Classification of Atrio-Ventricular Reentrant Tachycardia using Intracardiac Signals

Wajeeha Nafees, Bushra Riaz, Nauman Razzaq, Wardah Iftikhar, Tahir Zaidi

Abstract— **Electrophysiology study (EPS) has been serving as a diagnostic and curative tool for rhythm-related cardiac diseases for more than few decades now. Clinical EPS requires intense knowledge of numerous protocols and run-time analysis of various parameters in order to find the root-cause of the problem. The Intracardiac Electrograms available during EPS are investigated for abnormal activations. A particular sequence of the abnormal activations hints to a specific disease. This crucial diagnosis requires a high level of expertise. In this paper, an automated algorithm to detect AtrioVentricular Reentrant Tachycardia (AVRT), a type of Supraventricular Tachycardia (SVT), has been proposed to assist the beginners and support the decisions of the experts of EPS. After studying the underlying medical mechanisms, exploring the electrograms formed by reentrant circuit and analyzing temporal progressions of cardiac activations of AVRT, a novel algorithm exploiting the above relationships is presented. The algorithm detects AVRT with 87.06% sensitivity.**

I. Introduction

ACCORDING to a survey held by World Health Organization (WHO), cardiac diseases are the primary cause of death around the globe[1]. Cure of cardiac diseases via clinical Electrophysiology study (EPS) has gained popularity recently and EP has become an essential mainstream specialty within cardiology. EPS deals with the electrical activity of the heart. Physicians insert specialized catheters within heart chambers to study these activities. The electrode readings are collected in the form of Intracardiac Electrograms (ICEGs). Temporal relationships between signals obtained from different chambers/catheters are used to diagnose the type of disorder. Automation of the diagnostic procedure is of great importance in clinical EPS as it saves time and reduces the chance of human errors. This paper describes the automation of the arrhythmia detection process.

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Automated arrhythmia detection algorithms have been developed extensively for surface electrocardiograms (ECG) [2], [3]. The existing literature also includes algorithms based on ICEGs developed for usage in Implantable Cardioverter Defibrillators (ICD) [4]. However, programming routines specifically meant for clinical EPS are very scarce.

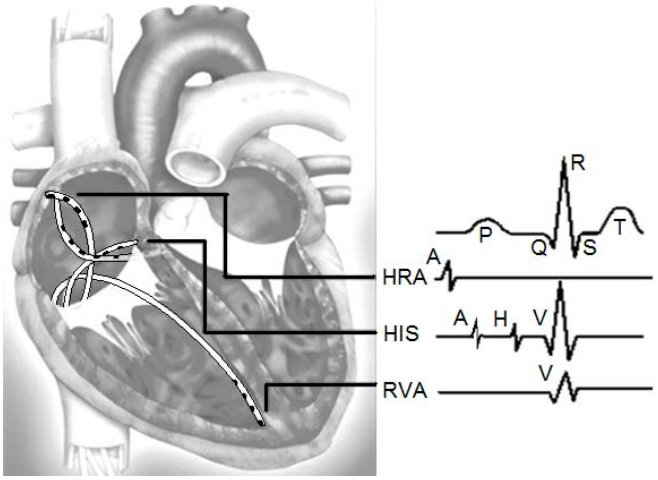

Fig.1. ICEG recorded by catheter

The key concept behind arrhythmia detection algorithms is the temporal relationships of the feature points within the electrograms under consideration. Classification of arrhythmias based on ICEGs requires the analysis of the onsets of characteristics waves: Atrial depolarization wave (A), His bundle depolarization wave (H) and Ventricular depolarization wave (V) as shown in Fig.1. The first waveform in Fig. 1 is the ECG signal and the lower three waveforms represent the intracardiac signals. Accuracy of classification algorithms is directly related to the extent of noise removed from these signals. In clinical EPS, one encounters signals subjected to various types of noise. Since ECG and ICEGs both represent electrical activity of the heart, filtering techniques applied on the ECG signals can be adapted and applied to the ICEGs [5]. Noise sources that corrupt the clinical EP signals are similar to those affecting the ECG signals. Noise removal techniques for electrical signals of the heart range from simple FIR filters to IIR filters, moving average filters to windowing methods and median filters [6]-[8]. Wavelet filters and Savitzky-Golay (S-G) filters have also been employed for the purpose of noise removal [9]-[11]. The shape of the characteristic waves in ICEGs differs from one patient to another, so

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morphological analysis on these signals is not a suitable method.

After pre-processing, the next phase of arrhythmia detection algorithm is the feature extraction. Feature-point extraction routines used for ECG signals extract the P, QRS, and T waves. QRS complex detection methods involving slope of the complex, pattern recognition method and pole-zero models with certain modifications may bear fruitful results in feature extraction for ICEGs [12]-[14]. Envelope detection can be used for the purpose of feature point extraction [15]. Arrhythmia classifiers have been developed which make use of the properties of the cardiac signals defined in time-domain and frequency-domain [16]. But in clinical EPS, doctors use timing information of the characteristic A, H and V waves to manually diagnose the disease and that is why time-domain analysis forms the foundation of this research. The approach presented in this paper uses adaptive thresholding techniques in combination with envelope detection for the localized extraction of feature points. For smoothing of the noisy signals, S-G filters have been employed.

The paper is organized in the following way. The detailed description of the different steps and the working involved in the automated detection approach is given in section II. Section III discusses the results of the proposed algorithm. Conclusion and future recommendations related to this research work are given in section IV.

II. Methodology

A. Overview of Algorithm

Automated detection of a cardiac disorder greatly depends on the accuracy of extraction of the feature points. Feature point extraction refers to estimation of the correct starting point (onset) of the A, H and V waves in multiple catheter recordings. Accurate detection will be possible when there is minimum noise in the input signals. The general idea of the algorithm is given in Fig. 2.

Fig. 2. Algorithm stages

B. Pre-processing

The pre-processing block is used to refine the noisy signals without loss of signal characteristics. Amplitude of the H wave is very small as compared to A and V waves, and because of this reason, inappropriate filtering will result in distortion of H waves. Some of the filters, like the median filter [17], were rejected purely on the basis that the H wave was completely eliminated in the filtrate. If noise removal is achieved using generic FIR filters then the signal tends to expand in time domain. Likewise if generic IIR filters are used then the waveform suffers from ringing/ripple effect. Alternatively, S-G filter provides us a suitable choice [11].

The S-G filter is a type of FIR filter that performs smoothing operation by using least-square polynomial fitting technique. The advantage of this technique is that it retains the height and width of the waveform peaks [18]. Also, impulse response of these filters is symmetric so frequency response is purely real. In essence, they perform a least-squares fit of the signal in such a way that computing the fitting polynomial p(n) of degree N at a central point in the data batch is equivalent to convolving the input with a fixed impulse response. The fitting polynomial p(n) is given as,

$$p(n) = \sum_{k=0}^{N} a_k n^k \ . \qquad (1)$$

In (1), a_k's are the polynomial coefficients. The luxury of using S-G filters is that the fitting polynomial depends on the size of the data batch (2M+1) and degree (N) of the polynomial but is independent of the actual values of input signal. This eliminates the need for calculating the polynomial for each new data set and the polynomial is calculated just once at the beginning of the smoothing operation as described in [18]. The S-G filter designed for smoothing of ICEGs in this approach had M=7 and N=2. Fig. 3 represents the input and output of the S-G filter implemented in this paper. The image is magnified to show how S-G filters preserve the height of the H wave.

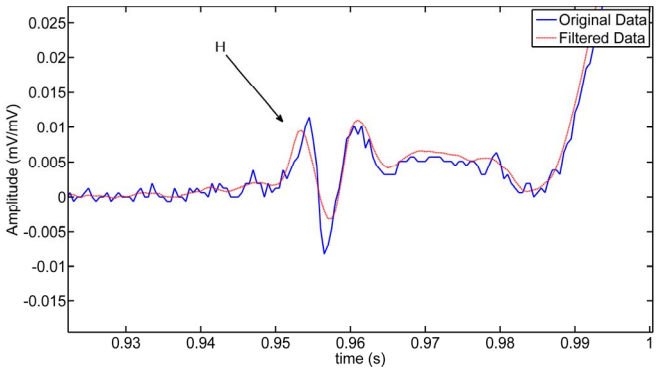

Fig. 3. Comparison of S-G Filter input and output

C. Feature Extraction

Multiple catheters can be inserted in the human heart for EP studies. But for the scope of this research we are only considering the recordings from three catheters labeled as the High Right Atrium (HRA), His Bundle (HIS) and Right Ventricular Apex (RVA) as shown in Fig. 1. HRA catheter records the deflections of the right atrium. The RVA catheter records the deflections of ventricular depolarization. The HIS catheter is placed along the junctional area of the atria and ventricles near the His bundle and it can record deflections of atrium, ventricles and the bundle of His [19].

1) HRA and RVA Catheter: Since the amplitude of A wave on HRA (A_{HRA}) and V wave on RVA (V_{RVA}) is much larger than the actual baseline, the onset of these waves is easier to find. a) The peak of the wave is located by thresholding techniques. The thresholds were found empirically. b) The onset of the wave is searched within a

30ms window from the peak, as in [15].

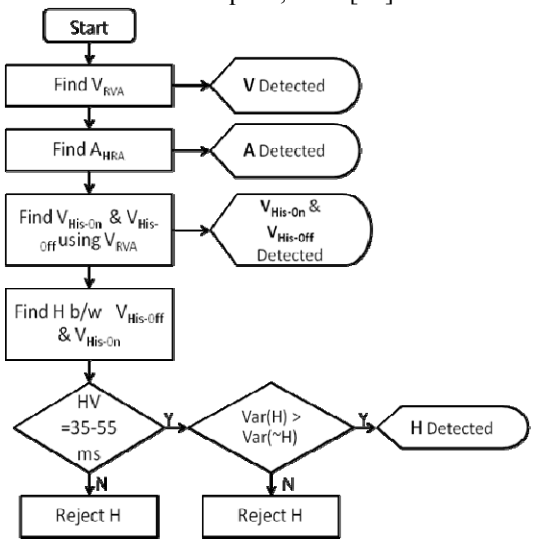

Fig. 4. Feature Extraction Algorithm

2) HIS Catheter: Next, locate the onset of characteristic waves on the His catheter. The His catheter recording contains the A_{HIS}, H and V_{HIS} waves as seen in Fig.1. a) The onset point of V wave on the His catheter, $V_{HIS\text{-}on}$, is searched in a 20 ms window around the V_{RVA} onset, as the ventricular depolarization is recorded at almost the same instant in RVA and His catheters. b) The offset point of V wave on His catheter, $V_{HIS\text{-}off}$, corresponding to each ventricular depolarization is then searched. c) The H wave is then searched in the window between the offset point of one V wave and onset point of next V wave on the His catheter electrogram. Envelope detection is used for this purpose [15]. d) Because the H wave is so small in amplitude, there is chance of its onset point being detected wrongly. Therefore, the starting point of the window for detecting H wave is adjusted from $V_{HIS\text{-}off}$ to $V'_{HIS\text{-}off}$ as given by (2).

$$V'_{HIS-off} = 0.5*(V_{HIS-off} + V_{HIS-on}) \qquad (2)$$

e) After locating H wave onset, it is subjected to a series of checks to further reduce the possibility of false detections. The first check disregards any H wave onset detected too near or too far from the $V_{HIS\text{-}on}$ location. H wave onset points which correspond to an HV interval outside the range 35-55ms are rejected [19]. f) The second check is associated with the variance of the signal. Here the main idea is same as that used by doctors, i.e. if the recording is too noisy then proper decisions cannot be made based on that; so that particular recording is discarded and a new recording has to be acquired. Likewise, we say that if the signal contains too much noise, then it is very likely that the detected onset point of the H wave is faulty. To incorporate this theme into our algorithm, HIS catheter electrogram within the local search window is divided into n parts. It is assumed that the H onset lies in the n^{th} part of this window. Variance of this part will be greater than other n-1 parts. If variance of the region not containing H onset is found to be higher than the region detected to contain H onset, then there is possibility of wrong detection and therefore H wave onset is rejected for this activation. Feature extraction algorithm is summarized in Fig. 4.

D. Arrhythmia Detection

Arrhythmia is a condition in which heart beats too slowly, rapidly or just irregularly. On the basis of heart rhythm rate, arrhythmias are divided into two categories: Bradycardias (slow) and Tachycardias (fast). The latter, being more life-threatening, has been taken up in this study. Doctors broadly classify tachycardia on the basis of their origin in the heart muscles. Tachycardias originating from the ventricles are called ventricular tachycardias (VTs) and those originating from regions above the ventricles are called supraventricular tachycardias (SVTs). SVTs are generally grouped depending upon the width of the QRS complex [20]. If QRS complex $\leq$ 120ms then it is called narrow complex tachycardia (NCT) [21]. Otherwise, it is termed as wide complex tachycardia. NCTs are further sub-divided in two sets based on whether the ventricular rate is regular or not. NCTs with regular ventricular rate are categorized as Atrial Tachycardias, Atrio-Ventricular Reentrant Tachycardia (AVRT) and Atrio-ventricular Node Reentrant Tachycardia (AVNRT). The classification scheme is shown in Fig. 5.

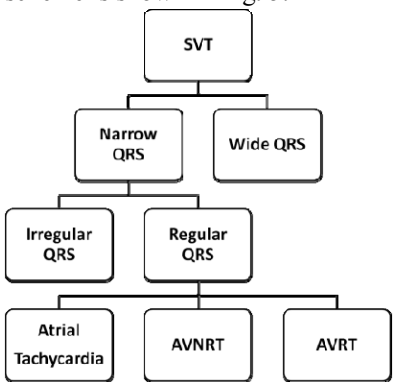

Fig. 5. SVT Classification

During EP study, a patient undergoes multiple protocols to determine the mechanism of tachycardia. These protocols constitute different types of external electrical stimulation delivered to the heart. In fact tachycardias are induced in the heart as a result of these stimulations. Once heart enters the state of tachycardia, the atrial and ventricular activations are studied to diagnose the cause of the problem. In AVRT, the electrical impulses flow in a continuous loop. One limb of the loop is the normal AV nodal pathway and the other one is an accessory pathway. During AVRT the atria and ventricles contract sequentially. The parameters used to distinguish AVRT from other tachycardias can be found in [19], [20], [22]. These parameters have been incorporated in the proposed algorithm in such a way that for each criterion the possibility of AVRT is ruled in/out as shown in Fig. 6.

If the ratio of atrial depolarization to ventricular depolarization is not 1:1, then the tachycardia cannot be AVRT. If atrial and ventricular depolarization occurs simultaneously then it is a characteristic of another type of tachycardia (AVNRT). For AVRT, the V-A time interval is

less than the A-V time interval. However, the V-A interval should be >= 45ms.

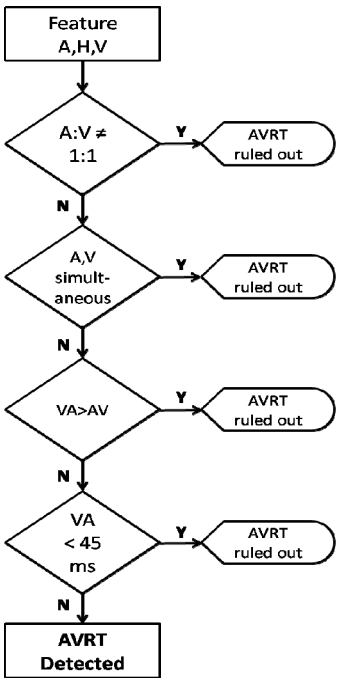

Fig. 6. AVRT Detection

III. Results and Discussion

The algorithm developed was tested on data from 15 patients collected from an EP lab. The data contained more than 4500 useful activations. The onsets of the feature points were marked by the doctors for comparison with the digitally calculated points and validation of feature extraction algorithm. If the digitally calculated points were within ±10ms of the corresponding points marked manually then they were considered as true positives. Anything detected beyond this limit was considered as false positive. Activations that are missed out are termed as false negatives. Having a large number of false negatives in the result is not as critical as having a large number of false positives. That is why a lot of stress was laid on the reduction of false positives in the previous sections. Table 1 shows the results of the feature extraction algorithm. The sensitivities of V, A and H waves found to be 99.63%, 96.08% and 94.63% respectively.

Table 2 summarizes the results of arrhythmia detection phase. When the heart is in normal sinus rhythm (SR), the algorithm does not wrongly classify it as any of the SVT, thus achieving 100% specificity; and removing the possibility of diagnosing a healthy rhythm as diseased one.

The results show that performance of the proposed algorithm for arrhythmia detection in clinical EPS is comparable to manual diagnostic procedures.

IV. Conclusion

Automated detection of arrhythmias can facilitate doctors in clinical EPS by saving time for manual calculations and making diagnostic procedures easy by indicating type of arrhythmia. The algorithm presented in this paper identifies A, H and V waves in ICEGs and diagnoses a single arrhythmia with high accuracy. The approach given in this paper can be modified to detect other types of arrhythmias and ultimately lead to the development of a general arrhythmia classifier based on intracardiac signals.

TABLE I
Results of Feature Extraction Algorithm

Feature	Total Activations	True Positives	False Positives	Sensitivity (%)
V Wave	2156	2149	0	99.63
A Wave	1230	1182	0	96.09
H Wave	1192	1128	8	94.63

TABLE II
Results of Arrhythmia Detection

Rhythm	Total Activations	Correctly Detected	Sensitivity (%)
SR	353	353	100
AVRT	309	269	87.06
Other SVTs	199	198	99.5

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