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PARAMETER EXTRACTOR FOR THE INTELLIGENT HOME HEALTHCARE EMBEDDED SYSTEM

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ABSTRACT

In recent years, there has been a rapid growth in the development of telemedicine systems and monitoring devices for patients with chronic diseases which require continuous telemonitoring treatment. However, most of these systems only provide telemonitoring services or basic information about the health condition of the patients. For this reason, an Intelligent Home Health Care Embedded System (IHHCS), which can provide patients with diagnosis about their health status at home, has been developed. This system mainly consists of three parts: an algorithm for processing the extracted parameters, a novel embedded medical transducer parameter detector/extractor, and an ARM-cored structure embedded with the µClinux system. This novel parameter detection and extraction algorithm, which utilizes the state-of-the-art wavelet signal processing technique, is built to interlink the algorithm and the ARM-cored system for elevating the overall performance of IHHCS. As a result, different types of pluggable medical transducers (*e.g.* electrocardiograph, sphygmomanometer and blood glucose meter) for patients with different illnesses can be flexibly connected to the interface of the embedded ARM-cored system. This approach introduces great flexibility to the IHHCS and enhances the versatility of the telemedicine system and monitoring devices.

INTRODUCTION

In the past, patients with chronic diseases often had to spend precious time and pay inconvenient visits to have their health checked at either hospitals or clinics. As our life quality is being improved, many telemedicine systems and monitoring devices are being developed, [1-3]. To reduce the inconvenience, we propose an Intelligent Home Health Care Embedded System (IHHCS) which can provide diagnosis about health status for patients directly at home. Patients can check their own health easily and advice about their health status can be displayed to them immediately.

According to the type of biomedical signals that needs to be obtained from the patients, different types of pluggable medical transducers will be connected to the embedded µClinux ARM-cored platform, [4], for signal acquisition. By feeding the digitized biomedical signals to our novel embedded medical transducer parameter detector/ extractor, relevant parameters will be extracted out by using promising techniques like wavelet transforms. Finally, these parameters will be sent to our expert system with updatable knowledge base, [5], for diagnosis of the health status. Primary diagnostic results directly related to discomfort possibly occurred, or a disease likely to be encountered, will be displayed as a preliminary advice to the patients. Patients will have a clearer idea about their health and can pay visits to their physicians only if their problem is deemed necessary.

The heart, which controls the life of every human being, is an important organ in our body. By studying the Electrocardiogram (ECG), valuable information about the health status of the patient can be obtained. Therefore, ECG analysis will be an indispensable part in our system. Although there are various types of QRS detection methods, wavelet is still adopted in our proposed system for the purpose of increasing the speed and reducing the size of the embedded system. In fact, wavelet manipulation can be implemented by using filters with different groups of coefficients, which implies the migration from software algorithm to hardware circuits.

Other analyses, like blood pressure and blood glucose which require fewer parameters (*e.g*. Systolic and Diastolic for blood pressure, glucose level for blood glucose), can be treated similarly to our treatment with the ECG signal as long as the transducers are well-designed. Therefore, in this paper, we will focus on the analysis of the ECG signals. In fact, all these transducers can be added to or removed from IHHCS according to the needs of the patient.

SYSTEM ARCHITECTURE

The IHHCS is developed over the ARM-cored structure embedded with the µClinux system, [4]. The ARM-cored developing board, which is equipped with a Samsung S3C44B0X CPU using an ARM7TDMI core, serves as the most important component of our system. Although an ARM CPU is more expensive, considering the computational power required by our expert system and the total cost of the platform, it is preferred for its powerfulness & cost-effectiveness, especially when compared to low end MCU like 8051 series (even with its advanced module). For the embedded OS, µClinux (a kernel-reduced micro Linux system) is chosen because of its suitability for the embedded application. It can provide a small kernel for limited storage space and abundant functions inherited from the pure Linux system such as network proficiency, memory management and so on. The µClinux publishing edition cannot directly support our S3C44B0X but with suitable configurations, the µClinux kernel has been revised to make our core function normally.

Next, biomedical signals are fed into IHHCS through the signal acquisition system (*e.g.* pluggable medical transducers for ECG or blood pressure), which changes them to the format that can be analyzed by our biomedical signal parameter extractor. Since different transducers have different communication protocols, configurations in the driver program of the embedded system are designed to fit for different transducers and the desired one is selected to work every time. In analyzing the biomedical signals, the embedded parameter extractor will use methods (as discussed in the following sections) to have characteristic points detection and parameter extraction.

Afterwards, all related parameters extracted will be read by the expert system to produce diagnosis. Our expert system includes a rulebase and the related inference to emulate humans'/experts' judgment based on experience. To implement it in our system, a new algorithm for an expert system was proposed, [5]. This new method can sufficiently reduce the huge resources required by a traditional expert system as well as their accompanied rulebase. To get the useful rulebase, descriptions of existing medical information are selected in our system and will be updated according to practical conditions.

Finally, the measuring and diagnostic results can be displayed explicitly on the display (*e.g.* LCD display) of the system. The system architecture is shown in Figure 1.

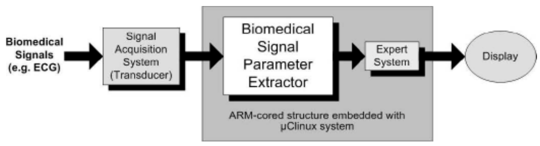

Fig. 1. System architecture of IHHCS.

METHODOLOGY

Once the ECG signal has been processed by the transducer, our parameter extractor will start the detection of the ECG waves and complexes, followed by parameter extraction.

The detection of the QRS complex is the most important task in automatic ECG signal analysis so it will be the first step in our parameter extractor.

Our QRS detection method mainly consists of three parts: baseline drift elimination, Quadratic Spline Wavelet Transform, [6][7], and determination of QRS complex positions using adaptive threshold values.

1. <u>Baseline drift elimination</u>

Baseline drift elimination can be done using two median filters (200-ms and 600-ms). The 200 ms median filter is used to remove QRS-complexes and P-waves while the 600-ms median filter is used for removing the T-waves. By subtracting the filtered signal from the original signal, a signal with baseline drift eliminated can be obtained. The process is shown in Figure 2.

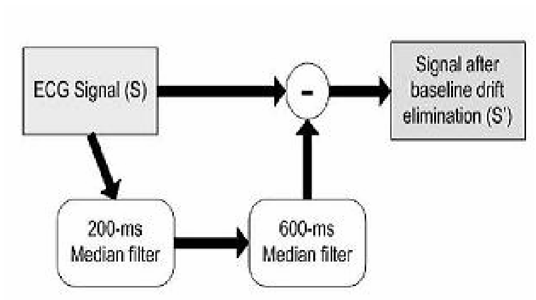

Fig. 2. Baseline drift elimination method. [7]

2. <u>Quadratic Spline Wavelet Transform</u> [6]

In the second step, Quadratic Spline Wavelet is chosen. Theoretically, the discrete and inflexion points of a signal can show different obvious characteristics in multi-resolution after wavelet transform. Making use of this advantage, the high pointed QRS wave in the ECG signal, after wavelet transform, will be transformed into pairs of positive maximum and negative minimum. Among all types of wavelets present, Quadratic Spline Wavelet is known to detect QRS complex well and so our parameter extractor is based on Quadratic Spline Wavelet.

Quadratic Spline Wavelet

The discrete Fourier transform of Quadratic Spline Wavelet $\hat{\psi}(w)$ is defined as:

$$\hat{\psi}(w) = iw\left(\frac{\sin(w/4)}{w/4}\right)^4$$

The symbol ^ represents the discrete Fourier transform. The filters H(w) and G(w) are:

$$H(w) = e^{iw/2}(\cos\tfrac{w}{2})^3 \; ; \; G(w) = 4ie^{iw/2}(\sin\tfrac{w}{2})$$

We perform the discrete Fourier transform of the wavelet transform ($D_1(w)$, $D_2(w)$, …, $D_j(w)$) and get the transform functions of the corresponding equivalent filter ($Q^1(w)$, $Q^2(w)$, …, $Q^i(w)$). The bandwidth range of the normal QRS complex (approximately 10 Hz~25 Hz) overlaps with the bandwidths of $Q^3(w)$ and $Q^4(w)$ (as shown in Figure 3); so the characteristic of the QRS complex is the most obvious in D_3 and D_4 Moreover, the number of maximum-minimum pairs are much fewer in higher scales as a significant high frequency noise gets decayed. Therefore, the maximum and minimum pairs are searched from the large scale wavelet transform. Although most noise has been reduced, there are still mis-detections caused by high frequency noise. In this case, appropriate threshold criteria are employed to delete extra detected point pairs.

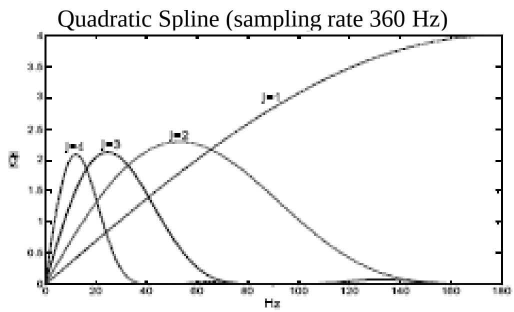

Fig. 3. The amplitude-frequency responses of filters $Q^j(w)$ at different scales corresponding to 360/s sampling rate. $f = 180\ \omega/\pi$.

3. <u>Determination of QRS complex positions</u>

The threshold values of each scale can be determined by the following equations:

Positive threshold value: $\varepsilon_n^{max} = \beta_n A_{max}^m$

Negative threshold value: $\varepsilon_n^{min} = \beta_n A_{min}^m$

where $A_{\max}^{m}$ or $A_{\min}^{m}$ is the average value of the maximum or minimum values of all 512-sample-window, and β_n is the weighted value of the corresponding scale n. The adjusted weighted value for each scale is shown in Table 1.

Table (1). Weighted values for each scale.

	β_1	β_2	β_3	β_4
Values after adjustment	0.32	0.3	0.25	0.28

The following is the procedure:

Starting from the high scale (*i.e*. D_4), search out all the positive and negative characteristic points (extreme values) which are over the corresponding threshold values ($\varepsilon_4^{\max}$ and $\varepsilon_4^{\min}$). Then at the next lower scale (*i.e*. D_3), in the neighboring regions of the characteristic points from the previous scale, search out the positive and negative characteristic points which are over the threshold values $\varepsilon_3^{\max}$ and $\varepsilon_3^{\min}$. Repeat this until Scale 1. As there may be characteristic points caused by noise, for points which can be in pair with more than 1 positive/negative point, the closest and the largest characteristic points will be taken and the rest will not be considered anymore.

Determination of the R-peak

Using the original ECG signal, in the corresponding neighboring regions of each pair of characteristic points in Scale 1, search for the positive peaks. All the peaks found are the detected R-peaks of the QRS complex.

Determination of Q and S

After finding out all R-peaks, the position of Q and S can be easily determined. For every R-R interval, search for the negative peak that is closest to the first R of the corresponding interval. The negative peak found will be the S of the QRS complex. To find Q, search for the negative peak (if Q is present) just before the second R peak.

RESULT AND DISCUSSION

The prototype system has been implemented and tested part by part. The ARM-cored structure embedded with the µClinux system and the expert system for processing the extracted parameters have been tested to have a good performance, [4,5]. The ECG and blood pressure transducers have been tested on normal persons and the results show that they operate well and the corresponding biomedical signals can be obtained clearly.

Twenty-three excerpts (each lasts for 10 minutes) of the MIT/BIH arrhythmia database, [8] have been taken to evaluate our parameter extractor. In testing, only channel 1 of the two-channel ECG signal in the database was used. The overall accuracy for the QRS complex detection was 99.6514%. The total number of beats is 16062 with 46 beats (0.2864%) of false positive (FP) and 10 beats (0.0622%) of false negative (FN). Among these records, more than half of the records are 100% accurate, the rest are over 99% accurate except record x_108 and record x_228 with accuracy 96.53% and 97.35% respectively. During 130 s - 150 s of record x_108 and during 215 s - 335 s of record x_228, the signals were quite noisy which increased the difficulty in QRS detection. The Quadratic Spline Wavelet Transforms of a sample ECG signal are shown in Figure 4, and the results of the R-peaks detection are shown in Figure 5. Detected R-peaks are shown in circles and annotations are shown with vertical dotted lines.

Original ECG signal and its Quadratic Spline Wavelet Transform (D1-D4)

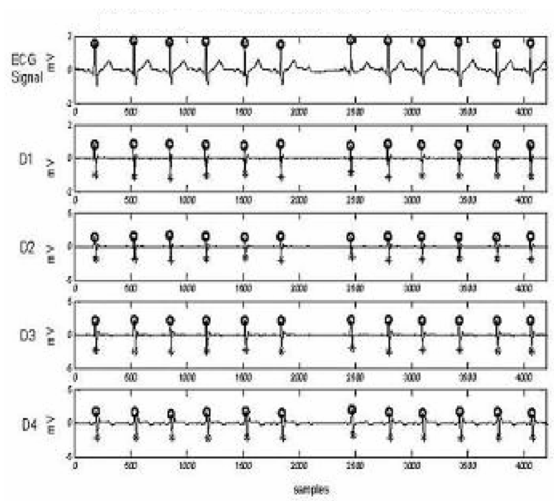

Fig. 4. ECG signal and its Quadratic Spline Wavelet Transform.

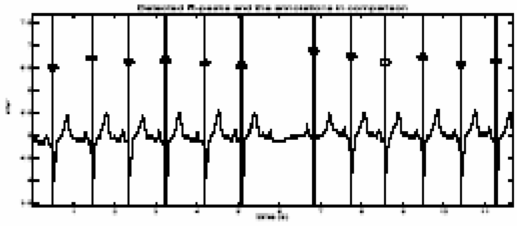

Fig. 5. Detected R-peaks and the annotations in comparison.

CONCLUSION AND FUTURE DEVELOPMENT

In this paper, we have briefly discussed our IHHCS system structure and have presented the embedded medical transducer parameter extractor of the IHHCS in which the Quadratic Spline Wavelet Transform has been adopted and the results of QRS detection are satisfactory. The IHHCS will help in providing patients with diagnosis immediately when they feel in discomfort. In future developments, more parameters of the ECG will be detected and extracted. Moreover, to increase the speed of the system, migration of the software to hardware filter will be investigated. Size-reduction and increment of diagnosis speed will then be considered the next step in improving our system.

REFERENCES

1. Yonghong Zhang, Jing Bai, Wen Lingfe, *Int. Conf. IEEE EMBS* **3**, 2282 (2000).

2. Jing Bai, Yonghong Zhang, Delin Shen, Lingfeng Wen, Chuxiong Ding, Zijing Cui, Fenghua Tian, Bo Yu, Bing Dai and Jupeng Zhan, *IEEE EMB Magazine* **18**(4), 63 (1999).

3. T. C. Chang, J. D. Lee and S. J. Wu, *Proc. 26th IEEE EMBS* 3392 (2004).

4. Shuo Tang, Weng Chi Chan, Mang I Vai and Peng Un Mak, *Proc. 26th IEEE EMBS* 3116 (2004).

5. Bing Nan Li, Ming Chui Dong, and Mang I Vai, *Proc. EPMESC IX* 963 (2003).

6. Cuiwei Li, Chongxun Zheng, Changfeng Tai, *IEEE Trans. Bio. Eng.* **42**(1), 21 (1995).

7. Yang Zheng Rong, A Method of QRS Detection Based on Wavelet Transforms (Master Thesis), National Sun Yat-Sen University (2003).

8. MIT-BIH Arrhythmia Database, available at www.physionet.org.