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High-Precision Real-Time Premature Ventricular Contraction (PVC) Detection System Based on Wavelet Transform

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Abstract This study presents a high-precision real-time detection system to detect arrhythmia of premature ventricular contraction (PVC). This system detects the peak of the R-wave based on wavelet transform (WT) and then uses a new algorithm to detect PVC. The proposed PVC detection algorithm combines the sum of trough and sum of R_peak with minimum to detect PVC. A crucial function of morbid warning is implemented in this system so that users receive an alert signal when PVC is detected. The proposed system is simulated and verified using the MIT-BIH Arrhythmia Database (mitdb). The system is also implemented by FPGA to illustrate its high precision and real-time performance.

Keywords ECG · FPGA · PVC · Wavelet transform

1 Introduction

Heart disease is one of the main causes of death for humans. Therefore, diagnosing and preventing heart diseases is a crucial subject. The most reliable manner to determine heart activity is to use an electrocardiogram (ECG), which records relevant electrical signals. Therefore, an ECG can provide the most accurate information for cardiac arrhythmia [1]. In the past, ECGs were performed in doctors' offices, clinics, and hospital emergency departments. After ECG examination, doctors can diagnose any abnormal situation. Based on ECG data, doctors can conduct further assessment or treatment. However, an ECG is inconvenient and uncomfortable for patients.

Heart disease has attracted increasing attention in recent years. Many heart diseases occur suddenly, making it difficult for doctors to determine the causes. To measure real-time physiology signals (such as ECG, EEG, and EMG), many researchers have investigated and discussed a personal physiology signal monitoring system [2–5]. If such a monitoring system can be integrated into an automatic detection system, it will be more convenient. Therefore, this study presents a high-precision, real-time premature ventricular contraction (PVC) detection system.

PVCs are premature heartbeats originating from the ventricles of the heart. PVCs are one of several arrhythmias. People can suffer from this symptom, irrespective of whether they have heart disease. PVCs may be a warning signal, alerting people to pay attention to this symptom and cure it early on. Otherwise, PVC can progress to serious heart disease that requires further medical treatment. Researchers have developed many PVC detection algorithms, including autoregressive models [6], symbolic dynamic analysis [7], correlation coefficient in ECG waveform [8], morphological transformation and cross-correlation [9], and the wavelet method [10]. Wavelet transform (WT) is a promising method for time-frequency analysis [11]. Therefore, the proposed design adopts the WT-based algorithm. Generally, PVC classification algorithms are developed using decision trees [12], neural networks [13, 14], and hidden Markov models [15, 16]. However, the proposed approach uses an energy-based algorithm to obtain higher accuracy.

2 System Block Diagram

A normal ECG consists of a P wave, QRS complex, and T wave. However, the QRS waveform is larger than others. To

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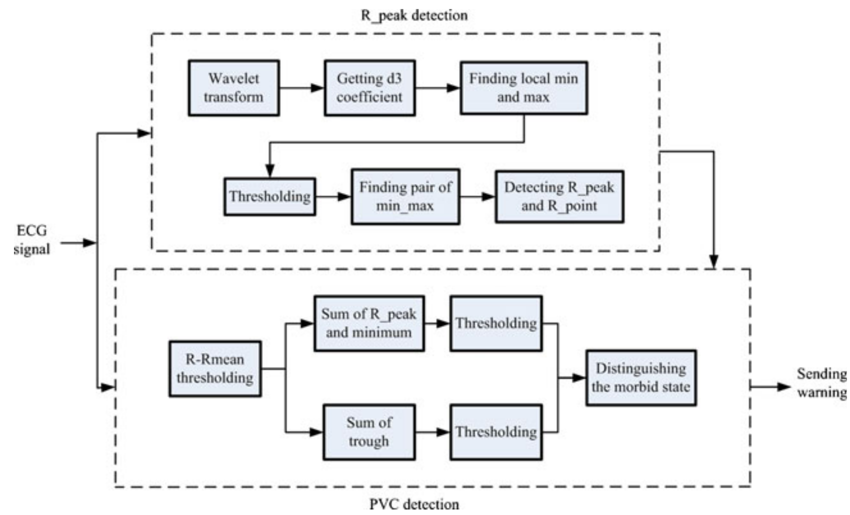

Figure 1 PVC detection system architecture.

diagnose heart diseases accurately, the ECG signals must be recorded in detail to diagnose waveform variations. Figure 1 shows the proposed architecture. The PVC detection system consists of two major parts: R_peak detection and PVC detection. After receiving the ECG signals, the first step is to detect the R_peak to locate the waveform, and the second step is to diagnose the occurrence of PVC. If PVC is detected, alert signals are generated.

2.1 ECG Signals

The MIT-BIH Arrhythmia Database (mitdb) [17–19] was the first available set of standard test material for evaluating arrhythmia detectors and for basic research in cardiac dynamics, and is used at more than 500 sites worldwide. Therefore, this study adopts the mitdb MLII to obtain ECG signals.

2.2 R_peak Detection

The QRS detection algorithm [20] can be modified to change into the R_peak detection algorithm.

a) Mallat Algorithm [21]

The dyadic WT of a digital signal *f(n)* can be calculated using the Mallat algorithm, as follows:

$$s_{2^j} f(n) = \sum \left[h_k s_{2^{j-1}} f\left(n - 2^{j-1} k\right) \right] \tag{1}$$

$$w_{2^j} f(n) = \sum \left[g_k s_{2^{j-1}} f\left(n - 2^{j-1} k\right) \right] \tag{2}$$

where $s_{2^j} f(n)$ is the digital ECG signal to be analyzed, $w_{2^j} f(n)$ is the dyadic WT of digital signal *f*(*n*), s_{2^j} is a smoothing operator, and h_k and g_k are coefficients of a low-pass filter *H(w)* and a high-pass filter *G(w)*, respectively.

b) Biorthogonal Spline Wavelet

This study uses a biorthogonal spline wavelet to detect ECG signals. According to (1) and (2), using h_k and g_k calculates the WT. The filter coefficients are

$$h_0 = 1/4, h_1 = 3/4, h_2 = 3/4, h_3 = 1/4 \tag{3}$$

$$g_0 = -1/4, g_1 = -3/4, g_2 = 3/4, g_3 = 1/4 \tag{4}$$

c) Lipschitz exponent α

The wavelet coefficient changes using different scales (*j*=1,2,3…). The rule of change depends on the Lipschitz exponent α [22]. As the scale *j* increases, the amplitude of the wavelet coefficient increases when $\alpha>0$, decreases when $\alpha<0$, and remains unchanged when $\alpha=0$.

R_peak detection is based on the wavelet to detect the R-wave of ECG signals. The R_point, the position of the peak

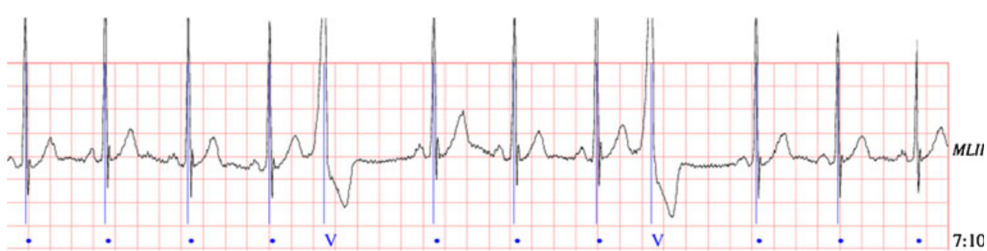

Figure 2 Typical PVC diagram, No.116.

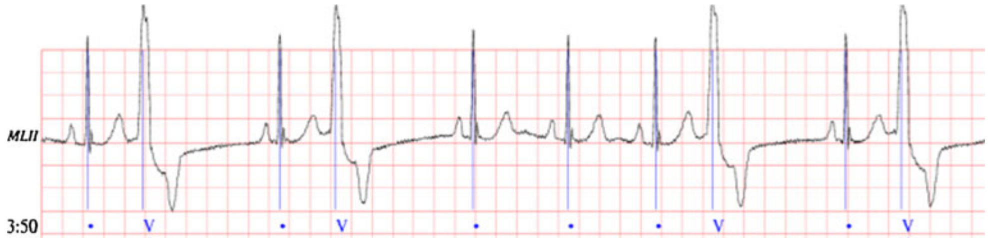

Figure 3 Typical PVC diagram, No.119.

of R-wave, is derived from R_peak detection. This process includes three major steps:

Step1. Finding negative minimum-positive maximum pair

Use biorthogonal spline wavelet to transform WT to obtain the third-order coefficients (d3), and then find the minimum and maximum values of coefficient d3. Finally, setting a threshold obtains the pair of minimum and maximum value.

Step2. Computing zero-crossing point

Use the results of Step 1 to calculate the position of the R_peak in coefficient d3.

Step3. Amending offset

The position of R_peak in coefficient d3 is not a real signal R_peak. There is an offset between the original signal and coefficient d3. Therefore, it is necessary to amend this offset to obtain the real position of the R_peak. The theoretical value of the offset is $\frac{2^{j-1}}{2}$.

2.3 PVC Detection

Figure 1 shows that the PVC algorithm is derived from two methods: the sum of the trough, and the sum of the R_peak with minimum. Section 3 details the PVC detection algorithm.

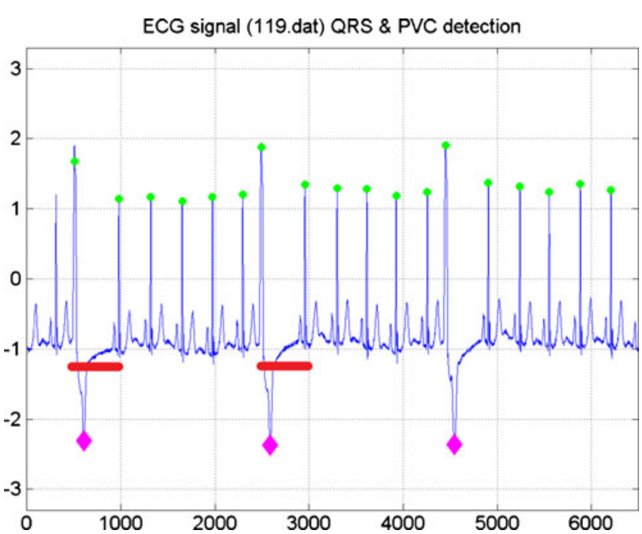

Figure 4 Sum of trough.

2.4 Sending Warning

From a medical viewpoint, if PVC occurs more than six times within 1 min, it is classified as morbidity. Therefore, sending a warning is a crucial function to alert the user.

3 PVC Detection Algorithm

PVC means that ventricular contraction is earlier than usual. For waveform, it means that the R_peak appears earlier. The R-wave to R-wave intervals (RRI) of PVCs are smaller than the mean RRI. Thus, the R-R threshold is set to remove most normal beats, and the PVC algorithm determines the occurrence of PVCs.

3.1 Sum of Trough

Figures 2 and 3 show two typical PVCs (No. 116 and No. 119), and their characteristics are described as follows:

When PVCs occur,

1. The QRS complex wave appears early; $RRI_{PVC}<RRI_{mean}$.
2. There is a huge and wide negative wave.
3. There is a compensatory pause.

Based on these characteristics, this study proposes using the sum of trough method to determine this type of PVC. The formula is given as

$$sum = \sum_{n=35}^{85} x[Rpoint[i] + n] \tag{5}$$

where *Rpoint* represents the position of the R_peak during PVC, *n* is the number of samples from the R_peak of PVC, and function *x* represents the amplitude of the original signal. In Fig. 4, if the sum is smaller than the threshold (marked as red rectangle), the system detects the occurrence of PVC and the points are marked as rhombuses.

3.2 Sum of R_peak with Minimum

Figure 5 shows the other typical PVC (No. 114), which has the following characteristics:

When PVCs occur,

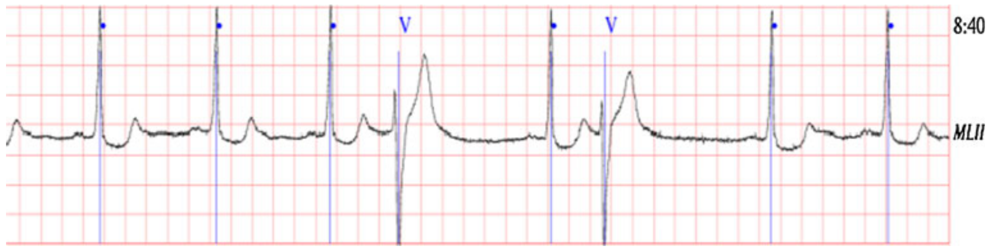

Figure 5 Typical PVC diagram, No. 114.

1. The QRS complex wave appears early; $RRI_{PVC} < RRI_{mean}$.
2. The R-wave is smaller than normal.
3. There is a huge negative wave.
4. There is a compensatory pause.

Based on these characteristics, this study proposes the algorithm of sum of R_peak with minimum. The formula is given by

$$diff = min + x[Rpoint[i-1]] \tag{6}$$

where *min* is the minimum value between two R_peaks, and the other parameters are the same as in the sum of trough. In Fig. 6, if the sum of the amplitude of minimum and R_peak is less than zero, the system finds a PVC and marks it as a rhombus.

4 Simulation Results

To obtain accurate and reliable simulation results, the following four conditions should be considered:

1. Normal beats with PVCs only (e.g. No. 119)
2. Only normal beats (e.g. No. 100)
3. Different types and numbers of PVCs (e.g. No. 116)
4. Mixed with other types of arrhythmia (e.g. No. 114)

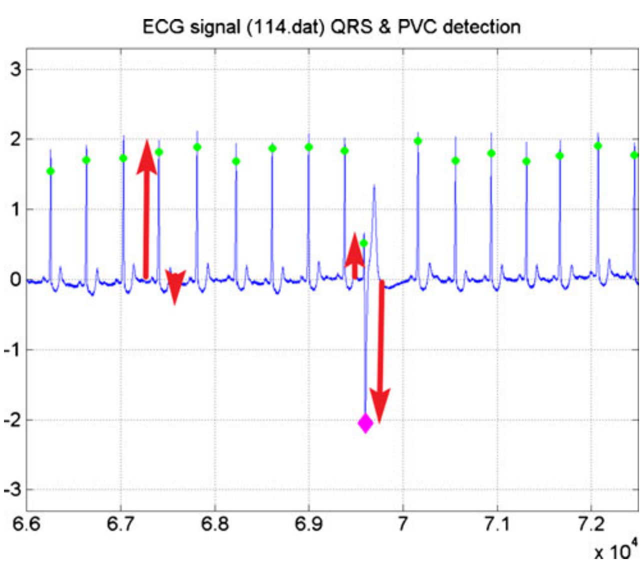

Figure 6 Sum of R_peak with minimum.

Based on these reasons, this study uses No. 100, No. 114, No. 116, and No. 119 as representative ECG signals. These four records contain different types and numbers of arrhythmia, as shown in Table 1.

In Table 2, No. 100 was tested for the last 5 min in Pachauri's work [23] because there is only a PVC in No. 100 at 25min18s. In this paper, No. 100 is tested for the last 15 min. For the other records, the first 5 min are tested in [23] and the first 15 min are tested in our work.

As Table 2 shows, the proposed system was tested on four databases. The accuracies are 100 %, 80.49 %, 98.41 %, and 100 % for No. 100, No. 114, No. 116, and No, 119,

Table 1 Arrhythmia types and numbers in 15 min.

Code Record	A	J	V	F
No. 100	21	–	1	–
No. 114	5	2	41	4
No. 116	1	–	63	–
No. 119	–	–	197	–

Beat annotations:

Code Description

A Atrial premature contraction (APC)

J Nodal (junctional) premature beat

V PVC

F Fusion of ventricular and normal beat

Table 2 Comparison of the accuracy of the system.

	[23] (5 min.)	New (15 min.)
No. 100	100 %	100 %
No. 105	100 %	–
No. 114	N/A	80.49 %
No. 116	N/A	98.41 %
No. 119	–	100 %
Mean of No. 114 and No. 116	72.96%[a]	89.45 %
Average	86.48 %	94.73 %

[a] The individual testing results of No. 114 and No. 116 are unavailable in [23]. To compare their performance, derive the average accuracy of No. 114 and No. 116 from the testing results of No. 100, No. 105, and their average accuracy

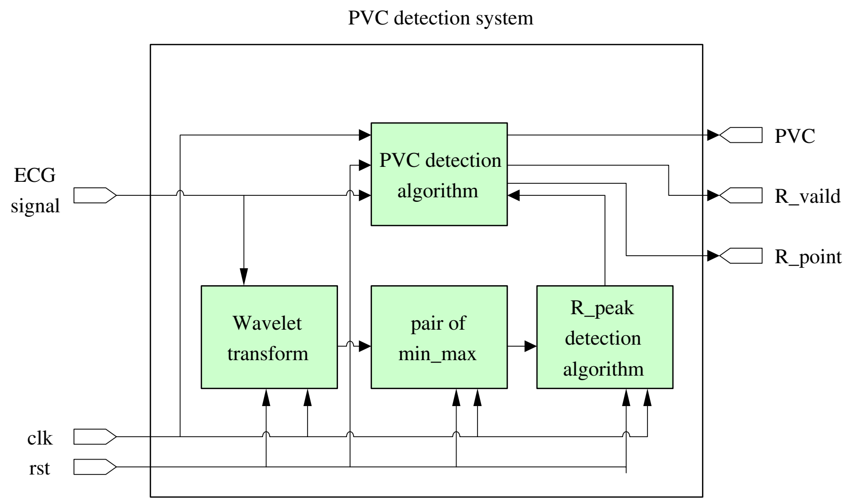

Figure 7 PVC detection system architecture.

respectively. The average accuracy of No. 114 and No. 116 is 89.45 %, which is 16.49 % higher than that in [23]. The average accuracy in this study is 94.73 %, which is 8.25 % higher than that in [23]. Simulation results show the high precision and superiority of the proposed system.

5 Implementation Results

The proposed system, as shown in Fig. 7, includes four modules: the WT, min_max pair, R_peak detection, and PVC detection. These hardware architectures are illustrated as follows:

5.1 WT Module

The WT module is used mainly to calculate the coefficient d3 (third-order wavelet coefficient). The total calculations are two scale coefficients (the first-order and second-order) and a wavelet coefficient (third-order wavelet coefficient).

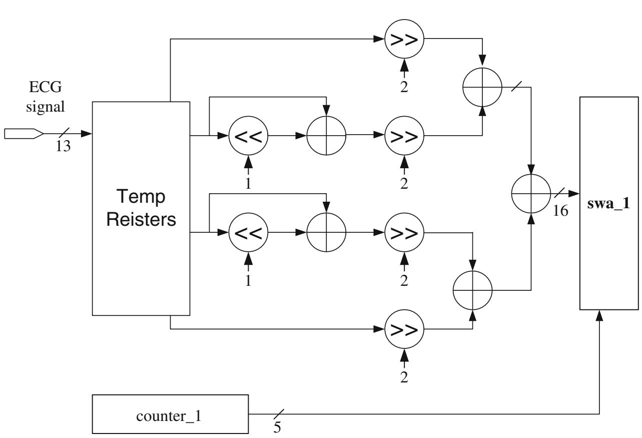

Figure 8 Hardware architecture of WT.

The first-order scale coefficient formula is given by

$$swa(1,i+3)=\frac{1}{4}*signal\left(i+3-2^{0*0}\right)+\frac{3}{4}*signal\left(i+3-2^{0*1}\right)+\frac{3}{4}*\ signal\ \left(i+3-2^{0*2}\right)\ +\ \frac{1}{4}*\ signal\ \left(i+3-2^{0*3}\right) \tag{7}$$

The second-order scale coefficient formula is given by

$$swa(2,i+24)=\frac{1}{4}*swa\left(1,i+24-2^{1*0}\right)+\frac{3}{4}*swa\left(1,i+24-2^{1*1}\right)+\frac{3}{4}*\ swa\ \left(1,i+24-2^{1*2}\right)\ +\ \frac{1}{4}*\ swa\ \left(1,i+24-2^{1*3}\right) \tag{8}$$

The third-order WT coefficient formula is given by

$$swd\ (3,i+24)\ =\frac{-1}{4}*\ swa\ \left(2,i+24-2^{2*0}\right)+\frac{-3}{4}*swa\left(2,i+24-2^{2*1}\right)+\frac{3}{4}*swa\left(2,i+24-2^{2*2}\right)+\frac{1}{4}*\ swa\ \left(2,i+24-2^{2*3}\right) \tag{9}$$

where *signal* is the 13-bit ECG signal, *swa* is the scale coefficient, and *swd* is the WT coefficient.

Figure 8 shows the proposed hardware architecture, using shift and addition to replace multiplication and division to complete the filter coefficients (1/4 and 3/4). This approach reduces hardware usage. This design uses three hardware groups to calculate WT, where each group contains 32 registers and three counters to store data and decide what information must be read.

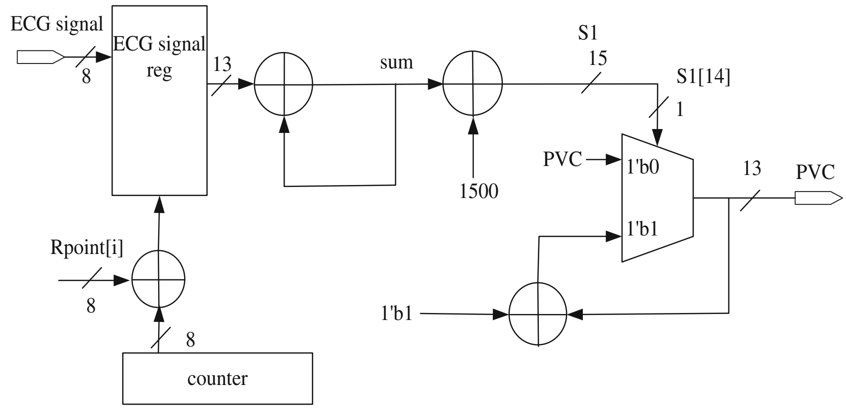

Figure 9 Hardware architecture of sum of trough.

5.2 Method_1: Sum of Trough

$$sum = \sum_{n=35}^{85} x[Rpoint[i] + n] \tag{10}$$

In (10), the total calculations are added 50 times using an adder to share and spend 50 clock cycles, allowing the system to save hardware resources. Figure 9 shows that if the result of sum adds 1500 is smaller than zero, it means that PVC occurs.

5.3 Method_2: Sum of R_peak with Minimum

$$diff = min + x[Rpoint[i-1]] \tag{11}$$

Figure 10 shows that the approach to find the minimum value is to use a subtractor for implementation by subtracting the input signal sequentially. Spending one R-R interval can yield the minimum value of the R-R interval. Finally, to add the min and the amplitude of the previous R-wave, if the result is smaller than zero, it means that PVC occurs.

6 Conclusion

This study converts the QRS detection algorithm [20] into the proposed R_peak detection algorithm. This study also proposes two new PVC detection algorithms to detect PVC arrhythmia. The most important practical function of this design, which is a morbidity warning system, can produce a warning signal when PVC occurs.

Simulation results show that the average accuracy of PVC detection is 94.73 %, which illustrates the high precision and superiority of the proposed system. The morbidity warning system can successfully send a warning signal to alert a user whether his or her heart is in normal condition. For real-time operation, the proposed system was implemented using the Xilinx Virtex4 XC4VLX60. The maximum operating frequency is 83.55 MHz, with 12,721 slices.

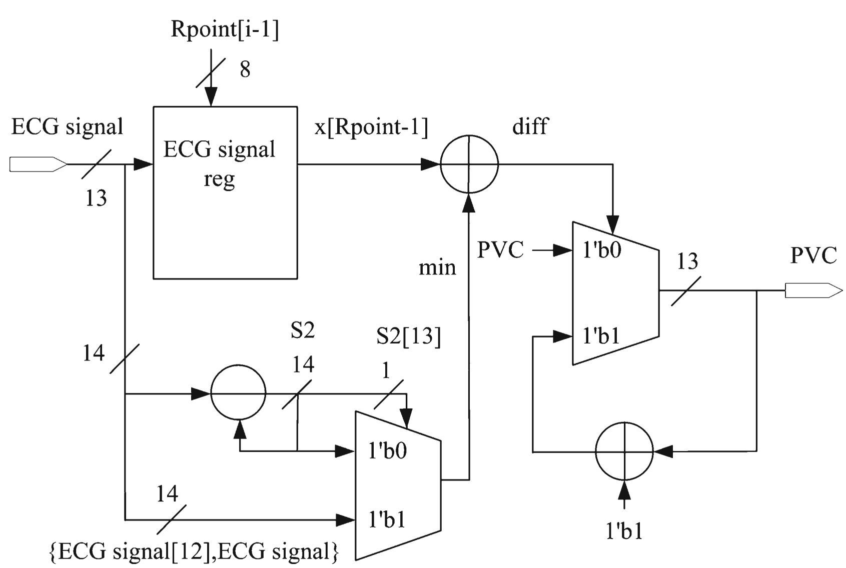

Figure 10 Hardware architecture of sum of R_peak with minimum.

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References

1. Alptekin, O., & Akan, A. (2010). Detection of some heart diseases by the analysis of ECG signals. In *Signal Processing and Communications Applications Conference (SIU)* (pp. 716–719). Diyarbakir, 22–24 April. doi:10.1109/SIU.2010.5654437.
2. Yuan, J., Tan, K. K., & Lee, T. H. (2010). Development of an e-Guardian for the single elderly or chronically-Ill patients. In *International Conference on Communications and Mobile Computing (CMC)*, vol. 3 (pp. 378–382). Shenzhen, 12–14 April. doi:10.1109/CMC.2010.167.
3. Marzencki, M., Hung, B., Lin, P., Huang, Y., Cho, T., Chuo, Y., & Kaminska, B. (2010). Context-aware physiological data acquisition and processing with wireless sensor networks. In *IEEE International Workshop on Medical Measurements and Applications (MeMeA)*, (pp. 53–56). Ottawa, ON, 30 April-1 May. doi:10.1109/MEMEA.2010.5480203.
4. Park, C., Chou, P. H., Bai, Y., Matthews, R., & Hibbs, A. (2006). An ultra-wearable, wireless, low power ECG monitoring system. In *IEEE Biomedical Circuits and Systems Conference (BioCAS)* (pp. 241–244). London, 29 Nov.–1 Dec. doi:10.1109/BIOCAS.2006.4600353.
5. Yang, Y., Huang, X., & Yu, X. (2007). Real-time ECG monitoring system based on FPGA. In *Annual Conference of the IEEE Industrial Electronics Society (IECON)* (pp. 2136–2140). Taipei, 5–8 Nov. doi:10.1109/IECON.2007.4459886.
6. Paul, J. S., Reddy, M. R. S., & Kumar, V. J. (1997). Automatic detection of PVC's using autoregressive models. In *Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBS)*, vol. 1 (pp. 68–71). Chicago, IL, 30 Oct.–2 Nov. doi:10.1109/IEMBS.1997.754465.
7. Zhao, L., Wiggins, M., & Vachtsevanos, G. (2003). Premature ventricular contraction beat detection based on symbolic dynamics analysis. In *International Conference on Circuits, Signals and Systems (CSS)* (pp. 48–50). Cancun, Mexico, 19–21 May. doi: From Proceeding (391) Circuits, Signals, and Systems - 2003.
8. Chiu, C. C., Lin, T. H., & Liau, B. Y. (2005). Using correlation coefficient in ECG waveform for arrhythmia detection. *Biomedical Engineering: Applications, Basis and Communications, 17*(3), 147–152.
9. Nahar, S., & ShahNoor bin Munir, M. (2009). Automatic detecion of premature ventricular contraction beat using morphological transformation and cross-correlation. In *International Conference on Signal Processing and Communication Systems (ICSPCS)* (pp. 1–4). Omaha, NE, 28–30 Sept. doi:10.1109/ICSPCS.2009.5306426.
10. Shen, Z., Hu, C., Liao, J., & Meng, M. Q.-H. (2010). An algorithm of premature contraction detection based on wavelet method. In *International Conference on Information and Automation (ICIA)* (pp. 1053–1058). Harbin, 20–23 June. doi:10.1109/ICINFA.2010.5512157.
11. Qiu, Y., Ding, X., Feng, J., & Mo, Z. (2006). QRS complexes detection based on Mexican-hat wavelet. *Journal of Biomedical Engineering, 23*(6), 1347–1349.
12. Fejtová, M., Macek, J., & Lhotská, L. (2001). ECG events detection and classification using wavelet transform and decision trees. In *Final Programme & Proceedings EUNITE* (pp. 496–499).
13. Inan, O. T., Giovangrandi, L., & Kovacs, G. T. A. (2006). Robust neural-network based classification of premature ventricular contractions using wavelet transform and timing interval features. *IEEE Transactions on Biomedical Engineering, 53*(12), 2507–2515.
14. Lim, J. S. (2009). Finding features for real-time premature ventricular contraction detection using a fuzzy neural network system. *IEEE Transactions on Neural Networks, 20*(3), 522–527.
15. Andreao, R. V., Dorizzi, B., & Boudy, J. (2006). ECG signal analysis through hidden Markov models. *IEEE Transactions on Biomedical Engineering, 53*(8), 1541–1549.
16. Gomes, P. R., Soares, F. O., Correia, J. H., & Lima, C. S. (2009). Cardiac arrhythmia classification using wavelets and hidden Markov models-A comparative approach. In *Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBS)* (pp. 4727–4730). Minneapolis, Minnesota, USA, 2–6 Sep. doi:10.1109/IEMBS.2009.5334192.
17. Moody, G. B., & Mark, R. G. (2001). The impact of the MIT-BIH arrhythmia database. *IEEE Engineering in Medicine and Biology Magazine, 20*(3), 45–50.
18. Goldberger, A. L., Amaral, L. A. N., & Glass, L. (2000). PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circulation, 101*(23), 215–220.
19. Mark, R. G., Schluter, P. S., Moody, G. B., Devlin, P. H., & Chernoff, D. (1982). An annotated ECG database for evaluating arrhythmia detectors. In *Annual International Conference of IEEE Engineering in Medicine and Biology Society (EMBS)* (pp. 205–210).
20. Zheng, X., Li, Z., Shen, L., & Ji, Z. (2008). Detection of QRS complexes based on biorthogonal spline wavelet. In *International Symposium on Information Science and Engineering (ISISE)* (pp. 502–506). Shanghai, 20–22 Dec., 2. doi:10.1109/ISISE.2008.61.
21. Mallat, S. (1992). Characterization of signals from multiscale edges. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 14*(7), 710–732.
22. Wang, C., & Lu, Y. (2011). Using biorthogonal wavelet filter band for ECG detection and reconstruction. *Beijing Biomedical Engineering, 20*(1), 25–29.
23. Pachauri, A., & Bhuyan, M. (2009). Wavelet and energy based approach for PVC detection. In *International Conference on Emergin Trends in Electronic and Photonic Devices & Systems* (pp. 258–261) Varanasi, 22–24 Dec. doi:10.1109/ELECTRO.2009.5441123.

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