Evaluation and Comparison of R-Peak Detection Methods
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Abstract—ECG analysis is one of the frequently researched topics in the diagnosis of cardiac disease. Many methods have been proposed for detection of different features of ECG. Each has its own significance. This paper explains 4 different existing methods for detection of R peak and two methods for detection of other features (P, Q, S, T peaks). The most commonly used method Pan-Tompkins method, Successive Differentiation method, Empirical mode decomposition method and Wavelet transform method have been performed and their performance have been evaluated for different ECG morphologies on the basis of false positive and false negative. Wavelet transform has shown comparatively better results.

Key words: ECG, EMD, Pan-Tompkins Method

I. INTRODUCTION

Most of the technologies are focusing on noninvasive methods for disease prediction. Cardiac disease has been considered as the first cause of death of people in large amount. ECG analysis is the most researched topic because it is non-invasive and also represents different conditions and functions of heart. Automated ECG analysis has presently become an important area of biomedical research due to its rapid, accurate and reliable diagnostic ability and its wide application in the field of telemedicine [4]. There has been a continuous development of QRS detection algorithms in the past 20 years [2]. Many methods have been proposed in this field for automatic detection of different features of ECG. Different QRS detection algorithms available in literature are broadly classified as amplitude and derivative based, digital filter based, template matching based, nonlinear transformation based and wavelet based [4]. A new and effective approach was implemented using a histogram and improved genetic algorithm to search and detect the QRS regions [4]. Artificial Neural Network or Support Vector Machine is also used as a classifier to detect the QRS complex [4]. The main reason for failure of many methods is the physiological variability of ECG, presence of noises and the demand in embedded real time monitoring application. This paper explains four existing methods related to linear and nonlinear transformation and compares their performance on the basis of false positive and false negative. These methods have been tested on 40 data of MIT/BH database. A comparison table is made as a result showing the performance of each method. At last for concluding a table has been made showing the sensitivity and positive predictivity of the methods.

II. METHODS

ECG characteristic features detection method follows the basic flow as shown in the figure 1.

Fig 1: Basic Flow of ECG R-Peak Detection.

Major changes take place in the transfer function block of the diagram. Pan-Tompkins apply squaring function as a transform function, successive differentiation method uses differentiation, EMD method uses IMF and wavelet method uses wavelet transform.

A. Pan-Tompkins Method:

This method uses cascaded high-pass and low-pass filters to attenuate noise. Information about the slope of the QRS is obtained in the derivative stage. The squaring process intensifies the slope of the frequency response curve of the derivative and helps restrict false positives caused by T waves with higher than usual spectral energies. The moving window integrator produces a signal that includes information about both the slope and the width of the QRS complex [1]. In the last step, two thresholds are adjusted, the first one identifies peaks of the signal and the second is used when no peak has been detected by the first one in a certain time interval. In this case, the algorithm has to search back in time for a lost peak by using a threshold lower than the first one.

Fig 2: Block Diagram Pan-Tompkins Method.

B. Successive Differentiation Method:

First differentiation: This enhances the higher frequency signals (R-peak) in ECG and attenuates the lower frequency signal (P and Q peaks). Thus this helps in proper detection of R-peak present in ECG.

Second differentiation: This step further enhances higher frequency component present in the signal i.e. R-peak. Moving average is applied to obtain a signal reflecting the short-period power of the filtered ECG signal.
C. Empirical Mode Decomposition Method [3]:

Through a sifting process, the EMD can decompose the signal into a series of intrinsic mode function (IMFs). An IMF is defined as a function with equal number of extrema and zero crossings (or at most differed by one) with its envelopes, as defined by all the local maxima and minima, being symmetric with respect to zero [3].

Firstly EMD method finds the local maximum and minimum of the signal \( a(t) \). Then all the local maximum and local minimum are connected by a cubic spline curve as the upper envelope \( u(t) \) and the lower envelope \( l(t) \). The mean of the two envelope can be calculated as \( me(t) = (a(t) + u(t))/2 \) and subtracted from the signal, so:

\[
a(t) - me(t) = r_1(t)
\]

This process is referred as the sifting process. If \( r_1(t) \) do not satisfy the definition of the IMF, the sifting process will be performed again on \( r_1(t) \) until the first IMF \( g_1(t) \) satisfies the IMF condition. Take \( g_1(t) \) out of the original signal, the residue is:

\[
a(t) - g_1(t) = r_1(t)
\]

Because the residue still contains some useful information, it is taken as a new original signal and the sifting process is carried on as above. The residue of each sifting process is called \( r_1(t), r_2(t), ..., r_N(t) \). Then all the local maximum and minima of the signal are connected by a cubic spline curve as the upper envelope \( u(t) \) and the lower envelope \( l(t) \). The mean of the two envelope can be calculated as \( me(t) = (a(t) + u(t))/2 \) and subtracted from the signal, so:

\[
a(t) - me(t) = r_1(t)
\]

The complete flow stops when the residue \( r_N(t) \) is either a constant, a monotonic slope, or a function with only one extremum. Combining the equations in (2) and (3) gives the EMD of the original signal:

\[
a = \sum_{i=1}^{N} g_i + r_N
\]

The outcome of the EMD is \( N \) IMFs and a residue. A commonly used criterion to stop the shifting process is the size of the standard deviation SD, set to \( e \), computed from the two consecutive sifting results. Usually, SD is set between 0.2 and 0.3, [3]

D. Wavelet Method:

The wavelet transform provides the time-frequency representation.

We pass the time-domain signal from various high pass and low pass filters, which filters out either high frequency or low frequency portions of the signal. This procedure is repeated, every time some portion of the signal corresponding to some frequencies being removed from the signal. In ECG feature detection process, the signal goes under wavelet decomposition process. In wavelet transform process selection of mother wavelet plays an important role in the outcome of the result. Here Debauchies wavelet transform has been tested.

After the wavelet decomposition process, it is seen that second level decomposition signal has clear R peaks. Therefore that signal is selected and by setting a threshold, R-peaks are detected. The position is then changed by multiplying with a constant so that it matches with the original signal.

Then only those peaks are taken which are 60 samples apart. These peaks are R peaks. After this the corresponding Q, S, T, P peaks are detected by following the duration method.

Output of four different methods is given below.

III. RESULT AND DISCUSSION

Four methods have been evaluated by taking the ECG signals from MIT/BIH database.

<table>
<thead>
<tr>
<th>SIGNAL AL NO</th>
<th>TP (TOT AL PEA KS)</th>
<th>PAN TOMPKINS</th>
<th>SUCCESSIVE DIFFERENTIATION</th>
<th>EMD</th>
<th>WAVELET TRANSFORM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F N</td>
<td>F P</td>
<td>FN</td>
<td>FP</td>
<td>F N</td>
</tr>
<tr>
<td>101</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>102</td>
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<tr>
<td>103</td>
<td>13</td>
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<td>105</td>
<td>15</td>
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<td>106</td>
<td>24</td>
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<tr>
<td>107</td>
<td>26</td>
<td>0</td>
<td>4</td>
<td>2</td>
<td>2</td>
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<tr>
<td>108</td>
<td>22</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>109</td>
<td>69</td>
<td>0</td>
<td>28</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>111</td>
<td>51</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Pan-Tompkins method has the highest sensitivity among other methods whereas EMD has the lowest. So it can be concluded that Pan-Tompkins gives the best performance in comparison to other methods.

**REFERENCES**


### Table 1: Result Table of Implemented Methods.

From the above table it can be inferred that Pan-Tompkins method performs the best in comparison to other methods. This is because of two threshold method that it employs to search for the missed R-peaks. This step makes it successfully to detect true R-peaks whereas other methods fail to do so in some signals. Pan-Tompkins fails in signal number 108 which is highlighted above in the evaluation table. This signal has lower SNR. Successive differentiation fails to detect true R-peaks in signal number 200. This shows that successive differentiation fails in case of low amplitude R-peaks and negative R-peaks. EMD method has more computation time. This method fails in some signals because it could not detect negative R-peaks. Wavelet transform method could not perform better in signals having low amplitude because it also comprises of single thresholding due to which many peaks get missed by the method.

From the above evaluation table it can be inferred that following can be the reasons for failure of methods:

- Low amplitude R peaks.
- Negative R peaks.
- Signal of low SNR.

### Table 2: Result of Different Methods In Terms of Sensitivity and Positive Predictivity.

<table>
<thead>
<tr>
<th>Method</th>
<th>FN</th>
<th>FP</th>
<th>Se (%)</th>
<th>+P (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pan-Tompkins</td>
<td>0</td>
<td>21</td>
<td>100</td>
<td>98.51</td>
</tr>
<tr>
<td>Successive Differentiation</td>
<td>152</td>
<td>2</td>
<td>94.1</td>
<td>99.79</td>
</tr>
<tr>
<td>EMD</td>
<td>43</td>
<td>9</td>
<td>89.89</td>
<td>91.27</td>
</tr>
<tr>
<td>Wavelet Transform</td>
<td>197</td>
<td>23</td>
<td>90.89</td>
<td>92.62</td>
</tr>
</tbody>
</table>

Sensitivity (Se) = \[
\frac{TP}{TP + FN}
\]

Positive Predictivity (+P) = \[
\frac{TP}{FP + TP}
\]

From the above table it can be concluded that Pan-Tompkins method has 100% sensitivity. Se indicates the percentage of true R peaks that were correctly detected by the algorithm. The positive predictivity +P indicate the percentage of R peaks detection that is in reality true peaks.