# QRS Detection and PVC Beat Recognition Using a Generalised Teager Energy Operator

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*Abstract:* -This paper presents a novel algorithm for automatic QRS complex detection and premature ventricular contraction (PVC) beat recognition based on a generalised Teager energy operator (GTEO). The algorithm is divided into two stages: QRS detection and PVC beat recognition. An optimal GTEO order is determined for each stage. A second order GTEO is used for QRS detection, and a seventh order GTEO is used for PVC beat recognition. The proposed algorithm was tested using ECG signals from two recognised arrhythmia databases, the MIT-BIH and the AHA database. The signals chosen contained PVC beats as well as normal beats. Sensitivity and specificity parameters were used to measure the accuracy of the proposed algorithm. The main advantages of using a GTEO are simplicity, robustness and speed. The sensitivities achieved using the proposed algorithm were 99.5% for QRS detection and 97.4% for PVC recognition. The specificities achieved were 99.8% for QRS detection and 99.1% for PVC beat recognition.

*Key-Words:* - Teager Energy, ECG, QRS Detection, PVC Recognition, SA Node, Purkinje Fibres.

## 1 Introduction

The ECG signal is a result of the contraction and expansion of the myocardium. The ECG signal consists of three major waves referred to as P, QRS complex, and T waves. The P wave represents the depolarisation of the atrium, the QRS complex wave reflects the ventricular depolarisation, and the T wave represents repolarisation of the ventricles.

It is relatively common for the heartbeat to be initiated by the Purkinje fibres rather than by the SA node. This causes ventricle contraction without atrium contraction first occurring. The resulting beat is called a premature ventricular contraction (PVC), also known as a ventricular premature beat (VPB). A single PVC beat does not usually pose a danger. However, frequent or consecutive PVC beats may be an indication of heart malfunction, which can cause sudden cardiac arrest (SCA) and sudden death. SCA is one of the main causes of natural death: in the USA, about 325,000 adults die of SCA each year. SCA is responsible for half of all deaths due to heart disease [1], so the detection of PVC beats is critical in clinical cardiology [2]. Indeed, most SCAs could be avoided if an early diagnosis is carried out by recording the ECG. However, some heart disorders cannot be detected by analysing short ECG recordings. So, long-term recording of the ECG is required. The purpose of this long-term recording (normally 24 hours) is to observe how the heart is functioning while the patient performs his or her daily activities. This type of recording is known as ambulatory, or Holter monitoring which is a suitable tool to detect and quantify PVC frequency.

PVC beats can easily be recognised by eye on recorded ECG signals, because they are very different from normal heart beats. However, longer-term monitoring systems such as Holter monitoring that record a large number of beats, necessitate automatic detection and classification.

In last few decades, researchers have developed and implemented many different QRS detector algorithms, based on different techniques in both the time and frequency domains. Oweis and Al-Tabbaa [3] classified QRS detection techniques into seven categories:

1. Time-domain thresholding - a 'statistical approach'
2. Spectral analysis
3. Geometry analysis
4. Principal component analysis
5. Fuzzy logic systems
6. Artificial neural networks
7. Neuro-fuzzy networks - 'hybrid systems'

Time-domain thresholding methodology is the preferred approach, especially in real-time processing. One of the most popular QRS detector algorithms based on the time-domain technique has been proposed by Tompkins and Pan [4]. The Pan-Tomkins algorithm consists of several consecutive steps: preprocessing the ECG, passing the preprocessed signal through a bandpass filter with upper and lower cut-off frequencies of 5Hz and 15 Hz respectively, a derivative filter to highlight the QRS complex, nonlinear operation where the signal is squared, and averaging the squared signal over 0.15 seconds to achieve detection function with one local maximum point corresponding to each QRS complex. Finally, Tomkins used a decision rule to localise the R position. After QRS detection and R point localisation, the next step is to recognise abnormal beats such as PVCs.

Several PVC recognising algorithms have been developed and implemented. Those algorithms are based on a different methodology to QRS detection. Frankiewicz and Al-Shrouf [5] used the linear prediction method for the classification of ECG beats. The researchers Chiu et al. [6] used correlation coefficients to recognise PVC beats. Al-Shrouf [7], and Martis et al. [8] used Wavelet transform and neural networks for ECG beat classification . Javadi et al. [2] used a combination of neural networks and expert systems to distinguish between normal beats and PVC beats[2]. Das and Ari [9] proposed a combination of S-transform and wavelet transforms for classifying normal heartbeats, PVC arrhythmias and other abnormalities of the heart [9]. For that reason, beat detection and PVC recognition were conducted using a generalised Teager energy operator (GTEO) in the present research.

## 2 Teager Energy Operator

The Teager energy operator (TEO) is a nonlinear operator [10], [11], [12], [13],[14],[15] which provides useful information about the changes occurring in the energy of the signal. Unlike the traditional definition of energy, which provides information about the total energy contained in the signal, TEO deals with instantaneous energy.

For an arbitrary continuous signal x(t), the Teager energy operator is defined in [10] as the following:

$$\psi[x(t)] = \dot{x}^2(t) - x(t)\ddot{x}(t) \quad (1)$$

where $\dot{x}^2(t)$ and $\ddot{x}(t)$ are first and second derivatives respectively. Let us consider the sinusoidal signal $x(t)$, with frequency f, amplitude A and phase shift θ, such that $x(t) = A\cos(\omega t + \theta)$. The Teager energy of this signal is calculated as follows:

$$\begin{aligned}\psi[x(t)] &= (-A\omega\sin(\omega t+\theta))^2 - \big(A\cos(\omega t+\theta)\big)\big(-A\omega^2\cos(\omega t+\theta)\big)\\ &= A^2\omega^2\sin^2(\omega t+\theta) - \big(A\cos(\omega t+\theta)\big)\big(-A\omega^2 cos(\omega t+\theta)\big)\\ &= A^2\omega^2\big(\sin^2(\omega t+\theta)+\cos^2(\omega t+\theta)\big)\\ &= A^2\omega^2 \quad (2)\end{aligned}$$

Analogous to the continuous case, the TEO for discrete signals is given by:

$$\psi[x(n)] = x^2(n) - x(n-1)x(n+1) \quad (3)$$

Research by Aihua, Long, and Hongsheng [11] finds out the same result for the discrete sinusoidal $x(n) = A\sin(\Omega n + \theta)$,where A is the amplitude, $\Omega = 2\pi f/f_s$, f is the frequency of the sampled signal, $f_s$ is the sampling frequency and θ is the phase angle.

$$\begin{aligned}\psi[x(n)] &= x^2(n) - x(n-1)x(n+1)\\ &= A^2\sin^2(\Omega) \quad (4)\end{aligned}$$

For sufficiently small Ω, $\sin(\Omega) \cong \Omega$ , so in this case the Teager energy is given by

$$\psi[x(n)] \cong A^2\Omega^2 \quad (5)$$

Sharmila and Reddy [13] concluded that the TE function reflects the positive value of energy in time domain when modelling the energy of a signal generated from a single source, and the negative value of energy for a signal generated from two different sources.

From equations 4 and 5, it is easy to conclude that two signals with same amplitude have different Teager energies. Moreover, the Teager energy operator reflects the signal amplitude and frequency at any particular point in time. The TEO is therefore very sensitive to changes in the frequency and the amplitude of the signal being tested [10], [11]. The TEO is also dependent on the energy of the system that generated the signal [13].

In this paper, the generalised Teager energy operator (GTEO) is introduced. The discrete Teager operator is generalised by replacing '1' with an integer constant M in equation (3) [10]. In this paper, the constant M will be referred to as the order of the GTEO. So the M- order generalised Teager operator can be written as:

$$[x(n)] = x^2(n) - x(n-M)x(n+M) \quad (6)$$

Considering the discrete sinusoidal

$x(n) = Acos(\Omega n + \theta)$

$$\begin{aligned}\psi[x(n)] &= A^2\cos^2(\Omega n+\theta) - [A\cos(\Omega(n-M)+\theta)\,A\cos(\Omega(n+M)+\theta)]\\ &= A^2\cos^2(\Omega n+\theta) - (A^2/2)[\cos(\Omega(n-M)+\theta+\Omega(n+M)+\theta) + \cos(\Omega(n-M)+\theta-\Omega(n+M)-\theta)]\\ &= A^2\cos^2(\Omega n+\theta) - (A^2/2)[\cos(2\Omega n+2\theta)+\cos(2\Omega M)]\end{aligned}$$

$$= A^2\cos^2(\Omega n+\theta) - (A^2/2)[1 - 2\sin^2(\Omega n+\theta) + 1 - 2\sin^2(\Omega M)]$$
$$= A^2\cos^2(\Omega n+\theta) - (A^2/2) + A^2\sin^2(\Omega n+\theta) - (A^2/2) + A^2\sin^2(\Omega M)$$
$$= A^2[\cos^2(\Omega n+\theta) + \sin^2(\Omega n+\theta)] - A^2 + A^2\sin^2(M\Omega)$$
$$= A^2\sin^2(M\Omega) = A^2\sin^2\left(\frac{f}{f_s}M\right) \quad (7)$$

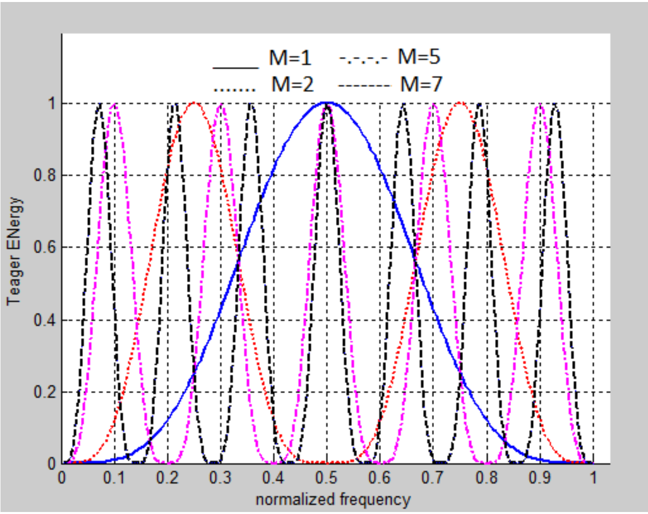


Figure 1. GTEO versus frequency for M = 1 2, 5 and 7

Figure 1 illustrates the Teager energy versus normalized frequency for sinusoidal signals with amplitudes of unity for the order M of the GTEO, with M = 1, 2, 5 and 7. If we consider GTEO as a system, equation (7) and Figure 1 could be considered as its frequency response. However, they could also represent the frequency spectrum if we treat GTEO as a signal. From equation (7) we can conclude many characteristics of the GTEO. Firstly, the phase shift has no effect on TE regardless of signal amplitude, frequency or the order M of the GTEO.

From equation (7) it is easy to assume that for specific GTEO order M, two signals with the same amplitude but different frequencies have different values for TE. However, for the same signal, the value of TE varies with the value of M. From equation (7) we can conclude that, unlike the TEO which is a function of two parameters, the GTEO depends on three parameters: signal amplitude, signal frequency, and the GTEO order. However, both GTEO and TEO are complex to calculate, as they each involve information from three signal samples. The difference is that in TOE the three signal samples are consecutive, 'n - 1, n, n + 1', whereas in GTEO the samples are not consecutive: 'n - M, n, and n + M'. The TEO and the GTEO are both non-causal, so a time delay is desirable in real-time monitoring. This time delay is greater in GTEO than in TEO, although values might be acceptable for small order values of GTEO ($M \ll f_s$).

## 2.1 GTEO of sum of two uncorrelated signals

Let us assume that two uncorrelated signals $x_1(n)$, and $x_2(n)$ are generated from two independent sources, and form a signal $x(n) = x_1(n) + x_2(n)$

The GTEO of the sum of those signals is:

$$E[(\psi[x(n))] = E[x^2(n) - x(n-M)x(n+M)] \quad (8)$$

Substituting $x(n) = x_1(n) + x_2(n)$ in equation (8) gives:

$$\begin{aligned}
E[(\psi[x(n))] &= E\,[(x_1(n)+x_2(n))^2 - (x_1(n-M) + x_2(n-M))(x_1(n+M) + x_2(n+M))] \\
&= E\left[x_1^2(n) + 2x_1(n)x_2(n) + x_2^2(n) - x_1(n-M)x_1(n+M) - x_1(n-M)x_2(n+M) - x_2(n-M)x_1(n+M) - x_2(n-M)x_2(n+M)\right] \\
&= E\,[x_1^2(n) - x_1(n-M)x_1(n+M)] + E\,[x_2^2(n) - x_2(n-M)x_2(n+M)] + 2E\left[x_1(n)x_2(n)\right] - E[x_1(n-M)x_2(n+M)] - E[x_2(n-M)x_1(n+M)] \\
&= E\,[x_1^2(n) - x_1(n-M)x_1(n+M)] + E\,[x_2^2(n) - x_2(n-M)x_2(n+M)] + 2E\left[x_1(n)\right]E[x_2(n)] - E[x_1(n-M)]E[x_2(n+M)] - E[x_2(n-M)]E[x_1(n+M)] \\
&= E\,[x_1^2(n) - x_1(n-M)x_1(n+M)] + E\,[x_2^2(n) - x_2(n-M)x_2(n+M)] + 2E\left[x_1(n)\right]E[x_2(n)] - E[x_1(n)]E[x_2(n)] - E[x_2(n)]E[x_1(n)] \\
&= E\,[x_1^2(n) - x_1(n-M)x_1(n+M)] + E\,[x_2^2(n) - x_2(n-M)x_2(n+M)] \\
&= E[(\psi[x_1(n))] + E[(\psi[x_2(n))] \quad (9)
\end{aligned}$$

From equation (9), we can say that the TE of the sum of two signals equals the sum of their TEs.

## 3 Methodology of QRS Detection and PVC Recognition

Almost all previous studies of TEO have considered that its output is proportional to the product of the amplitude and frequency of the input signal. All of these studies have taken into account the fact that the TEO can simultaneously reflect the instantaneous amplitude and frequency information of the input signal. Aihua et al. explained that the instantaneous amplitude and instantaneous frequency refer to the amplitude and frequency of the dominant sinusoidal component at any particular time [11]. This is not true in the case of a GTEO, because its output depends on the amplitude and the frequency of the signal as well as on the GTEO order form equation. For example, let us consider a signal consisting of two sinusoidal signals with different frequencies, one of which is dominant. For a specific order value, M, of the GTEO, the dominant signal is eliminated and the less dominant signal is increased. The opposite effect can be achieved with a different value of M. Both signals can be eliminated or increased or decreased by equal amounts for yet another value of M.

Normal ECGs consist of three basic waves: the QRS complex, the P wave and the T wave. The frequency spectrum of the QRS complex is around 15 - 17 Hz with a bandwidth of about 10 Hz. The frequency spectrum of the P wave is around 10 Hz, and that of the T wave is around 6 Hz. Abnormal ECG signals, for example PVC beats, have a different frequency spectrum to a normal beat.

Using these GTEO features and based on frequency characteristics of ECG waves, QRS detection and PVC recognition are performed using GTEO.

The first task is to determine the GTEO order M to be used in detection and recognition. ECG records from the American Heart Association (AHA) and MIT-BIH database were used as the experimental source of information. Records of both normal and abnormal ECG beats were chosen, exhibiting different noise levels. Figures 2 and 3 show two ECG signals and their GTEO for several values of M. Those signals are taken from N14 and V72 records respectively. Investigations of several AHA and MIT-BIH ECG records, and the information in Figures 2 and 3, indicate that the best order value of GTEO for beat detection is M = 2. However, the best order value for PVC recognition is M = 7. Figures 4 and 5 show two different ECG signals from N14 and V72 records respectively, for the GTEO order values of M = 2 and M = 7.

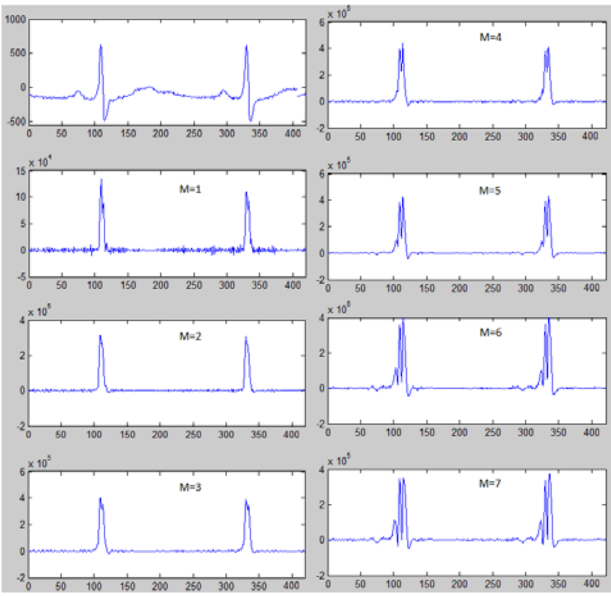

Figure 2. Normal ECG beats and their GTEO for M = 1-7

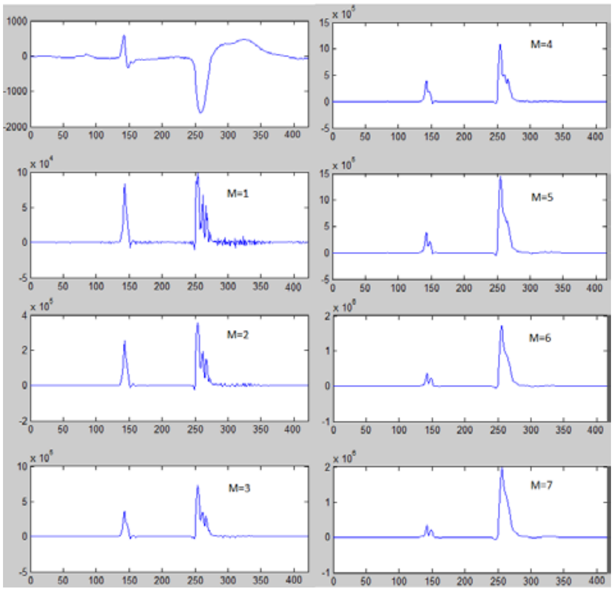

Figure 3. Normal and PVC beats and their GTEO for M = 1-7

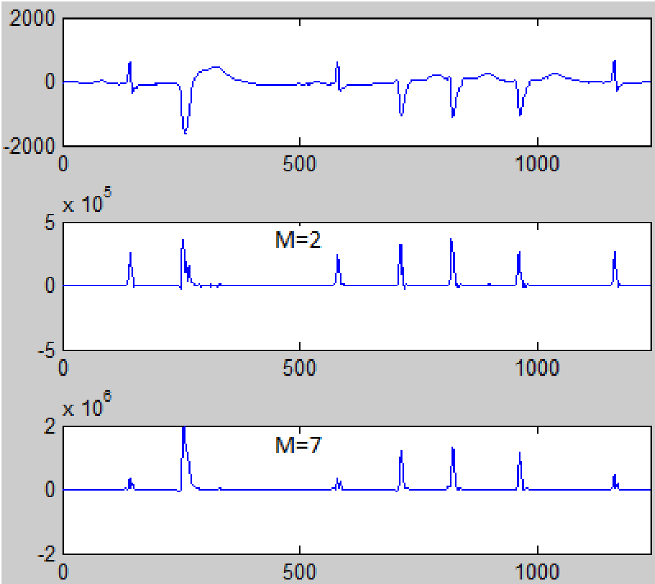


Figure 4. Normal ECG beats and their GTEO for M = 2 and M = 7

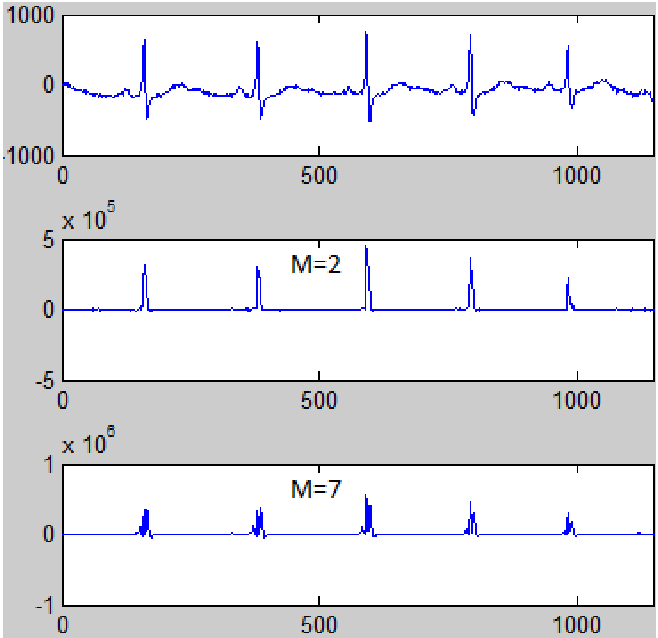


Figure 5. Normal and PVC beats and their GTEO for M = 2 and M = 7

## 3.1 QRS Detection

Traditionally, QRS detectors involve several stages: bandpass filtering, a derivative filter, nonlinear operation, and a moving averaged filter. In second order GTEO, there is no need to use a bandpass filter, nor a derivative, because the P wave, T wave and baseline are laminated and only the QRS complex is highlighted. So, in a second order GTEO-based QRS detector, the detection function is achieved directly. However, in some cases, more than one local maximum can be observed. To overcome this problem, a five-sample moving average filter is used. This results in a detection function with one local maximum point corresponding to each QRS complex. To find the nth local maximum point, an adaptive threshold is determined as follows:

$$Th_n = 0.85 * \max(Df_{n-1}) \quad (10)$$

where $Th_n$ is the nth threshold and $\max(Df_{n-1})$ is the local maximum of the detection function corresponding to the previous beat. The first local maximum is defined as the maximum point during the first two seconds. To increase the efficiency of the detector, two strategies are adopted: the Search Back Strategy (SBS) and the Turn Off Strategy (TOS). The search back strategy is used to avoid missing any low-amplitude QRS, and involves reducing the threshold value and restarting the search for the local maximum. The SBS is activated if the RR interval exceeds a specified time: this time is two seconds in the proposed QRS detector. The Turn Off Strategy is used to reduce the computation time, and is achieved by halting the search for the local maximum for 0.2 seconds.

## 3.2 PVC Recognition

A premature ventricular contraction beat has two main characteristics:

i. it is wider than a normal QRS complex (≥ 120 ms) with abnormal morphology
ii. it occurs earlier than would be expected for the next beat.

These two features are used to recognise PVC beats.

In this paper, the normal beat and PVC beats are treated as two uncorrelated signals generated from two independent sources. As shown in equation (9), the GTEO of those two signals is the sum of the GTEO for each individual signal. The frequency and the amplitude of those two signals are different. As shown in equation (7), the GTEO depends on three parameters: signal amplitude, signal frequency and GTEO order M. The first two parameters are inherent in the signal, so we have no influence over them. The only parameter that is within our control is the order of the GTEO. As shown in the preceding discussion, there are values for the order M of the GTEO for which the TE of normal beats and PVC beats are approximately equal. There is also a value of M for which the GTEOs are completely different, which makes it easy to distinguish between them. The present research used a seventh order GTEO to distinguish PVC beats from normal beats. For more certainty in identifying PVC beats, the RR interval is taken into account, using the identifying characteristic of a

PVC beat as occurring earlier than would be expected for the next beat.

PVC recognition is carried out as follows. After detecting a beat using a second order GTEO and calculating the RR interval, the seventh order GTEO is calculated for this beat. If the seventh order GTEO is more than 0.5 of the second order GTEO and the RR interval is less than 0.6 seconds, the beat is classified as a PVC beat.

## 4 Results and Discussion

ECG signals from the AHA and MIT-BIH databases were used to investigate the applicability and efficiency of the proposed algorithm for QRS detection and PVC recognition. Some of the records displayed normal beats; others displayed PVC beats. The results obtained have been compared with the results from Awandekar's et al. study [16]. To give a meaningful comparison, the same two performance parameters were used: sensitivity and specificity. Sensitivity measures the accuracy of detecting PVC beats; specificity represents the accuracy of rejecting normal beats as non-PVC beats. The sensitivity parameter $S_e$ is calculated using the following equation:

$$S_e = \frac{T_p}{T_p + F_N} * 100\% \tag{10}$$

The specificity parameter $S_p$ is calculated as follows:

$$S_p = \frac{T_p}{T_p + F_p} * 100\% \tag{11}$$

where, $T_P$, $F_N$ and $F_P$ are true positive, false negative and false positive respectively. True positive is the number of true classified PVC beats. False negative is the number of PVC beats not classified as PVC beats. False positive means the number of non-PVC beats that are classified as PVC beats. The sensitivity parameter and the specificity parameter were also used to examine the accuracy of the proposed QRS detector. In this case, $T_P$, $F_N$ and $F_P$ are defined as follows. True positive is the number of QRS complexes detected correctly. False negative is the number of existing QRS complexes that are not detected. False positive is the number of non-QRS complexes detected as QRS.

The results from the QRS detector are shown in Table 1., while Table 2 depicts the results of PVC recognition testing.

Table 1. QRS detector results

| Data-base | ECG record | Nr. of beats | $T_P$ | $F_P$ | $F_N$ | Se | Sp |
|---|---|---|---|---|---|---|---|
| MIT-BIH | 105 | 2572 | 2567 | 2 | 5 | 99.8 | 99.9 |
| | 106 | 2027 | 2021 | 2 | 6 | 99.7 | 99.9 |
| | 119 | 1987 | 1969 | 3 | 18 | 99.1 | 99.8 |
| | 124 | 1619 | 1612 | 0 | 7 | 99.6 | 100 |
| | 200 | 2601 | 2590 | 5 | 11 | 99.6 | 99.8 |
| | 233 | 3079 | 3061 | 8 | 18 | 99.4 | 99.7 |
| AHA | V71-76 | 361 | 411 | 2 | 1 | 99.8 | 99.5 |
| Total | | 14246 | 14231 | 22 | 66 | 99.5 | 99.8 |

Table 2. PVC recognition results

| Data-base | ECG record | Nr. of PVC beats | $T_P$ | $F_P$ | $F_N$ | Se | Sp |
|---|---|---|---|---|---|---|---|
| MIT-BIH | 105 | 41 | 39 | 1 | 2 | 95.1 | 97.5 |
| | 106 | 520 | 508 | 3 | 12 | 97.7 | 99.4 |
| | 119 | 444 | 433 | 5 | 11 | 97.5 | 98.9 |
| | 124 | 47 | 45 | 1 | 2 | 95.7 | 97.8 |
| | 200 | 826 | 806 | 6 | 20 | 97.6 | 99.3 |
| | 233 | 831 | 809 | 7 | 22 | 97.4 | 99.1 |
| AHA | V71-76 | 81 | 78 | 2 | 3 | 96.3 | 97.5 |
| Total | | 2790 | 2718 | 25 | 72 | 97.4 | 99.1 |

The results obtained by Awandekar et al. [16] are Se = 96.2% and Sp = 93.6%. However they did not mention which ECG records they used, nor how many beats there were. Also, the researchers Sharmila and Reddy [13] found Se = 98-100% but did not calculate the specificity of their proposed algorithm. Moreover, their algorithm potentially increases the computation time because it involves calculating first the cosine transform and then its Teager energy. As well, the two studies used multi phases, time consumption QRS detector. In the present paper, the sensitivities achieved were 99.5% and 97.4 for QRS detector and PVC recognition respectively. The specificities achieved were 99.8% and 99.1 for QRS detection and PVC recognition respectively.

## 5 Conclusion

This paper introduces the concept of the generalised Teager energy operator technique. It demonstrates that the order value chosen for the GTEO depends on the nature of the signals and on the reason for the analysis. QRS complex detection and PVC beat recognition were carried out using the GTEO technique. Two different GTEO orders were used: a second order GTEO was used for QRS detection, and a seventh order GTEO was used for identifying PVC beats. Employing the GTEO technique for

ECG signal processing was simple, effective and robust. Only three samples of the signal were required for calculating the instantaneous GTEO. The proposed algorithm was tested using ECG signals from the MIT-BIH and AHA databases. Six ECG signal records were taken from each database, containing a total of 11,901 beats. These results show that the proposed system can detect QRS complexes effectively and recognise PVC beats accurately. However, artificial intelligence techniques should be used to improve the efficiency of PVC detection in the future.

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