Short Paper

R Peak Detection in ECG signals using Chebfun

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***Abstract*—Automatic patient monitoring for cardiac diseases has been one of our prime requirements, and would certainly continue to be in the future years. Electrocardiogram (ECG) is highly adopted as a primary diagnostic tool for cardiovascular diseases. Heart monitoring requires extraction of important features from the ECG signal. R peak detection is necessary to determine abnormal heart function diseases including Arrhythmia, Myocardial infarction, etc. There have been several methods like Pan Tompkins, Wavelet Decomposition, etc. using which R peaks are detected. In this paper, we explore Chebfun for computing the R peaks and compare its performance with the existing standard methodologies viz. Variational Mode Decomposition(VMD) and Pan Tompkins.**

Keywords: R peak detection, ECG, Chebfun, Variational Mode Decomposition, Pan Tompkins

I. Introduction

Electrocardiogram(ECG) represents the electrical activity of heart muscle over time [1] which occurs due to polarisation of heart chambers.ECG signals are segmented into P wave, QRS complex, ST segment and T wave. Feature extraction is an important part in ECG analysis. [9] where components of prime importance to an analysis are extracted.This is to optimise the requirements in resource and computations. In analysis of complex data, one of the major problems stems from the number of variables involved. Analysis of large number of variables requires huge amount of memory and computation resources [16]. Moreover, it may take a long time to train the classifier, or may even overfit the algorithm over training samples and generalize poorly over new samples. Choosing the right features gives access to necessary information.

The R wave amplitude is maximum due to high voltage required to depolarize the muscle as ventricular walls are thick in nature. The R peak of the QRS complex is of paramount importance in ECG analysis [9] as it is an indicator of any heart related ailments.

The detection of R peaks has been carried out using several standard methods. Pan-Tompkins is one such famous algorithm [1]. This standard algorithm is easy to use and takes less time to detect the R peaks, but complexity of the algorithm is high and peak detection accuracy is moderate [1] [9].

A. Chebfun

Chebfun is an open source package compatible with MATLAB for numerical computations providing upto 15-digit accuracy [2]. Implementation of Chebfun is based on polynomial interpolation of Chebyshev points, enabling it to represent smooth functions effectively with minimal number of data points. In cases where functions are piece-wise smooth, Chebfun concatenates the smooth pieces, each called a 'fun', with its own polynomial representation. ECG signals, being piecewise smooth, can be effectively represented using Chebyshev points which reduces the computational complexity. The R peaks are detected using the inbuilt functionalities of local extrema of Chebfun.

1) Chebyshev Points: Chebfun uses polynomial interpolation at specific points known as Chebyshev points. To understand Chebyshev points, let us consider the interval of [-1,1], and n which is a positive integer. The n+1 points $\{z_j\}$ called (2n)th roots of unity lie on the closed upper half of the unit circle in the complex plane at equispaced angles θ_j ranging from 0 to π, as shown in Fig. 1. [2]. The Chebyshev points associated with the n+1 points are the real parts of these points represented as

$$x_j = Rez_j = \frac{1}{2}z_j + z_j^{-1}, 0 \leq j \leq n \quad (1)$$

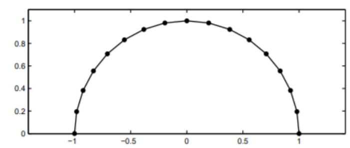

Fig. 1: Equispaced Chebyshev points on the upper half of the unit circle [2]

II. Related Works

In the literature survey, we came across conventional methods used to detect R peaks in an ECG, such as methods based on derivatives [12], digital filters [1] [11], Wavelet transform [6], Empirical Mode Decomposition (EMD) [12], and neural networks approach [15].Generally, most of the methods require a pre-processing stage where different signal processing techniques are applied to suppress the noise in the signal [17]. In [1], the results depend on the size of the moving window and the filter bandwidth. In [12], the EMD based approach taken for R-peak detection has the drawback of having to choose the right Intrinsic Mode Function (IMF). In EMD, level of decomposition of the signal is sensitive to noise level. Hence, it can be carried out using a trial and error method only. This drawback of EMD is handled in VMD. To

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denoise ECG effectively, the noisy ECG signal is decomposed into modes, also called Variational Mode functions (VMFs) using Variational Mode Decomposition(VMD) [5] where noise is filtered out from the modes. The modes are compact around a central frequency which is computed during decomposition of the original signal.

In [18], Chebyshev interpolation has been used to improve the performance of epoch extraction from telephonic speech signals. Similarly, in [14], ECG signals have been approximated using Chebyshev interpolation for effective representation and storage of huge volumes of the signals. Chebfun has not been explored much with respect to R peak detection in ECG signals, hence our attempt is to draw a comparison between the established techniques of VMD and Pan Tompkins against Chebfun.

III. Dataset Description

In our work, we have used the MIT-BIH Arrhythmia database. The open dataset has 48 two channel half-hour recordings,and a sampling rate of 360 samples per second per channel with 11-bit resolution over a 10 mV range [3]. For every signal we have analysed 10,000 data points due to restricted computational resource availability.

IV. Methodology

A. Data Pre-processing

The dataset consists of 2 channels of data and annotations [3] which is extracted using the WFDB toolbox [8].The first channel has been used in our experiments since the second channel was found to be noisy. For Chebfun, no data preprocessing has been applied for our experiments. For VMD, the mode signals are normalized to remove the P-wave and T-wave from the decomposed signal which are unnecessary in R peak detection.The normalized signals are squared to obtain only R peaks. For Pan Tompkins, the algorithm in itself has a preprocessing step to denoise and enhance R peaks.

B. Proposed Architecture

In this work, we have used VMD, Pan Tompkins and Chebfun individually, to compare the efficiency of R Peak detection. In Chebfun, the data was directly fed without any preprocessing and the results were calculated.

R peaks are detected in Chebfun using local maxima or minima (for inverted ECG signals) points of the signal. Local extrema of smooth functions is obtained by computing the zeroes of the derivative. Alternatively, it can also be found using the 'minandmax' function in Chebfun [2]. The R-peaks are obtained from the extrema by choosing appropriate threshold values to filter out the extrema points detected due to artefacts (False Positives). Fig 2 depicts the methodology followed for detection of R peaks using Chebfun. For VMD, 5 modes are used for our experiments [7] and the values for bandwidth have been tuned experimentally.

The parameter tuning is done based on True Postive(TP), False Positive(FP) and True Negative(TN) metric values, focusing on minimising number of False Positives.

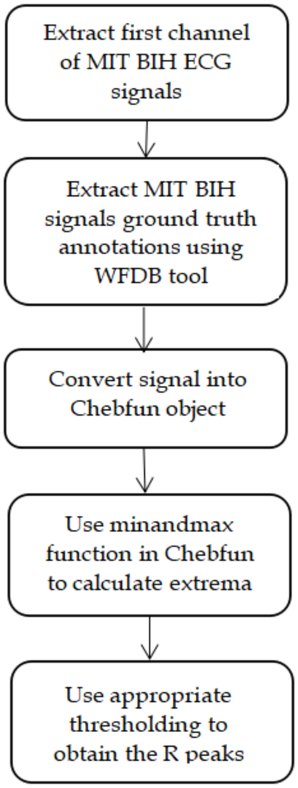

Fig. 2: Proposed methodology using Chebfun

V. Experimental Results and Discussion

The MATLAB in-built functions along with the Chebfun package was used for the implementation of our models. The Chebfun experiments were executed on an 12GB RAM, Intel Core i5, 10th Gen machine with 512GB SSD.

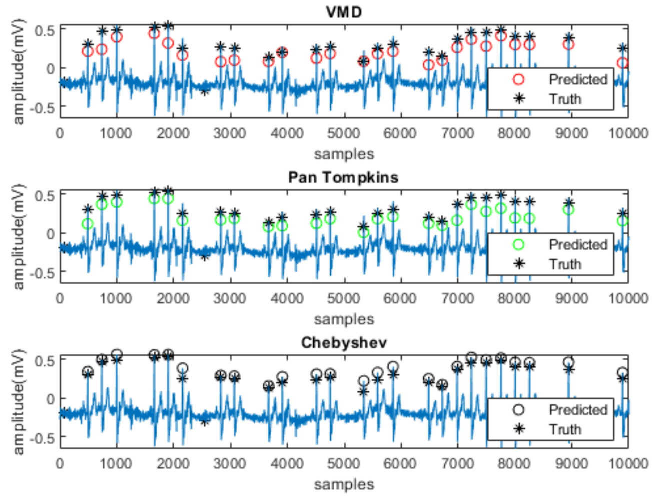

Fig. 3: Sample result of record 232 depicting comparison of the proposed method with existing methods

TABLE I: Evaluation metrics for R-peak detection using Chebfun

Record	True Positive	False Positive	False Negative	Detection Error Rate	Sensitivity	Positive Predictivity	Accuracy
100	33	0	1	0.0303	0.9705	1	0.9705
101	31	0	0	0	1	1	1
102	29	1	3	0.137	0.906	0.966	0.8787
103	30	1	1	0.0667	0.9677	0.9677	0.9375
104	37	67	1	1.837	0.9737	0.3558	0.3524
105	38	0	1	0.0263	0.9744	1	0.9744
106	31	0	2	0.0645	0.939	1	0.939
107	31	1	2	0.0968	0.9394	0.9688	0.9118
108	30	18	1	0.6333	0.9677	0.6250	0.6122
109	38	7	7	0.3684	0.844	0.844	0.7308
111	32	0	1	0.0313	0.9697	1	0.9697
112	41	0	1	0.0244	0.9762	1	0.9762
113	27	0	1	0.037	0.9643	1	0.9643
114	25	6	1	0.28	0.9615	0.8065	0.7813
115	29	0	1	0.0345	0.9667	1	0.9667
116	36	1	1	0.0556	0.973	0.973	0.9474
117	23	0	1	0.0435	0.9583	1	0.9583
118	27	0	5	0.1852	0.8438	1	0.8438
119	32	18	1	0.5938	0.9697	0.64	0.6275
121	27	0	2	0.0741	0.871	1	0.871
122	42	3	1	0.0952	0.9767	0.9333	0.913
123	22	0	1	0.0455	0.9565	1	0.9565
124	23	0	1	0.0435	0.9583	1	0.9583
200	41	8	2	0.1	0.9535	0.8367	0.8039
201	40	0	1	0.025	0.9756	1	0.9756
202	24	0	1	0.0417	0.96	1	0.96
203	52	26	3	0.5577	0.9455	0.6667	0.642
205	41	0	1	0.0244	0.9762	1	0.9762
207	28	24	1	0.8929	0.9655	0.5385	0.5283
208	50	17	1	0.36	.9804	0.7463	0.7353
209	43	0	1	0.0233	0.9773	1	0.9773
210	44	5	1	0.1136	0.9778	0.89	0.88
212	42	0	1	0.0238	0.9767	1	0.9767
213	51	0	1	0.0196	0.9808	1	0.9808
214	34	0	2	0.0588	0.9444	1	0.9444
215	50	3	1	0.08	0.9804	0.9434	0.9259
217	33	0	1	0.0303	0.9706	1	0.9706
219	33	0	1	0.303	0.9706	1	0.9706
220	34	0	0	0	1	1	1
221	36	3	1	0.111	0.973	0.9231	0.9
222	36	3	2	0.1389	0.973	0.9474	0.9231
223	35	1	1	0.0571	0.9722	0.9722	0.9459
228	39	3	2	0.1282	0.9512	0.9286	0.8864
230	38	0	4	0.1053	0.9048	1	0.9048
231	29	0	2	0.069	0.9355	1	0.9355
232	25	0	2	0.08	0.9259	1	0.9259
233	50	0	1	0.02	0.98	1	0.98
234	42	0	1	0.0238	0.9767	1	0.9767

A. *Evaluation Metrics*

We have chosen the value for location of R peak to be 10% of the sampling frequency of the ECG signal based on literature [15].

Based on the values of False Positives, False Negatives and True Positives from the confusion matrix, performance of the R-peak detection is evaluated. Detection Error Rate (DER), Sensitivity, Precision or Positive Predictivity and Accuracy are the evaluation metrics used [15].

B. *Results*

Experimental results for Chebfun are provided in Table 1. A comparative study of Chebfun, VMD and Pan Tompkins methods for the most noisy signals has been provided in Table 2. For an effective understanding of computational aspects, the memory usage and the time for execution has also been compared for the three methods. A visual comparison of the metrics Sensitivity, Detection Error rate, Predicted Positivity, Accuracy for the records mentioned in Table 2 has been shown in Fig.4.

Performance comparison of the proposed R peak detection algorithm using Chebfun has been shown in Fig.3 for a sample ECG record 232 for which the proposed method has lesser number of FP compared to the existing R peak detection algorithms.

TABLE II: Evaluation of the algorithms

Record	VMD				Pan Tompkins				Chebfun			
	DER	PP	SE	Acc	DER	PP	SE	Acc	DER	PP	SE	Acc
104	0.111	0.947	0.947	0.9	0.375	0.842	0.842	0.727	1.837	0.355	0.973	0.352
105	0.025	1	0.975	0.975	0.25	1	0.975	0.975	0.026	1	0.974	0.974
109	0	1	1	1	0	1	1	1	0.364	0.844	0.844	0.730
201	0.024	1	0.976 0	0.976	0.024	1	0.976	0.976	0.025	1	0.975	0.975
203	0.191	0.903	0.921	0.839	0.06	0.96	0.98	0.94	0.557	0.667	0.945	0.642
208	0.12	0.945	0.94	0.88	0.272	0.88	0.88	0.78	0.36	0.746	0.980	0.735
210	0.04	0.977	0.977	0.955	0.095	0.954	0.954	0.913	0.113	0.89	0.977	0.88
217	0.029	1	0.971	0.971	0.29	1	0.971	0.971	0.030	1	0.970	0.970
228	0.05	0.974	0.974	0.95	0.108	0.948	0.948	0.902	0.128	.928	0.951	0.886
232	0.115	0.963	0.928	0.896	0.115	0.963	0.963	0.896	0.08	1	0.926	0.926
Avg Memory(MB)	2221				2628				2528			
Avg Execution Time(s)	1.88				0.6				2.96			

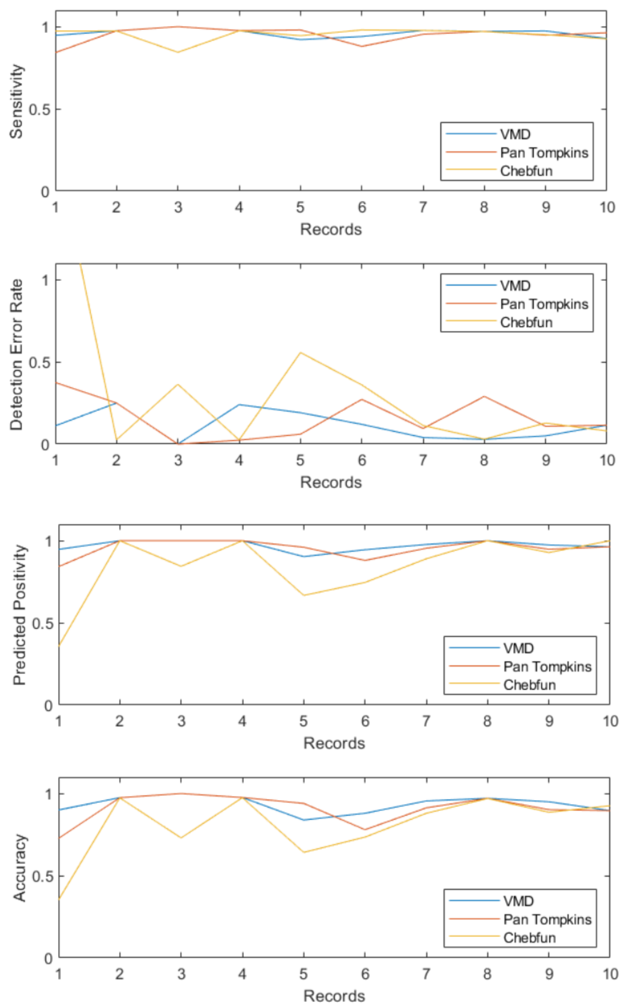

Fig. 4: Visual comparison of Evaluation Metrics for VMD, Pan Tompkins and Chebfun

C. Discussion

In the MIT-BIH dataset, ECG records 104, 105, 108, 200, 203, 210, and 228 contain high frequency noise and artefacts. Sudden changes in signal and baseline wander is observed in records 108, 111, 112, 116, 201, 203, 205, 208, 210, 217, 219, 222, and 228. Records 201, 202, 203, 219 and 222 have varied irregular rhythmic patterns. Signal 104 and 203 have high grade artefacts resulting in reduced performance of R peak detection using Chebfun. This reflects in our experimental results as well (Refer to Fig 4). Record 109, 112 have a global maximum which differs drastically from other peaks. Hence, the threshold value had to be varied accordingly. Record 108 has inverted peaks for which global minimum based threshold was set in the range of 30-70 percentage of the global minimum.

The comparative study of the three methods for R peak detection have shown that Chebfun is efficient for predicting R-peaks in ECG even without any pre-processing, provided the signal peaks are entirely positive or entirely inverted, since R peaks are predicted based on local maxima and minima values. For records like 200 and 203, a healthy trade-off between FNs and FPs has to be carried while identifying the optimal threshold value, since many intermediate local maxima or minima also get detected which are not the R-peaks. Other scenarios observed are in records 118 and 121 where some positive peaks have negative amplitude values. Hence, Chebfun would be more efficient for one-sided spectrum signals or signals with a clear segregation of positive and negative peak values.

VI. Conclusion and Future Scope

From the experimental results obtained using Chebfun without any data pre-processing are almost at par with other standard algorithms which undergo data pre-processing. It is observed that Chebfun is a simple, yet an efficient method to detect R Peaks provided the signals have less artefacts. Thus, to reduce the FPs and FNs, Chebfun needs denoising of the input signal as a part of preprocessing. VMD, on the other hand, involves a tedious process of parameter tuning along with data preprocessing. It is noted that the evaluation metrics for VMD, Pan Tompkins and Chebfun lie in a similar range for less noisy signals.

As a future scope, we wish to observe performance of chebfun on a preprocessed input signal, and also explore other functionalities of Chebfun, and also to observe its performance after preprocessing the input signal.

VII. Acknowledgement

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