Detection of VT,VF Sounds Using SVM & Zero Crossing Rate

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Abstract—*Correct detection and classification of ventricular fibrillation (VF) and rapid ventricular tachycardia (VT) is of pivotal importance for an automatic external defibrillator and patient monitoring .Early detection of life threatening arrhythmias such as ventricular fibrillation and ventricular tachycardia is most essential for an automatic external defibrillator and remote cardiac patient monitoring. A wide variety of detection algorithms are in existence which are based on complexity parameters extracted from the ECG. However, these algorithms are mostly constructed by considering each parameter individually. Here we present a detection method which consists of four stages1.dft based noise removal 2.addition of random noise 3.zero crossing rate 4.detection rule. Here detection is done based on the addition of random noise and zero crossing detection rule. The method is tested from Meta data. Different types of noises including base line wandering, power line interface, muscle artifacts are removed in this test. The proposed method with additive random noise and single ZCR feature can achieve better detection rates compared with the existing methods which are based on combination of morphological, spectral, time-frequency, complexity features such as neural networks, support vector machine(SVM).*

Keywords— Arrhythmias,ventricular fibrillation,ventricular tachycardia, defibrilator,random noise,zero crossing detector.

I. INTRODUCTION

SUDDEN CARDIAC DEATH (SCD) is defined as death which occurs within one hour of onset of symptoms due to cardiac causes. A sudden cardiac arrest occurs when the electrical impulse system of the heart malfunctions, disrupting regular heart beat. It is more dangerous than a heart attack because the rate of survival in case of sudden cardiac arrest is very low.

Among cardiac arrhythmias, life threatening arrhythmias such as ventricular fibrillation (VF) and ventricular tachycardia (VT) are dangerous arrhythmic events leading to sudden cardiac death. Early detection of VTVF is most essential for an external defibrillator. Ventricular fibrillation (VF) and rapid ventricular tachycardia (VT) are dangerous arrhythmic events leading to inevitable death if no defibrillation shock is applied to the subject within a few minutes. Defibrillation is a procedure used to treat life threatening conditions that affect the rhythm of the heart such as cardiac arrhythmia, ventricular fibrillation and pulse less ventricular tachycardia.

The procedure involves the delivery of an electric shock to the heart which causes depolarization of heart muscles and re-establishes normal conduction of the heart's electrical impulse. The machine used to deliver this therapeutic shock to the heart is called a defibrillator. The different types of defibrillators used include external defibrillators, transvenous defibrillators and implanted defibrillators.

In the last decades, a number of methods for detecting VF and VT have been proposed. These methods are based on temporal, spectral, time frequency, wavelet transform, and machine learning techniques such as fuzzy neural networks and support vector machines [1] – [10].

Though these methods had better detection rates, they are complicated for real time implementation. They are unsuitable for use in implantable devices. Here we attempt to present a simple robust detection method for detecting VTVF events in the ECG signal.

II. LIFE THREATENING ARRHYTHMIAS

Sudden cardiac arrest (SCA) is a condition in which the heart suddenly and unexpectedly stops beating. If this happens, blood stops flowing to the brain and other vital organs. The heart has an electrical system that controls the rate and rhythm of the heartbeat. Problems with the heart's electrical system can cause irregular heartbeats called arrhythmias. There are many types of arrhythmias. During an arrhythmia, the heart can beat too fast, too slow, or with an irregular rhythm. Some arrhythmias can cause the heart to stop pumping blood to the body—these arrhythmias cause SCA. ventricular fibrillation and ventricular tachycardia are the life threatening arrhythmias which lead to sudden cardiac arrest.

Ventricular tachycardia is a fast heart rhythm that starts in the lower part of the heart (ventricles). If left untreated, some forms of ventricular tachycardia may get worse and lead to ventricular fibrillation, which can be life-threatening.

Ventricular tachycardia is a fast but regular rhythm. It can lead to ventricular fibrillation, which is fast and irregular. With ventricular fibrillation, the

heartbeats are so fast and irregular that the heart stops pumping blood. Ventricular fibrillation is a leading cause of sudden cardiac death.

Most of the cardiac arrhythmias are having the short and long PR interval and TP interval. In the previous studies, the threshold crossing sample count and mean absolute value for discriminating VTVF from other pathological signals. Under different ECG noises and time varying PQRST morphologies these features have not detected in better detection rates.

In this work detection of VTVF is done by addition of random noise to the noise free ECG signal. ECG signal comprises of internal noise which occurs due to muscle contractions and due to atrial variations. So in order to remove these internal noises random noise is added to the ECG signal. Zero crossing rates are estimated before and after adding the random noise. Noise free ECG signals have zero crossings that are not separable. After adding random noise to noise free ECG signals, it is noted that the VTVF episodes are having much lesser ZCR values. This is the basis for the proposed method of detecting VTVF episodes by adding random noise and measuring the zero crossing rates.

III. PROPOSED VT/VF DETECTION METHOD

Here, we attempt to present a simple robust detection method for accurately detecting the VT/VF episodes under resting and ambulatory recording conditions, wherein the ECG signals are often corrupted with different types of noise such as baseline wander (BW), power-line interface (PLI), muscle artifact and instrumentation noise.

While recording an ECG signal, it is subjected to different kind of noises which have different frequency ranges. The low-frequency range signifies baseline wander (BW), the medium frequency signifies the power line interface (PLI) and the high frequency (EMG) signals signify the electromyography noise. Power line interference (PLI) coupled to signal carrying cables is particularly troublesome in medical equipment. Cables carrying signals are prone to electromagnetic interference of frequency (50 Hz or 60 Hz) by supply lines. Sometimes the recordings (ECG or EEG) are totally dominated by this type of noise.

Variations in electrode-skin impedance and activities like patient's movements and breathe cause baseline wander. The range of frequency in which baseline wander is dominant is typically less than 1.0 Hz. It is caused by changes in electrode to skin polarization voltages, or by electrode movement, or by body movement.

The electrical equipment which issued in ECG measurements also contributes noise. Electrode probes, cables, signal processor/amplifier is the major sources of instrumentation noise. Instrumentation noise cannot be eliminated but it can be reduced through higher quality equipment and careful circuit design.

The proposed detection method consists of five stages : (1) discrete Fourier transform(DFT) based filtering ; (2) moving average filtering ;(3) adding the random noise to the filtered signal; (4) estimating the number of zero crossings ; (5) comparing the estimated zero crossing rate(ZCR) with a predefined ZCR value for classifying into VTVF and non-VTVF.

A. DFT-based BW and PLI removal

Discrete Fourier transform (DFT) converts a finite sequence of equally spaced samples of a function into an equivalent length sequence of equally spaced samples of the discrete time Fourier transform (DTFT) which is a complex valued function of frequency.

The DFT is the most important discrete transform, used to perform Fourier analysis in many practical applications. In digital signal processing, the function is any quantity or the signal that varies over time or sampled over a finite time interval. In this subsection, we implement the discrete Fourier transform (DFT) filtering approach for removal of baseline wander and PLI noises from ECG signal.

Let x[n] be the input ECG sequence with length of N samples, then discrete Fourier transform (DFT) of x[n] is computed as

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-(j\pi 2kn)/N}$$

Where x[k] is the kth DFT coefficient. Here we implement the DFT filtering approach for simultaneous removal of BW and PLI noises. The design of digital high pass filter is difficult to remove PLI. The DFT coefficient indexes that are corresponding to the frequency ranges of the BW and PLI are computed as

$$k = \frac{N \times f_k}{F_s}$$

Where fs are the sampling rate of the signal and fk is the frequency of the kth DFT index. By zeroing the DFT coefficients of those frequency components and then finding inverse DFT of the coefficients.

All external noise which occur due to electrode skin impedance mismatch , propagation loss due to transducers , oxygen pump adjusting meter are removed after applying DFT. Features are extracted after applying DFT

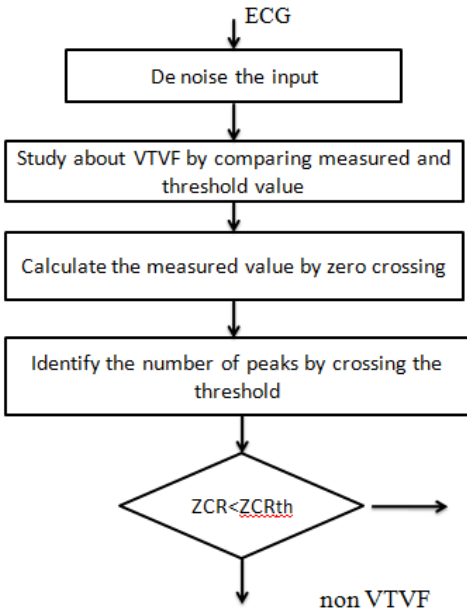


Fig: Algorithm of the proposed VTVF detection method

B. *Noise smoothing filter*

Savitzky-Golay smoothing filters are typically used to "smooth out" a noisy signal whose frequency span is large. This filter perform much better than standard averaging FIR filters ,which tend to filter out a significant portion of the signal's high frequency content along with the noise.

Y = sgolayfilt(x, order, framelen)

The above equation applies a savitzky-golay FIR smoothing filter to the data in vector x. if x is a matrix, sgolayfilt operates on each column.

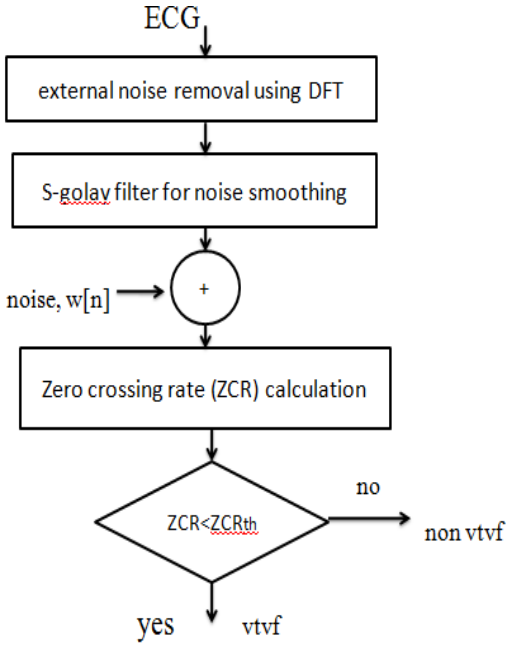


Fig : flow chart of the proposed VTVF detection method

C. *Signal plus random noise and ZCR measurement*

Random noise is the noise comprising large number of frequent transcient impulses occurring statistically at random time intervals.

ECG signal comprises of internal noise which occurs due to atrial variations, due to muscle movements. EMG signals also add some amount of noise in ECG signal.

To remove the internal noise random noise is added to the input. Flow diagram shows the random noise w[n] is added to the input. This random noise gets added to the internal noise and this is given as input to zero crossing detectors. Zero crossing detectors differentiate the input which consists of internal noise and which does not consists of internal noise.

The zero-crossing detector object counts the number of times the signal crosses zero, or changes sign. The zero-crossing rate is the rate of sign-changes along a signal, i.e., the rate at which the signal changes from positive to negative or back .In some cases only the "positive-going" or "negative-going" crossings are counted, rather than all the crossings.

Here zero crossing rate is used as feature for discriminating the VTVF episodes from the other cardiac arrhythmias .the featured signal z[n] is computed as the additive mixture of the filtered signal s[n] and the random noise w[n] that are generated with higher zero crossing rate. The featured signal z[n] is given by

Z[n] = s[n] + w[n]

For the noisy ECG signal, the zero crossing rates are computed as shown below.

$$ZCR = \frac{1}{N}\sum_{n=0}^{N} |sgn(z[n]) - sgn(z[n-1])$$

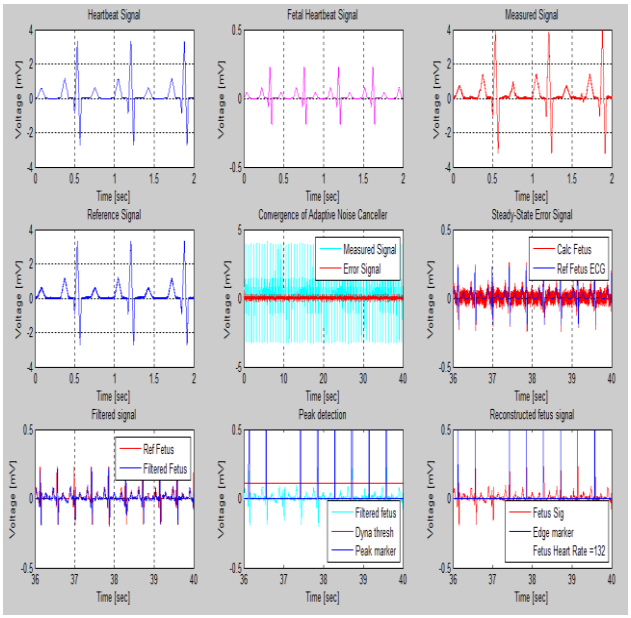
Where 'N' denotes the number of samples. The ZCR estimate for the input is as shown in fig. after adding the random noise to the filtered signal.

D. *Detection of VTVF events*

Here, the detection of VTVF is done by comparing the ZCR of the input with a predefined threshold value. In this work, the input ECG signal is classified as VTVF and non-VTVF by comparing ZCR value of the input with a pre defined threshold value. Detection is done by identifying the number of peaks that crosses the threshold. Here the threshold value is defined by using an adaptive filter.

The detection rule is defined as

Output = { VTVF episode, ZCR < ZCRth ; Non-VTVF, otherwise.



IV. RESULTS AND DISCUSSIONS

Here, the effectiveness of the proposed method is done based on the addition of random noise and zero-crossing rate feature.

The measured signal is obtained from heartbeat and fetal heartbeat signal. The error between the measured and fetal heartbeat signal is considered as the measured signal. The measured signal is compared with the reference signal. The error signal is shown in fig 5. The error signal thus obtained is considered as calculated fetus signal. The obtained calculated fetus is compared with reference fetus shown in fig 6.the obtained calculated fetus is filtered to identify the peaks. The filtered fetus and reference fetus are shown in fig 7.

A dyna threshold is defined by using an adaptive filter. The numbers of peaks in the filtered fetus crossing the dyna threshold are detected by peak detection.

The heart rate is calculated by edge marker and peak marker in the fetus signal. The calculated heart rate indicates 133 beats per minute indicating that it is a fetal heart beat signal and requires immediate treatment.

CONCLUSION

This is a simple robust method for detecting VTVF events by using random noise and zero crossing rate information. The proposed method consists of DFT based external noise removal, Sgolay smoothing filtering, addition of random noise, zero crossing rate (ZCR) estimation and detection rule. The existing detection methods are based on the

combination of morphological, spectral, time-frequency, neural networks, and support vector machines (SVM), fuzzy neural networks. The proposed method when compared with the existing methods can achieve better detection rates.

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