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Optimal Kernels application to improve late ventricular activity detection

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ABSTRACT

Sometimes when a myocardium infarct occurs, small abnormalities in conduction are present over the infarcted zone. These components are known as Ventricular Late Potentials (VLP) and are associated with ventricular arrhythmias and sudden cardiac death. They are components of ventricular conduction activity that are attenuated, fragmented and delayed over the QRS complex of an electrocardiogram (ECG). VLP are often used as non-invasive markers of arrhythmia risk and while their detection is difficult, there are non-invasive methods proposed for improved detection. The classical time domain method is the most often used for VLP detection in the analysis of high resolution ECG (HRECG) on post-infarction patients. Nonetheless, it brings low predictive values, high sensibility to noise and excludes in its analysis patients with bundle branch blockage. In this paper the different morphologies of VLP are used for deducting a bi-dimensional Kernel in the time-frequency domain, so that it can be adapted to changing VLP structures according to each post-infarct patient. Also, both the reduction of false negatives and an increase in true positives of the automatic diagnosis can be achieved. A database of 132 HRECG signals was analyzed and a substantial increase in predictive values was obtained over diagnostics. In the analysis, attenuated sensibility to noise compared to the classical temporal domain method was also shown.

Key Words:
Ventricular Late Potentials, High Resolution ECG, Time-Frequency Analysis, Dependent Kernel, Post-Infarction, SAECG.

RESUMEN

Después de que ocurre un infarto de miocardio, a veces se presentan pequeñas anormalidades de conducción sobre la zona infartada. A estos componentes se les llama potenciales tardíos ventriculares (VLP), y se les asocia con las arritmias ventriculares y muerte cardiaca súbita. Son componentes en la actividad de conducción ventricular que se atenúan, se fragmentan y se retrasan sobre el complejo QRS del ECG. Los VLP son muy usados como marcadores no invasivos de riesgo arrítmico, y aunque su detección es muy difícil, existen propuestas de métodos no invasivos para mejorarla. El método del dominio temporal clásico es el más utilizado para la detección de VLP, en el análisis de señales ECG de alta resolución (HRECG) de pacientes post-infartados. Sin em-

bargo, presenta valores predictivos bajos, alta sensibilidad al ruido y excluye en su análisis a los pacientes con bloqueo de rama. En este trabajo se prueban las distintas morfologías que presentan los VLP para la obtención de un Kernel bidimensional en tiempo-frecuencia, que se adapte a las estructuras cambiantes de los VLP para cada paciente post-infartado, y logre disminuir los casos negativos falsos, pero que aumente los casos positivos verdaderos en el diagnóstico automatizado. Se analizó una base de datos de 132 señales HRECG, y se obtuvieron resultados substanciales en cuanto al aumento de los valores predictivos del diagnóstico. En el análisis, también se observó una menor sensibilidad al ruido que en el método del dominio temporal clásico.

Palabras clave:
Potenciales tardíos ventriculares, señales ECG de alta resolución, análisis tiempo-frecuencia, kernels dependientes, post-infarto, SAECG.

INTRODUCTION

In the event of survival to a myocardium infarct, the zone of affected cardiac tissue can produce in most cases malign arrhythmia, being the most dangerous those located at the ventricles because of their ability to produce sustained ventricular tachycardia and/or ventricular fibrillation and consequently bring sudden death.

Malignant ventricular tachycardia is a pathology present in a great number of patients who are in a partial myocardium infarct recovery process[1]. From these events a great interest is born in many scientist and researchers to study new effective prediction techniques for ventricular tachycardia risk factors that may permit a cardiologist to prevent sudden death in post-infected patient.

The most effective methods to date are invasive in nature, so they are inconvenient for requiring surgery to the patients[2]. To avoid risk factors brought by surgery, some researchers have proposed the use of some electrophysiological characteristics that behave as arrhythmia risk flags for the development of non-invasive methods of sudden cardiac death.

The tissue zone damaged by an infarct goes through a physiological process in a healing effort. In any event, the tissue makes a partial recuperation and its effects carry in many cases lethal consequences because part of the electrical activity originated from the cardiac depolarization wave front suffers attenuation, fragmentations and time lag, bringing malignant ventricular tachycardia[3]. These irregularities in ventricular conduction have been denominated ventricular late potentials (VLP)[4,5], and can be registered by superficial techniques of electrocardiography (ECG) known as high resolution ECG (HRECG)[6].

HRECG are used with much frequency by most non-invasive methods mentioned in literature, such as time domain[7], frequency domain[8], spectro-temporal[9], and others[10-13]. The most accepted but also standardized method for detecting VLP is the time domain, known as classic time domain method[14]. Unfortunately, it gives low predictive values and post-infarcted patients with branch blockage must be excluded from analysis[15].

As time progresses, it is known of more research being made with the objective of refining VLP detection and analysis where techniques as complex as time-frequency representations[16,17], and wavelet transform are used[18,19]. All these search one common objective, to raise the predictive values of automated diagnosis. Perhaps the wavelet transform is one of the techniques to have brought best results in VLP detection[20]. On the other hand, in all these proposals there is a lack of normalization and standardization regarding their ventricular conduction abnormality criteria, for such a reason, varied results are currently being generated.

METHODOLOGY

The structural morphology of VLP varies from patient to patient, because it depends on the type and age of the infarct, it also depends on the patients genetic and physiological characteristics. These morphologic variations and its noise sensibility are some of the elements generating false positive and false negative VLP detection. In Figure 1

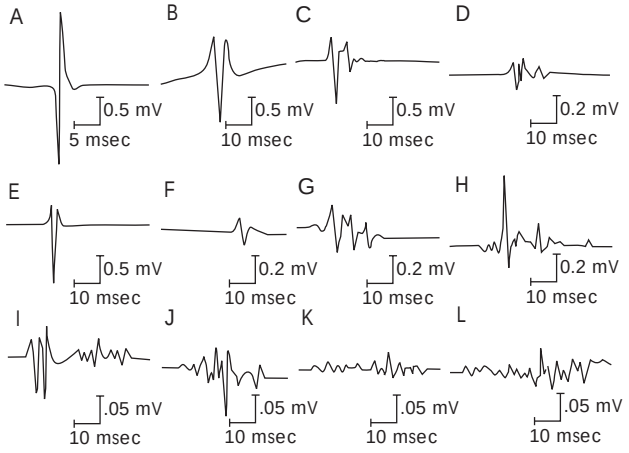

Figure 1. VLP taken from different patients. (a), (b) and (c) registered 5 days after infarct event, (d) and (g) taken 2 weeks after infarct event, (h), (k) and (l) taken 2 months after infarct event, (e), (f), (i) and (j) taken 6 months after infarct event. (from Garnder P. et al. Electrophysiologic and anatomic basis for fractionated electrocardiograms recorded from healed myocardial infarcts. Circulation. 1985;72:596-611. Figure taken with permission of Kluwer Academic Publisher. Ref: Gomes, Signal Averaged Electrocardiography, pp.19, figure 6, 1993).

are shown twelve VLP taken over the epicardic infarcted zone, where it is easy to notice differences between each other.

This paper proposes a technique applying kernel design for time-frequency analysis such that a kernel may be adapted in an optimal manner to the VLP changing structural characteristics present into a particular HRECG.

KERNEL FUNCTIONS

The ambiguity function (*AF*), is a bidimensional function, related to the winger distribution (*WD*), it is obtained by the following mathematic procedure:

$$AF(\theta,\tau) = \iint WD(t,f)\, e^{-j2\pi(\theta t - \tau f)}\, dt\, df,$$

Where:

$$WD(t,f) = \int x\left(t+\frac{\tau}{2}\right) x^{*}\left(t-\frac{\tau}{2}\right) e^{-j2\pi f t}\, dt.$$

Both WD and AF produce non-desirable artifacts over a time-frequency domain, which are called interference terms[17]. These artifacts can be attenuated by means of bidimensional filters, known as kernel functions (KF).

KF work as low pass filters over the AF in a bidimensional domain as follows.

A time-frequency representation (TFR) is a member of the Cohen class, if and only if it can be deduced from a WD convolution a KF, i.e.:

$$A\ TFR \in \text{Cohen Class} \Leftrightarrow$$

$$TFR_x(t,f) = \iint WD_x(t',f')\,\psi_{TFR}(t-t', f-f')\,dt'\,df',$$

Where: ψ is a KF in the time-fr

This convolution can be a simple multiplication if it is taken to a frequency domain by means of the bidimensional Fourier transform, this way we have:

$$TFR_x(t,f) = \iint AF_x(\tau,\nu)\,\phi_{TFR}(\tau,\nu)\, e^{j2\pi(t\nu - f\tau)}\, d\tau\, d\nu,$$

where: ϕ is the Kernel Function on the correlative plane to the time - frequency plane.

If the AF interference terms are concentrated out from the origin, and the signal terms are over and near the origin on the plane, then a multiplication with the KF will produce cancellation of some cross terms and others will only be attenuated[21].

When the KF design is not dependent from the signal, disturbance and distortions are produced over some signal terms on the time-frequency plane. To avoid this, some authors propose the use of optimal kernel functions, also known as signal dependent kernels, because both their form and volume are adapted to the form and volume of the signal terms over the bidimensional domain that the AF generates[22].

KERNEL FUNCTION APPLICATION ON HRECG

If we consider that a TFR may be obtained using an inverse bidimensional Fourier transform (2DFT) from

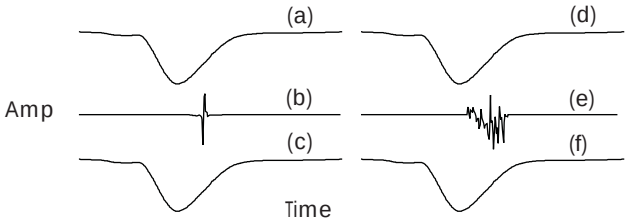

Figure 2. (a) HRECG taken from a clinically diagnosed patient without risk of arrhythmia, and low pass filtered at 25 Hz cut frequency, (b) VLP similar to that shown in figure 1(A) (out of scale), (c) HRECG signal product of sum from (a) and (b), (d) VLP similar to that shown in figure 1 (L)(out of scale), (e) HRECG signal product of sum from (a) and (d). All VLP have an amplitude below 25uV, HRECG have an amplitude between 1.5 and 2 mV.

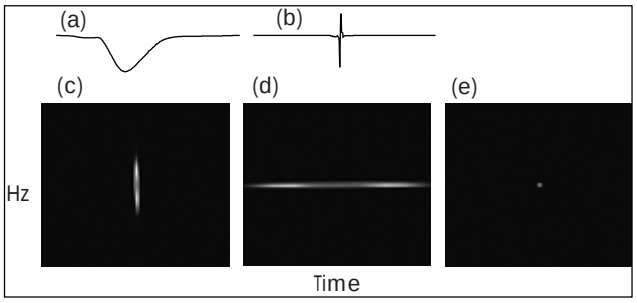

Figure 3. (c) Ambiguity Function (AF) gotten from (a) HRECG added to (b) VLP, which is the same than figure 2(c). (d) optimal radialy Gaussian Kernel (ORGK) for VLP shown in (b) (out of scale), and (e) result of the product from (c) and (d).

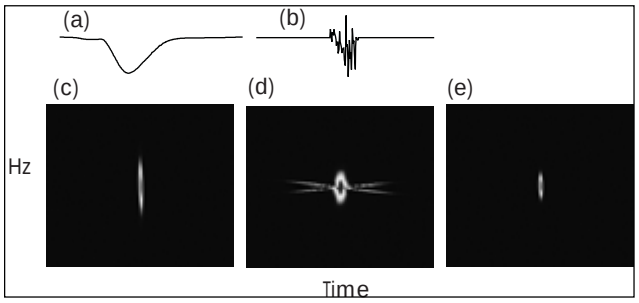

Figure 5. (c) ambiguity function (AF) from HRECG signal plus VLP (a) (same as shown in figure 2e), (d) optimal radialy Gaussian Kernel (ORGK) for VLP shown in (b) (out of scale), (e) represents the product of (c) and (d).

the product of the AF with the KF from the analyzed signal: RTF = (AF)(KF), then it is possible to state that the most adequate KF will be the one adapting to the VLP signal terms over the time-frequency plane.

In order to detect VLP, we will use optimal Gaussian Kernel types (ORGK)[23]. In Figures 2(a) and 2(d), is shown the same HRECG signal, taken from a patient whom has been clinically diagnosed not to have risk of arrhythmia. This signal was low pass filtered at 25Hz with the objective of adding VLP shown in Figure 2(b) and 2(e), respectively. The results of summation for each case are illustrated in Figures 2(c) and 2(f).

The VLP ORGK is extracted and shown in Figure 2(b), consequently an inverse 2DFT is calculated, from the product of ORGK with the AF taken from the HRECG signal shown in Figure 2(c), the TFR is generated from Figure 4(c). The ORGK, the AF and the product of both time-frequency planes are shown in Figures 3(c, d, and e), respectively.

We can appreciate the localization of VLP in a time-frequency plane as illustrated in Figure 4(c), when the AF is multiplied by the ORGK, obtained from the same VLP added to the HRECG signal (see Figure 3). When the ORGK is obtained from the VLP shown in Figure 5(b), the temporal localization in a time-frequency plane shown in Figure 2(f), 5(a) ó 4(e), is not as effective as expected. Again, this result is because the ORGK obtained from the VLP shown in Figure 3(b), permit to pass less HRECG signal terms than the ORGK gotten from the VLP that were added to the HRECG (see Figure 5(b)).

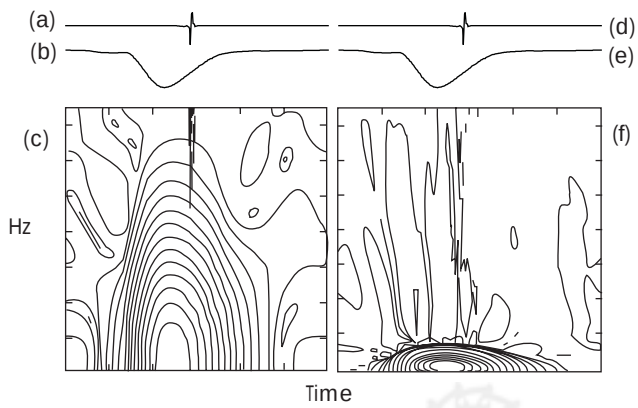

Figure 4. (b) same HRECG as shown in figure 3(a). (a) VLP added to (b) are shown out of scale for its temporal identification over the time-frequency plane (c) by means of its bidimensional Fourier transform (2DFT) from (b). (d) and (e) are the same as (a) and (b), they are shown with the object of temporal identification of VLP (d) over the time-frequency plane (f).

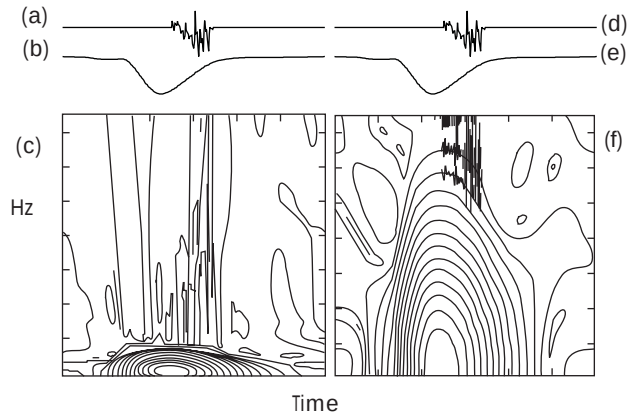

Figure 6. (b) same HRECG signal as that in figure 5(a). Sum of VLP (a) and HRECG (b) are again shown to visualize temporal identification of VLP over the time-frequency plane in (c) by means of the calculus of bidimensional inverse Fourier transforming (2DFT) on (b). (d) and (e) are the same as (a) and (b) and are also shown with the objective of temporal visualization of VLP (d) on a time-frequency plane (f).

Table I. Predictive values achieved through the classic time domain method (QRSd = QRS duration), and with the optimal radialy Gaussian kernel method (ORGK-VLP).

Method	LAR Group (n = 73)		VT Group (n = 59)	Total (n = 132)	
	PF	NV	NF	PV	DET
ORGK-VLP	9	64	7	52	116
QRSd	11	62	10	49	111

PF = false positives, NV = true negatives, NF = false negatives, DET = correctly detected cases.

ORGK and its product with the AF, for each case, are shown in Figure 3 and 5 respectively.

Now, if VLP of Figure 2(e) are added to the HRECG signal of Figure 2(d), the HRECG signal of Figure 2(f) is achieved. As can be seen, just like in the previous case, VLP can not be seen with the naked eye in the HRECG signal. Once again, if the AF of the HRECG is multiplied by the ORGK of the VLP (see Figure 5), and the inverse 2DFT is obtained, it yields the time-frequency representation of Figure 6(c). The time-frequency representation of Figure 6(f) is obtained using the previous procedure, but with the use of ORGK from Figure 3(d) obtained by VLP from Figure 3(b). As can be seen, VLP detection is substantially increased using ORGK as in Figure 3(d), due to the filtering of excessive signal components because of the ORGK adaptation to the VLP signal representation over its AF.

RESULTS

A database of 132 HREGC signals was analyzed, and organized in the following categories:

VT Group (myocardium infarct with ventricular tachycardia risk). Built from 59 HRECG signals taken from post-infarcted patients. These patients were treated at the veterans Affairs Medical Center in Oklahoma City, where an electrophysiological study was done after having survived a myocardium infarct.

LAR Group (No infarct to the myocardium, under risk of ventricular tachycardia). Built from 73 HRECG signals of patients to whom no signal of previous myocardium infarct could be diagnosed. The electrophysiological study was also made by the Veterans Medical Center in Oklahoma City.

High resolution (16 bits), bipolar, orthogonal high resolution registers where gathered from the X, Y and Z leads.

Leads where gathered using the SAECG PREDICTOR system of Corazonix Corp. A sampling frequency of 2 KHz was used. By averaging the signal, a noise level lower than 0.4 µV RMS was achieved for both groups. The noise measurement was made with the magnitude vector over the ST segment in a high pass band with cut frequency of 40 Hz.

Table 1 shows false positive cases (FP), the true negative cases (TN), false negative cases (FN), true positive cases (TP), and the total of correctly diagnosed patients (DET). These diagnostics represent both those produced by the classical time domain method as well as in the use of ORGK in detection of VLP, when the 132 HRECG signal database was analyzed (i.e., LAR and VT Group). One can observe in Table 1 how the ORGK technique generates only 9 FP and 7 FN, while the time domain technique produces 11 FP and 10 FN. Consequently, the ORGK technique diagnoses correctly more patients (i.e., 116) compared to the classic time domain method (i.e., 111).

DISCUSSION

An optimal Gaussian type kernel (ORGK) was used for detection of ventricular late activity or ventricular late potentials (VLP). This kernel automatically adapts to the VLP signal terms generated by the ambiguity function (AF), which is obtained by the inverse bidimensional Fourier transform (2DFT). Once the ORGK is determined, it is multiplied by the AF obtained from the high-resolution electrocardiographic signal (HRECG), and the time-frequency representation is obtained by means of an inverse 2DFT. In the analysis of 132 HRECG signals, 12 ORGK where tested obtained from 12 VLP. The ORGK with best results shown, was the one obtained from the signal illustrated in Figure 3(b), which is similar to the one in Figure 1(A).

The predictive values obtained with this analysis were superior to those given by the classic time-domain analysis; regardless, to establish an abnormality criterion with the proposed techniques, there remains a need to develop an automated quantification method of ventricular abnormality, while the results shown in this paper are evaluated over a visual type analysis.

CONCLUSIONS

With the results achieved from analysis of the database, it has been shown that with the application of these techniques in the analysis of HRECG, it's

possible to detect late ventricular activity in post-infarcted patients.

There is a need to test a great number of cases with a new database in order to compare results from analysis and have more judgment elements regarding the benefits of the method proposed.

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