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Quantification of fragmented QRS complex using intrinsic time-scale decomposition

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ABSTRACT

The QRS complex recorded from the surface electrocardiogram (ECG) arises from electrical activation of the ventricular myocardium through the normal conduction system. The presence of a fragmented QRS (fQRS) complex reflects abnormal electrical activation and has been recently shown to identify patients with heart disease at risk of sudden cardiac death (SCD). The evaluation of fQRS is currently performed qualitatively by visual inspection which can be time consuming and subject to interpretation. Moreover, qualitative assessment of QRS for fragmentation may be insensitive to more subtle deflections in the QRS complex that may be equally prognostic. This study proposes an automated method to quantify QRS fractionation using intrinsic time-scale decomposition (ITD). Instantaneous morphology features are extracted from the decomposed QRS signal to index variations in its shapes. Our quantitative fQRS metric was found to be significantly greater in QRS complexes with fragmentation compared to normal QRS complexes derived from real-world ECGs in the Physikalisch-Technische Bundesanstalt (PTB) database. ROC analysis showed an area under the curve of 0.96 when fQRS was quantified from the precordial ECG leads, V1–V6. Thus, quantification of fQRS using the proposed ITD-based method can accurately identify fQRS. Our approach shows tremendous potential and could be investigated further for SCD risk assessment in patients with heart disease by improving the identification of fQRS that may or may not be visually apparent.

1. Introduction

Sudden cardiac death (SCD) is the leading cause of death in North America with the majority of cases arising from ventricular tachyarrhythmias [1]. The normal ventricular myocardium is activated synchronously through the His-Purkinje conduction system; thereby generating a narrow QRS complex on the surface electrocardiogram (ECG). In the setting of heart disease with impairment of His-Purkinje conduction and myocardial scar, electrical conduction can be markedly delayed which will in turn prolong the QRS complex. Slow electrical conduction increases the risk of reentrant ventricular tachyarrhythmias and QRS prolongation is a risk marker for SCD. However the predictive accuracy of QRS prolongation alone is poor and there is a growing need to improve risk assessment in cardiomyopathy patients. To address this need, a novel QRS marker known as fragmented QRS (fQRS) has been proposed which has been shown to predict arrhythmic events in patients with heart disease [2]. The available information about this morphological ECG abnormality and its significance in various cardiac conditions has been summarized in [3]. Currently, fQRS is defined qualitatively based on visual inspection of the QRS morphology for various morphologic deviations, including the presence of one or more additional R waves, or notching in the nadir of the R wave or the S wave [2]. However, manual fQRS labeling could be tedious and time consuming and the subjective identification of fQRS may lead to potentially large observer variability. Thus, an automated, quantitative assessment of fQRS is needed to improve the reliability as well as sensitivity of this metric and broaden its clinical application in risk assessment [4].

The qualitative definition of fQRS provides the framework for quantitative fQRS analysis. Existing fQRS quantification is therefore mainly based on the identification of transient high frequency riding waves superimposed on the normal QRS complex which has inherently larger amplitude and lower frequency [5]. In literature, researches have been focused on identifying and associated the

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presence of high frequency power in QRS complex to various cardiac conditions [6–10]. On the other hand, this frequency-domain description of fQRS is inadequate since fQRS are uniquely characterized in the time domain as transient signals [11] with no defined frequency range, which leads to the isolation of the fragmentation by filtering or spectral analysis more challenging. A few attempts have thus been made to quantify fQRS morphology in time domain [11]. However, either relatively lower sensitivity reported [11], or the adoption of predefined parameters such as cutoff frequency for signal preconditioning [12,13] and the pre-selected basis for signal decomposition [14] inspires further research of a fQRS morphology quantification method with comparably high detection accuracy but less dependency on predefined parameters. Also, the potentially useful original morphology of the fragmentation could be preserved if the signal could be decomposed using its nature basis without preconditioning.

This study thus attempts to develop a robust diagnostic metric for quantifying the fQRS morphology in temporal domain based on the temporal locations and morphologies of the fragmentations, with no assumption on the frequency range of fQRS and thus no predefined parameters required. Given the characteristic responses of a complex system, the QRS complex cannot be easily decomposed into regular harmonics or any predetermined basis function, which makes the Fourier based analysis less suitable. On the other hand, wavelet analysis [15–18] is able to ensure a more accurate quantification of abrupt signal changes, but its success relies heavily on the a priori construction of basis function and its associated properties. This inherent property of wavelet limits its application in fQRS morphology quantification where various unknown morphological deviations are present in the normal QRS complex. In contrast, empirical mode decomposition (EMD) provides an alternative solution by decomposing data into functions that are indicative of the physical signal's intrinsic oscillatory modes [19]. However, the requisite sifting process for proper rotation baseline extraction prevents faithful extraction of the fQRS morphology and thus restrains the practical use of EMD in fQRS quantification.

Recently, a new data-driven technique, referred to as intrinsic time-scale decomposition (ITD), has been introduced by Frei and Osorio [20] for analyzing data from nonstationary and nonlinear processes. The usability of this technique has been investigated for other areas of biomedical signal processing such as automated seizure prediction [21]. It constructs the baseline signal in a real-time manner as a linearly transformed contraction of the input signal for intrinsic decomposition with accurate temporal localization of morphology information. The approach does not require sifting and thus avoids the practical limitations of EMD. The aim of our study is to develop a novel fQRS quantification method based on ITD which accurately reflects the intrinsic characteristics of the fQRS complex. The accuracy of our approach in quantifying fQRS was evaluated in real world ECGs from the Physionet-PTB diagnostic ECG database [22].

In Section 2, we will describe the signal characteristics of the QRS complex and introduce the proposed fQRS quantification methods. Our results will be presented and compared with conventional signal processing techniques in Section 3, followed by our conclusions in Section 4.

2. Methods

The outline of the method is illustrated in Fig. 1 with individual steps being elaborated in the following subsections. The proposed method first decomposes the input ECG signals X into four components $C_{\{1,\ldots,4\}}$ with well defined instantaneous frequency and amplitudes carrying precise temporal information and high temporal resolution. The second and third components $C_{\{2,3\}}$ are adopted to delineate QRS complex from the continuous ECG signals. The morphology features $|A|$ and f are then extracted via single-wave analysis of the delineated first component C_1, and matrix M is eventually computed for the quantification of fQRS complex.

2.1. Signal decomposition by ITD

The fQRS complex is identified as transient waves with low-amplitude and relatively higher frequency (as compared to the underlying QRS complex) being superimposed on the normal QRS complex with inherently larger amplitude and relatively lower frequency. Without a priori knowledge on a specific fQRS complex, we define the ECG signal X as the sum of a monotonic trend and proper rotation components, for which each component has strictly positive values at all local maxima and strictly negative values at all local minima [19]. The instantaneous amplitude and frequency can thus be well defined in the defined proper rotation components.

Intrinsic time-scale decomposition (ITD) is specifically formulated for application in non-linear or non-stationary signals with underlying dynamics that change on multiple time-scales simultaneously. As introduced in [20], an input signal $X(t)$ can be decomposed into a baseline $\mathcal{L}X(t)$, with $\mathcal{L}$ being a baseline signal extraction operator, and a proper rotation component $\mathcal{H}X(t) = X(t) - \mathcal{L}X(t)$ with the highest relative frequency present in the input. Here, $\mathcal{H} = 1 - \mathcal{L}$ is a proper-rotation-extracting operator. The process can then be iterated by reapplying $\mathcal{L}$ on the baseline signals extracted as:

$$\begin{aligned} X(t) &= \mathcal{L}X(t) + \mathcal{H}X(t) \\ &= (\mathcal{H} + \mathcal{L})\mathcal{L}X(t) + \mathcal{H}X(t) \\ &= \left(\mathcal{H}\sum_{i=0}^{p-1}\mathcal{L}^i + \mathcal{L}^p\right)X(t) \\ &= \sum_{i=0}^{p-1} C_{i+1} + \mathcal{L}^p X(t) \end{aligned} \tag{1}$$

In this equation, $\mathcal{L}$ is the piece-wise linear baseline-extracting operator between successive extrema with temporal locations denoted by $\tau_{\{k|k=1,2,\ldots,K\}}$ with K as the total number of extrema in a finite signal $X(t)$. Please note that K would not have fixed value when the decomposition is applied on real time signal. Here, C_{i+1} denotes the $(i+1)$th level proper rotation component, $C_{\{1,2,\ldots,p\}}$, and $\mathcal{L}^p X(t)$ is the lowest frequency baseline extracted before the decomposition is stopped. The value of p can either be set to extract the monotonic baseline signal, or it can be chosen to control when the decomposition stops. In this paper, the information of QRS complex has been observed to be always confined within the first 3 proper rotation components. $p = 3$ is therefore chosen which decomposes the input ECG signal into 3 proper rotation components C_1, C_2, C_3, and 1 baseline component.

More specifically, assume $X(t)$ has real values between $t \in (0, \tau_{k+2}]$ and both $\mathcal{L}X(t)$ and $\mathcal{H}X(t)$ are defined on $[0, \tau_k]$, the piece-wise baseline-extracting operator could be defined for $t \in (\tau_k, \tau_{k+1}]$ as:

$$\mathcal{L}X(t) = \mathcal{L}X(\tau_k) + \left(\frac{\mathcal{L}X(\tau_{k+1}) - \mathcal{L}X(\tau_k)}{X(\tau_{k+1}) - X(\tau_k)}\right)(X(t) - X(\tau_k)), \tag{2}$$

with

$$\mathcal{L}X(\tau_{k+1}) = \frac{1}{2}[X(\tau_k) + X(\tau_{k+1})] + \frac{1}{2}\left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k}\right)(X(\tau_{k+2}) - X(\tau_k)) \tag{3}$$

The decomposition is initialized in the interval $t \in [0, \tau_1]$ as $\mathcal{L}X(t) = (X(0) + X(\tau_1))/2$. The baseline constructed preserves the monotonicity of the input signal $X(t)$ between extrema, while the