INFONET Seminar Application Group
Frequency Domain Compressive Sensing for Ultrasound Imaging

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Journal Club Meeting, 19 March, 2013

Introduction

Conventional Ultrasound imaging systems rely on Shannon-Nyquist theorem. Often US devices use a sampling rate that is at least four times the central frequency.

Consequently large amount of data imply problems in:

- Real-time imaging (especially 3D)
- Data-transfer
- Grows of machinery size

Compressive sensing allows reduce volume of data directly acquiring compressed signal. Recently CS framework was adopted to ultrasound imaging [10-15] (all paper except one are conference papers), Ultrasound Doppler [16-17] or Photoacoustic [18]

Sampling a signal

Sampling can be summarized by measuring linear combination of an analog signal

$$y_k = \langle \varphi_k, f \rangle, \quad \text{for } k = 1, \ldots, m, \quad (1)$$

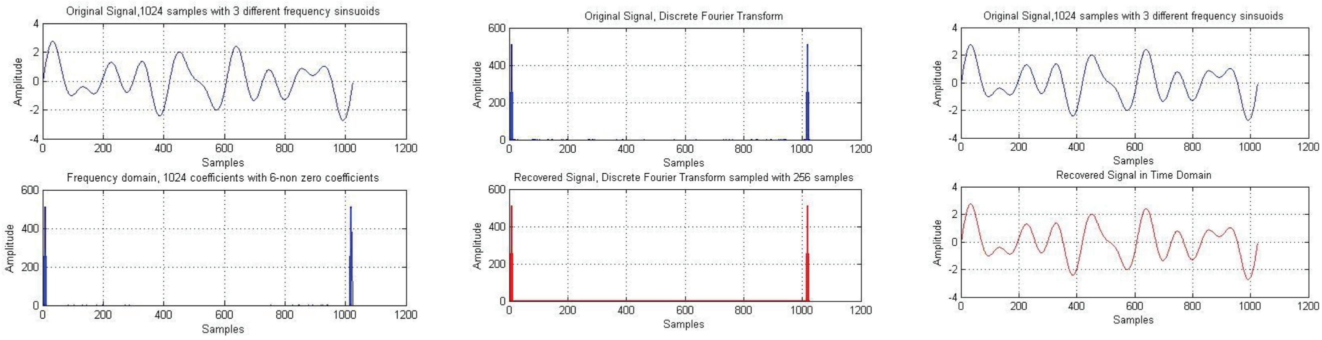
Where y_k are the measurements, φ_k are sampling vectors, and m is the number of measurements. The most common sampling protocol consist of vectors of Dirac's at equal time. The measurements then simple discretization of $f(t)$.

In CS, the number of measurements is m << n. However, when the number of measurements is smaller then the signal size, then it is ill-posed inverse problem. If Φ is a matrix of size $m \times n$, concatenating the sampling vectors φ_k, then $y = \Phi f$. The signal $\hat{f}$ corresponding to the measurements y has infinity many solutions.

CS shows that $\hat{f}$ can be reconstructed if it has sparse representation in a given basis and that the measurements are incoherent with that basis.

Concept of Sparsity

Sparsity is the idea that signal may have a concise representation in a given basis.



Hence a dense signal in the time domain can be coded with only a few samples. Mathematically it translates as follows:

$$f(t) = \sum_{i=1}^{n} x_i \psi_i(t) \quad (2)$$

Where $f(t)$ is the original signal, x_i are the coefficients of the signal in sparse basis, and $\psi i(t)$ is an orthonormal basis. The S largest coefficients x_i are noted x_S, and the corresponding signal $f_S(t)$ If $f(t)$ is sparse in the basis Ψ composed of the vectors ψ_i, then $f = \Psi x$ and the error $\|f - f_S\|_2$ is small.

Concept of Sparsity

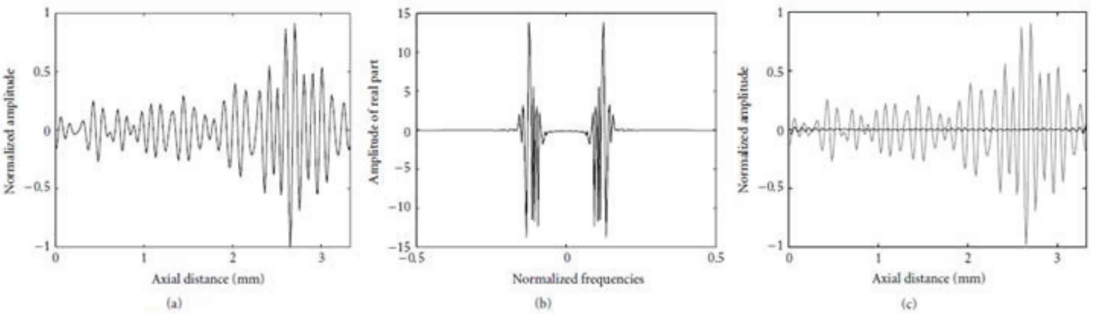


Figure 1: (a) A full US RF signal and (b) its sparse representation via Fourier transform. Most of the coefficients are equal or close to zero. (c) Compressed US RF signal (gray), corresponding to 30% of the largest Fourier coefficients, the rest of them being set to zero. The difference between the full and compressed US RF signal (black) is minimal.

- Sparsity therefore leads to compressive nature of signal: if signal has sparse rep resentation, then the information coding that signal can be compressed on a fe w coefficients.
- However directly acquire only significant coefficients without knowing their po sitions is impossible.
- CS overcomes this issue via an incoherent sampling.

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Incoherent Sampling

The term Incoherent sampling conveys the idea that the sampling protocol φ_k in (1) has to be as little correlated as possible with sparse representation ψ_i in (2).

$$y_k = \langle \varphi_k, f \rangle, \quad \text{for } k = 1,\ldots,m, \quad (1) \qquad f(t) = \sum_{i=1}^{n} x_i \psi_i(t) \quad (2)$$

The mathematical definition of incoherence is:

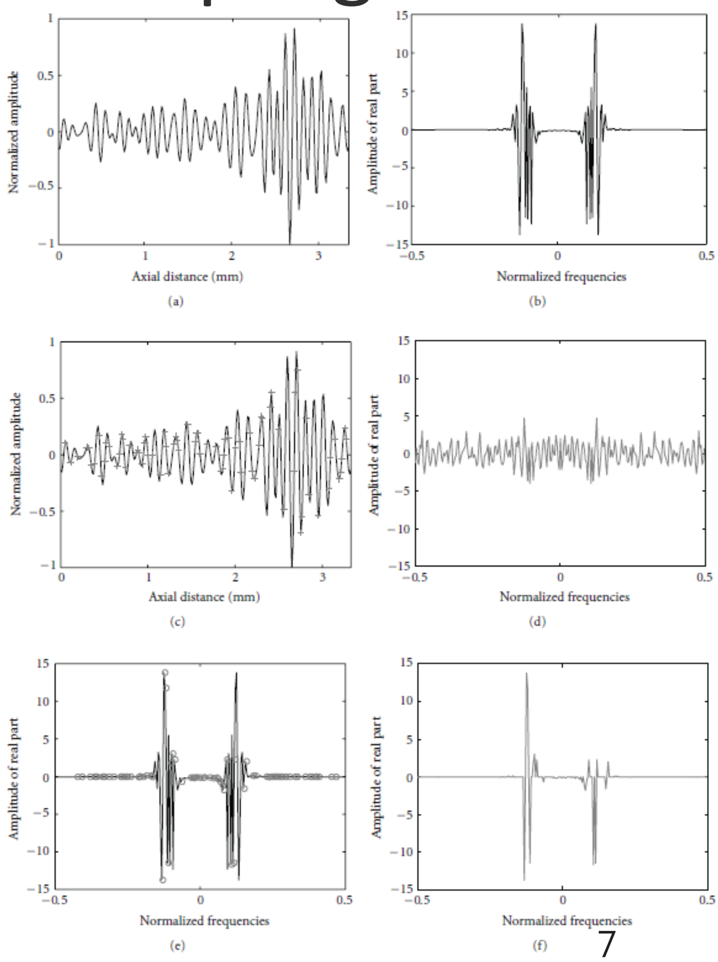
$$\mu(\Phi,\Psi) = \sqrt{n} \max_{1 \le k, j \le n} \left| \langle \phi_k, \psi j \rangle \right|, \quad (3)$$

Where Φ is the sampling basis and Ψ is the sparsifying basis. If the two bases are strongly correlated, then μ will be close to $\sqrt{n}$, and if the are not correlated, then it will be close 1.

- CS requires incoherence .
- If the sampling basis completely random , then it will be maximally incoherent with sparsifying fixed basis.

Incoherent Sampling

- (a) A full US RF signal
- (b) its sparse representation FT
- When sampling is incoherent with the sparsifying basis then the meas urements in that basis are dense (c, d)
- When the sampling basis and the s parsifying basis are coherent (e,f), t he measurements in the sparsifying basis are themselves sparse. There i s significant information missing
- Knowing sparsifying basis and incoh erent measurements in cs make it p ossible to reconstruct original signal using optimization.



Signal Reconstruction through Optimization

Reconstruction performed via convex optimization:

$$\min \|\hat{x}\|_1 \quad \text{subject to } y = \Phi f = \Phi\Psi\hat{x}, \quad (4)$$

$\hat{x}$ is the reconstructed sparse signal.

The optimization searches amongst all the signals that verify the measurements y , the one with the smallest l1 norm, that is the sparsest.
Optimization removes the interferences caused incoherent under sampling from t he sparse representation of the measurements.

Sampling Protocols in Ultrasound

The data acquisition in US is performed in spatial domain. The sampling basis has to be in coherent with sparsifying basis. There are several sampling protocols adapted and incohe rent with sparsifying basis. Basically they all consist in taking samples at random locations (taking samples at specific times on RF signal or taking some RF lines at specific locations) .

- Eight different protocols are proposed:

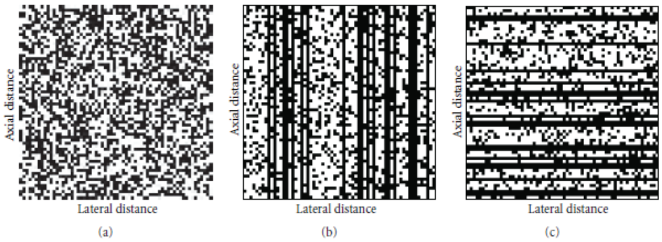
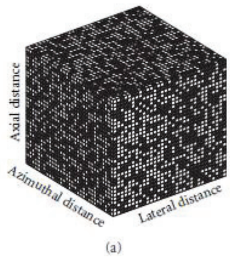


Figure 6: Sampling masks Φ_1 (a), Φ_2 (b), and Φ_3 (c) adapted to a spatial sampling of the US images. The white pixels correspond to the samples used for CS. The proportion of samples here is 50% of the original image.



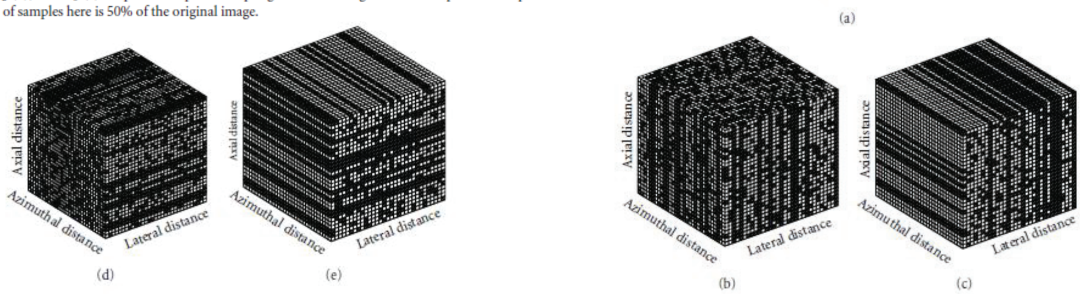


Figure 7: Sampling masks Θ_1 (a), Θ_2 (b), Θ_3 (c), Θ_4 (d), and Θ_5 (e) adapted to a spatial sampling of the 3D US volumes. The white pixels correspond to the samples used for CS. The proportion of samples here is 50% of the original volume.

Reconstruction of Ultrasound Images

The acquisition consist in taking samples of the RF signals. This sampling protocol is simila r to a basis of Diracs. Basis incoherent with Diracs and where US images are sparse is need ed. Fourier basis is maximally incoherent with Diracs and because the US image k-space is sufficiently sparce. The function to minimize is

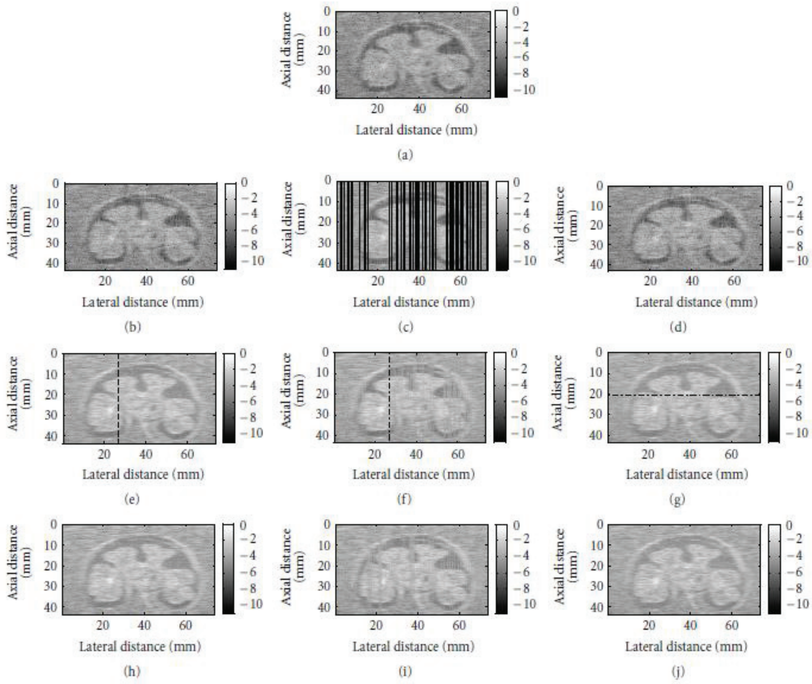
$$\arg\min_{M} \|AM - y\|_2 + \lambda |M|_1, \quad (8)$$

where M is the k-space of the US RF image m (M= $\mathcal{F}$m), and A is the sampling scheme (A = $\Phi\mathcal{F}$), y are the RF US image measurements and λ is a coefficient weighting for sparsi ty.

Results on a 2D Simulation Image

The proposed CS method was used to reconstruct the k-space of an RF image simulated using the Field ii simulation program. Map of kidney used with linear transducer. Sampli ng frequency 20 MHz.

The sampling Φ_1, Φ_2, Φ_3 were studied to compare CS recons truction using a fixed optimal set to 0.005 and the reweight ed λ minimization ℓ_1



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Results on a 2D Simulation Image

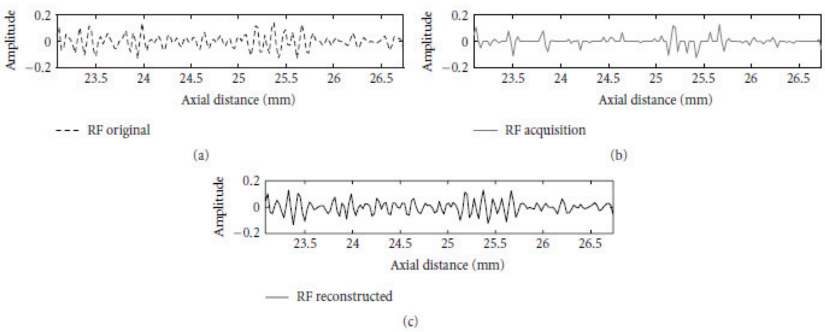

FIGURE 9: An example of a local region of an RF line after CS reconstruction using Φ_1 sampling pattern, corresponding to the dotted line in Figure 8(e).

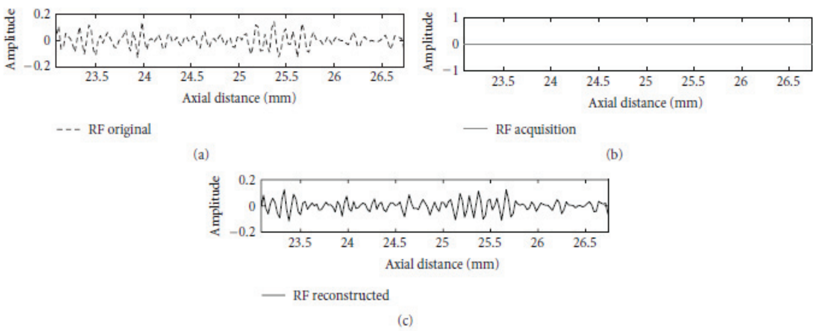

FIGURE 10: An example of a local region of an RF line after CS reconstruction using Φ_2 sampling mask, corresponding to the dotted line in Figure 8(f). This line was not sampled at all.

Results on a 2D Simulation Image

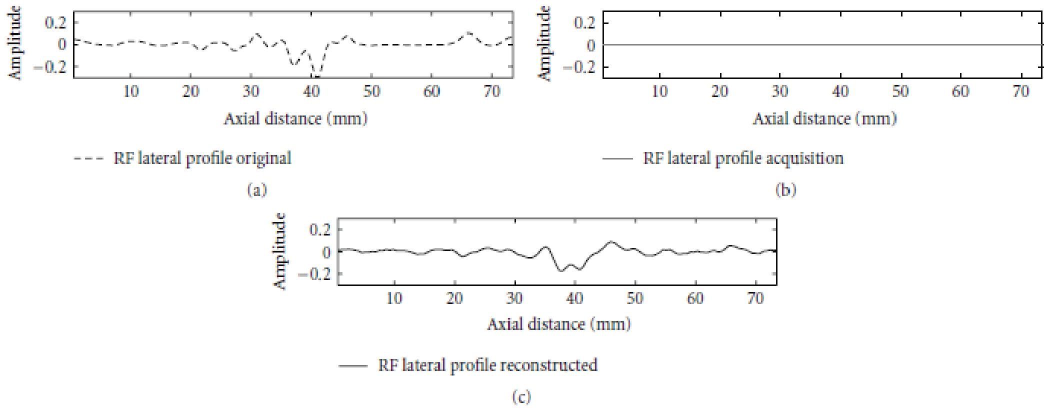

Figure 11: An example of a lateral profile of aN RF image after CS reconstruction using Φ_3 sampling mask, corresponding to the dotted line in Figure 8(g). This lateral profile was not sampled at all.

Table 1: NRMSE between the CS-reconstructed RF US image and the original simulated image of a kidney for different sampling ratios and patterns.

		Φ_1	Φ_2	Φ_3
	25%	0.48	0.58	0.6
Classic ℓ_1 minimization ($\lambda = 0.005$)	33%	0.33	0.45	0.49
	50%	0.15	0.28	0.29
	25%	0.51	0.56	0.64
Reweighted ℓ_1 minimization	33%	0.36	0.47	0.49
	50%	0.17	0.24	0.3

Discussion and Conclusion

Sampling using high sampling rate is neither easy nor cost-effective in high frequency a pplications.
It was showed potential of CS to reduce data volume and wrap acquisition at the price of a reconstruction using the ℓ_1 norm.

Future work

- Better sparsity basis
- Investigation of several optimization routines
- The aim is to reach fastest and most reliable reconstruction from as little amount of data as possible.

Thank you

Brain Computer Interface-Based Smart Living Environmental Auto-Adjustment Control System in UPnP Home Networking

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IEEE SYSTEMS JOURNAL. (2012.04)

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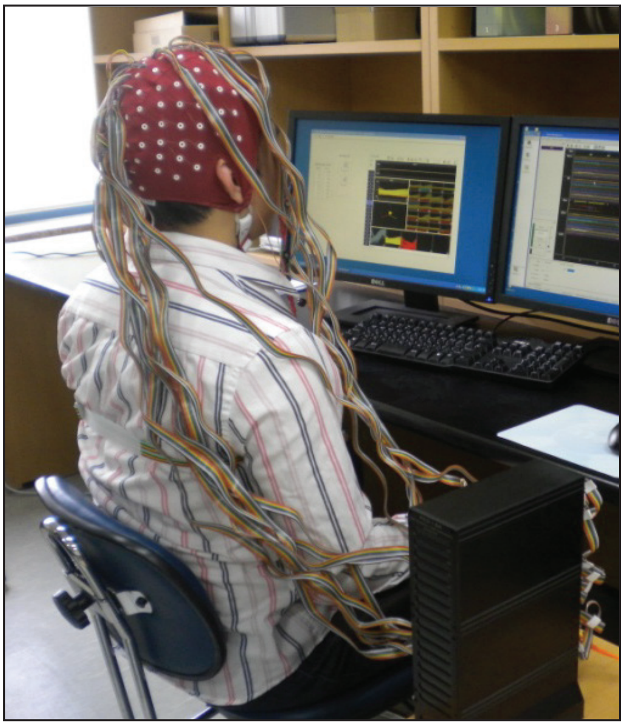
Background

- Wired BCI system



- Wireless BCI system

Introduction

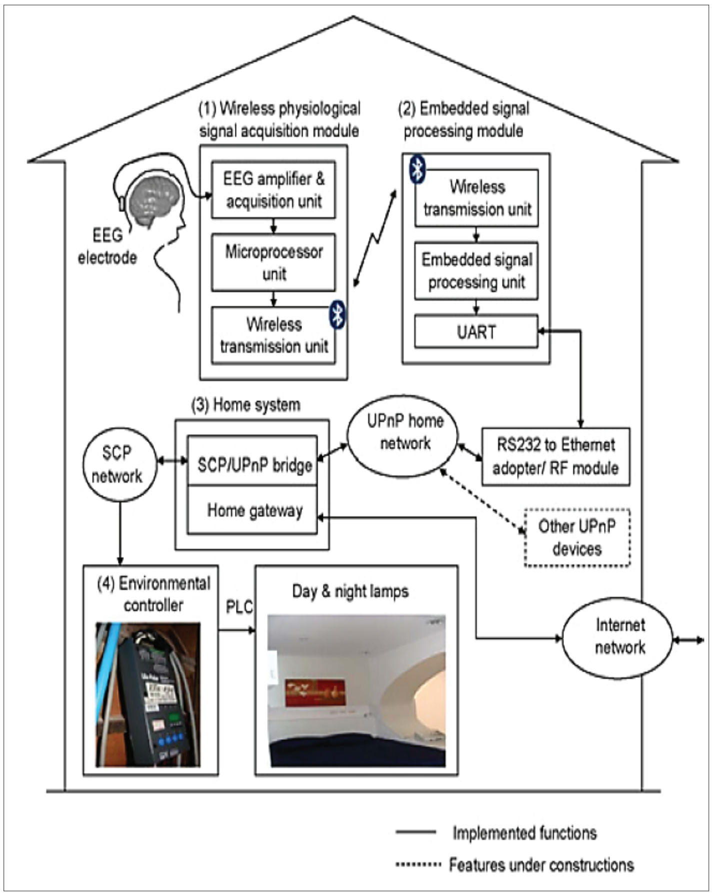
- Recently many studies are trying to develop commercial products to bring the convenience to people in their usual life.
- Some environmental control systems in a smart house employed radio frequency identification (RFID), external sensor modules, and voice recognition as the controlled signals.
- By combining with universal plug and play (UPnP) home networks, users could send out service requests from their personal digital assistant, mobile phones, a wearable appliance, or external sensors to home server, graphic user interface, or motion.
- With the development of BCI, it is an new option to apply the physiological signals as the stimulus of environmental control system in a smart house.
- However, Most of the existing BCI-based environmental control systems require the user's active mental command to control external device.

Introduction

- These systems lack the capability to control devices automatically and adaptively according to the user's current cognitive state.
- Most of current BCI-based environmental control system are inconvenient because bulky and expensive EEG machines and computer are both required for signals acquisition and backend analysis, which will limit the flexibility and portability of these systems.
- The goal of this paper is to propose a cost-effective, simply extendable and easy to use BCI-based smart living environmental auto-adjustment control system (BSLEACS) to control electric home appliances based on the change of user's cognitive state (drowsiness or alertness).
- Their proposed wireless physiological signal acquisition module and embedded signal processing module contain the advantages of small volume and low power consumption, and are more suitable for practical application.

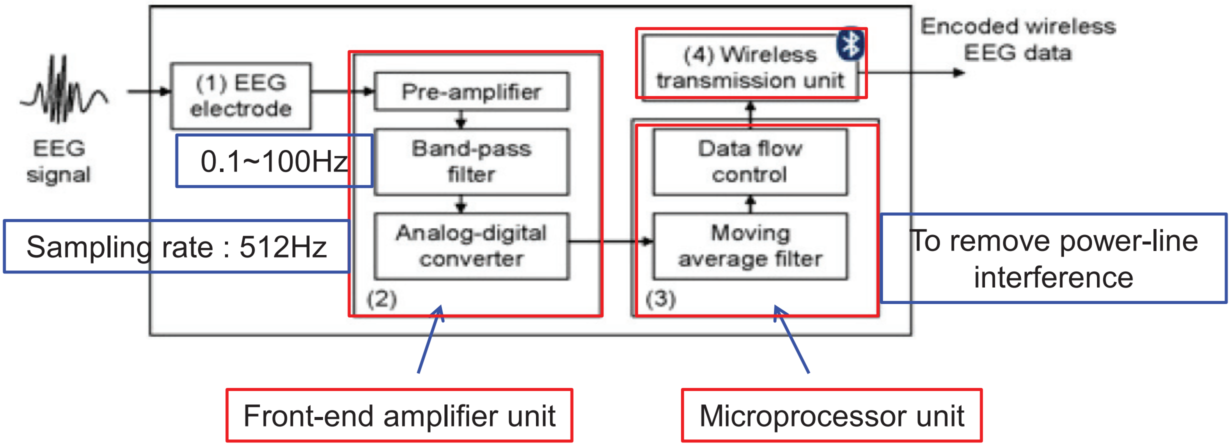
System Architecture

- (1) is designed to acquire and transmit an EEG signal to the embedded signal processing module via Bluetooth.
- (2) is designed to estimate the user's cognitive state from his or her EEG, and provides the estimated cognitive state to the host system.
- (3) is designed for data storage /display, and is also served as an UPnP control point to manage the request from UPnP control device.

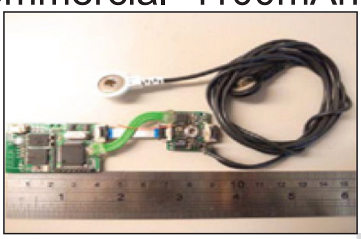


System Architecture

A) Wireless Physiological Signal Acquisition Module

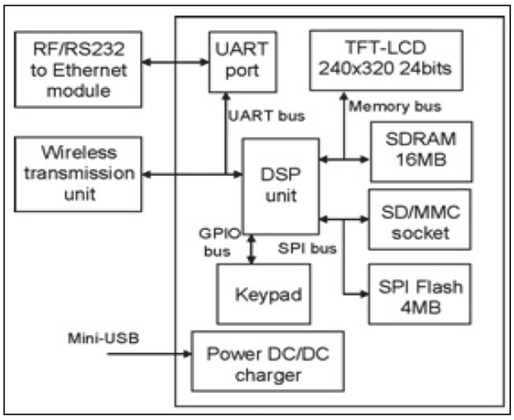


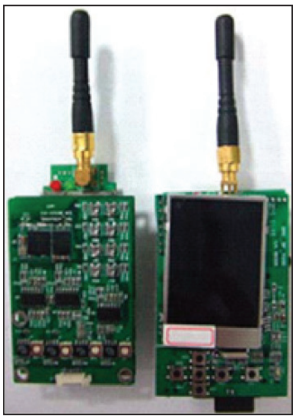
- EEG data digitized by ADC will be stored into memory.
- This module operates at 31 mA with 3.7V DC power supply, and continuously operate over 33 h with a commercial 1100mAh Li-ion batter.
- The volume is about 4 cm * 2.5 cm * 0.6 cm.



System Architecture

B) Embedded Signal Processing Module





3.7V DC power

Over 45 h

6.4cm*4.4cm*1cm

- This module contains a powerful computation capability and can support various peripheral interface.
- This module is developed to perform the real-time cognitive state detection algorithm.
- This module is also evaluated as the UPnP control device to send out the estimated cognitive state and EEG signal to host system to drive environmental controller via UPnP home networking.

System Architecture

B) Embedded Signal Processing Module

- The received EEG data will be real-time processed, analyzed and displayed by the embedded signal processing module.
- When the change of cognitive state of the user is detected, the corresponding command will be transmitted either by RF module or by Ethernet through UPnP.

C) Host System and Environmental Controller

- The host system is an UPnP/SCP bridge and is also served as the home gateway to internet network.
- A SCP-based environmental controller with four-channel AC/DC power line control output is used to control home equipment.
- The SCP-based environmental controller is used to control the day and night lamps in the showroom.

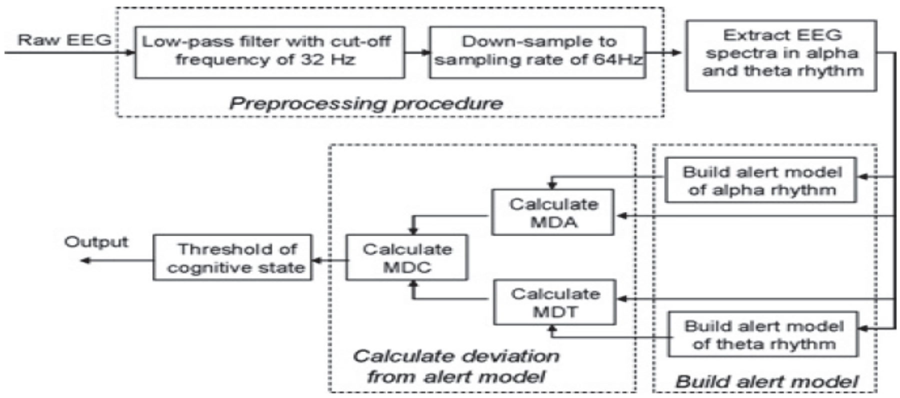
Methods

A) Real-Time Cognitive state Detection

- When alert person is becoming drowsy, his or her EEG power in both theta and alpha rhythms will increase.
- If the subject remains alert, his or her EEG spectra in theta and alpha rhythms should match the alert model. Otherwise, his or her EEG spectra will diverge from the alert model if the subject is under drowsy state.
- They observe that the alpha and theta rhythm of EEG spectra in the occipital midline (the location Oz in the international 10-20 EEG system) can provide discriminating power and they have high correlation with cognitive state.
- A single EEG channel is used in their system to monitor EEG signal in the occipital midline.

Methods

A) Real-Time Cognitive state Detection



- A 512-point FFT with 448-point overlap is used to obtain the EEG spectra, and then the EEG spectra in alpha and theta rhythms are extracted to build up the alert model.
- A new alert model will be constructed separately.
- The distribution of power spectrum in the alert state can be modeled by a multivariate normal distribution $N(\mu,\Sigma^2)$. μ : mean vector

Σ^2: variance-covariance

Methods

A) Real-Time Cognitive state Detection

- (μ_A, Σ_A^2): alpha rhythms, (μ_T, Σ_T^2): theta rhythms.
- After building the alert mode, the Mahalanobis distance from the alert mode of the alert mode of alpha rhythm (MDA) and that of theta rhythm (MDT) will be calculated.
- Mahalanobis distance is a distance measure based on correlations between variables by which different patterns can be identified and analyzed. It takes into account the correlations of the data set and is scale-invariant.

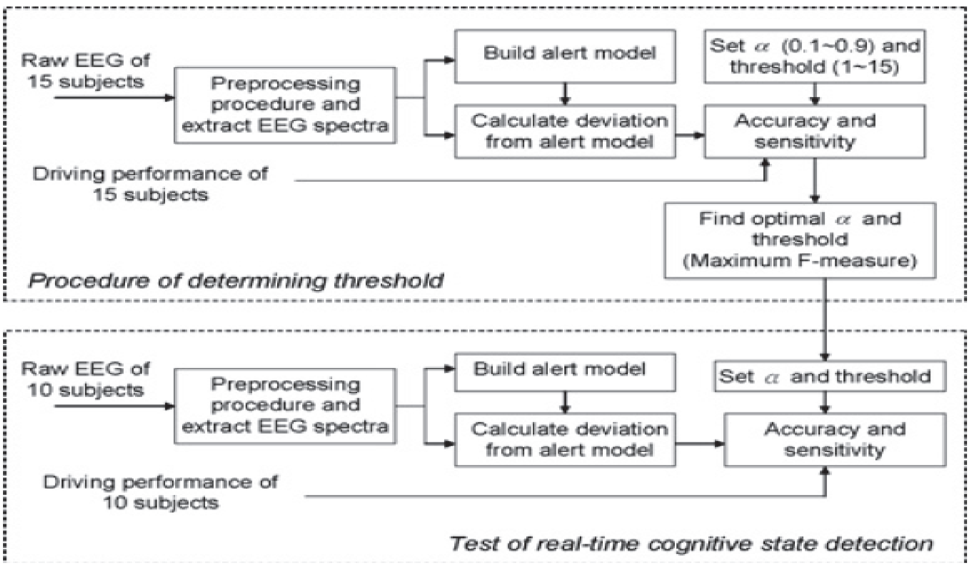
$$MDA(x_A) = \sqrt{(x_A - \mu_A)^T (\Sigma_A^2)^{-1} (x_A - \mu_A)} \;, MDT(x_T) = \sqrt{(x_T - \mu_T)^T (\Sigma_T^2)^{-1} (x_T - \mu_T)}$$

$$MDC = \alpha \times MDA + (1-\alpha) \times MDA, 0 \le \alpha \le 1$$

- They use the linear combination MDC of MDT and MDA to estimate the user's cognitive state.
- If the value of MDC is larger than the threshold, the subject can be treated as his or her cognitive state trends to drowsy state; otherwise, it trends to alert state.

Methods

B) Performance Evaluation



- F-measure, the harmonic mean of precision [positive predictive value (PPV)] and recall (sensitivity), is used to find out the threshold of Mahalanobis distance to decide the cognitive state.

$$F = 2 \times \frac{precision \times recall}{precision + recall}$$

Results

A) Performance of BSLEACS for cognitive state Detection

Subject	F-measure (%)	PPV (%)	Sensitivity (%)
1	77.7	75.5	80
2	72.2	78.8	66.7
3	89.1	80.4	100
4	87.5	77.8	100
5	87.4	77.6	100
6	88.9	80	100
7	83.5	78.7	88.9
8	81.1	77.9	84.6
9	66.1	65.5	66.7
10	86.8	76.6	100
Average	82	76.9	88.7

- A total of 1370-trial response time and Mahalanobis distances from 15 subject were analyzed to determine the maximum F-measure value. $\boxed{(\alpha = 0.1 - 0.9, threshod = 1 - 15)}$
- The maximum value 77.6% of F-measure (PPV=69.2% & sensitivity = 88.3%) was determined with $\boxed{(\alpha = 0.9, threshod = 7.5)}$
- 1000-trial response times and Mahalanobis distances from ten subjects for testing session were used to test the performance of this system.

Results

B) Performance of BSLEACS for controlling Home Application

- BSLEACS is used to control day and night lamps.
- Criterion 1) when the trend of cognitive state is alert, the major day lamp is on and the night lamp is off.
- Criterion 2) when the trend of cognitive state is drowsy, the major day lamp is off and the night lamp is on.
- A total of 75-trial system responses and questionnaire results from 15 subjects were cross referenced and analyzed.
- The F-measure of system control performance is 75.27% (PPV = 70% & sensitivity = 81.4%).<effectively control home appliance>

		System Control Output	
		Control Criterion 1	Control Criterion 2
Cognitive state (questionnaire)	Drowsy	8 (FN)	35 (TP)
	Alert	17 (TN)	15 (FP)

Conclusion

- In this paper, they proposed a BCI-based smart living environmental auto-adjustment control system (BSLEACS).
- BSLEACS only needs single EEG channel to recognize cognitive state by monitoring EEG signal in the location of Oz.
- BSLEACS has been verified in a practical environment and shows that the light/lamp can be adjusted in real time based on the change of the user's cognitive state.
- BSLEACS provides a system prototype for environmental control, and can be generalized for other applications and constructed in an UPnP-based smart house.

Thank you!