Identification of Sudden Cardiac Arrest (SCA) using Modified Wavelet Transform

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ABSTRACT
Electro Cardiogram (ECG) is used to measure and diagnose electrical activity of heart. R peak detection from ECG signal is our main goal. It is the basic mark for identification of different arrhythmias. In this paper, R wave extraction is performed by using Wavelet Transform for the identification of Sudden Cardiac Arrest (SCA). Sudden cardiac death (SCD) is a global health issue. Analysis revealed that millions of people all around the world die as the result of SCD. We need to purpose a suitable and accurate method for its identification. Modified Wavelet Transform method is used for the extraction of R peaks from ECG signal and then RR interval is extracted from ECG signal with the help of MATLAB software to identify SCA. Here a brief comparison is performed to identify SCA patient with Normal Patient. The MIT BIH database has been utilized for evaluating the algorithm.

CCS Concepts
• **Theory of computation → Pattern matching.**

Keywords
ECG signal; R-wave; QRS complex-R interval; wavelet transform; Peak detection; Sudden Cardiac Arrest.

1. INTRODUCTION
Electrocardiogram (ECG) represents the electrical movement of the heart demonstrating the contraction and Relaxation of heart muscle. ECG is the diagnostic tool for the identification of electrical activities of heart. R peak detection form ECG signal is responsible for its identification. If arrhythmias are not treated properly then it causes sudden cardiac death [1]-[2].

In the previous couple of decades few techniques are evolved for ECG analysis and arrhythmia detection to enhance its accuracy and sensitivity. These methods include Wavelet coefficient [3], Autoregressive Modelling [4], RBF Neural Networks [5], self-organizing map [6], and fuzzy c-means clustering techniques [7]. Figure1 shows the typical ECG waveform with R-R interval and basic waves such as P, Q, R, S, T and U [8] .

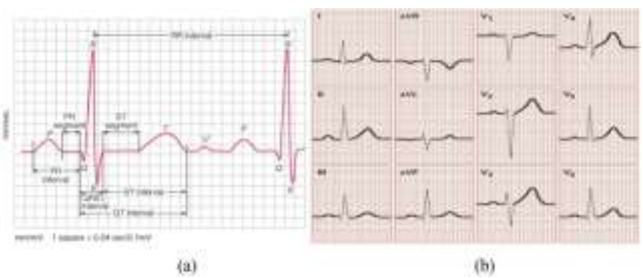

Figure 1. ECG signal generation using MATLAB and its Real image.

In the literature, ECG signal processors operate at different frequency ranging from 0.25 Hz to 400 kHz [9]–[12]. ECG Signal detection includes elimination of different noises like baseline drift [10]-[14], waveform detection [15]-[17], feature extraction [18], and heart rate classification [19]-[28]. Among the several techniques investigated in the literature are included time domain analysis [29]–[32], statistical approach [33]–[35], hybrid features [36], [37], frequency-based analysis [38], and time–frequency analysis [39]–[41] for feature extraction of ECG signals. These feature extraction tools are combined with classification algorithms such as linear discriminants [29], [30], [42], neural networks [35], [39], [41], neuro-fuzzy approach [43], and support vector machines (SVMs) [33], [34], [36], [44]-[48] to provide efficient detection and analysis of cardiac abnormalities.

Heart Rate classification techniques were also used by several researchers, some of them have used waveform features extraction techniques [19]-[26] and some have used wavelet transform [23]-[24] method for its extraction. Cardiac arrest occurs when beating of heart and its electrical activity stops [52]. Sudden Cardiac Death (SCD) refers to death within 2 h of onset of symptoms or during sleep due to a cardiac cause [53-65].

Figure 2 shows the variation of Heart Rate (HR) of Normal subject obtained from Matlab software by using MIT BIH database.

ICBIP '17, August 23–25, 2017, Kitakyushu, Japan

ACM ISBN 978-1-4503-5268-0/17/08…$15.00
https://doi.org/10.1145/3133793.3133799

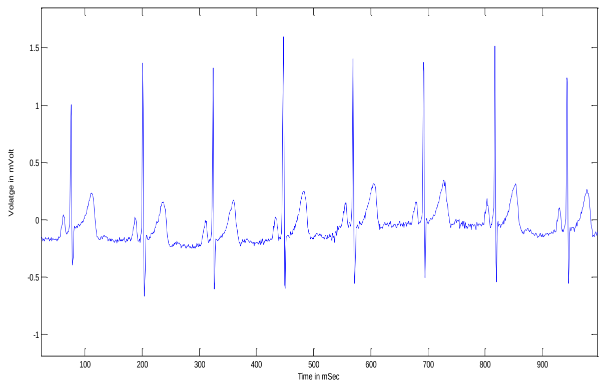

Figure 2. ECG signal of Normal Person generated using Matlab.

Figure 3 highlights the HR variations in the presence of SCA .A holter based SCD signal is utilized for evaluating the results. MIT BIH database is used for SCD signal and Matlab is used for the detection of SCA using Modified Wavelet Transform.

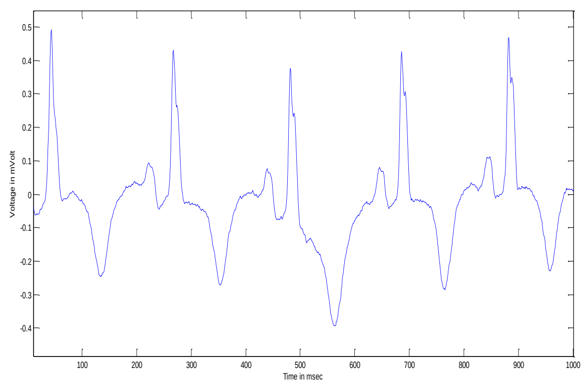

Figure 3. ECG signal of SCA Patient generated using Matlab

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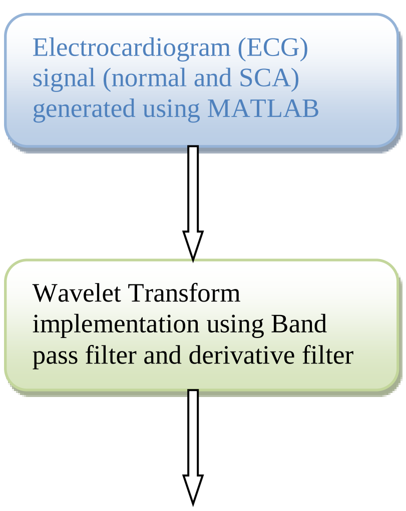
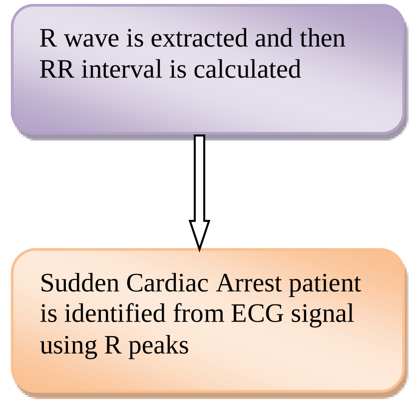
2. METHODOLOGY

Flow Chart for the identification of SCA using Modified Wavelet Transform is demonstrated below:





3. RESULTS

Fig 4-5 show the implementation of modified Wavelet Transform algorithm for R-wave detection and shows the original Real Time ECG signal generation using MATLAB. Band pass filter is used to remove base line wander and muscle noise and filtered signal is squared to highlights the R wave [50]. And Then Threshold Filter is applied to find Peaks of R-wave from ECG signal [13] and R-R interval is determined. Figure 4 and 5 highlights the R wave detection from ECG signal of normal and abnormal (SCA) person with the help of Wavelet Transform and Pan-Tompkins algorithm. Here 5000 samples of normal person ECG and 5000 samples of SCA patient ECG are taken for performing our analysis

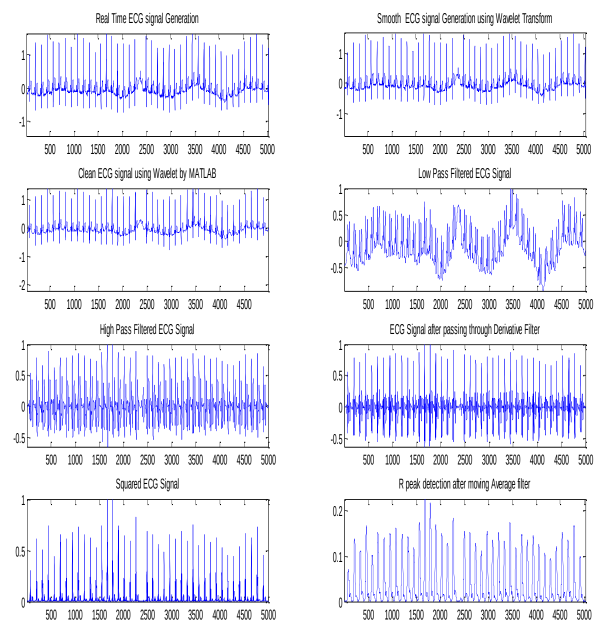


Figure 4. Implementation of Modified Wavelet Transform algorithm for R-wave detection from normal person ECG.

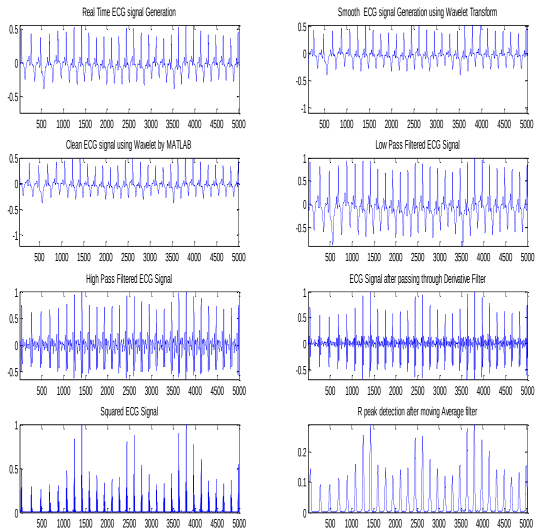


Figure 5. Implementation of Modified Wavelet Transform algorithm for R-wave detection from SCA patient ECG.

Table 1 highlights the R-wave detection using MATLAB by the implementation of modified WAVLET TRANSFORM accurately by processing of normal person ECG. Here R peak location and its R-R interval are calculated and analyzed.

Table 1. R peak detection using Modified Wavelet Transform from 5000 samples of normal person ECG

SR #	R PEAK LOCATION	R-R INTERVAL
1	75	126
2	201	122
3	323	123
4	446	122
5	568	124
6	692	124
7	816	127
8	943	124
9	1067	126
10	1193	124
11	1317	121
12	1438	114
13	1552	113
14	1665	114
15	1779	116
16	1895	121
17	2016	121
18	2137	121
19	2258	234
20	2492	115
21	2607	117
22	2724	120
23	2844	120
24	2964	117
25	3081	121
26	3202	122
27	3324	120
28	3444	121
29	3565	120
30	3685	119
31	3804	120
32	3924	120
33	4044	117
34	4161	122
35	4283	122
36	4405	122
37	4527	124
38	4651	124
39	4775	124

Table 2 highlights the R-wave detection using MATLAB by the implementation of modified WAVLET TRANSFORM accurately by processing of Sudden Cardiac Death (SCD) person ECG. Here R peak location and its R-R interval are calculated and analyzed.

Table 2. R peak detection using Modified Wavelet Transform from 5000 samples of SCD patient ECG

SR #	R PEAK LOCATION	R-R INTERVAL
1	44	225
2	269	215
3	484	204
4	688	196
5	884	188
6	1072	177
7	1249	171
8	1420	167
9	1587	175
10	1762	168
11	1930	173
12	2103	171
13	2274	168
14	2442	167
15	2609	172
16	2781	170
17	2951	171
18	3122	172
19	3294	170
20	3464	166
21	3630	167
22	3797	171
23	3968	169
24	4137	171
25	4308	171
26	4479	171
27	4650	172
28	4822	169

Table 3 highlights the comparison of R-R interval detection of both normal and SCA person for 1000, 2000.3000,4000 and 5000 samples.

Table 3. Comparison of Normal person and SCD patient on the basis of no. of R peaks

Sr#	Category	No. of R peaks/samples
1	Normal Person	08/1000
2	SCA Patient	05/1000
3	Normal Person	16/2000
4	SCA Patient	11/2000
5	Normal Person	24/3000
6	SCA Patient	17/3000
7	Normal Person	32/4000
8	SCA Patient	23/4000
9	Normal Person	39/5000
10	SCA Patient	27/5000

4. DISCUSSION

After using Wavelet transformation, we can easily detect R wave. R-R interval is also calculated after R wave extraction .It is concluded from Table 3 that Number of R wave in case of SCD is less as compared to normal person.

5. CONCLUSION

It is concluded that Wavelet Transformation provide us accurate and efficient result regarding R-peak detection and its results are accurate. It is concluded that No. of R peaks in case of SCD is less than normal person R peaks .And R-R duration is more in case of SCD as compared to Normal person. Sudden cardiac arrest is easily detected and identified by performing this type of algorithm .

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