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Morphologically constrained signal subspace characterization of electrograms during ventricular fibrillation

Krishnanand Balasundaram[a,*], Stephane Masse[b], Talha Farid[b], Krishnakumar Nair[b], John Asta[b], Robert J. Cusimano[c], Edward Vigmond[d,e], Kumaraswamy Nanthakumar[b], Karthikeyan Umapathy[a]

[a] Department of Electrical and Computer Engineering, Ryerson University, Toronto, Ontario, Canada
[b] Department of Cardiology, THFCFM Laboratory, Toronto, Ontario, Canada
[c] Department of Cardiology, Toronto General Hospital, Toronto, Ontario, Canada
[d] LIRYC Electrophysiology and Heart Modelling Institute, Pessac, France
[e] Laboratory IMB, University of Brodeaux, Talence, France

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ABSTRACT

Ventricular fibrillation (VF) is a lethal cardiac arrhythmia traditionally believed to be chaotic in nature. However, recent research studies have shown that certain events of interest during VF may exhibit local (or regional) organization. These time-varying and spatially migrating organized activities manifest themselves into different signal morphologies within electrograms acquired during VF. Performing targeted (or constrained) signal decomposition of electrograms to extract such signal morphologies associated with events of clinical interest will be of significant value.

We present one such targeted adaptive signal decomposition of intra-cardiac electrograms during VF, to automatically extract morphologies previously observed in relation to the vicinity of rotor phenomenon (i.e. an event of interest during VF). Using a Gabor dictionary and Matching Pursuits (MP), the proposed method successfully performed targeted signal decomposition in highlighting signal structures that could be used to determine the ventricular electrogram's vicinity to a rotor in the epicardium. A comparative analysis using the MP with a proposed choice function ($P < 0.001$) against the standard choice function ($P < 0.5688$) performed better in segregating the electrogram data (130 electrograms from 7 isolated human hearts) based on the signal structures.

1. Introduction

Sudden cardiac death remains one of the leading causes of deaths in the United States, with nearly 300,000 deaths reported annually [26], most of which are attributed to ventricular fibrillation (VF). Currently, the common treatment option for VF is defibrillation by an electric shock. However, recent works are attempting to modulate VF using spatially-local ablation methods [20]. While VF is generally regarded as a chaotic event causing uncoordinated ventricular contractions, it has recently been reported that there may be organized activities or events of interest that may present themselves as repeatable and/or unique electrogram signal structures. These repeatable and/or unique electrogram signal structures could arise from the manifestation of spatio-temporal events of clinical interest in the myocardium, which are usually inaccessible in a real world scenario. However, these spatio-temporal events can be identified indirectly from the accessible electrogram signal structures associated to some time–frequency (TF) subspace. Further, multi-channel surface electrocardiogram signal structures could serve as indirect guidance maps to assist clinicians and implantable devices in choosing effective strategies in modulating or treating VF [12,28]. If the TF subspace of the signal morphologies of clinical interest were to be found, then using automated algorithms, near real-time detection is plausible, which could assist in ablation procedures and implantable devices.

Electrogram patterns have been previously observed during VF. For instance, a pattern commonly described as "double potential" has been observed near regions of conduction blocks [8], which also has a relation to the region where there is an interaction of healthy and scar tissue. The occurrence of an amplitude variation in the unipolar electrical activation, where the amplitude varies from a low to high signal amplitude, was also a determinant on whether a

* Corresponding author.
E-mail address: kbalasun@rnet.ryerson.ca (K. Balasundaram).

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defibrillating shock would be successful [11]. It was observed that the region of high amplitude was more receptive to a successful defibrillation shock than the region of low amplitude. Electrical activation maps were used to determine the organizational aspects of the arrhythmia by identifying normal bipolar electrical activation from the electrogram [23]. A conference proceeding by our group had highlighted that different distributions of a few repeating electrogram patterns in different subjects co-exist, which may be indicative of various events of interest that could be used in characterizing ventricular arrhythmias [1]. In another recent article published by our group [2], we observed that electrograms in the vicinity (within a radius of 2 cm) of a rotor (a spatio-temporal phenomenon) have a stronger and repeating envelope amplitude variation than the electrograms that are not in the vicinity of a rotor. This was quantified using an amplitude variation feature. Rotor theory [21,17,19] is one hypothesis on the initiation and maintenance of VF. Rotors, as per rotor theory, are centers of organized, rotating, and migrating spatio- temporal electrical activity and are believed to be the drivers of VF. However, the tracking of rotors is particularly difficult due to spatial resolution limitations and the inaccessibility of electrograms. If such events were to be associated with electrogram or multi-channel electrocardiogram signal structures, it may be beneficial in assisting clinicians or implantable devices in choosing an appropriate therapy.

The automation of identifying signal structures and targeted signal subspaces has been used in different types of applications [7,10,5,22,18][7,10,5,22,18], where Matching Pursuits (MP) was employed. MP is a greedy iterative algorithm that tries to model a signal using basis functions (atoms) from an over-complete TF dictionary. The TF dictionary is a collection of atoms with varying translation, scale, frequency and phase parameters. This algorithm iteratively selects an atom from its TF dictionary that best fits a specified criterion function. By default, the algorithm aims to minimize the signal residue at each iteration. For the purpose of detecting the electroencephalogram transients, Durka and Blinowska used the TF maps from the MP decomposition to identify specific spindles (signal morphology), thereby identifying a specific signal subspace in the TF map [5]. In order to segregate the atrial and ventricular activities of the electrocardiogram, Escoda et al. had identified the structures for each type of activity [7]. Pantelopoulos and Bourbakis had used an artificial neural network based on features from the MP decomposition to detect abnormal beats in the electrocardiogram [18]. These studies [5,7,18] reveals the effectiveness of using the signal subspace to identify relevant morphologies within the signal for bio-medical applications.

Since the focus is to analyze electrograms during VF, which are time-varying in nature, adaptive signal decomposition tools would be highly suitable. Specifically, in extension to our previous work [2], the aim of this work is to automate the extraction of relevant signal structures in the electrograms and/or the TF subspace (during VF) that is associated with events of clinical interest. Although the proposed work uses a specific event (the rotor phenomenon [19,17]) as an application example, by generalization, the proposed approach could be used to capture any targeted signal structures that may be representative of a subgroup of VF characteristics or an arrhythmic event.

The adaptive signal decomposition in this work will be performed using a MP algorithm with a TF dictionary. A MP framework allows constraints to be added to the parameters used for signal decomposition, as well as adapting the criterion function to focus on specific signal structures. These signal structures, which would be characteristics of the electrogram morphological patterns during VF, could be associated with specific events of clinical interest (i.e. identifying the spatial vicinity of rotors) for diagnosis and/or treatment planning. The paper is organized as follows: Section 2 highlights the MP and the adaptation of the choice function, Section 3 presents the performance results of the choice function on synthetic and electrogram data, Section 4 highlights the observations of this study and Section 5 provides a summary of the article.

2. Methodology

This section discusses the MP methodology [15], along with the modification of the choice function for the application in hand. The Matching Pursuit Tool Kit [14] was used for the implementation of the original MP as well as the MP with the modified choice function.

2.1. Matching Pursuits (MP)

Matching Pursuits is a greedy algorithm that models any given signal using atoms selected iteratively from a dictionary. The nature of the decomposition depends on the the type of the dictionary. Any given signal can be decomposed into a set of atoms $g_\gamma(x)$, where x is the discrete time sample. The TF atom can be defined by Eq. (1) [15].

$$g_\gamma(x) = \frac{1}{\sqrt{s}} g\left(\frac{x-u}{s}\right) e^{i\xi x} \tag{1}$$

From Eq. (1), the terms u, s and ξ represent the translation, scaling and center frequency of a single window function g respectively. Therefore, an atom with the parameters γ is centered around a time neighborhood u, a frequency neighborhood ξ with a scale of s. The term γ refers to a single set of translation, scaling and frequency parameter for any given iteration. It should be noted that the scale s determines the size of the window used by the function and it is not the frequency of the window function g. These atoms form the basis functions that MP use to decompose a signal. An example of a basis function is the Gabor atoms, which is used for the analysis in this study due to its optimal TF resolution [4]. A signal $f(x)$ can be represented in terms of the TF atoms $g_\gamma(x)$ using Eq. (2).

$$f(x) = \sum_{n=0}^{+\infty} b_n g_{\gamma_n}(x) \tag{2}$$

For a given expansion n, the atom selected is $g_{\gamma_n}(x)$ with parameters γ_n. The term b_n represents the expansion coefficient at the nth expansion. The signal $f(x)$ is decomposed using a combination of atoms $g_{\gamma_n}(x)$ with varying expansion coefficients b_n. For signal approximation, the summation of the atoms $g_{\gamma_n}(x)$ is limited to a finite number of atoms n. In the standard implementation of MP, an atom is selected by computing the inner product between the atom and the signal (as seen for the first iteration in Eq. (3)) and then selecting the atom with the maximum inner product.

$$b = \langle f, g_\gamma \rangle = \sum f(x) g_\gamma^*(x) \tag{3}$$

The term g_γ^* represents the complex conjugate of atom g_γ and b is the inner product. Decomposing a signal f into the form defined by Eq. (2) is the final goal of MP. Suppose that the decomposition has completed $n-1$ iterations. The general form of the residue at the nth iteration is as follows (given that $n \geq 0$).

$$\begin{aligned} R^n f &= b_n g_{\gamma_n} + R^{n+1} f \\ &= \langle R^n f, g_{\gamma_n} \rangle g_{\gamma_n} + R^{n+1} f \end{aligned} \tag{4}$$

The residue $R^n f$, which was produced at the $n-1$ iteration, is decomposed by the atom g_{γ_n} and produces the residual $R^{n+1} f$. The expansion coefficient b_n is selected by maximizing the projection of atom g_{γ_n} onto the residual signal $R^n f$ at iteration n. The residual $R^{n+1} f$ after iteration n is the difference between of the projected atom g_{γ_n} and the signal $R^n f$. It should be noted that $R^n f$ is the same as f when $n = 0$. The MP algorithm is repeated on every residue until