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VLSI Implementation for R-wave Detection and Heartbeat Classification of ECG Adaptive Sampling Signals

V.Karthikeyan[1] and S.Kowsalya[2]

[1]*Assistant Professor, Department of ECE, Vivekanandha College of Engineering for Women (Autonomous), Tiruchengode, Tamilnadu, India.*
[2]*PG Scholar, Department of ECE, Vivekanandha College of Engineering for Women (Autonomous), Tiruchengode, Tamilnadu, India.*

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ABSTRACT

Heartbeat classification and R-wave location have been widely used to spot people's health condition. And battery-power devices are mainly applied to wearable scenario, which can examine people's health all day long, so high energy efficiency is very important under such circumstance. This paper proposes an improved DWT (Discrete Wavelet Transform) algorithm to achieve time- frequency characteristics of adaptive sampling ECG signals to locate the R-waves and calculate RR-intervals, and further applies KNN (K-Nearest Neighbor) as a classifier to classify heartbeats, then presents a power-efficient VLSI architecture for the proposed algorithms. Experiments with the MIT-BIR Database show that the proposed DWT algorithm obtains Se (sensitivity) of 96.29% and Pp (positive predictive) of 90.26% compared to 66.44% and 70.43% respectively by the original DWT algorithm under noise level of SNR=8.And the accuracy of the heartbeat classification is 87.7%. The VLSI is implemented using SMIC 65nm CMOS expertise and the power spending is 112.7 p W at 2 alternating frequencies of 60 and 360 Hz.

Keywords: KNN (K-Nearest Neighbor), DWT, ECG, MIT-BIR Database and R-wave location.

1. INTRODUCTION

Heartbeats can reveal health condition of human body. Some kinds of heartbeat types designate a great threat to life, which require immediate detection. Battery-power devices are the main trends to long-term's monitor of people's health condition. A software implemented classification system is low power-efficient in a real-time incident, which is proved below. thus we need to develop a low power hardware classification system. Adaptive sampling has been proposed in several works [I] [6] to adapt the sampling rate based on the activities of the input data. Thus it is normally used to reduce power consumption of the whole system, which is more acceptable in battery-used devices. Figure I shows that high sampling frequency is used for the possible R- wave area and low sampling frequency for none R-wave area. However the adaptive sampled signals are usually mixed with noises for adaptive sampling is mainly based on the time domain characteristics. There is a high possibility that the low frequency sampled region may contain R-waves. Our research shows that as the SNR goes down, the obviousness accuracy will significantly decrease. In order to explain the problem, an improved DWT algorithm is projected to locate the R-wave point of sampled ECG signals. And the KNN system is used as a classifier since heartbeat types are highly related to the RR-intervals. The rest of the paper is organized as follows: Section 2 describe the algorithm of optimized DWT with adaptive sampling; Section introduces the KNN classifier; Section 4 details the construction of the whole system; Section 5 shows the results and Section 6 makes a conclusion.

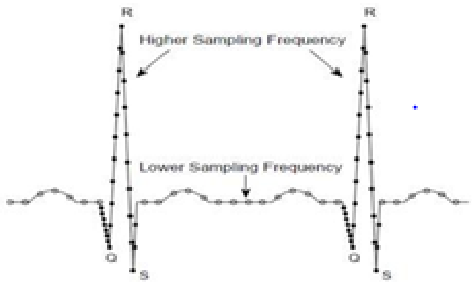

Figure 1. Adaptive sampling

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2. OPTIMIZATION OF DWT WITH ADAPTIVE SAMPLING

ECG signals shows great arbitrariness along with noise most of the time. DWT is good at extracting the exact frequency characteristics of heartbeats, which can tell between the ECG signals from the noise. The traditional way to estimate DWT [4] is using Mallat's Algorithm shown in Eq. (1), where j denotes the scale coefficients of the wavelet.

$$Qj(aJ) = G(2J\text{-}1aJ)IT^{\,j-2} H(2^k aJ)_{(l)\ k}=() \qquad (1)$$

The filter H((j)) and G((j)) are only suitable for certain sampling frequency, while in an adaptive case system, the occurrence will change and the fixed filter H((j)) and G((j)) will be no longer fit. As shown in Table 1, the frequency band-pass of the equivalent filter Q ((j)) change as the sample frequency vary. An optimized DWT is proposed in this paper to change the frequency band-pass of the filters to match the sampling frequency changes. Using OJ 1 denote the higher sampling frequency, OJ 2 denoting the lower sampling frequency and p= OJ / OJ 2, we have

$$M(OJ) = H(OJ] / p)H(2OJ] / p)H(4OJ] / p)G(8OJ] / p) \quad (2)$$

Table 1. 3dB Band-pass for different sampling frequency
(250 Hz, 360 Hz and 500 Hz) at j=4

Sampling frequency	Lower cut-off frequency	Upper cut-off frequency
250Hz	6	14
360Hz	7	20
500Hz	10	28

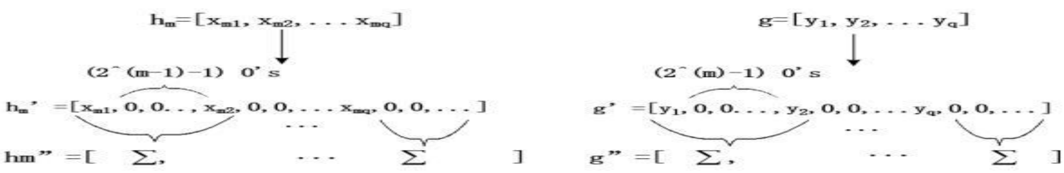

Figure 2. The way to get optimized DWT filters.

Figure 2 shows the way to get optimized DWT filter. To calculate filter hen) and g(n) that are suited for sampling frequency OJ 2> we need to insert 2/\(m-2) O's at the end of each coefficients in hen) and g(n), where m = 2, 3, ..., n, and n is the order of the Mallat's Algorithm, to get h'(n) and g' (n) (where hm(n) resources the m'th iteration of filter hen)). Since the 2nd iteration of filter hen), we calculate the summing up of the p successive coefficients of hm 'en) as the new coefficient of filter hm"(n). Then, we get the filter adapted for the new sample frequency. Finally the zero-crossing method [4] is used to locate the R-wave face based on the DWT result.

3. KNN ALGORITHM

KNN is a method to classify different types of data based on the majority of the nearest neighbors [7]. In order to classify the heartbeats, we choose the KNN algorithm analyzing RR-intervals, which are imitative from the DWT result. K undeviating distances are stored as a class. We calculate the distances between unlike groups and the new data using Euclidean distance.

The data will be assigned to the nearest group. After that, we compare the new distance with the k distances in that group to select the new k shortest distances and points. Figure 3 shows that different types of heartbeats are gathered in diverse groups. We firstly train the KNN classifier based on the training data from MIT-8IH Database (approximately 50% of total data). We use RR_ l (the latest RR-interval), RR_8 (the average RR-interval of the last 8 R-wave) and RR_64 (the average RR-interval of the last 64 R-wave) as three magnitude.

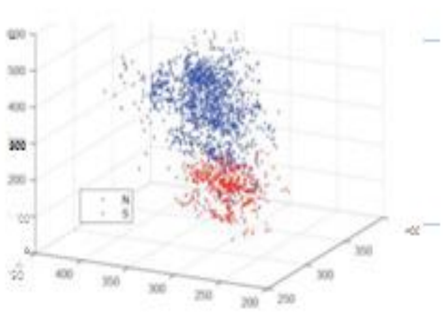

Figure 3. The distribution of heartbeats 'N' and'S'.

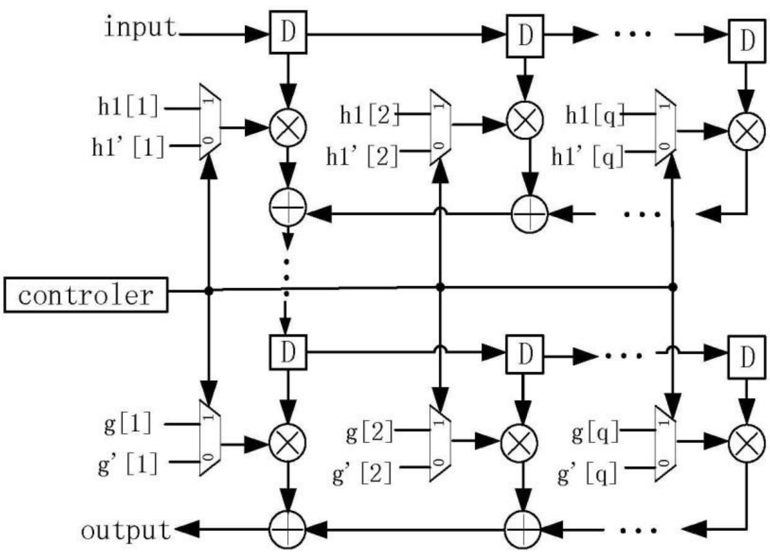

Figure 4. Optimized DWT structure.

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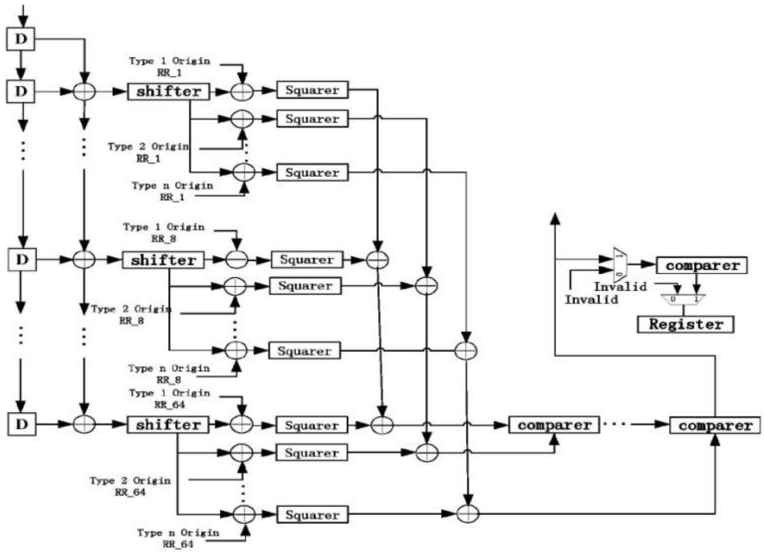

Figure 5. The structure for KNN.

4. HARDWARE ARCHITECTURES

Figure 4 SHOWS the proposed structure of the DWT module. Since there are two frequencies used in adaptive sampling, different hen) and g(n) filters are needed. The controller module controls coefficients of the filters, and the alternation between CLK I and CLK2. Figure 5 proposes the VLSI structure of the KNN algorithm. 64 registers and shifters are used to calculate the RR I, _8 and RR_64. Squarer is used to calculate the distances between the input point's location and the five different origin points. The comparator determines the shortest distance. Thus we can classify the type of that heartbeat. After that, the new distance will be put into the register and the value in the register will be updated. That type's origin point's position will also be revived.

5. RESULTS

We use Se and Pp to measure the performance of the classification system. MIT-BIH Arrhythmia Database and MIT-BIH Noise Stress Test Database are utilized to test the performance of different algorithms. DWT result is shown in Figure 6. Performance of the traditional DWT algorithm is averagely 22.3% lower than the improved algorithm.

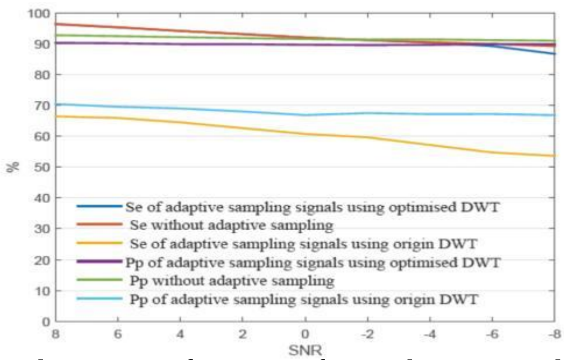

Figure 6. R-wave detection performance of non-adaptive sampling signals using DWT, adaptive sampling signals using DWT, and adaptive sampling signals with improved DWT.

Table 2 KNN Result

		Reference Label				
		N	S	V	F	Q
Predicted Label	N	29268	1366	1232	461	0
	S	196	1709	265	423	0
	V	210	162	1046	133	0
	F	32	8	I	191	0
	Q	0	0	0	0	0

KNN's result is shown in Table 2, i.e. the Se and Pp of heartbeat N is 98.53% and 90.54%, the Se and Pp of heartbeat S is 52.67% and 65.91%, and the total classification truth of the heartbeat type is 87.7%, which is plausible among related works [2] [3] [5]. The KNN algorithm is also implemented in software on OVPsim Virtual Platform employing an orl k RISC processor. And the simulating results show that 1000 sample require about 5 million directions to be classified in time. That means, to realize real-time classification of heartbeats, a RISC processor shall run at a frequency of at least 5,000 times of the sampling frequency, which is quite not power-efficient. in the interim, the hardware solution is implemented using SMIC 65nm CMOS technology and its results show that the area of the KNN's result is shown in Table 2, i.e. the Se and Pp of heartbeat N is 98.53% and 90.54%, the Se and Pp of heartbeat S is 52.67% and 65.91%, and the total classification truth of the heartbeat type is 87.7%, which is plausible among related works [2] [3] [5]. The KNN algorithm is also implemented in software on OVPsim Virtual Platform employing an orl k RISC processor. And the simulating results show that 1000 sample require about 5 million directions to be classified in time. That means, to realize real-time classification of heartbeats, a RISC processor shall run at a frequency of at least 5,000 times of the sampling frequency, which is quite not power-efficient. in the interim, the hardware solution is implemented using SMIC 65nm CMOS technology and its results show that the area of the system is about 2272641J m^2 and the total power consumption is 112.7 IJ W at 2 alternate frequencies of 60 and 360 Hz. Thus it is an energy-efficient solution for the detection and classification of ECG adaptive sampling signals.

6. CONCLUSION

This paper presents hardware construction of the heartbeat classification system for adaptive sampling ECG signals. An optimized DWT algorithm is projected, which greatly improves the detection accuracy of R-wave points under noise. This also guarantees the high accuracy of heartbeat classification. The VLSI architectures are residential to realize real-time detection of arrhythmia heartbeats and greatly reduce the influence consumption.

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