Assessment of Hamilton-Tompkins Algorithm in a Noise Contaminated ECG Signal Environment

SaekaRahman, Mohammad Anwar Rahman

Abstract*—Accurate parameter detection is an integral part of the use of electrocardiograms (ECGs) in the healthcare system. Advances in technology have resulted in a considerable increase in the number of portable, battery-operated ECG instruments including in developing countries. A growing concern is that algorithms that diagnose ECG signals should be tested at different noise circumstances to verify the reliability and efficiency of signal interpretation. This study investigates the accuracy and reliability of the Hamilton-Tompkins (H-T) algorithm using simulated ECG signals generated by MATLAB. In the test process, randomly generated noises are added to simulated input signals to represent high-level noise contaminated surroundings. Simulation results show that the H-T algorithm accurately detected peaks every time it has been tested. The algorithm's performance parameter diagnosis for the Q, R and S wave peak was 99.96%, 99.97% and 99.93% accuracy, respectively. Test results indicate the H-T algorithm is reliable in detecting accurate ECG signals even in aggravated noise surroundings.

Index Terms*—ECG, Hamilton-Tompkins algorithm, Noise, QRS complex.

I. INTRODUCTION

In recent years the usage of portable ECG devices and processing of ECG signals have drawn much attention because of the unusual circumstances that patients go through while the ECG devices are in use and signals are continually recording. It is important to recognize accurate signals from the ECG devices to retrieve critical information from cardiac patients under at any circumstances. Advances in technology have resulted in an increase in the number of portable wireless-external battery-operated ECG instruments in hospitals, ambulances, clinics and other areas. The portable ECG devices facilitate real time ECG recording and analysis and are truly useful for cardiac patients who need continuous monitoring while they are engaged in daily activities at home or in the workplace outside the caregiver facilities. The recording and collection of ECG data from portable devices are widely varied and range from one hour up to 180 days. An automated ECG signal analyzer is essential to retrieve such a vast amount of data and detect the accurate signal information instantly in a short period of time. This instantaneous data analysis capability is an integral part of modern computerized ECG monitoring systems. There are currently a number of algorithms available to analyze data collected from portable ECG devices and identify the signals. It is very important that these algorithms perform invariably in all situations.

Researches must test the performance of many of these signal processing and recognizing algorithms under a variety of circumstances.

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SaekaRahman, Artificial Intelligence Department, Catholic university in Belgium, leuven.

Mohammad Anwar Rahman, Industrial Engineering Department, University of Southern Mississippi, Hattiesburg, MS, USA.

In developing countries, the use of portable ECGs in the urban areas has increased significantly. Because of the population volume, environment, economy, slow communication and inadequate healthcare providers, cardiac patients often are not located near immediate treatment. It has become crucial for healthcare providers in developing countries to increase technical capability to instantaneous heath service response ability to cardiac patients. Although the uses of portable ECG devices have significantly increased, the challenge is immense due to lack of communication facilities and the presence of abundant noise in the surroundings, making it increasingly important to test the performance of these ECG recognition algorithms under extreme noise situations.

Recognition and accurate detection and analysis of ECG signals are essential to provide beneficial services for cardiac patients. There are several algorithms commonly used to detect cardiac electric signals such as Multiplication of Backward Difference (MOBD), Okada, Pan-Tompkins, and Hamilton-Tompkins methods used for reliable QRS detection. The Hamilton-Tompkins algorithm is one of the most popular QRS detection methods [4], which is an improved variation of that originally proposed by Pan and Tompkins in 1985 [5] that uses a patient-specific threshold for QRS peak detection. This study considers assessing the Hamilton-Tompkins algorithm ability to detect ECG signals from noise and extract the corresponding parameters accurately. In the test procedure, the input ECG signals and noise are simulated separately using MATLAB code. Random noise is generated with mean zero and standard deviation of one. This noise is added to the input ECG signal. The noise contaminated ECG is applied as input to test the algorithm. The study then investigated the efficiency, accuracy and reliability of the Hamilton-Tompkins algorithm to recognize and accurately detect parameters, such as QRS complexes, based upon digital analysis of slope, amplitude and width from a simulated noisy signal.The algorithm has been tested with a simulated ECG waveform.

II. ECG SIGNALS AND TEST ALGORITHM

The heart continuously produces electric signals through constant depolarization and the corresponding depolarization systems. This electrical activity is measured by ECG signals, consisting of the Q, R and S wave, a complex wave system that occurs in rapid succession. In the QRS complex, a Q wave is any downward deflection after the P-wave (due to depolarization, usually 0.08 to 0.1 seconds in duration). An R wave is an upward deflection, and the S wave is any downward deflection after the R wave. ECG instruments are designed to enhance the ECG signal from the background of noise and artifacts and make it possible to derive accurate parameters. Because of its specific shape, the QRS complex serves as an entry point for almost all automated ECG analysis algorithms and detection of the QRS complex is the most important task in automatic ECG signal analysis [1]. In

ECG signal analysis, the main task of an algorithm is to detect QRS complexes and the estimation of instantaneous heart rate by measuring the time interval between two consecutive R waves [2]. The ECG is recorded at a speed of 25 mm/sec, and the voltages are calibrated so that 1 mV = 10 mm in the vertical direction. Therefore, each small 1-mm square represents 0.04 sec (40 m-sec) in time and 0.1 mV in voltage [3].A detailed ECG tracing that produced different waves is shown in Figure A.1, in Appendix.

The QRS complex detection is a major challenge. The Hamilton-Tompkins algorithm for QRS detection is divided into two sections. The preprocessor section performs linear and nonlinear filtering of the ECG signal and produces a set of periodic vectors that describe events. The decision rule section operates on the output of the preprocessor, classifies each event as either a QRS complex or noise, and saves the temporal location of each of the identified QRS complexes. The decision rules for a QRS detector are generally built from a number of components each having experimentally determined parameters. The most important task of the decision rule section is the determination of detection thresholds. Other common components of QRS decision rules are blanking, where events immediately following a QRS detection are ignored for a set time, search back, where previously rejected events are reevaluated when a significant time has passed without a detection, and use of slope to distinguish between T waves (due to ventricular repolarization) and early occurring ectopic beats.

A. Filtering

In ECG signals analysis, various filters are used to attenuate noise. The low-pass and high-pass filters together form a band-pass filter, implemented here with integer arithmetic to provide real-time operation. This procedure is followed by a differentiation, squaring, and time averaging of the signal. A separate derivative of the original ECG is used for T wave discrimination. The low-pass filter is one of a class of filters described by Lynn, implemented with the difference equation [5].

$$y(nT) = 2y(nT - T) - y(nT - 2T) + x(nT) - 2x(nT - 6T) + x(nT - 12T) \qquad (1)$$

where$T$ is the sampling period and n is an arbitrary integer. The high-pass filter is implemented with the difference equation

$$y(nT) = x(nT - 16T) - [y(nT - T) + x(nT) - x(nT - 32T)]/32 \qquad (2)$$

The difference equation for the derivative is

$$y(nT) = 2x(nT) - x(nT - T) - x(nT - 3T) - 2x(nT - 4T)/8 \qquad (3)$$

The nonlinear squaring function squares each output data point. Time averaging is done by adding together the 32 most recent values from the squaring function and dividing the total by 32.

B. Peak Detection

It is often easy to visually identify one large peak from a typical large waveform produced by the time-averaged window for a QRS complex. However, simple peak detection algorithms may falsely detect multiple peaks due to ripples in the wave. Although both peaks result from the same QRS complex, one peak is classified as resulting from a QRS complex, the other is classified as noise. The detector algorithm finds peaks in the final output of the filtering stages and stores the maximal levels encountered in the signal since the last peak detection. A new peak is defined only after a level is encountered that is less than half the height of the maximal, or peak level. Detection occurs halfway down the back side of the peak. This approach eliminates multiple detections from ripple around the wave peak. When ECG signals have prominent T waves, the time averaged waveform for a heart cycle sometimes appears as one long wave formed from the combination of waves produced by the QRS complex and the T wave. The time of occurrence of the peak detected in the preprocessed signal is important for placing the fiducial mark. With a prominent T wave, the detection may be delayed by the duration of the lengthened wave. To avoid this delay, in addition to the previously stated conditions for detection, a QRS complex is detected by the peak detector if 175 milliseconds elapses from the occurrence of the maximal positive slope in the time-averaged signal.

C. Figures

The method of local peak level estimation is an important performance factor in the QRS detection algorithms that use adaptive detection thresholds. The relative performance of mean, median and iterative peak level estimators are considered. The mean estimator determines the local peak level as the mean of a specified number of past peaks whereas the median estimator uses the median peak level. The first-order iterative estimator has the general form

$$\text{Estimate}(n) = (1 - A)\times\text{Estimate}(n-1) + A \times \text{Peak}(n) \quad (4)$$

where A is a positive coefficient less than one.

D. Peak Estimator Performance

One estimator may yield a consistently low peak prediction, and another with a better mean square error might give inconsistent predictions. The consistent predictor is preferable because it will produce less false positive and false negative detection if the proper relative detection threshold is used.

$$\text{Detection threshold} = B\times\text{Peak level estimate} \qquad (5)$$

The detection threshold coefficient B is set to values between zero and one. Any peaks larger than the detection threshold are classified as QRS complexes and are used to update the detection threshold. Noise peaks are ignored.

In these tests of peak level estimators, a simple detection threshold scheme which relied only on the QRS peak level estimate is used. Both QRS peak and noise peak level estimates may be used to determine the detection threshold. The threshold equation used in [3] is the following,

$$DT = NPL + TC \times (NPL - QRSPL) \qquad (6)$$

whereDT is the detection threshold, NPL is the noise peak level, TC is the threshold coefficient, and $QRSPL$ is the QRS peak level.

III. ALGORITHM TESTING AND PERFORMANCE EVALUATION

The ECG simulator enables normal and abnormal ECG waveform analysis without actually using the ECG machine. In testing the algorithm, simulated ECG signals developed by a MATLAB simulator is used.The use of a simulator has many advantages. First, it is convenient to testthe algorithm with any level of noise implication to represent surrounding noise inference without requiring invasive and non-invasive ECG procedure. Second, simulator generates arbitrary heart beat rate with any level of amplitude for each wave and its peak. Noise due to electrodes is also simulated using this simulator. Next, a data logger is used to acquire the ECG signal from electrodes, and amplified and transmitted to a computer. This arrangement is shown in Figure 1.

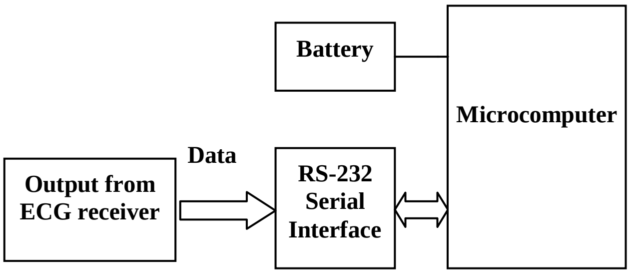


Fig.1: Laboratory setup of data acquisition systems

Data acquisition through computers not only results in a substantial saving of time and effort, but also reduces the number of errors in the data. The digital computer serves as an automated filing system in which information is automatically entered as it is generated. These files can be stored as long as necessary and updated whenever appropriate to provide tabular or graphic output reports. Analysis of the ECG waveform requiresan appropriate level of amplitude and intervals of the ECG to be recognized and identified. It is often necessary that important features of a physiological waveform or an image be identified. In monitoring and screening, it is often necessary to determine when a measured variable exceeds certain limits. The ECG can be checked whether the parameters fall within pre-established “normal range” or exceedthe limit. Thisscreening technique detects any ECG irregularities in the procedure. In a test with biomedical signal in a controlled setting, three standard pre-gelled disposable ECG electrodes are used. The placement of the electrodes is at chest, right arm and right leg. The signal from the right leg electrode is grounded and the other two connected to the differential input of the amplifier. The QRS complex of ECG waveform is observed clearly on the oscilloscope. The assembly setup to test an amplified signal is shown in Figures2.

a. Testing amplified ECG b. ECG waveformobserved

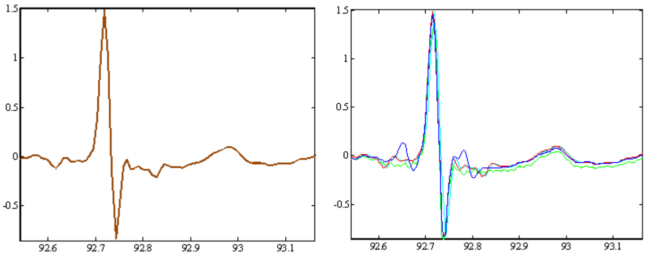
Fig. 2: Test of an amplified circuit using sinusoidal signals

The raw ECG signals voltage ranges from 0.11 mV to 1.6 mV and the frequency range of this is 1.3 Hz to 20 Hz. Toobserve signals of such low amplitude and low frequency, the signal needs to be amplified, and the signal to noise ratio is to be very high. The offset voltage is nullified. At first the amplifier is tested using a sinusoidal signal provided by the signal generator. In this case, input voltage is 5mV peak to peak from the signal generator, further reduced to 0.45mV using voltage divider arrangement. Gain stability is observed from frequency 10 Hz to 100Hz and CMMR is about 90 dB.The parameter specifications of a simulated ECG waveform which has been used for testing the parameter detection algorithm are shown in Table 1.

TABLE 1: SPECIFICATIONS FOR SIMULATED ECG

Heart beat: 72		
Amplitude	Q wave	0.025 mv
	R wave	1.50 mv
	S wave	-0.6 mv
Duration	RR interval	0.0138s

The simulator produces an ECG waveform with different leads and generates as many arrhythmias as possible. Since it is a MATLAB based simulator, it produces a normal lead II ECG waveform.The simulated ECG waveform using the parameters presented in Table 1 is shown in Figure 3.



a. ECG Signal with Noise b. ECG with Post filtering

Fig. 3:Simulated ECG using parameter in Table 1

With the simulated ECG signal the illustration of ECG Signal with Peak Detections is shown Fig. 4.

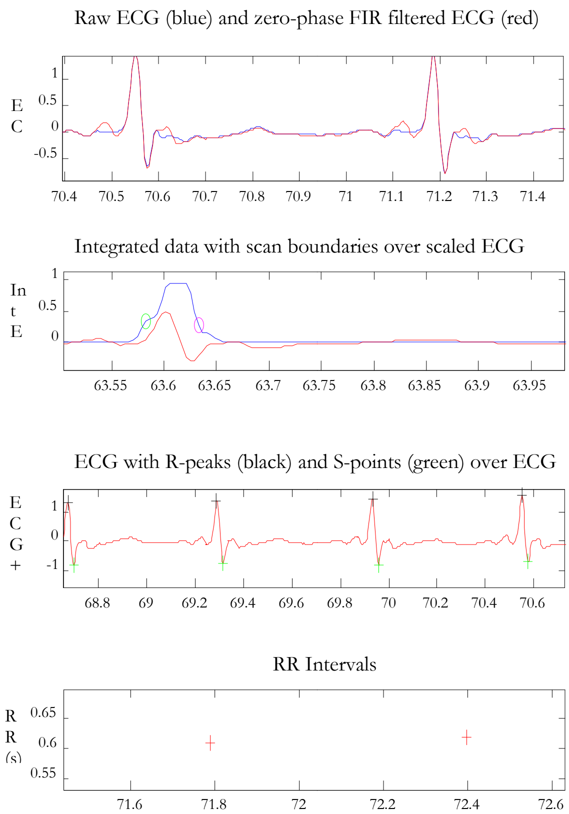


Fig. 4: ECG Signal with peak detections

IV. RESULTS

The database of the simulated ECG signal is applied as an input to the algorithm. According to the H-T algorithm, first the signal is transformed into non-sampled waves and then filtered. The waveform at each stage is produced accordingly. The detected parameters from the noise contaminated ECG signals using the H-T algorithm are shownin Table 2.

TABLE II: ECG DETECTED BY H-T ALGORITHM

Heart beat: 71.43		
Amplitude	Q wave	0.0223mv
	R wave	1.49 mv
	S wave	-0.56 mv
Duration	RR interval	(0.6-.614)s = 0.014s

The algorithm reliably detects QRS complexes using slope, amplitude, and width information. The signals are passed through several steps. First, in order to attenuate noise, the signal passes through a digital band pass filter composed of cascaded high pass and low pass filters. The next process after filtering is differentiation, which is followed by squaring, and moving window integration. 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 width of the QRS complex. The algorithm is able to correctly detect QRS complexes in the presence of the severe noise typical of the ambulatory ECG environment. Another important feature of this algorithm is refractory blanking. Once a valid QRS complex is recognized, there is a 200ms refractory period before the next one can be detected since QRS complexes cannot occur more closely than this physiologically. This refractory period eliminates multiple triggering on the same QRS complex during this time interval. To achieve a reliable diagnosis, a QRS detection algorithm must adapt each of its parameters with time and proper orientation ofthe ECG's morphology changes in a single patient.

In this algorithm, each threshold automatically adapts periodically, based upon the peak values of the signals and noise. The QRS complex of the electrocardiographic signal has the normal duration from 0.06s to 0.1s and provides information about the heart rate, the conduction velocity, and the condition of tissues within the heart and various abnormalities. The shape, duration and time of occurrence provide valuable information about the current state of the heart. The parameters are compared between the actual simulated ECG signals and noise contaminated signals after the parameter detection by the H-T algorithm. The accuracy of the parameters is shown in Table 3.

TABLE III: ECG DIAGNOSIS USING H-T ALGORITHM

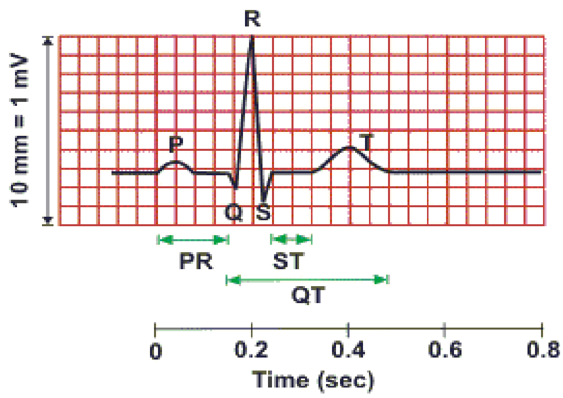
Accuracy	Calculation	Percentage
Detect Q peak	100-(0.023-0.0223)/0.023	99.96
Detect R peak	100-(1.5-1.495)/1.5	99.97
Detect S peak	100-(0.6-0.56)/0.6	99.93

V. CONCLUSION

The ECG is an important diagnostic tool, which measures functional status of the heart. Improving the quality health care service has been a priority for many years, particularly in the developing countries. Recent technological advancement has brought about a considerable increase in the number of portable, battery operated, ECG instruments with wide range of capacity and application in both urban and rural hospitals and clinics worldwide. The test of accurate ECG pattern recognition drives improved monitoring of the patients heart disease and provide diagnosis when someone has chest pain or palpitations.Such type of mobile ECG recorder is essential for continuously monitoring cardiac patients. These types of long term monitoring capability plays a key role in heart disease analysis and automate ECG event classification in order to enhance further medical treatment. The authors intend to present certain recommendation that testinggoverning algorithms is vitally important to check the algorithms performance and its reliability at worst case scenarios. A simulated test-base method or non-invasive test procedures often ensure precise information and provide analyze of an algorithm performance impact on medical service.

In this test procedure, the input ECG signal is simulated by MATLAB for testing the Hamilton-Tompkins algorithm.The algorithm performances are evaluated in two ways. The test process uses noise contaminated simulated ECG signal to verify the detector. In terms of detection peaks the algorithm's accuracy is 100% i.e., it detects QRS complexes every time it has been tested. In terms of parameter extraction the algorithm's accuracy is also found to be very high. In estimating Q, R and S peaks, the accuracy reaches 99.96%, 99.97% and 99.93%, respectively. The Hamilton-Tompkins algorithm for QRS detection noise is found very reliable. With the use of the Hamilton-Tompkins algorithm and software a reliable extraction of the characteristic ECG parameter which is essential for can be achieved. The algorithm's performance is comparable with other ECG parameter detection algorithms. Further clinical testsmay be required to verify algorithm functionality under at extreme situations.

APPENDIX



where
P-wave: (0.08 – 0.10) seconds
QRS: (0.06 – 0.10) seconds
P-R interval: (0.12 – 0.20) seconds
Q-T_c interval (≤ 0.044) seconds
$QT_c = QT/\sqrt{(RR)}$

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SaekaRahmanis currently enrolled in a graduate program in Artificial Intelligence Department at Catholic university in Belgium, leuven. She served as a visiting lecturer in Asian University in Bangladesh.

Mohammad Anwar Rahman is an assistant professor at the University of Southern Mississippi (USM), USA. His research interests include stochastic supply chain modeling, global supply chain, time series forecasting, humanitarian supply chain and decision-making problems under uncertainty. He is engaged in several research projects funded by Pan-American Advanced Studies Institutes Program, US Department of Transportation, Mississippi Department of Education and Mississippi Department of Transportation. He is affiliated with Center for Freight and Infrastructure Research and Education (CFIRE) and Center for Logistic Trade and Transportation (CLTT).