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Selective Subband Entropy for Motor Imagery Detection in Asynchronous Brain Computer Interface

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***Abstract*— The motor imagery detection is a very important problem in the asynchronous control for direct Brain Computer Interface. To address this issue, this paper proposes a novel detection method based on subband entropy analysis in a selected frequency band. The basic idea of this method is that, in some specific frequency band, the complexity (or randomness) of brain signal during the stage of concentrating on the motor imagery is lower than that of free thinking. Once the optimal frequency band is selected, the subband entropy, -an indicator of complexity and randomness-, can be used for detecting the motor imagery. In this work, we develop the method using only one dipolar EEG channel. Furthermore, we propose a system calibration method based on an empirical measurement what we refer as unsupervised discriminative index (UDI). The proposed calibration method is rapid and able to avoid a typical problem of asynchronous BCI training that is the correct labeling of continuous EEG signal. The proposed method not only improve the accuracy of the detection but free from parameter tweaking. The experiment conducted on three different subjects shows advantage of the proposed method over the conventional framework based on fixed-band filter and energy feature. A detection accuracy up to 77% at false positive rate of 2% was obtained without any subject training.**

I. INTRODUCTION

Brain-Computer Interface (BCI) [1] is the system which captures and decodes the brain signal in order to transform the human intentions directly into actions. This helps the paralyzed, brain injured, and spinal cord injured patient to restore their abilities, particularly in communication, wheel-chair control or rehabilitation. Although many modalities are possible for BCI, the current research is mainly focused on the electroencephalogram (EEG) signals. The advantage of EEG based BCI is very clear: this is non-invasive, technical less demanding and widely available at relatively low cost. There are two types of BCI, according to the mode of operation. The synchronous BCI allows the user only to response to the external stimuli. In this mode, the processing is fixed in predefined time windows. Alternatively, the asynchronous BCI [2], decodes the user's intentions in continuous time and without stimuli. This mode is more complex but provide more natural communication as the user can decide when to start the system. An asynchronous BCI basically consists of two steps: the detection of motor imagery occurence [3]; and the classification of the detected signal into certain classes sich as left/right hand movement imaginations [1]-[2], [4].

In present time, the Neural Signal Processing group at Institute for Inforcomm Research, Singapore is working on two applications of asynchronous BCI: the control of functional electrical stimulation (FES) and the rehabilitative robot aim (RRA), for treatment and rehabilitation of the motor disable people, respectively. During the context of projects, we found that that the motor imagery detection is more important and challenging as the classification was quite well studied in the literature [4].

Despite the importance of the motor imagery detection, only few number of studies were noticed in the literature. The available methods can be separated into two schemes: the open-classification [5] and the Low Frequency-Asynchronous Switch Design (LF-ASD)[2]. The first scheme integrates the motor imagery detection inside the classification by thresholding the classification scores. The LF-ASD scheme detects the motor imagery prior to the classification and this is done by comparing the normalised energy in a specific frequency band. Although, the methods are evaluated in different ways, it seems that the LF-ASD scheme could achieve, in some cases, relatively higher accuracy. One possible reason could be that the former scheme uses CSP feature what is specially designed to discriminate different motor imageries rather than detect the motor imagery from the free thinking (taken as "idle" stage). At the same time, the feature space for motor imagery has not been well studied. In the above mentioned LF-ASD, the method detect high energy in low frequency band, assuming that no any heightened activtity is occured during the "idle" stage. This is questionable due the large variation of EEG signals in this stage. Another problem is that the prior arts in motor imagery detection did not address the frequency selection and verious bands were seen in use [2], and [6].

To address these issues, this paper proposes a novel setection method based on subband entropy analysis in a

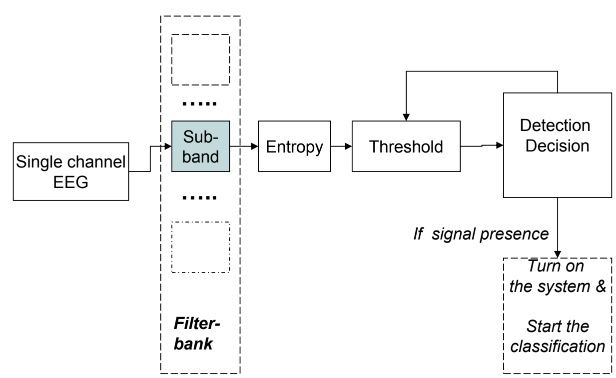

Fig. 1. The selective subband entropy scheme applied for motor imagery detection in asynchronous BCI

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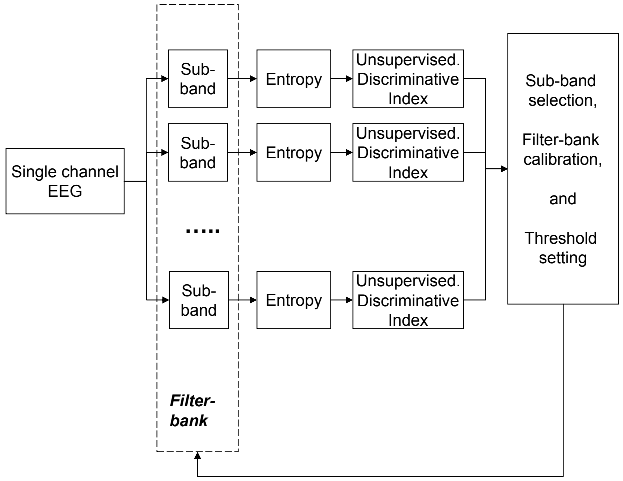

Fig. 2. The processing scheme for system calibration

selective frequency band. The basic principle here is the fact that, in some specific frequency band, the complexity or randomness of the brain signal during stage of concentrating on motor imagery is lower than that of free thinking. Once the optimal frequency band is selected, the subband entropy, -an indicator of complexity and randomness- can be used to differentiate motor imagery againtst the ”idle” stage. Note that the entropy was successfully applied on EEG signal for some apllication such as ischemia detection [7].

The processing scheme of asynchronous BCI with selective subband entropy is illustrated in Fig.1. The dipolar EEG signal is filtered by a selected filter from a filterbank. The subband entropy is continuously monitored and compared to a threshold to make a detection decision. Once the motor imagery is present, the system will automatically turn on and the motor classification will follow. In this work, we focus only in the detection part. The scheme for system calibration including filter number optimization, subband selection and threshold setting is illustrated in Fig.2. This is done by using an empirical measurement called unsupervised dicriminative index (UDI) what indicates the distance between the low set of observed entropy to the medium level. The proposed calibration method is rapid and suitable in the real time processing where calibration needs to be repeated many times. Hereafter, we describe the method in more details.

II. Subband Entropy

We consider the analysing EEG signal as the potential's difference between dipolar electrodes C_3 and C_4. These channels are chosen as they are centre of the motor imagery activity area [3].

$$x(t) = C_3(t) - C_4(t) \tag{1}$$

From the practical point of view, the few-channel approach is more preferable due to the compactness, the mobility and the low cost what would make the BCI reliable in the real life application.

A. Filter-bank

In contrast of conventional methods where a fixed-band filter is used, we adopt a filterbank set, covering all of the possible frequency range. The optimal subband is selected from the calibration. The system of Chebysev bandpass filters with equal frequency band are used. Denoting the system of N filters by their impulse responses

$$\mathbf{h}(t) = \{h_1(t), h_2(t), ..., h_N(t)\}, \tag{2}$$

the filtered signal in each subband is a convolution expressed as follows

$$y_k(t) = x(t) * h_k(t). \tag{3}$$

B. Subband entropy

The key point of this paper is the use of subband entropy, what is continuously estimated in each subband.

$$e_k(t) = entropy[y_k(t)] \tag{4}$$

Here, the differential entropy of a random variable x is defined as

$$H(x) = -\int p(x)\log p(x)dx. \tag{5}$$

There may exist a lot discussions on what is truly represented by entropy but this measurement is well known to be an indicator of the complexity or randomness of an observation. In practice, the entropy (5) is estimated from an observation of random variable $X\{x_1, , x_N\}$. For the entropy estimation, we adopt the method based on sample-spacing, which stems from order statistics [8]. This estimator is adopted because of its consistency, rapid asymptotic convergence, and simplicity. Given an observation of X, first these samples are sorted in increasing order such that $X\{x'_1 \leq, \leq x'_T\}$. The m-spacing entropy estimator is given by:

$$H(x) = \frac{1}{T-s}\sum_{i=1}^{T-s}\log\frac{(N+1)\left(x'_{i+s} - x'_i\right)}{s}. \tag{6}$$

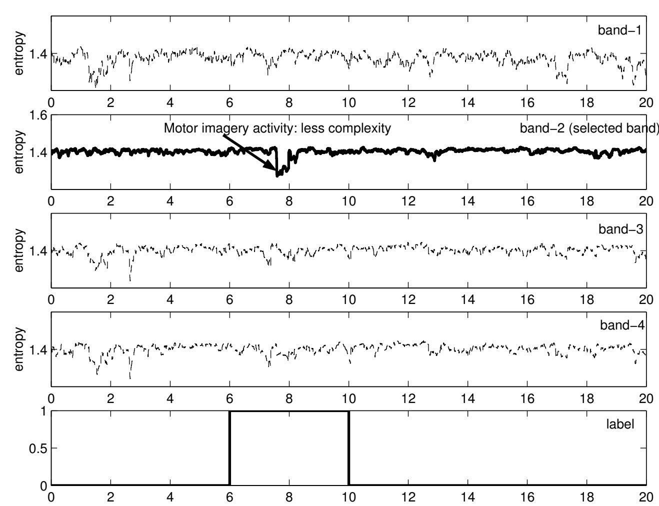

Fig. 3. Sample of subband entropy analysis from a single channel EEG

Typically, $m = \sqrt(T)$. To eliminate the effect of amplifiers, we normalize the entropy to the standard deviation,

$$H_{norm}(x) = H(x) - \log(std_x). \tag{7}$$

To continuously monitor the subband entropy, the estimation (4) is carried out in a segment-by-segment manner. Particularity, 4s-length window and 0.1s-shift were used in our implementation. Fig.3 shows an example of subband entropy analysis of dipolar EEG signal (1) with 4-band filter system, covering the frequency range of 0-50Hz. The estimations of subband entropy in each band are illustrated in upper figures and the label is shown in the lowest one. From the figure it can be seen that the second band is the best one for detecting the motor imagery action but this band (12.5Hz-25Hz) is neither exact alpha nor beta bands. This confirms the consideration of that the optimal frequency band for should not be fixed in advance.

III. System calibration

In this section we discuss the system calibration including the subband selection, the number of filter optimization and the detection threshold setting. We propose an unsupervised method to calibrate the system. The main reason why we did not choose a supervised method is difficulty in providing exact labeling of motor imagery for training. Moreover, in practice, the systems always need to be re-calibrated many times and thefefore the rapidcity is an imporatant issue.

A. Unsupervised Dicriminative Index

To qualify the detection capacity in subbands, we propose an novel empirical measurement called unsupervised discriminative index (UDI) expressed as follows

$$UDI(k) = medium[e_k] - mean[e_k | e_k \leq quantile(e_k, q)], \tag{8}$$

where $0 < q < 1$ is a quantile value, e_k is the estimated entropy in the $k-$subband. The UDI can be understood as the difference between the medium (or median) level of the entropy sequence to its lower set, characterizing the period of motor imagery intention. Therefore, this measurement can be used to predict the detection capacity of the subband. In practise, for the calibration, we can ask the subject to think of motor imagery and then get rest. Since the entropy during the motor imagery is concentrated in the low set, the average level of this set is not sensitive if q is set lower than "true" value. In this work we set $q = 0.1$.

B. System calibration

This paragraph describes how the UDI is used to calibrate the filter system, particularly the subband selection and the number of filter optimization.

1) Subband selection: Given the number of filters, the optimal subband is selected as the best UDI-scored

$$k_{select}(N) = \arg\max_k [UDI_k | N]. \tag{9}$$

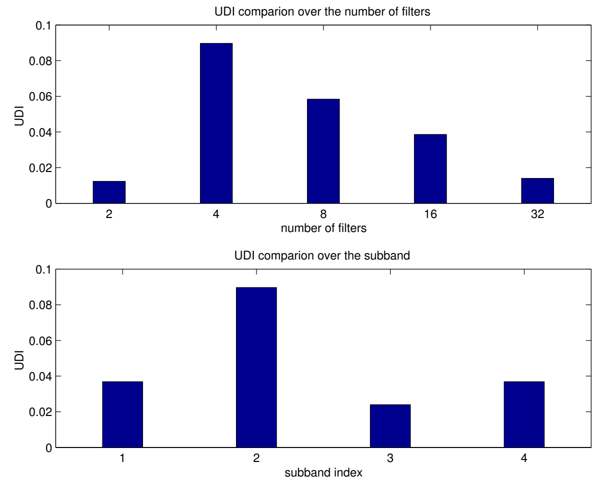

Fig. 4. Example of UDI comparison over several filter-bank configuration

2) Number of filter optimization: In the next step we optimize the number of filter by comparing its best UDI score. Since in our system the bandwidth is equal for all the filters the number of filters will define the filter-bank system configuration. In the processing, we iteratively increase the number of filter until the best UDI score (9) stops increasing. In this work, we start from 2-filter system.

$$N_{select} = \arg\max_N \left\{ \arg\max_k [UDI_k | N] \right\} \tag{10}$$

Once the number of filters is chosen the selective subband is given by (9). Fig.4 illustrates an example of filter calibration based on UDI using the same signal whose entropy is plotted in Fig.3. The upper part plots the maximum UDI over filter-bank systems with different number of filters. In this case, the 4-filter system is supposed to be the best. For this configuration, the distribution of UDI over subband indexes is shown in the lower part. The second band is selected according to its maximum UDI score. This result agrees to the visual observation illusrated in Fig.3.

3) Threshold setting: Another issue of the system calibration is the threshold setting for the final detection decision. The fact that the selective subband entropy during the stage of motor imagery intention is located in the lowest set in the graphic makes the calibration feasible. For this task, we set the threshold as the q-quantile value from the estimated subband entropy in the selected subband.

$$threshold = quantile\left[y_{k_{selected}}(t), q\right] \tag{11}$$

Same as in UDI estimation, we used $q = 0.1$.

IV. Experiment

In this section we report a preliminary experiment on the proposed method. In the data collection, we adopt the simulated asynchronous BCI framework proposed in [5].

A. Data collection

Three subjects were participated in the data collections. The 64-channel Neuroscan EEG system was used and the

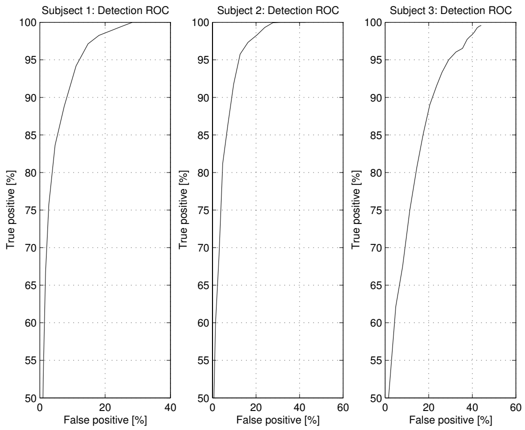

Fig. 5. Detection ROC of proposed method evaluated on 3 subjects

amplified EEG was sampled at 250 Hz. Two channels $C3$ and $C4$ were used for the detection. The data collection is briefly described as follows. A subject seats in a comfortable chair with arms resting on armrests. A 20-round section of cue-task-rest was done for each dataset. 2-second visual cue (arrow sign) indicates the following 3 states that the subject should perform: (L)- left, (R)-right motor imageries, and (B) baseline-relax. Next the subject has to perform the given task for 4 seconds. During the motor imagery, the subject imagines the respective hand movement. A stop signal indicates the end of task. Subject takes relaxes for another 4 seconds before the next arrow. Each session runs of 40 trials each with randomized cues (20 left and 20 right). The label is marked as according to the actions resulting in having cue (C), left (L), right (R) and baseline (B) intervals.

B. Segment-by-segment evaluation

In order to perform the offline evaluation we transform the continuous EEG data into "samples" by a segment-by-segment processing. Each segment is labeled into "event" (i.e. the motor imagery) or "non-event" (i.e. the rest or baseline). Since the aim of this study is to detect the motor imagery rather than classify them, the "event" subset contains both left and right motor imagery. Two avoid the uncertain situation when a segment might contain more than one class we evaluate the segments fully lying on either event (L/R) or nonevent (B) intervals. In this work, the segment length and shift are 4s and 0.1s, respectively.

C. Evaluation results

We first evaluate the Receiver Operating Characteristic (ROC) of the proposed detector. In this evaluation, the automatic threshold setting is ignored. Fig.6 illustrates the ROC curves evaluated from three subjects. We can see that the middle points of ROCs (i.e. where True Positive Rate (TPR)= False Positive Rate (FPR)) is less than 10% for subjects 1-2 and around 17% for subject 3. If set the false positive below 2% the TPRs are 70%, 77%, and 55%, respectively. Next we evaluate the method with the automatic threshold setting. As references, two other methods are also implemented:

TABLE I

DETECTION PEFORMANCE OVER SUBJECTS (TRUE POSITIVE RATE [%] / FALSE POSITIVE RATE [%])

Subjects	Fixed-band Energy (LF-ASD)	Selected-subband Energy	Selected-subband Entropy
Subject 1	69% / 9%	70% / 8%	75% / 3%
Subject 2	68% / 8%	75% / 7%	80% / 5%
Subject 3	55% / 11%	60% / 10%	60% / 3%

1) fixed alpha-band filter ($8-13Hz$) with energy feature (original LF-ASD);
2) selected subband with energy feature (we refer this as Selected-band Energy).

Table 1 summarises the peformances in terms of TPR/FPR over subjects. Although the results are not as good as we expected, the selected subband framework overcome the fixed-band method (LF-ASD) and the entropy feature is shown to be much better than energy, particularly in the reduction of False Positive rates. In present time, the method is under way to test in online experiment and to improve by optimizing the shape of filter-bank system.

V. CONCLUSIONS

We propose a novel motor imagery detection in asynchronous BCI applications based on subband entropy analysis in a selected frequency band. Furthermore, we develop a rapid and robust unsupervised method to calibrate the system without any training. A preliminary experiment on three subjects show a significant improvement on the detection performances compared to the conventional framework based on fixed-band filter and energy feature.

REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, T. M. Vaughan, Braincomputer interfaces for communication and control, *Clinical Neurophysiology* vol. 113, pp. 767-791, 2002.
[2] S. G. Mason and G. E. Birch, A Brain-controlled switch for asynchronous control applications, *IEEE Trans. Biomed. Eng.*, vol. 47, pp. 12971307, 2000.
[3] J. E. Huggins, S. P. Levine, S. L. Bement, R. Kushwaha, L. A. Schuh, E. A. Passaro, M. M. Rohde, D. A. Ross, K. V. Elisevich, and R. J. Smith, Detection of event-related potentials for development of a direct brain interface, *Clinical Neurophysiology*., vol. 16, pp. 448455, 1999.
[4] Dornhege, G., Blankertz, B., Krauledat, M., Losch, F., Curio, G., and Muller, K.-R. Optimizing spatiotemporal filters for improving BCI, *In Advances in Neural Info. Proc. Sys.*, 2006.
[5] G. Townsend, B. Graimann, and G. Pfurtscheller, Continuous eegclassification during motor imagerysimulation of an asynchronous-bci. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 12, no. 2, pp. 258265, 2004
[6] G. Pfurtscheller, G. R. Mller-Putz, J. Pfurtscheller, and R. Rupp, EEG-Based Asynchronous BCI Controls Functional Electrical Stimulation in a Tetraplegic Patient, *EURASIP Journal on Applied Signal Processing*, vol. 2005, no. 19, pp. 3152-3155, 2005.
[7] H. A. Al-Nashash , N. V. Thakor Monitoring of global cerebral ischemia using wavelet entropy rate of change, *IEEE Trans Biomed Eng.*, vol. 52, pp.2119-22, 2005.
[8] E. G. Learned-Miller, J. W. Fisher III, ICA Using Spacings Estimates of Entropy, *J. Machine Learning Research*, vol. 4, pp.1271-1295, 2003.