DESIGN AND IMPLEMENTATION OF WIRELESS MULTI-CHANNEL EEG RECORDING SYSTEM AND STUDY OF EEG CLUSTERING METHOD

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ABSTRACT

A multi-channel wireless EEG (electroencephalogram) acquisition and recording system is developed in this work. The system includes an EEG sensing and transmission unit and a digital processing circuit. The former is composed of pre-amplifiers, filters, and gain amplifiers. The kernel of the later digital processing circuit is a micro-controller unit (MCU, TI-MSP430), which is utilized to convert the EEG signals into digital signals and fulfill the digital filtering. By means of Bluetooth communication module, the digitized signals are sent to the back-end such as PC or PDA. Thus, the patient's EEG signal can be observed and stored without any long cables such that the analogue distortion caused by long distance transmission can be reduced significantly. Furthermore, an integrated classification method, consisting of non-linear energy operator (NLEO), autoregressive (AR) model, and bisecting k-means algorithm, is also proposed to perform EEG off-line clustering at the back-end. First, the NLEO algorithm is utilized to divide the EEG signals into many small signal segments according to the features of the amplitude and frequency of EEG signals. The AR model is then applied to extract two characteristic values, i.e., frequency and amplitude (peak to peak value), of each segment and to form characteristic matrix for each segment of EEG signal. Finally, the improved modified k-means algorithm is utilized to assort similar EEG segments into better data classification, which allows accessing the long-term EEG signals more quickly.

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1. INTRODUCTION

The methods in examining brain diseases are improving continuously in recent years. Due to the advantages of non-invasive measurement and the capability of long term monitoring of the EEG signal, the electroencephalograph machine plays an important role in brain examination and study. Especially, in the diagnosis of brain disease such as epilepsy, sleeping disorder and abnormal behavior, this machine is used most commonly [1-2].

During the last few years, studies on EEG machine showed that the EEG recorder based on personal computer (PC) had to communicate with the medical instrument through the computer I/O interface. The above methods usually adopted a wired serial port interface, such as RS-232C standard, to transmit the

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measured the EEG signal, and were inconvenient in general use because of transmission lines between the instrument and human brain activity measurement device. When the conventional EEG acquisition equipment is intended to transfer to a portable device, such as personal digital assistant (PDA), wired transmission always caused inconvenience in mobilization. If the technical advantages of wireless communications, such as the Bluetooth technology, are used, the application field of EEG machine can be extended more widely. Besides, the computer usually lacks an effective program to read, analyze, and then display the EEG signals stored in conventional EEG machines. If the recorded EEG data can be treated more completely, the serviceability of the EEG acquisition system would be enhanced significantly.

The one of purposes of this study is to improve the conventional architecture of electroencephalograph. In this work, a multi-channel EEG recording system is proposed. The Bluetooth module is adopted as transmission interface such that the wire lines between the EEG acquisition circuit and computer interface are removed. This also avoids serious signal distortion and provides better quality EEG signals. Owing to the features of energy-saving and easy development, the TI-MSP 430 chip is utilized for serving as core processor in the digital circuit. Therefore, the digital filter can be implemented in the digital circuit to filter out the noise from the EEG signal and make the electroencephalogram reproduce with low distortion. Using the system, the non-successive brain activities such as epilepsy, sleeping disorder and abnormal behavior can be measured. To provide an effective EEG reading program on PC or PDA, a simple but effective classification process of the EEG signal is conducted. Under the condition of long-term recording of EEG signal, the activities of penitent always cause disturbance during observation. To achieve correct reading for EEG signals, it is necessary to develop a specific algorithm to perform signal processing tasks. Therefore, this work divides the processing task for recorded EEG signal into sub-tasks including segmentation, characteristics extracting, and clustering. A modified bisecting k-means algorithm is also proposed to classify the EEG signals into simple and understandable groups of waveforms. For doctors or researchers, this algorithm is applicable to syndrome diagnosis from the acquired specific EEG signal of sleeping and can facilitate the follow-up study of brain diseases.

2. SYSTEM DESCRIPTION

In the acquisition process, the EEG signals sensed by the electrode are amplified, filtered. After digitizing the EEG signals by an A/D converter built-in MSP 430 chip, the digitized signals are digitally filtered and then transmitted to a PC or PDA by the Bluetooth module. As a result, further processing and data storage can be done in the PC or PDA. The system architecture of the entire system is illustrated in Fig. 1, in which the analogue and digital portions of the system are also indicated. The function of each block is described as follows.

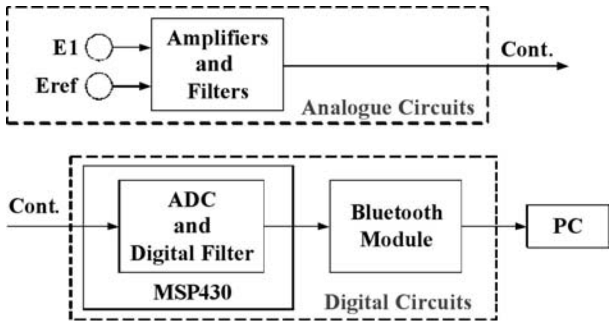
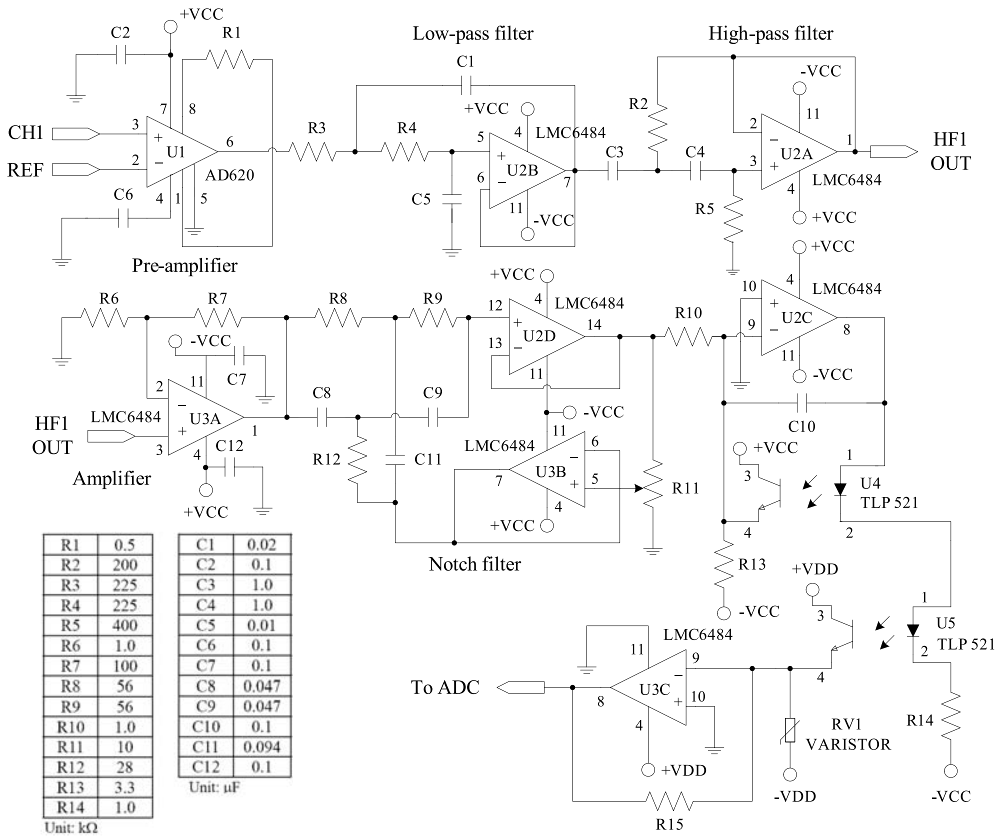


Fig. 1. System architecture of the wireless EEG acquisition circuit with Bluetooth communication module.

(1) Electrodes: These components acquire the EEG signals generated by cerebral cortex.
(2) Amplifier and Filter Circuit: The amplifier circuit mainly amplifies the EEG signal in μV to the extent that can be processed by the recorder, and incorporates appropriate filter circuit to filter out unnecessary noise.
(3) ADC: The ADC circuit converts the analogue EEG signals into digital form.
(4) PC or PDA: This back-end device receives digitized EEG data and executes classification program for clustering. Thus, digital recording is now employed to facilitate classification and diagnosis of the EEG signal.

The schematic diagram of analogue circuit is illustrated in Fig. 2. The amplifier and filter circuit can be further sub-divided into pre-amplifier, high-pass filter, low-pass filter, notch filter and gain amplifier. As shown in the figure, the overall gain of the analogue circuit is 13130, cut-off frequency of high-pass filter is set at 0.56 Hz and that of low-pass filter is set at 70 Hz. The core of the digital circuit is a TI-MSP430 microprocessor, which possesses the functions of A/D conversion, digital filtering, and serial port transmission. The signal processing flowchart of digital circuit is depicted in Fig. 3. The TI-MSP430 microprocessor is utilized primarily to convert the analogue EEG signals into digital ones on eight channels respectively [3]. By the way, the firmware



R1	0.5
R2	200
R3	225
R4	225
R5	400
R6	1.0
R7	100
R8	56
R9	56
R10	1.0
R11	10
R12	28
R13	3.3
R14	1.0

Unit: kΩ

C1	0.02
C2	0.1
C3	1.0
C4	1.0
C5	0.01
C6	0.1
C7	0.1
C8	0.047
C9	0.047
C10	0.1
C11	0.094
C12	0.1

Unit: μF

Fig. 2. The schematic diagram of one channel EEG circuit (analogue portion).

mainly processes the A/D conversion of the analogue EEG signals in MCU (microprocessor control unit) unless 8-channel conversion is completed. Then the microprocessor transmits the filtered EEG digital signals to the PC end via the Bluetooth module. The process of conversion and transmission is repeated executed unless the device is shut down.

There is a digital filter implemented in the MCU. The aim of this digital filter is to remove 60 Hz power-line interference. Because the sampling frequency is preset at 240 Hz, the zero of the digital filter can be chosen at $\pi/2$ [4]. To improve the filtering, zero-pole positions of transfer function for the designed filter are set as double-zero and four poles, and bandstop width of filter is set as $\pm$ 5 Hz, respectively. Hence, the transfer function is obtained as:

$$H(z)=\frac{1+2z^{-2}+4z^{-4}}{1+1.5z^{-2}+0.57z^{-4}} \tag{2-1}$$

Difference equation that represents equation (2-1) is obtained as:

$$y[n]=-1.5y[n-2]+0.57y[n-4]+ \\ x[n]+2x[n-2]+x[n-4] \tag{2-2}$$

According to the above equation, we can write a program on MSP 430 chip to fulfill the digital filter design [5].

3. SIGNAL PROCESSING

Once the EEG signals had been acquired, they were converted by ADC circuit into digital form and then pre-filtered by the digital filter built-in MSP 430 chip. These pre-processed data remove the outliers and make subsequent signal clustering task easier and better. The processed signals are transmitted to the back-end via the Bluetooth module. The proposed classification algorithm is applied to the recorded signals to execute off-line analysis, which is described in detailed as follows.

First, the non-linear energy operator (NLEO) [6-9] method is used to partition the signals into several small segments according to the amplitude and frequency features of the signals. Then, the characteristic extraction to every small segment of the signals is conducted by the AR model method to obtain the frequency characteristic value of every small section. The characteristic matrices of the whole EEG signals consist of frequencies and amplitudes features in each small EEG segment. Finally, the characteristic matrices were treated as input to the modified bisecting k-means algorithm, which can classify EEG segments that possess similar features to the same group. For easier identification, the grouped segments are highlighted in a fashion of color-marked presentation. The segmentation, feature extraction, and classification of pre-processed EEG data complete the signal clustering task. The flow chart of EEG signal classification is illustrated in right hand side of Fig. 3. A detailed introduction of segmentation, characteristic extraction, and sequence of classification are described in the following.

3.1 Signal Segmentation of EEG

Signal segmentation is usually based on the energy and frequency of signal [7-8], and the difficulty mainly comes from that the energy and frequency may vary simultaneously. In general, the EEG signal changes due to different physiological and psychological status, and is called a time-varying signal. Therefore, for analysis of the EEG, the signal has to be divided according to its characteristics. The EEG signals in various time points possess different statistic feature. This means that the EEG signal is a non-stationary signal and is very hard to be described via a mathematic equation. To analyze it, the starting points of EEG signal characteristic changing need to be found out first. And then EEG signal is divided into quasi-stationary signal segments based on the selected starting points. Basically, the signal segmentation is performed according to the variations in signal's amplitude and energy. However, in the same time point, the amplitude and the frequency of EEG signal maybe change altogether. Therefore, it is necessary to find out a method that can transform two coupled variables into one, but still are able to express the variation of the amplitude and frequency of EEG signal appropriately. The non-linear energy operator (NLEO) pertains to this character [6-9].

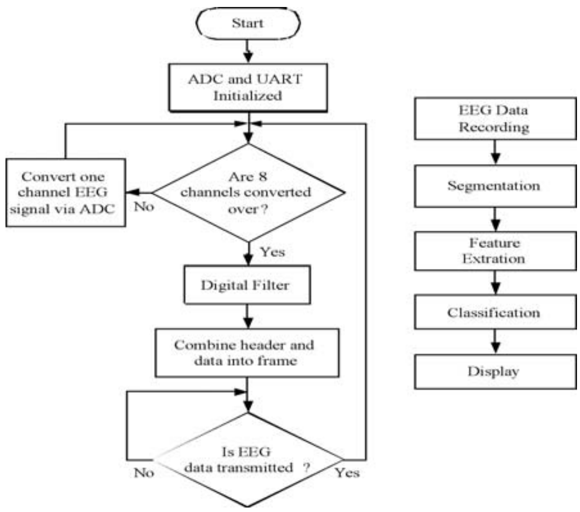


Fig. 3. Flowchart for EEG signals processing from data acquisition to classification.

Consider the following equation for NLEO:

$$E\{\psi[x(n)]\}=E[\,x(n-1)\,x(n-2)-x(n)x(n-3)\,]$$
$$=A^2\ \sin(2\Omega)\ \sin(\Omega)\approx 2A^2\,\Omega^2 \qquad (3\text{-}1)$$

where $x(n)$ is the input EEG signal at current time n and $\psi[(x(n)]\equiv x(n-1)\,x(n-2)-x(n)\text{-}x(n-3)$ is the non-linear energy operator. Parameters A and Ω are the amplitude and frequency of the EEG signals, respectively. Equation (3-1) calculates the energy-like quantity at time n. According to the following windowing and thresholding equations, the trend of the above mentioned quantity can be found and hence the significant level can be obtained by the defined threshold.

$$G_{nleo}(n)=\left|\sum_{k=n-W+1}^{n}\psi([x(k)])-\sum_{k=n+1}^{n+W}\psi([x(k)])\right|,$$

$$2W\text{: window length} \qquad (3\text{-}2)$$

$$T(n)=\max\left[G_{nleo}(n-L/2:n+L/2)\right],\ L\text{: window length} \qquad (3\text{-}3)$$

$$G(n)=\begin{cases}G_{nleo}, & \text{if } G_{nleo}(n)\geq T(n)\\ 0, & \text{if } G_{nleo}(n)<T(n)\end{cases} \qquad (3\text{-}4)$$

where $G_{\mathrm{nleo}}(n)$ is the energy change in the window obtained by using a moving window with length $2W$ at center n, and $T(n)$ is the threshold value obtained by using another moving window with length L. $G(n)$ represents the significant energy change after thresholding. To perform segmentation, NLEO is firstly adopted to find $\psi[(x(n)]$. Once $\psi[(x(n)]$ is found, $G_{\mathrm{nleo}}(n)$ is then calculated using the moving window method and T(n) is computed from (3-3). Finally, $G_{\mathrm{nleo}}(n)$ and T(n) are compared to get a final boundary value according to $G(n)$. When the NLEO method is utilized to divide the signal, it is necessary to adjust W and L parameters. This moving window method is to compare the energy change of signal before and after some point. Therefore, the window length must be long enough to detect slow wave in rhythm signals, but also can not too long to lose a crucial transient state.

3.2 Characteristic Extraction of EEG Signal

According to the above EEG signal segmentation result, the original EEG signals have been cut into many small segments. In this stage, the average of the amplitude (peak-to-peak value) and the characteristic frequency of every EEG segment are chosen as the parameters for classification and form a 1×2 characteristic vector. If there are totally N segments, an $N \times 2$ characteristic matrix is formed. To compare the characteristic values on a fair base, every characteristic value in the characteristic matrix is first normalized and confined within [-1, 1]. For example, the proposed method normalizes the amplitudes of each segment and then finds the average amplitude. According to the discussion in the related literatures of EEG [10-11] and the references therein, many characteristics had been thoroughly studied by researchers. In this study, there are two characteristic values that are adopted to describe EEG signals, i.e., average amplitude and frequency.

Calculation of average amplitude is done by adding the amplitudes of all points in the same segment and divided by the total length of the segment. The formula for average amplitude is

$$A = \frac{1}{L_S} \sum_{n=1}^{L_S} |x(n)| \tag{3-5}$$

where $x(n)$ is the input signal and L_S is the length of each signal segment.

To extract the characteristic value of frequency, the AR model method is used and given below.

$$x(n) = -\sum_{i=1}^{p} a_p(i) x(n-i) + e(n) \tag{3-6}$$

where p is the order of the AR model, a_p is the parameter of AR model, $e(n)$ is the white noise, and the corresponding transfer function of AR model is

$$H_{AR}(z) = \frac{X(z)}{E(z)} = \frac{1}{1 + \sum_{i=1}^{p} a_p(i) z^{-i}} = \frac{1}{A(z)} \tag{3-7}$$

Using the signal of each segment partitioned by NLEO as the input data, the coefficients of the AR model for each segment can be found by Levinson-Durbin algorithm [10]. As to the order of AR model, it depends on the condition of application. Generally, the higher order obtains the better accuracy of the model but increases calculation burden.

3.3 Classification of EEG Signal Segments

In this study, the modified bisecting k-means algorithm is adopted as the classification method [12-13]. The algorithm includes the following steps.

(1) Consider all data as one group and calculate the total number of subgroups needed to be divided.
(2) Set $k = 2$ and then use the bisecting k-means algorithm to perform binary sub-grouping from a specific group.
(3) Repeat step (2) to complete division of all groups.
(4) Repeat steps (2) and (3) until the number of subgroups is reached the setting of number calculated in step (1).
(5) If the number of divided subgroups is larger than that of targeted groups, conduct merging procedure to aggregate the subgroups to a new larger group according to the mean of groups, named group center.

The flowchart of the modified k-means algorithm is illustrated in Fig. 4. The flowchart indicates that the original data are firstly divided into small subgroups and then aggregate the subgroups backwards until the desired number of groups (or clusters) is reached. In this paper, it is assumed that the EEG signals are desired to be classified into 5 groups for illustration. For completeness, the calculation steps of the related bisecting k-means algorithm used in step (2) are stated as follows:

Step 1. Determine how to divide the object to different groups. Set the number of groups, k.

Step 2. Pick k initial values of the group centers from all objects.

Step 3. Calculate the distance of group center from each object to the group center.

Step 4. Allocate the object to the closest group center to form a sub-group.

Step 5. Calculate the average value of all members in the group to form a new group center.

Step 6. Repeat Steps 2 to 5 until there is no other object will be catalogued to a new group.

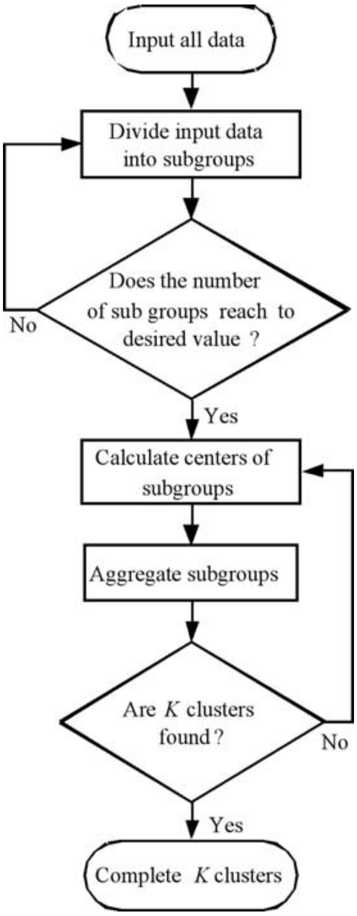


Fig.4. Flowchart of modified k-means algorithm.

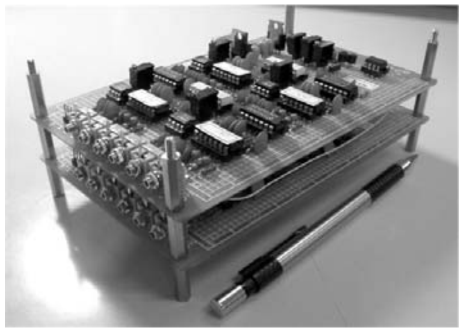
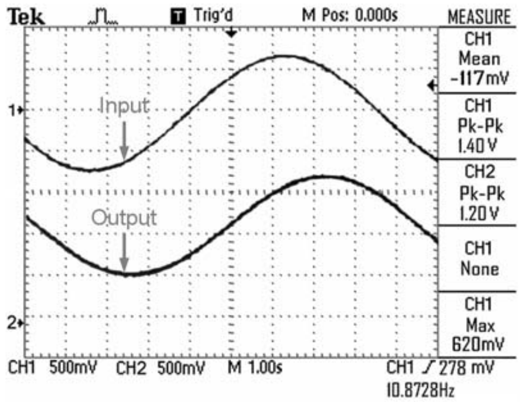


Fig. 5. The proposed EEG acquisition circuit unit with dimension of 6.5 cm by 10.5 cm.



(a)

(b)

Fig. 6. Experimental result for a testing sinusoidal signal (a) the generated sinusoidal wave and (b) received signal.

4. RESULTS

Using the aforementioned acquisition circuit to acquire EEG signals and employing the developed clustering program to classify the EEG signals at back-end, we obtain the following results. Figure 5 shows the EEG acquisition circuit and there are a total of 8 channels. The overall circuit is connected on the same circuit board by module per 4 channels unit.

To verify the correctness of the EEG acquisition circuit, a sinusoidal wave with frequency of 11 Hz and peak-to-peak magnitude of 1.4V is used as a testing signal. By using a resistive voltage-division circuit, the signal is firstly decreased by 15000 times in magnitude to the order of μV and then fed to the acquisition circuit. This acquired signal is then amplified by the gain of 13130 again and displayed on the oscilloscope as shown in Fig. 6(a). The waveform shows that the functionality of EEG acquisition circuit is normal and the error is acceptable. According to the system architecture, the amplified signal is also digitized and filtered by the MSP430 and transmitted to the PC end by way of the Bluetooth module. The display window of received testing signal is depicted in Fig. 6(b). From the experimental results, it is obvious that the proposed EEG recording system performs well and the designed architecture is feasible.

After completing the recording system test, an experiment of the proposed clustering algorithm is done to examine its practicality. The EEG data in the Hospital of National Taiwan University database are adopted as the testing signal. The reference points were taken at A1 and A2 by calculating the average,

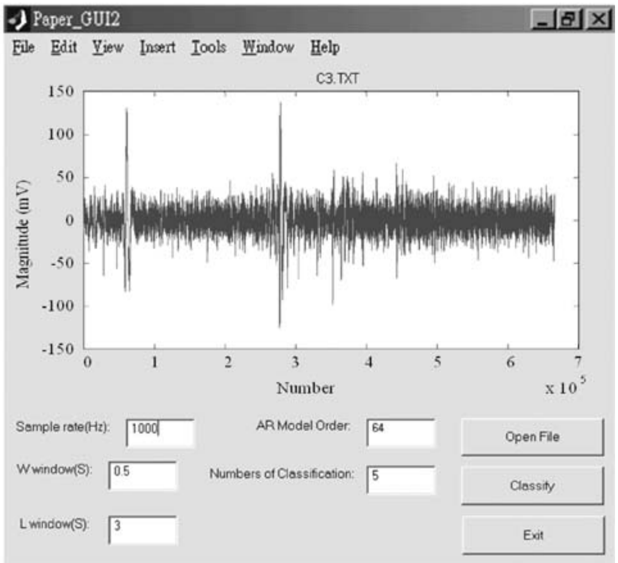


Fig.7. The EEG wave in the Hospital of National Taiwan University database (C3 electrode).

(A1+A2)/2. The EEG signal for each lead can be obtained and analyzed by use of the average as a reference value. In the sequel, the classification for signals acquired by electrode C3 is discussed and the analysis of other leads is similar. In this experiment, the length of window *W* and *L* were set as 0.5 sec and 3 sec, respectively. The characteristic value of frequency of the recorded EEG data is extracted using AR model with 64 orders. The sample rate is 1000 Hz and the classified groups are set as 5. According to the EEG segmentation result, two characteristic matrices of frequency and amplitude can be obtained. Using these matrices as input of the modified *k*-means algorithm, five groups of EEG signals classification can be extracted. Fig. 7 is an interface graphical interface (GUI) that can indicate the input signal and set related parameters for analysis. The classification results of 60×10^4 EEG samples are shown in Fig. 8. From Fig. 8 and the corresponding characteristic matrices, it is found that the signal in about 10 minutes is partitioned into 95 segments and the average magnitudes of these segments have no significant differences. Also, the frequencies of the segments mainly reside in the range less than 10 Hz.

5. CONCLUSIONS

The architecture of Bluetooth-based wireless multi-channel EEG recording system is studied in this paper. The wireless transmission mechanism eliminates wire-line connections. Also, the signal filtering and digitization in the system reduce the possible noise interference. In contrast with the current EEG recording systems, such improvements make this

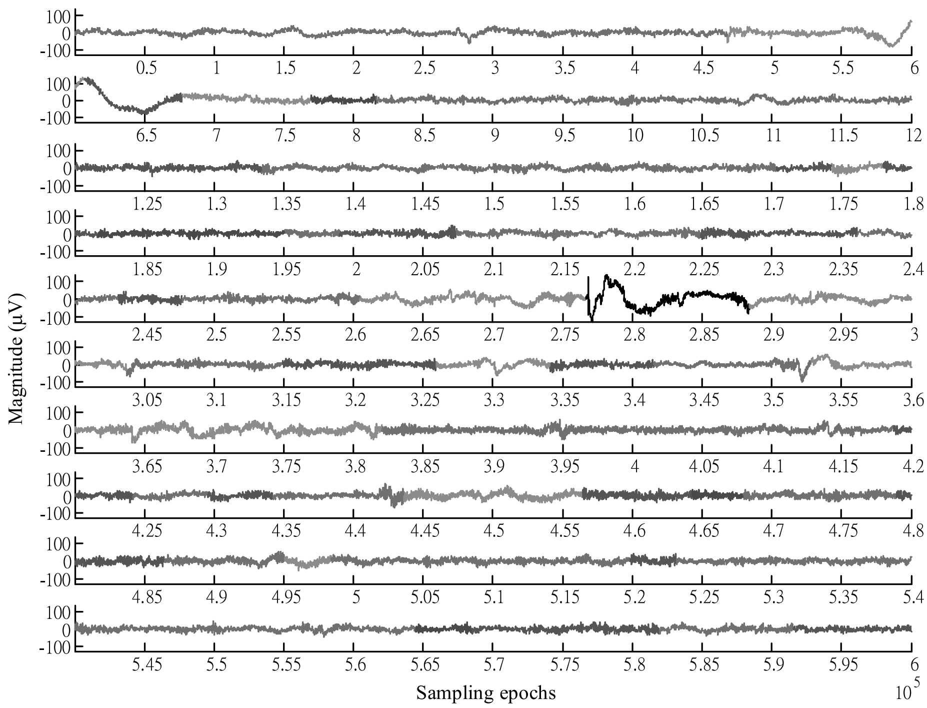


Fig. 8. The result of classification for EEG signals (C3).

multi-channel EEG signal measuring system more applicable to studying on non-consecutive brain diseases. To verify the practicality of the proposed system, a sinusoidal testing signal is transmitted via the Bluetooth module. From the experimental results, it is seen that the received signal is reconstructed with ignorable distortions and can be on-line shown in the display window at back end. In addition, a classification method, which integrates the NLEO, AR model, and modified *k*-means algorithm, is introduced to partition the considered EEG signals into groups with the same characteristics. Using the adopted method, the sample data in National Taiwan University Hospital EEG database is partitioned into 95 segments for five groups. Each segment in the same group has similar average amplitude and frequency characteristic. In the future, the proposed multi-channel wireless EEG recording system can be accompanied with the classification method as an automatic EEG monitoring system.

REFERENCES

1. Webster JG: Medical Instrumentation: Application and Design, 3rd edition, John Wiley and Sons Inc, New York, 1998.
2. Dunseath WJR and Kelly EF: Multi-channel PC-Based Data Acquisition System for High-Resolution EEG. IEEE Trans. Biomed Eng 1995; 42: 1212-1217.
3. Texas Instruments: MSP430x4xx Family User's Guide, 2002.
4. Ifeachor EC and Jervis BW: Digital Signal Processing: A Practical Approach, 2nd edition, Prentice Hall, New York, 2002.
5. Tompkins WJ: Biomedical Digital Signal Processing: C Language Examples and Laboratory Experiments for the IBM PC, Prentice Hall, Englewood Cliffs, NJ, 1993.
6. Liu HS, Zhang T and Yang FS: A Multistage: Multimethod Approach for Automatic Detection and Classification of Epileptiform EEG. IEEE Trans. Biomed Eng 2002; 49: 1557-1566.
7. Agarwal R, Gotman J, Flanagan D and Rosenblatt B: Automatic EEG Analysis During Long-term Monitoring in the ICU. Electroencephalography and Clinical Neurophysiology 1998; 107: 44-58.
8. Agarwal R and Gotman J: Adaptive Segmentation of Electroencephalographic Data Using a Nonlinear Energy Operator. Proc. IEEE ISCAS' 1999; 4: 199-202.
9. Kaiser JF: On a Simple Algorithm to Calculate the 'Energy' of a Signal. Proc. IEEE International Conference Acoustics, Speech, and Signal Processing 1990; 1: 381-384.
10. D.G. Childers: Probability and Random Processes: Using MATLAB with Applications to Continuous and Discrete Time Systems, Irwin, Chicago, 1997.
11. Guler I, Kiymik MK, Akin M and Alkan A: AR Spectral Analysis of EEG Signals by Using Maximum Likelihood Estimation. Computers in Biology and Medicine 2001; 31: 441-450.
12. Jain AK, Murty MN and Flynn PJ: Data Clustering: A Review, ACM Computing Surveys, 1999; 31: 264-323.
13. Pan CC, An Adjustable Bisecting Clustering Method, Master Thesis, Department of Management Information System, Chung Yuan Christian University, 2003. (in Chinese)