Available: https://doi.org/10.1109/ELNANO.2018.8477528

[9] G. M. Nijm, S. Swiryn, A. C. Larson, and A. V. Sahakian, "Estimation of t-wave alternans from multi-lead ecg signals using a modified moving average method," in *2008 Computers in Cardiology*, 2008, pp. 517–520. [Online]. Available: https://doi.org/10.1109/CIC.2008.4749092

[10] S. Ayub, G. Gupta, and Y. Kumar, "Heart rate calculation and detection of t-wave alternans by correlation method," in *2016 8th International Conference on Computational Intelligence and Communication Networks (CICN)*, 2016, pp. 200–203. [Online]. Available: https://doi.org/10.1109/CICN.2016.45

[11] T. W. Shen and Y. T. Tsao, "An improved spectral method of detecting and quantifying t-wave alternans for scd risk evaluation," in *2008 Computers in Cardiology*, 2008, pp. 609–612. [Online]. Available: https://doi.org/10.1109/CIC.2008.4749115

[12] B. D. Nearing, A. H. Huang, and R. L. Verrier, "Dynamic tracking of cardiac vulnerability by complex demodulation of the t wave," *Science*, vol. 252, no. 5004, pp. 437–440, 1991. [Online]. Available: http://doi.org/10.1126/science.2017682

[13] B. Ghoraani, S. Krishnan, R. J. Selvaraj, and V. S. Chauhan, "T wave alternans evaluation using adaptive time–frequency signal analysis and non-negative matrix factorization," *Medical Engineering & Physics*, vol. 33, no. 6, pp. 700–711, 2011. [Online]. Available: https://doi.org/10.1016/j.medengphy.2011.01.007

[14] A. Khaustov, S. Nemati, and G. D. Clifford, "Twanalyser - a t-wave alternans detector," *Computers in Cardiology*, 2008. [Online]. Available: https://bit.ly/36nUz5L

[15] G. B. Moody, "The physionet/computers in cardiology challenge 2008: T-wave alternans," in *2008 Computers in Cardiology*, 2008, pp. 505–508. [Online]. Available: https://doi.org/10.1109/CIC.2008.4749089