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Real-Time nonlinearBio-signalsdetectionusing fuzzy logic for wireless brain computer interface

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Abstract—**Biomedical signal monitoring systems have beenrapidly advanced with electronic and information technologies inrecent years. However, most of the existing physiological signalmonitoring systems can only record the signals without the capabilityof automatic analysis. In this paper, we proposed a novel architecture that can acquires bio-signals in real-time to monitorhuman physiological as well as cognitive states through wireless and in turn it will detect noisy signal in the analysis and it remove completely so it is easier to detect the drowsiness properly. While transmitting bio-signal through wireless excessive noise will be added, so it is very important to remove those noises. An algorithm that merges the most relevant blink features (duration, percentage of eye closure, frequency of the blinks and amplitude-velocity ratio) using fuzzy logic with help of Discrete Walsh-Hadamard transform(DWHT)to remove noise is proposed. The main advantage of this algorithm is that it is independent from the driver and it does not need to be tuned and noise can be effectively removed. Moreover, it provides good results with more than 80% of good detections of drowsy states.**

Index Terms—electroencephalogram(EEG), wireless, fuzzy logic, brain computer interface.

1. INTRODUCTION

The advance in sensor technology and informationtechnology reduces the power consumption of the sensorsand make the cost of production cheaper. These trends make it possible to embed sensors in different places or objects tomeasure a wide variety of physiological signals. A physiologicalsignal monitoring system will be extremely useful in manyareas if they are portable and capable of wirelessly monitoringtarget physiological signals and analyzing them in real time.However, most of the existing physiological signal monitoringsystems can only record the signals without the capability of automaticanalysis. Lot of algorithms was proposed for the development of brain-computer interface for drowsiness detection.

Here to improve such an interface noise removal system or suitable processing technique is needed. Recently, with the development of embeddedsystem and signal processing technique, there is a tendency toapply the embedded system technique to brain–computer interface(BCI). An electroencephalogram (EEG) based BCI providea feasible and noninvasive way for the communication betweenthe human brain and the computer [1]–[7].

Traditionally, thevariations of brain waveforms are measured and analyzed bypersonal computers (PCs). Due to the inconvenience of PCbased BCI that limits the user's mobility, portable and inexpensiveBCI platform—small devices with long battery life that canbe carried indoors or outdoors—are desired [8].There are some studies regarding the portable BCI devices[9]–[11].Gao*et al.* [9] used steady-state visual evoked potential(SSVEP) to control environmental device, such as TV, videotape recorders, or air-conditioners. A portable pocket PC-basedBCI was developed by Edlinger*et al.* [10]. In [11],Whitchurch*et al.* developed a wireless system for long term EEG monitoringof absence epilepsy. In [12], Obeid *et al.* proposed atelemetry system for single unit recording. However, these systemsmainly focused on the monitoring hardware, but not onreal-time analysis.

Real-time embedded systems combined withwireless transmission have become a trend of developing diagnosisor homecare systems [13]–[17], because they provide aplatform to build sensing and inexpensive BCI systems.

Our previous studies discovered that some features in human EEG signals are highly related to drowsiness level [18], [19], and they can be used for estimating driver drowsiness.

Real time systems using DSP were discussed by T. Kobayashi in [20] and by J. W. S. Liu in [21].Manyextended applications may be more practicable to implement onthe newer platforms whenever the smaller and more powerfuldevices are developed.Electrooculogram (EOG), which is the measurement of the eye electrical muscles activity, has been widely used in the literature to estimate drowsiness.

EOG is the most reliable technique to detect and characterize blinks due to its high sample rate (from 250 Hzto 500 Hz) and it is used as a reference by expert doctors to evaluate drowsiness. Unfortunately, EOG requires at least three electrodes placed on the driver's skin, which is not pleasant. So, for obvious ergonomic reasons, research community has focused on the use of video to track the driver's eyes and face and thus detect whether he is drowsy or not. The goal of this paper is to develop a real-time wireless architecture for removing non-linearity in the EEG and ECG signal.

2. PROPOSED ARCHITECTURE

The proposed architecture is shown in fig 1. The subjects had to drive through nighttime freeway scenery, and while doing so, underwent two tests. The first, a tracking test, was to control the steering and accelerator to keep a cursor aligned with the image of the preceding vehicle. The second, a reaction time test, was to press a button on the dash the moment a red square appeared on the screen. A VCR recorded changes in blinking behavior as the subjects grew drowsy. Also monitored were the subjects' brainwaves, eye movements and other physiological indicators. The subjects evaluated their own subjective state of alertness by pushing buttons for slightly sleepy, moderately sleepy and very sleepy.

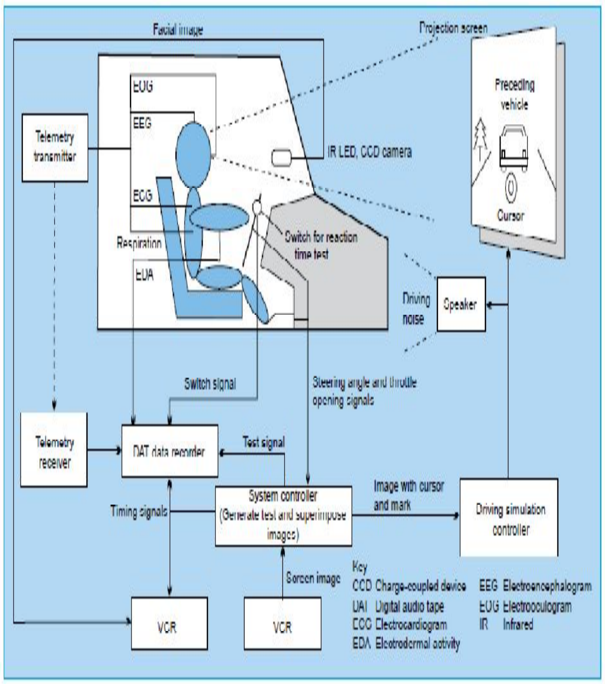

Figure.1. Block diagram of the proposed architecture.

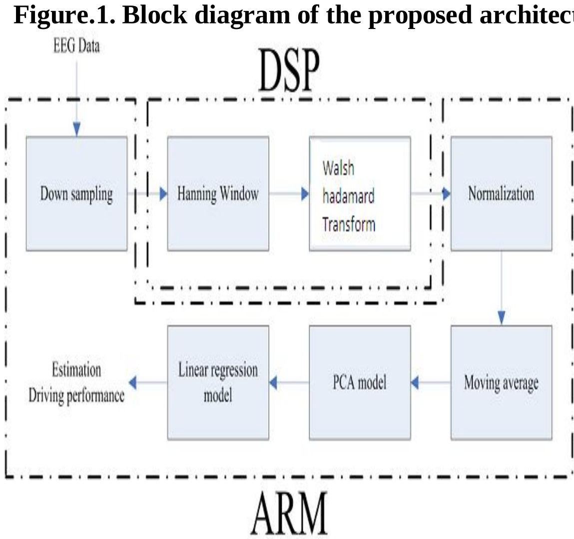

Figure. 2. Flowchart of the proposed EEG signal analysis procedure.

Figure. 2 shows the flowchart for EEG and ECG signal analysis. Here, using flag register can reduce the amount of memory needed because one declared variable can contain many flags characteristics of the processors, the calculation of driving error estimation needed to process a long period of EEG data, so itwas implemented in ARM processor. In previous work, theHanning windowing and short-time FFT is used which needs heavy computation,and thus is implemented in the DSP core to balance thecomputation load. The remaining processes were implementedin ARM because they need relatively less computations. Here in our proposed algorithm model instead of FFT transform discrete Walsh Hadamard transform is used to reduce complexity. Here the work is mainly concentrated on removing noise and to make bio-signal more linear and hence reducing the complexity of the signals.

3. DISCRETE WALSH-HADAMARD TRANSFORM (DWHT)

The Walsh-Hadamard transform (WHT) is a suboptimal, non-sinusoidal, orthogonal transformation that decomposes a signal into a set of orthogonal, rectangular waveforms called Walsh functions. The transformation has no multipliers and is real because the amplitude of Walsh (or Hadamard) functions has only two values, +1 or -1. WHTs are used in many different applications, such as power spectrum analysis, filtering, processing speech and medical signals, multiplexing and coding in communications, characterizing non-linear signals, solving non-linear differential equations, and logical design and analysis. This provides an overview of the Walsh-Hadamard transform and some of its properties by showcasing two applications, communications using spread spectrum and processing of ECG signals. Walsh functions are rectangular or square waveforms with values of -1 or +1. An important characteristic of Walsh functions is sequency which is determined from the number of zero-crossings per unit time interval. Every Walsh function has a unique sequency value.. Length eight Walsh functions are generated as follows. Length of Walsh (Hadamard) functions HadamardMatrix =

$$\begin{matrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 & 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 & 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 & 1 & -1 & -1 & 1 \\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 \\ 1 & -1 & 1 & -1 & -1 & 1 & -1 & 1 \\ 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 \\ 1 & -1 & -1 & 1 & -1 & 1 & 1 & -1 \end{matrix}$$

The rows (or columns) of the symmetric hadamardMatrix contain the Walsh functions. The Walsh functions in the matrix are not arranged in increasing order of their sequencies or number of zero-crossings (i.e. 'sequency order') but are arranged in 'Hadamard order'.

The Walsh matrix, which contains the Walsh functions along the rows or columns in the increasing order of their sequencies is obtained by changing the index of the hadamardMatrix as follows.

The forward and inverse Walsh transform pair for a signal x(t) of length N are

$$y_n = \frac{1}{N}\sum_{i=0}^{N-1} x_i WAL(n,i), n = 1,2,\ldots,N-1 \quad (1)$$

$$x_i = \sum_{n=0}^{N-1} y_n WAL(n,i), i = 1,2,\ldots,N-1 \quad (2)$$

Fast algorithms, similar to the Cooley-Tukey algorithm, have been developed to implement the Walsh-Hadamard transform with complexity O(NlogN). Since the Walsh matrix is symmetric, both the forward and inverse transformations are identical operations except for the scaling factor of 1/N. The functions fwht and ifwht implement the forward and the inverse WHT respectively. It is an is an identity matrix because the rows (or columns) of the symmetric Walsh matrix contain the Walsh functions.

Fast Walsh-Hadamardtransform
y1 =

$$\begin{matrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{matrix}$$

AWHT in ECG and EEG signals processing

Often, it is necessary to record electro-cardiogram (ECG) signals of patients at different instants of time. This results in a large amount of data, which needs to be stored for analysis, comparison, etc. at a later time. Walsh-Hadamard transform is suitable for compression of ECG signals because it offers advantages such as fast computation of Walsh-Hadamard coefficients, less required storage space since it suffices to store only those sequency coefficients with large magnitudes, and fast signal reconstruction.

4. EXPERIMENTAL RESULTS

Three types of experiments were performed to remove the non-linear parameters of bio-signals. 1) Experiment results using DWHT 2) Experiment Results by applying fuzzy logic 3) Experiment for Building the ANFIS Model for fuzzy. This experimental results show that our proposed algorithm is effectively removing non linear characteristics of bio-signals.

1) Experiment results using DWHT

Experiment 1

This experiment is performed to remove excessive noise in bio signals (EEG) with the help of DWHT.The results show clearly that noise in EEG signal is effectively removed.Figure. 3 shows Noisy EEG, Processed EEG, Noiseless EEG signal. During telemetry application noise will be heavily added to bio-signals, so it is very important to reduce such noises (non-linear parameters) to process those signals.

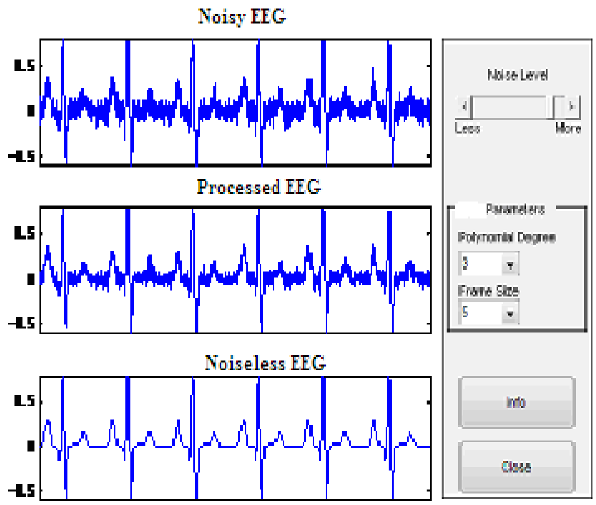

Figure.3 Noisy EEG, Processed EEG, Noiseless EEG

Experiment 2

This experiment 2 is performed to remove excessive noise in ECG signal using DWHT technique. In previous work FFT technique is used which increases the complexity of the system and the noise is also not removed completely using it. Here using DWHT non linear parameters are identified and removed easily.

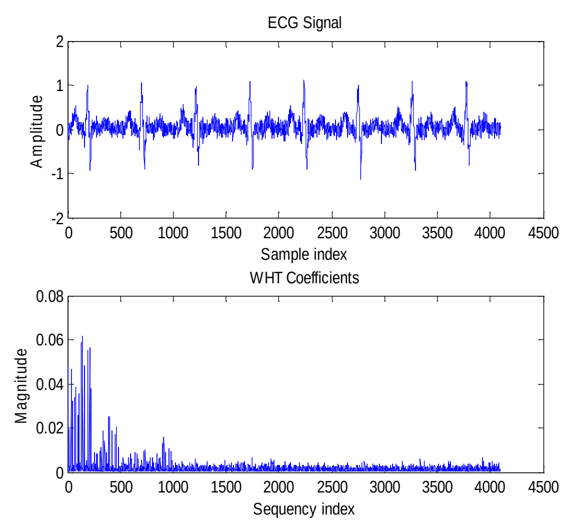

Figure. 4 ECG signal and WHT coefficients

Figure. 4 shows the ECG signal and WHT coefficients of DWHT.As can be seen in the above plot, most of the signal energy is concentrated at lower sequence values. For investigation purposes, only the first 1024 coefficients are stored and used to reconstruct the original signal. Truncating the higher sequence coefficients also helps with noise suppression. The original and the reproduced signals are shown below. Figure. 5 shows the Original signal and Reproduced ECG signal.

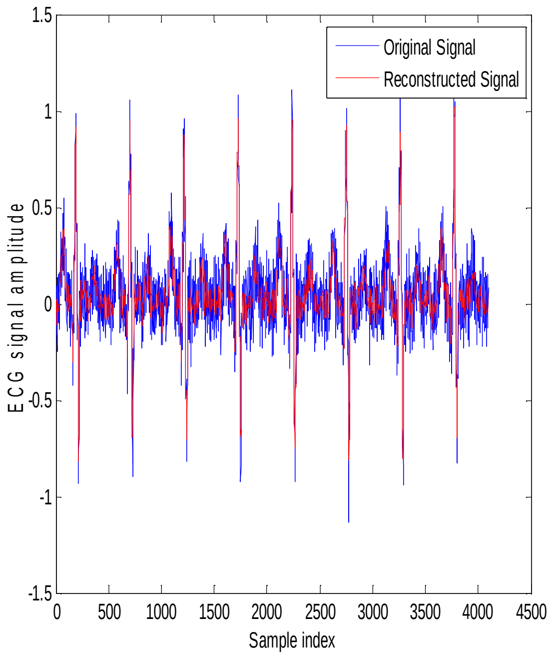

Figure. 5 Original and Reproduced ECG signal

The reproduced signal is very close to the original signal.To reconstruct the original signal, we stored only the first 1024 coefficients and the ECG signal length. This represents a compression ratio transform. Using the sequence location at a which a peak occurs, the corresponding Walsh-Hadamard code (or the Walsh function) used can be determined. The plot below shows that Walsh-Hadamard codes with sequency (with ordering = 'hadamard') 60 and 10 were used in the first and the second transmitter, respectively. This results clearly illustrates that DWHT is very efficient in removing excessive noise in bio-signals both in EEG and ECG. The proposed algorithm is very compact and hence complexity of the system is also reduced . It is clearly shown that non-linearity structure of bio-signals is characterized easily with the help of proposed hadamard transform.

2) Experiment Results by applying fuzzy logic

This experiment is performed for removing non linearity's in bio-signals with the help of fuzzy. Here below is a hypothetical information signal x sampled at 100Hz over 6 seconds. Unfortunately, the information signal x cannot be measured without an interference signal n2, which is generated from another noise source n1 via a certain unknown nonlinear process.

The plot below shows the information signal and noise source n1.Figure. 6 shows the Information signal and Figure. 7 shows the noise source n1.

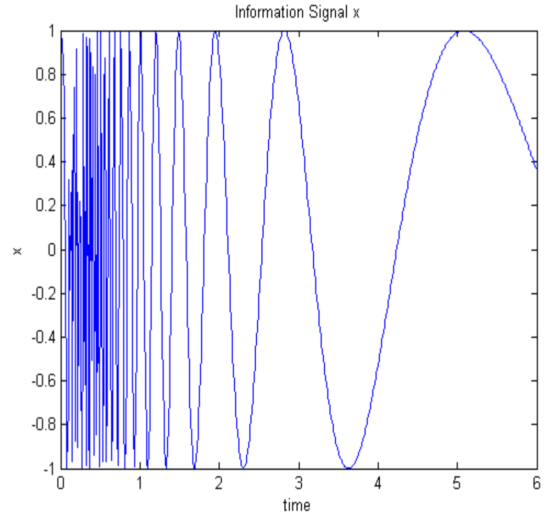

Figure. 6 Information signal

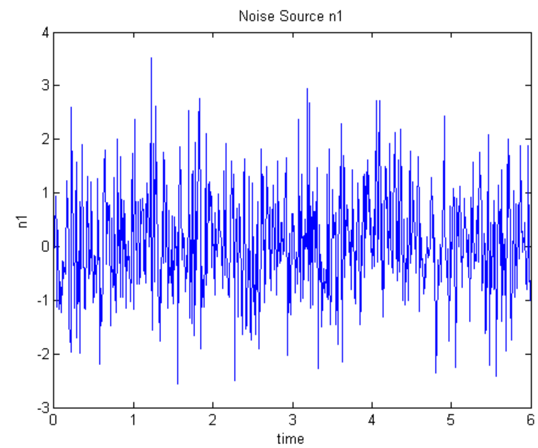

Figure. 7Noise source n1

The interference signal n2 that appears in the measured signal is assumed to be generated via an unknown nonlinear equation:

n2(k) = 4*sin(n1(k))*n1(k-1)/(1+n1(k-1)^2)(3)

This nonlinear characteristic is shown as a surface in the window. Fig 8 shows the unknown channel characteristics that generate interference. Figure.9 shows the Noise source n1 and interference source n2 and Figure. 10 shows the Measured signal for finding nonlinear characteristics.

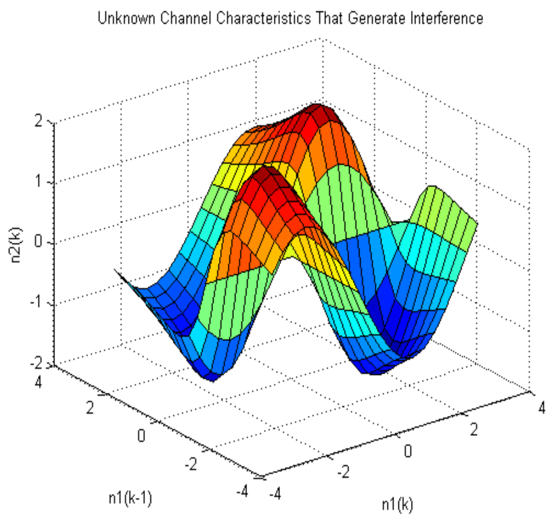

Figure. 8Unknown channel characteristics that generate interference

The noise source n1 and interference n2 are shown together in Figure. 9. Note that n2 is related to n1 via the highly nonlinear process shown previously; it is hard to see if these two signals are correlated in any way. Here the non linear signals are clearly identified and is easily used to remove those non –linearities.

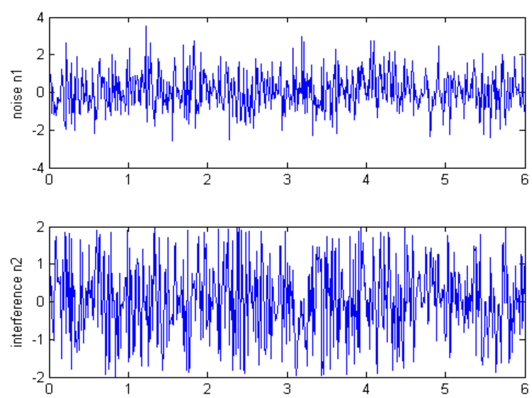

Figure. 9 Noise n1 and interference n2

The measured signal m is the sum of the original information signal x and the interference n2. However, we do not know n2. The only signals available to us are the noise signal n1 and the measured signal m, and our task is to recover the original information signal x. The plot is the measured signal m that combines x and n2. It is shown in Figure. 10

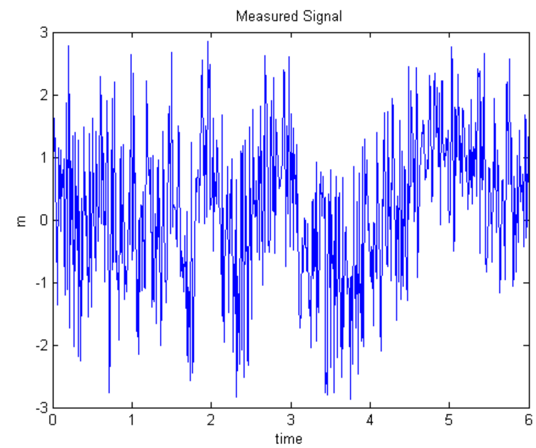

Figure. 10Measured signal for finding nonlinear characteristics

3) Experiment for Building the ANFIS Model

We will use the function ANFIS to identify the nonlinear relationship between n1 and n2. Though n2 is not directly available, we can take m as a "contaminated" version of n2 for training. Thus x is treated as "noise" in this kind of nonlinear fitting.

Here we assume the order of the nonlinear channel is known (in this case, 2), so we can use 2-input ANFIS for training. We assign two membership functions to each input, so the total number of fuzzy rules for learning is 4. Also we set the step size equal to 0.2. You should be able to see all the training information in the MATLAB® command window.

ANFIS info:

Number of nodes: 21
Number of linear parameters: 12
Number of nonlinear parameters: 12
Total number of parameters: 24
Number of training data pairs: 601
Number of checking data pairs: 0
Number of fuzzy rules: 4

Start training ANFIS ...

1 0.737955
2 0.726454
3 0.718352
4 0.713803
5 0.711315

Step size increases to 0.220000 after epoch 5.

6 0.70904
7 0.707269
8 0.70685
9 0.70593

Step size increases to 0.242000 after epoch 9.

10 0.705693

Designated epoch number reached --> ANFIS training completed at epoch 10.After training, the estimated n2 is calculated using the command EVALFIS. The original n2 and estimated n2 (output of ANFIS) are shown above. (Note that n2 is unknown.) Fig 11 showsunknown signal n2 and estimated signal n2

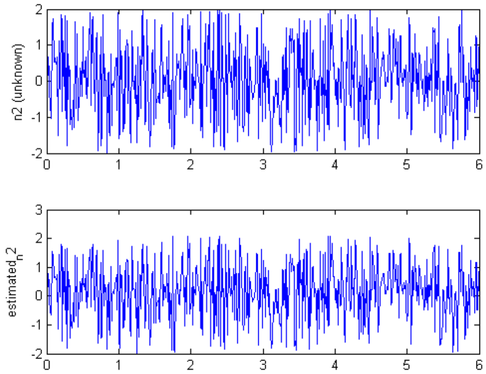

Figure. 11unknown signal n2 and estimated signal n2

The estimated information signal x is equal to the difference between the measured signal m and the estimated interference (that is, ANFIS output). The original information signal x and the estimated x by ANFIS are plotted. Without extensive training, the ANFIS can already do a fairly good job. Figure. 12 shows the unknown signal x and estimated signal x

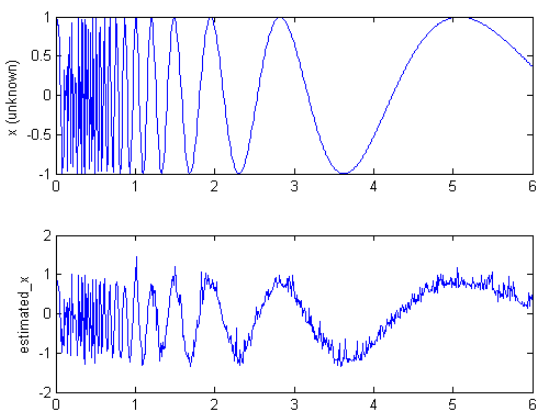

Figure. 12unknown signal x and estimated signal x

warning device will be triggered. The correlation coefficient between the predicted drowsiness levels and

5. CONCLUSION

A wireless embedded BCI system with real-time biosignalsprocessing ability to remove effective noise in bio-signals by means of Discrete walshhadamard transform (DWHT)with help of fuzzy logic system is proposed in this paper.. The EEG signal was first acquired by signal-acquisitionand amplification unit, and then, transmitted from wireless datatransmitter to wireless data receiver. The wireless-transmittedEEG/ECG signals were processed by the data processing unit, here signal is processed with the help of DWHT to remove excessive noise in bio-signals and theprocessed results were further transmitted to the sensing systemfor data storage. The results shows noise is removed completely with the help of our proposed system.

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