Continuous Wavelet Transformation the Wavelet Implemented on a DSP Chip for EEG Monitoring

Chien-Yue Chen
National Yunlin University of Science and Technology
Department of Electronic Engineering
Douliou, Yunlin, Taiwan
chencyue@yuntech.edu.tw

Ming-Da Ke
National Yunlin University of Science and Technology
Graduate School of Engineering Science & Technology
Douliou, Yunlin, Taiwan
g9710808@yuntech.edu.tw

Cheng-Deng Kuo
Taipei Veterans General Hospital
Biophysics Laboratory
Department of Research and Education
National Yang-Ming University
Institute of Emergency and Critical Care Medicine,
Taipei, Taiwan
cdkuo@vghtpe.gov.tw

Abstract—*In this paper, a biomedical signal development module based mainly on a digital signal processing (DSP) chip is used to provide real-time electroencephalograph (EEG) monitoring. Besides, TMS320C6713 DSP starter kit from Texas Instruments is applied to compile a most appropriate mother wavelet algorithm and the continuous wavelet transform (CWT) analysis program to achieve real-time EEG monitoring.*

Keywords-continuous wavelet transform (CWT); digital signal processing (DSP); electroencephalograph (EEG), daubechies (db);most appropriate mother wavelet

I. INTRODUCTION

With recent developments in medical science and technology, the integration of information technology into medical systems in order to save considerable human and material resources as well as lower misdiagnosis rate, has been receiving wider attention. A human electroencephalograph (EEG) was first successfully recorded in 1924 by Hans Berger, a German scientist [1]. Currently in the area of biomedicine, the studies of medical science adopting wavelet analysis have a wide range of applicability, such as utilizing continuous wavelets to filter out non-EEG noise and other biological signals from EEG signals [2,3,4], and also applying continuous wavelets to analyze the changes of EEG of a patient to detect the possibility of early Alzheimer's Disease [5].

Many biomedical signal analyzers do wavelet transformation did not choose the proper mother wavelet function, the mother wavelet they chosen was always lacked of orthogonal and compact support in frequency domain. The choice of improper mother wavelet will result in the problem of energy leakage and will generate many artifacts in the power spectral density, then the clinical diagnostic pitfall should be happened. Therefore, in 2008, we proposed finding the most appropriate mother wavelet by using the least square method, which can help the biomedical signal analyzers do an optimal wavelet transformation [6].

TMS320C6713 DSP Starter Kit (DSK) from Texas Instruments (TI) was used in the system as the hardware development platform. The algorithms of optimal mother wavelet and wavelet analysis were executed and then integrated into the hardware platform.

II. THEORY

Fourier analysis is commonly used in signal analysis, but it lacks local time resolution. Short-time Fourier Transform (STFT), introduced by Dennis Gabor in 1964, overcomes the inability of traditional Fourier analysis for local analysis; however, it has a significant statistical error and is extremely biased [11]. Therefore, Fourier analysis is only suitable for analyzing stationary signals.

Wavelet analysis is a localized analysis method with variable time and frequency windows, and it can be used instead of traditional Fourier transforms. For an arbitrary function $f(x) \in L^2(R)$, the function of a continuous wavelet is:

$$W_\psi f(a,b) = |a|^{-\frac{1}{2}} \int f(x)\overline{\psi(\frac{x-b}{a})}dx \quad (1)$$

where a is a dilation factor defining the dilation-contraction ratio of a wavelet , b is a shift factor ($a, b \in R$, $a > 0$), $\overline{\Psi_{a,b}(\frac{x-b}{a})}$ is convolution integration, and $\Psi(t) \in L^2(R)$ is a energy-limited space of square integrable functions.

Daubechies (db N) wavelets were used in this study - cluster of compactly supported orthogonal mother wavelets that were introduced by Ingrid Daubechies in 1988. Daubechies wavelets are represented as db N (N=1、2、…、43). Except db1, all other wavelets have no specific equations, while the square modulus of their transform function can be expressed as:

$P(y) = \sum_{k=0}^{N-1} C_k^{N-1+k} y^k$, where C_k^{N-1+k} is a polynomial coefficient , thus:

$$\left|m_{0(w)}\right|^2 = (\cos^2 \frac{\omega}{2})^N P(\sin^2 \frac{\omega}{2}) \text{ , where}$$

$$m_0(w) = \frac{1}{\sqrt{2}} \sum_{k=0}^{2N-1} h_k e^{-ik\omega} . \quad (2)$$

One problem which has been encountered frequently during wavelet analysis was the selection of mother wavelets.

Different mother wavelets can sometimes lead to different results even when analyzing the same signal. As a result the solution to the problem traditionally relies on a researcher's experience.

In 2003, Pega adopted db4 mother wavelets to detect abnormal EEG signals [9]. Liu et al proposed using mother wavelets from the db family for computation and analysis in their study of automatically detecting and classifying EEG in epilepsy syndromes [10]. Nevertheless, they did not state the reasons for the chosen mother wavelets, so it is impossible for us to learn from the experiences of past studies. As a consequence, we decided to use the optimal mother wavelet algorithm introduced in 2007 [6], based on the following assumption:

$$(\boldsymbol{F}(\mathrm{S}))^2 = ((\boldsymbol{F}(\mathrm{D1}))^2 + (\boldsymbol{F}(\mathrm{D2}))^2 + (\boldsymbol{F}(\mathrm{D3}))^2 + (\boldsymbol{F}(\mathrm{D4}))^2 + (\boldsymbol{F}(\mathrm{D5}))^2 + (\boldsymbol{F}(\mathrm{A5}))^2, \quad (3)$$

where S is the input signal, $D1$,$D2$, $D3$, $D4$, $D5$ and $A5$are decomposed signal components after wavelet analysis, and F represents Fourier analysis. It can be observed from equation 3 that the resulting power spectral density after wavelet analysis should be the same as the power spectral density of raw signal. Yet our experiments showed that wavelet analysis could cause energy leakage. To improve this situation, both the least square and sum of squared error methods were used in our algorithm to find which mother wavelet that would result in minimal energy loss. The equation was:

$$SSE = \sum_{i=1}^{n} d_i^2 = \sum_{i=1}^{n} [y_i - f(x_i)]^2 \quad , \quad (4)$$

where (x_i, y_i) defines the height of sample points on the ith curve, and $d_i = y_i - f(x_i)$ is the bias of the ith point [6]. Hence the resulting mother wavelets were the most appropriate ones for signal analysis.

III. System

Figure 1 shows the block diagram of the system. The system was comprised of five parts. The first was the wavelet system. The second and third parts were the RTDX Host and RTDX Client systems respectively. RTDX host and RTDX Client systems, provided by TI, were functions providing communications between a personal computer and DSP chips, so that instant information exchange could be attained in the system via these functions. The fourth part was a monitor and result display system, which mainly dealt with the control and result display of the DSP chips. The fifth part was a MP150 biological signal acquisition system, capturing human EEG physiological signals and keeping records on the computer. The wavelet system also consisted of two parts – hardware and software. The hardware was developed upon a TMS320C6713 DSK board featured by TI. The programs executed on the DSP platform included optimal mother wavelet and continuous wavelet analyses. The operation of these programs are described below.

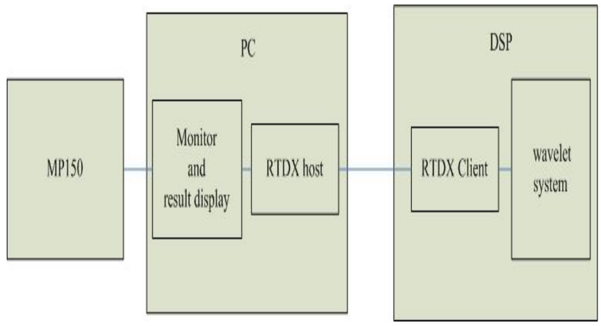

Figure 1 System Block Diagram

Firstly, fast Fourier analysis was performed to compute the power spectral density of the input signal. Then, the input signal was decomposed into six levels by means of wavelet multi-resolution analysis starting with the db1 mother wavelet. Meanwhile, the power spectral density of each level was computed by Fourier analysis and later summed up. The result of summations was recorded, until the analysis finished with the db6 mother wavelet. Finally, the power spectral density value of the raw signal and the value after wavelet analysis were compared by using a least square method. The least value was then found after comparison, and the mother wavelets corresponding to the least value were chosen as the most appropriate ones for EEG analysis [6].

Figure 2 is a flowchart illustrating the process of continuous wavelet transform together with an optimal mother wavelet algorithm. At the beginning of execution, the system captured the EEG signals in the first 20 seconds, and found the appropriate mother wavelet via the optimal mother wavelet algorithm. Later the mother wavelet was used in the continuous wavelet analysis to analyze the EEG signals. The analysis results were returned to the computer for display.

The DSP/BIOS library included a real time data exchange (RTDX) function. The function enabled the DSP chip to communicate and exchange information with the PC via a USB interface, so that DSP chip could directly exchange information with PC without discontinuing the execution of current jobs. The programs executed by the PC consisted of the monitor system and results display system. The monitor system mainly monitored the executions on the DSP chip, and the display system showed the analysis results.

IV. Discussions

The system used in the study could be divided into two parts. The first part used continuous wavelets to analyze the EEG signal, which mainly dealt with transplanting the program, which was executed by the PC in Wavelet Real Time Monitoring System: A case study of the musical influence on electroencephalography, into DSP chip [8]. The second part introduced the optimal mother wavelet algorithm into the DSP chip, and found the most appropriate mother wavelet for signal analysis from the Daubechies wavelet family.

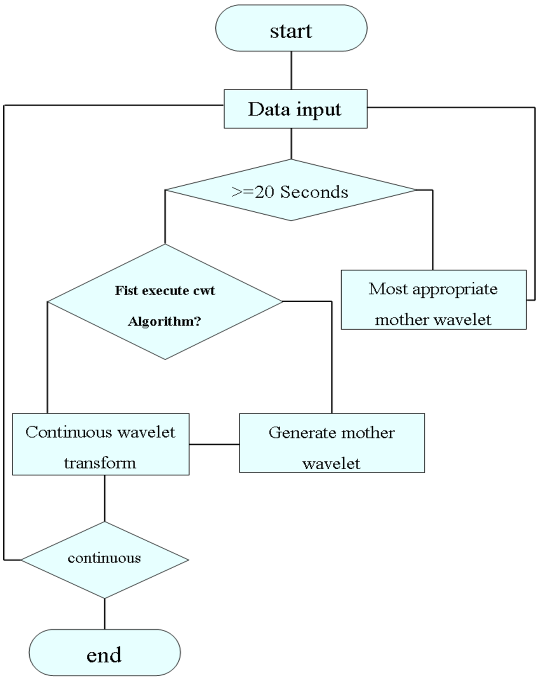

Figure 2 Integrated Algorithm Of Optimal Mother Wavelet And Continuous Wavelet Analysis

According to our experiments, if the sampling frequency was 200Hz, only db1~db3 were the appropriate mother wavelets for the system, while the number of suitable mother wavelets increased if the 0.5Hz to 1Hz frequency band in the EEG were ignored. However, the 0.5Hz to 1Hz frequency band belong to δ wave in the EEG single, some research in sleep monitor was interested in this band[12]. In order to avoid missing information and the use of more db mother wavelets in the system, the sampling frequency of the EEG signals was lowered to 100Hz.

Figure 3 shows the analysis of a 30-minute-long EEG signals of ten males, whose ages were within 20 to 25 years, with a sampling frequency of 100Hz, using continuous wavelet transform and the optimal mother wavelet; in addition, the appropriate mother wavelets were found by analyzing the EEG signals recorded in the first 20 seconds with the optimal mother wavelet algorithm. It can be discovered from Figure 3, that the execution times for a continuous wavelet transform performed on the signals from the volunteers were all less than 7 minutes; whereas the execution time on some volunteers was shorter than that of others, and the reason was that N varied with each volunteer, thus resulting in differing execution times.

Figure4 illustrates the relation between execution time of the continuous wavelet transform and db mother wavelets.

In this study, despite the fact that the usable mother wavelet in the matlab soft(R2007a) could reach db45, when EEG signal was analyzed using continuous wavelet transform, the system failed in execution due to overflow; consequently, the mother wavelets shown in Figure 4 only reached db6. As N in db N increases, the execution time of continuous wavelet transform increases. The reason for this is that as N increases, the number of wavelet coefficients rise, and the computational work of DSP increases during the convolution integration. Hence, the execution time of a continuous wavelet transform also increases. When N in db N was greater than 6, the wavelet coefficients generated from continuous wavelet transform exceeded the available range of system memory, thus resulting in a system overflow and a failure to execute. Therefore, the mother wavelets that fit in the study were for N ≤6.

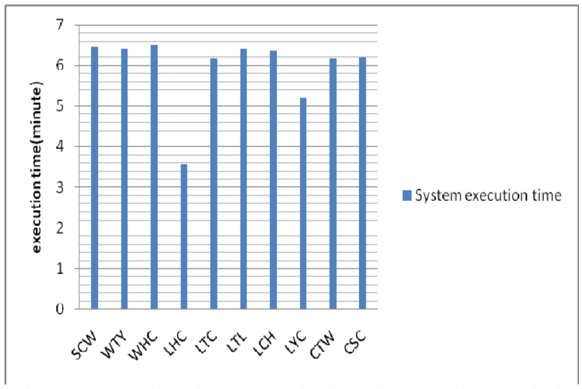

Figure 3 Execution Time For Optimal Mother Wavelets Analysis

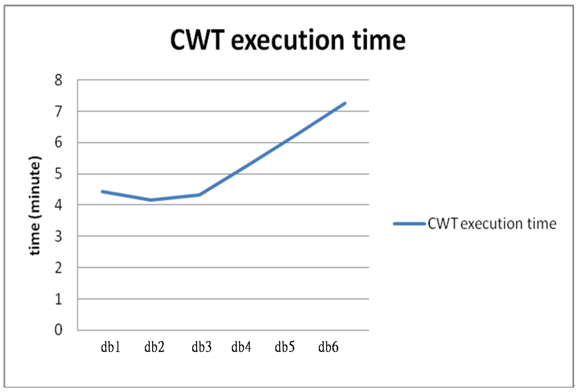

Figure 4 Relation Between Execution Time For Continuous Wavelet Transfrom And db Mother Wavelets

Figure 5 shows the execution results of EEG signals analyzed by optimal mother wavelet programs executed in MATLAB and DSP respectively, with the signals recorded from ten 20-to-25-year-old males. The results of continuous wavelet transform in MATLAB and DSP are also compared in Figure 5. It can be observed from the figure that the continuous wavelet transform in MATLAB and DSP have the same accuracy. It can be thus concluded that the optimal mother wavelet algorithm in DSP was accurate.

The EEG signals taken to find the optimal mother wavelets were recorded in the first 20 seconds, and the execution time for optimal mother wavelet algorithm was 1.2 minutes, which is too long. Trials like increasing the input of system information and reducing the number of system executions of optimal mother wavelet algorithm were taken to increase execution time. Yet, the increase in the input of information was limited due to the limitation of the hardware, and thus there was no significant improvement in the optimal mother wavelet program. In the future, it is expected that the execution speed of the optimal mother wavelet algorithm will be improved by upgrading the hardware.

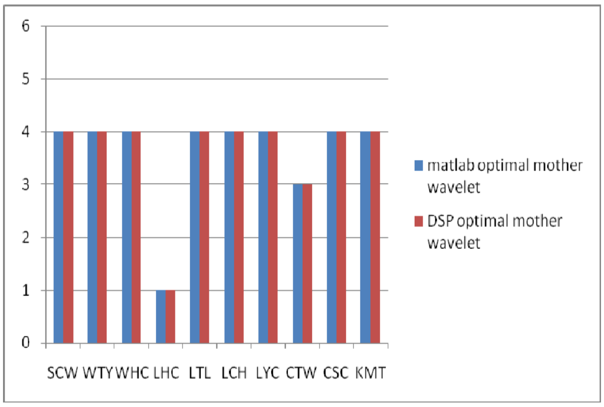

Figure 5 The Accuracy Of Optimal Mother Wavelet In DSP And MATLAB

V. CONCLUSION

Currently, the sampling frequency of EEG signals that could be processed by the system was 100Hz, and the available mother wavelets were db1~db6. It took only 7 minutes to analyze a 30-minute-long EEG signal using continuous wavelets. After applying the optimal mother wavelet, the execution time for analyzing the 30-minute-long EEG signal was also within 7 minutes. As a result, we can state that the integrated method of continuous wavelet transform and optimal mother wavelet in the study has the ability to instantly analyze EEG signals, and the algorithms of optimal mother wavelet and continuous wavelet analysis are accurate. For future improvement of the system, the memory of the hardware should be increased so that the system can generate more db mother wavelets. In addition, in future research, it is expected to develop an algorithm of fast continuous wavelet transform that suits the analysis of EEG signals, and improve the hardware architecture, as well as develop a portable EEG data acquisition system.

REFERENCES

[1] Haas, L. F., 2003, "Hans Berger(1873-1941), Richard Caton(1842-1926), and electroencephalography, Journal of Neurology Neurosurgery and Psychiatry, 74:9, Jan.

[2] Abdulhamit Subasi, EEG signal classification using wavelet feature extraction and a mixture of expert model, Expert Systems with Applications Volume 32, Issue 4, May 2007, pages 1084-1093.

[3] Neep Hazarika, Jean Zhu Chen, Ah Chung Tsoi and Alex Sergejew, Classification of EEG signals using the wavelet transform, Signal Processing Volume 59, Issue 1, May 1997, Pages 61-72

[4] Joe-Air Jiang, Chih-Feng Chao, Ming-Jang Chiu, Ren-Guey Lee, Chwan-Lu Tseng, An automatic analysis method for detecting and eliminating ECG artifacts in EEG, Computers in Biology and Medicine, Volume 37, Issue 11, Pages 1660-1671.

[5] Ashok Raman, Xia Lin, Mohnish Suri, Monica Hewitt, Cris S. Constantinescu and Margaret F. Phillips, A presenilin 1 mutation(Arg278Ser) associated with early onset Alzheimer's disease and spastic paraparesis, Journal of the Neurological Sciences Volume 260, Issues 1-2, 15 September 2007, Pages 78-82

[6] Chien-Yue Chen, Cheng-Deng Kuo, Yan-Kwang Chen. The most appropriate Daubechies mother wavelet for multiresolution analysis of heart rate variability. WSEAS Trans Inform Sci Appl 2007; 4: 674-679.

[7] Sherman DA, An introduction to wavelets with electrocardiology applications, Herzschr Elektrophys, vol. 9, pp42-52,1998

[8] Chien-Yue Chen, Wing-Kwong Wong, Cheng-Deng Kuo, Yun-Tzai Liao, Ming-Da Ke, "Wavelet Real Time Monitoring System: A case study of the musical influence on electroencephalography". WSEAS Trans on SYSTEMS2008;7:56-62

[9] Pega, Z., 2003, "Discrete Wavelet Transform Based Seizure Detection In Newborns EEG Signals", IEEE International Conference on, 2: 256-265.

[10] Liu, H. S., Zhang, T. and Yang, F. S., 2002, A multistage, multimethod approach for automatic detection and classification of epileptiform EEG, Biomedical Engineering, IEEE Transactions on, 12(49): 1557-1566.

[11] Metin Akay, Time Frequency and Wavelets in Biomedical Signal Processing, November 1997, W iley-IEEE Press

[12] Julie Carrier, Jean Paquet, Marta Fernandez-Bolanos, Laurence Girouard, Joanie Roy Brahim Selmaoui, Daniel Filipini, Effects of caffeine on daytime recovery sleep: A double challenge to the sleep–wakecycle in aging, Sleep Medicine(2009),pages 1-9