ISSN : 0974 - 7435 Volume 7 Issue 12

BioTechnology

An Indian Journal

FULL PAPER

BTAIJ, 7(12), 2013 [537-542]

Research on the application of the brain-computer interface based on electrocorticographic signals

Yue Chen, Shaobai Zhang*

Computer Department, Nanjing University of Posts and Telecommunications, 210003, Nanjing, (CHINA)

ABSTRACT

Brain–computer interfaces (BCIs) enable users to control devices with electroencephalographic (EEG) activity from the scalp or with single-neuron activity from within the brain. Both methods have disadvantages: EEG has limited resolution and requires extensive training, while single-neuron recording entails significant clinical risks and has limited stability. In the light of these problems, the electrocorticographic (ECoG) signals recorded from the surface of the brain can enable users to control a one-dimensional computer cursor rapidly and accurately. The classification MATLAB experiment of the motor imagery of the left little fingure and the tongue has reached a high classification accuracy of 94%. This result reveals that compared to the EEG signals, ECoG signals can accurately locate the function cortex and avoid the changes of amplitude, frequency and phase at the same time. In addition, our results suggest that an ECoG-based BCI could provide for people with severe motor disabilities a non-muscular communication and control option that is more powerful and effective than EEG-based BCIs in the two- dimensional joystick movements.

KEYWORDS

Brain-Computer Interface;
EEG;
ECoG;
Motor Imagery.

INTRODUCTION

Brain–computer interfaces (BCIs) convert brain signals into outputs that communicate a user's intent. Because this new communication channel does not depend on peripheral nerves and muscles, it can be used by people[1] with severe motor disabilities. BCIs can allow patients who are totally paralyzed (or 'locked in') by amyotrophic lateral sclerosis (ALS), brainstem stroke or other neuromuscular diseases to express their wishes to the outside world. However, practical applications of BCI technology to the needs of people with severe disabilities are impeded by the limitations and requirements of current BCI methodologies.

BCIs can use non-invasive or invasive methods[2-5]. Non-invasive BCIs use electroencephalographic activity (EEG)recorded from the scalp. They are convenient, safe and inexpensive, but they have relatively low spatial resolution, are susceptible to artifacts such as electromyographic (EMG) signals, and often require extensive user training. Invasive BCIs use single-neuron activity recorded within the brain. While they have higher spatial resolution and might provide control signals with many degrees of freedom, BCIs that depend on electrodes within cortex face substantial problems in achieving and maintaining stable long-term recordings. The small, high-impedance recording sites make penetrating electrodes susceptible to signal degradation due to encapsulation. Also, small displacements of the tiny penetrating electrodes can move the recording sites away from the cortical layers that contain the large easily recorded neurons, such as pyramidal neurons in layer 5 of motor cortex. These issues are crucial obstacles that currently prohibit their clinical use in humans[6].

THE COMPARISON BETWEEN EEG AND ECOG

An intermediate BCI methodology, using electrocorticographic activity (ECoG) recorded from the cortical surface, could be a powerful and practical alternative to these extremes. ECoG has higher spatial resolution than EEG (i.e., tenths of millimeters versus centimeters[8]), broader bandwidth (i.e., 0–200 Hz versus 0–40 Hz), higher amplitude (i.e., 50–100 μV maximum versus 10–20μV), and far less vulnerability to artifacts such as EMG. At the same time, because ECoG is recorded by subdural electrode arrays and thus does not require electrodes that penetrate into cortex, it is likely to have greater long-term stability and might also be safer than single-neuron recording.

This study set out to explore the potential value for BCI applications of ECoG activity recorded over sensorimotor cortex in humans. We studied four patients in

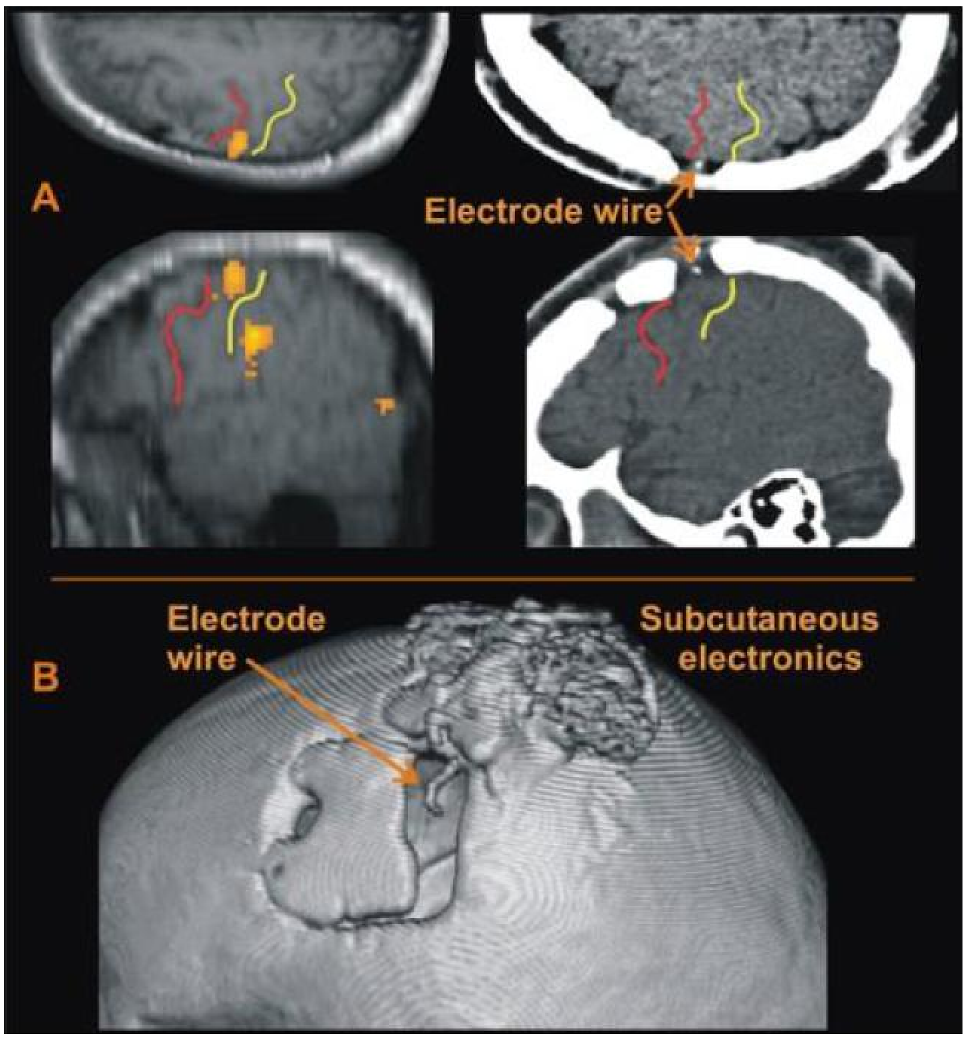

Figure 1 : Electrode location in the participant's cerebral cortex.(A) Left panels: Axial (top) and sagittal (bottom) slices showing brain activity along the precentral gyrus during a word generation fMRI task prior to implantation. Red lines denote pre-central sulcus; yellow lines denote central sulcus. Right panels: Corresponding images from a post-implant CT scan showing location of electrode. (B) 3D CT image showing electrode wire entering dura mater. Subcutaneous electronics are visible above the electrode wire, on top of the skull

whom subdural electrode arrays were implanted for 3–8 days in preparation for surgery to remove an epileptic focus (see TABLE 1 for clinical profiles). All four provided informed consent for the study, which had been reviewed and approved by the Washington University School of Medicine Institutional Review Board.

The experimental approach was developed based on current understanding of sensorimotor rhythms and on the methodology of current EEG-based BCIs that use these rhythms. Sensorimotor rhythms comprise μ (8–12 Hz), β (18–26 Hz) and γ (>30 Hz) oscillations. They are thought to be produced by thalamocortical circuits and they change in amplitude in association with actual or imagined movements. BCIs based on EEG oscillations have focused exclusively on μ and β rhythms because γ rhythms are inconspicuous at the scalp. In contrast, γ rhythms as well as μ and β rhythms are prominent in ECoG. This paper is the first report of a study that applies ECoG activity to online operation of a BCI system. We identified the locations and frequency bands of ECoG sensorimotor rhythms associated with specific movements or speech, or with imagery of those actions, and then determined whether people could learn to use these rhythms to control a cursor on a computer screen.

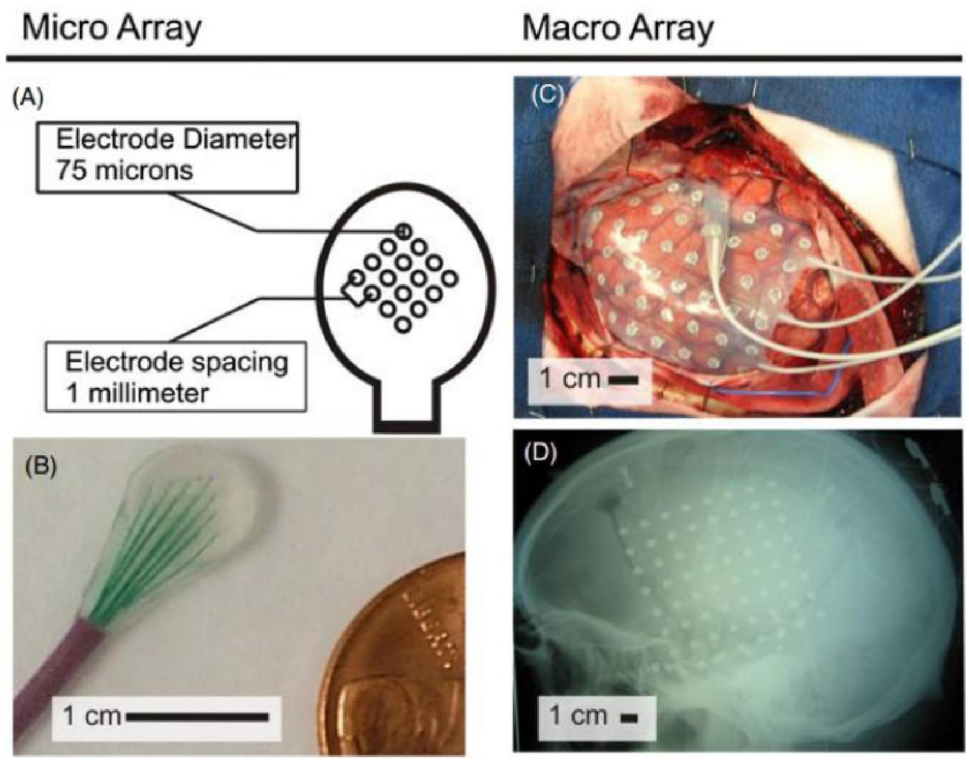

Figure 2 : Micro and macro grid arrays. (A) and (B) Micro array size and configuration. (C) Intraoperative view of the macro grid array. (D) Lateral radiograph of the skull with a macro array

THE EXPERIMENT

Data resource

Experiment data stems from document[8], and the subject is required to complete two thinking tasks: imagining moving little finger of left hand and imagining moving the tongue separately. Inside S's skull sits a 8x8(64-micro-electrode) ECoG data acquisition plate, which is used for acquiring the motion perception cortical potentials on the right wing on condition of data acquisition rate registering 1000Hz. Upon receiving a temporary visual hint, the subject imagines moving the little finger of left hand or moving the tongue continuously and consecutively, which is recorded by 1 and -1. The subject acquires data for 3 seconds while undergoing thinking tasks, and to avoid the effect of VEP, each data acquisition is conducted 0.15 second ensuing the visual hint. Such experiment is completed in 2 stages. In the first stage, two thinking tasks are completed for 139 times each, which serves as training data. On the other day which falls within 1 week away, the subject goes through same experiment repeatedly, and completion of two thinking tasks for 50 times each serves as test data.

Feature extraction

Given the inconsistency of experiment time, that is to say, it is not possible to mark the time task begins, therefore, ECoG cannot be used for comparison in terms of time. As a result, the signals are processed in frequency domain. In light of the randomicity of EEG, this research deals with spectral estimation of the analytic-al signal via PSD in the AR model. Research of functional magnetic resonance imaging shows that motor cortex activity is closely related to body organization activity. Central sulci bilaterally are located with two fields (see pic3) that are sensitive to imaginative motions of lip, hand and elbow symmetrically. μ rhythm of EEG is generated in the motion perception cortical regions, and as it mirrors the motion or motor imagery, the research features ECoG power of this frequency band[9].

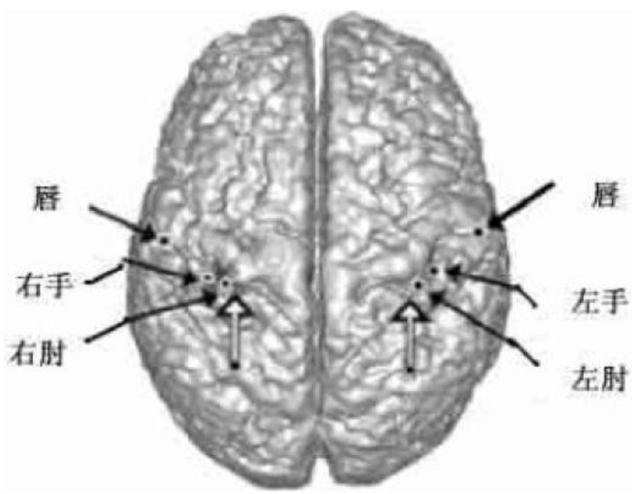

Figure 3 : Motor perception cortex area

Micro-electrode plate not only covers the whole motor cortex, but also lays over some part of the surrounding cortex. Among the 64 electrode potentials, ECoG data collected by some of them exerts big difference in task distinction while data acquired by the rest potentials are redundant, and even lowers the accuracy of final classification. To begin with, manual selection is adopted regarding PSD. Training data is classified into two groups by means of task mode, 139 times each. PSD average is carried out, which gives birth to 64 pictures of PSD for the 64 electrode ECoG data. Significant differences can be told from these picture by naked eys. Take electrode-39 and electrode-1 for example, PSD shows clear distinction in that the two curves stay the farthest in the 8-13HZ range, while the two task curves are almost coincident with each other. In light this, the two distinguishing electrode potentials in 8-13 HZ range are roughly selected by a low threshold value, and they are meant for further process.

While the subject is performing the imagery task, working staff mark the sequence of both tasks by 1 and -1 simultaneously. Four data acquisition will be born: A. ECoG data acquisition from 278 groups; B. mark acquisition (composed of 1 and -1) from 278 tasks; C. ECoG data acquisition from 100 groups; D. mark acquisition (composed of 1 and -1) from 100 tasks. Calculation is carried out towards A and C for feature extraction, and it yields the characteristic acquisition: T-A, T-C of A and C; taking T-A and B as training sample, T-C as the testing sample, therefore leading to mode perception of two sorts of questions. Task mark responding to C can be predicted, and the final classification rate can be obtained from comparing that with the actual task mark acquisition of C.

Experiment result

According to the power spectrum difference degree in 8-13 Hz range answering to the two tasks, 11 signals with significant differences are selected from the 64 signals by utilizing the low threshold value, and the electrodes are marked as 12,21,22,29,30,31,37,38, 39,40,46. Signals are sifted for these 11 electrodes by means of CSP method. This is because even-numbered signals are bound to be generated from CSP filter, with maximum 10 groups. And by culling the two groups with least difference, 8 groups are finalized and their features are used for final classification feature.

Figure 5 is the PSD average comparison of the 8 groups of data generated via CSP filter for the training sample, with bold and fine lines marking two tasks respectively. Significant differences can be seen from the 8 groups of data in the pic, and it is nowhere to see the almost-coincident scene as is in Figur 4(b).

By means of K nearest neighbor method, the value of K matters the most, as it has to be equal to or less than 278 when taken a small part from the overall training sample. Therefore, k should be no more than 10. K has to be selected based on training data first in case

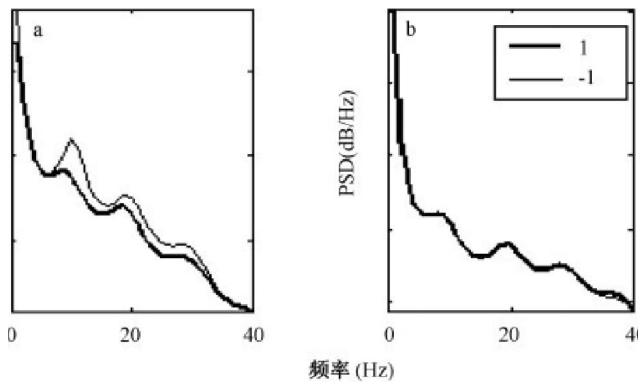

Figure 4 : The contrast diagram of the PSD (the bold line and the thin line represent the two different tasks respectively). a shows the electrode 39, and b shows the electrode 1

that the task type of testing data is not available. Abiding by below-mentioned m-fold cross-validation method, k (9) is obtained.

Training data of the 278 samples are divided into N pieces. Take N-1th as the new training sample, and the remaining 1 piece as the new testing sample. Since the task type of the new testing sample is known ahead, prediction accuracy can be obtained in this fashion. There are N ways of extraction of this sort, N prediction accuracy can be gotten and the average of the N pieces is available then. Furthermore, as the original testing sample is predicted on basis of original training sample in the

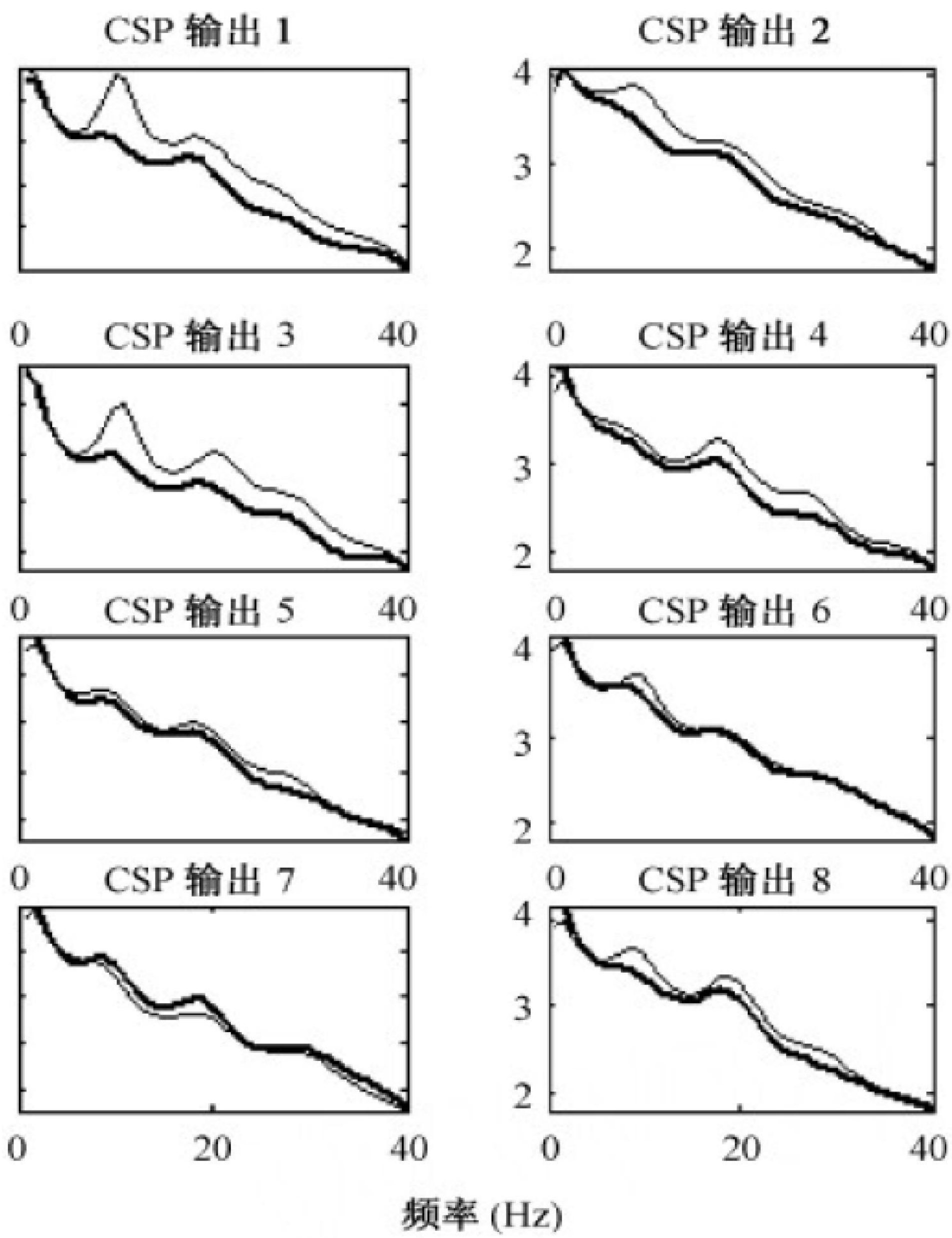

Figure 5 : The contrast diagram of the PSD after the CSP filtering of the training samples

FULL PAPER

end, the new training sample has to amount to around 278, and N=278 at this point. To have the new testing sample number reach near 100, N shall be at 3. At length, N ranges from 3 to 278 and averages consequently, thus giving birth to the average of 276 prediction accuracy. In this sense, there are N prediction accuracies corresponding to each N; and each K has 276 N. The picketage index of K is based on twice-averaged accuracy and is marked as α. In light of the analysis of training sample, when K=4, α is at highest, therefore, K is pinned at 4.

Take the features of training samples and testing samples for normalization separately, by utilizing 4-nearest-neighbor-filter, prediction task type of the testing data can be obtained. Compared with final testing data, the prediction accuracy rate reaches 94%. Should it be without CSP filtering, perception rate just accounts for 85%, and K reads 7 at the time.

CONCLUSIONS

By analyzing multi-dimension ECoG signals, accuracy of predicting two motor imageries reaches 94%. Below conclusion can be asserted from this experiment: firstly, corresponding motor imagery can be well perceived by means of μ rhythm of motion perception cortex EEG; secondly, on condition of extracting valid features, no big difference exists between different kinds of grader, while the best nearest neighbor value by means of cross-validation method can enhance the effect of K nearest neighbor grader; lastly, long as preliminary process, feature extraction and assortment method are appropriate, as the effects of motor imagery perception brought by factors that time lag may do some detriment to S's physical and mental divergence plus experiment error are not glaring, when ECoG is compared with EEG, not only can it be accurate in locating the functional cortex, but also avoids signal changes in terms of range, frequency, phase, etc. At present, brain-embedded electrode is not uncommon. It is highly believed that these factors and progress of EEG processing are to expedite BCI practicality.

ACKNOWLEDGEMENTS

The research work was supported by National Natural Science Foundation of China under Grant No. 61073115 and No. 61373065.

REFERENCES

[1] J.R.Wolpaw, N.Birbaumer, D.J.McFarland, T.M.Pfurtscheller Gand Vaughan; Brain–computer interfaces for communication and control Clin. N europhysiol., **113**, 767–91 **(2002)**.

[2] C.Neuper, G.R.Muller, A.Kubler, N.Birbaumer, G.Pfurtscheller; Clinical application of an EEG-based brain–computer interface: a case study of a patient with severe motor impairmentClin. Neurophysiol., **114**, 399–409 **(2003)**.

[3] D.M.Taylor, I.Tillerysubject, A.B.Schwartz; Direct cortical control of 3D neuroprosthetic devices Science, **296**, 1829–32 **(2002)**.

[4] J.R.Wolpaw, D.J.McFarland; Two-dimensional movement control by scalp-recorded sensorimotor rhythms in humans Abstract Vi ew er/ Itinerary P lanner (Washington, DC: Society for Neuroscience) program no, **607**, 2 **(2003)**.

[5] G.Pfurtscheller, D.Flotzinger, J.Kalcher; Brain–computer interface—a new communication device for handicapped persons J.Microcomput.A ppl., **16**, 293–9 **(1993)**.

[6] Pradeep Shenoy, Kai J.Miller, Jeffrey G.Ojemann, Rajesh P.N.Rao; Generalized Features for Electrocorticographic BCIs. IEEE Transactions on biomedical engineering, **55(1)**, JAN., **(2008)**.

[7] Eric C.Leuthardt, Gerwin Schalk, Jonathan R.Wolpaw, Jeffrey G.Ojemann, Daniel W.Moran; A brain–computer interface using electrocorticographic signals in humans. Journal of neural engineering. J.Neural Eng., **1**, 63–71 **(2004)**.

[8] B.Blankertz; IEEE BCI Competition III [DB/OL]. http://ida. first. fraunhofer. De/projects/bci/competition-iii, 2005- 07- 16/2005- 09- 01, **(2005)**.

[9] An Bin, Jiang zhao-hui, Ning yan, Classifying ECoG-Based Motor Imagery Tasks. Chinese journal of biomedical engineering, **26(1)**, 89-94 **(2007)**.