A Study on Application of Reliability Based Automatic Repeat Request to Brain Computer Interfaces

Hiromu TAKAHASHI, Tomohiro YOSHIKAWA, and Takeshi FURUHASHI

Nagoya University
Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan
takahashi@cmplx.cse.nagoya-u.ac.jp
{yoshikawa,furuhashi}@cse.nagoya-u.ac.jp

Abstract. Recently, a lot of research on a Brain Computer Interface (BCI) which enables patients like those with Amyotrophic Lateral Sclerosis to control some equipment or to communicate with other people has been reported. One of the problems in BCI research is a trade-off between the speed and the accuracy. In the field of data transmission, on the other hand, Reliability-Based Hybrid ARQ (RB-HARQ) has been developed to achieve both of the performances. In this paper, therefore, BCIs are considered as communications between users and computers, and Reliability-Based ARQ, similar to RB-HARQ, is applied to BCIs. Through simulations and experiments, it is shown that the proposed method is superior to other methods.

1 Introduction

Recently, a lot of research on a Brain Computer Interface (BCI) which records brain activities, discriminates the thoughts, and then enables patients like those with Amyotrophic Lateral Sclerosis (ALS) to control some equipment or to communicate with others has been reported. The authors also have been studying on a BCI based on Electroencephalogram (EEG), which is considered as one of the most reasonable measurements since it is non-invasive and costs less [1]. In fact, EEG-based BCIs have been researched well; for example, Thought Translations Device (TTD) [2] by Birbaumer et al.; and Graz-BCI [3] by Pfurtscheller et al. [3], which employs the band power from 8 to 13 Hz (alpha band) as the feature of EEG, and applies Linear Discriminant Analysis (LDA) [4] to it. The accuracy, however, is not high since biological signals such as EEGs contain much noise, partly due to users' physical or mental conditions. On the other hand, it also has been suggested that the longer EEG data is used for one discrimination, the more accuracy could be achieved [3, 5, 6]. It could be possible to say that high accuracy can be gained in exchange for speed in those methods; here seems a trade-off between the accuracy and the speed. The purpose of this study, therefore, is to develop a BCI which accomplishes both the accuracy and the speed simultaneously.

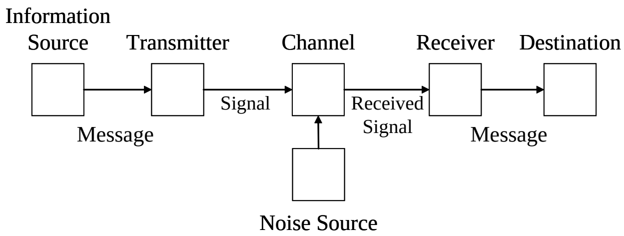


Fig. 1. Shannon's Communication Model

In the field of data transmission, there are some error control methods; for instance, Forward Error Correction (FEC), which allows the receiver to detect and correct errors; Automatic Repeat reQuest (ARQ), which asks the transmitter to repeat code words; and Hybrid ARQ (HARQ), which is a combination of ARQ and FEC. In the past several years, Reliability-Based Hybrid ARQ (RB-HARQ) has been proposed [7]. This method is a variation of HARQ, in which the requests are based on reliability of each bit in code words. It also has been reported that RB-HARQ can provide performance close to the channel capacity. In this paper, BCIs are considered as communications between users and computers or other people, are modeled using Shannon's communication model, and then Reliability-Based ARQ (RB-ARQ) is applied to BCIs. This paper compares the proposed method with other possible methods and it shows that the proposed method is effective for BCIs in terms of both the accuracy and the speed.

2 Proposed Method

2.1 Modeling of BCIs

In EEG-based BCIs, firstly scalp potentials, which reflect the users' will, are recorded. Then the recorded EEG data is classified by statistical classifiers such as LDA, and translated into commands to control some equipment or to communicate with others. In these processes, distractions such as hunger, sleepiness, fatigue, and electric noises would affect the EEG data, which leads misclassifications or mistranslations as a result. Figure 1 shows Shannon's Communication Model. BCIs could be regarded as communications between users as information source and computers as destination when nerves, electrodes, cables, and classifiers are regarded as channels. Note that users also take a role of a transmitter and computers take that of a receiver in Fig. 1.

2.2 Applying RB-ARQ to BCI

Automatic Repeat reQuest (ARQ) is an error control method for data transmission, in which the receiver requests the transmitter to send the data again if errors are detected. In this paper, a method requesting a retransmission based on the reliability is called RB-ARQ, and the RB-ARQ is applied to BCIs. Note that RB-ARQ does not include FEC because the process of FEC would be difficult for users, who take the role of the transmitter.

Suppose users have one thought in their mind out of two (i.e. binary selection), and p-dimensional feature vector is obtained from EEG data. Corresponding to these, let $u_i \in \{0, 1\}$ be the ith information bit and $\boldsymbol{y}_i^t \in \mathbb{R}^p$ be the received analog information at time t. Suppose $f_k(\boldsymbol{y})$ is the class-conditional probability density function of $\boldsymbol{y}$ in $u_i = k$. Then, the log-likelihood ratio can be obtained as follows:

$$\lambda_i^t = \ln \frac{Pr\left(u_i = 0|\boldsymbol{y}_i^1, \ldots, \boldsymbol{y}_i^t\right)}{Pr\left(u_i = 1|\boldsymbol{y}_i^1, \ldots, \boldsymbol{y}_i^t\right)} \tag{1a}$$

$$= \sum_{j=1}^{t} \ln \frac{f_0(\boldsymbol{y}_i^j)}{f_1(\boldsymbol{y}_i^j)}. \tag{1b}$$

$|\lambda_i^t|$ represents the reliability; the larger it is, the higher the probability of correct decoding is. Hence, when a certain λ is given and $|\lambda_i^t| < \lambda$ is true, the receiver requests the same information and decodes it again; otherwise the ith information bit can be estimated as follows:

$$\hat{u}_i = \begin{cases} 0 & \lambda_i^t \geq 0 \\ 1 & otherwise. \end{cases} \tag{2}$$

The proposed method assumes that $f_0(\boldsymbol{y}), f_1(\boldsymbol{y})$ are p-dimensional Gaussian distributions with mean vector: $\boldsymbol{\mu}_0, \boldsymbol{\mu}_1$, covariance matrix: $\Sigma_0 = \Sigma_1 = \Sigma$, because of their simplicity and less computational cost. Especially when $\lambda = 0$, this is identical to LDA. Equation (3) is called discriminability, representing how easily the data can be discriminated [8],

$$d = \frac{|\boldsymbol{\mu}_0^T \boldsymbol{w} - \boldsymbol{\mu}_1^T \boldsymbol{w}|}{\sqrt{\boldsymbol{w}^T \Sigma \boldsymbol{w}}}, \tag{3}$$

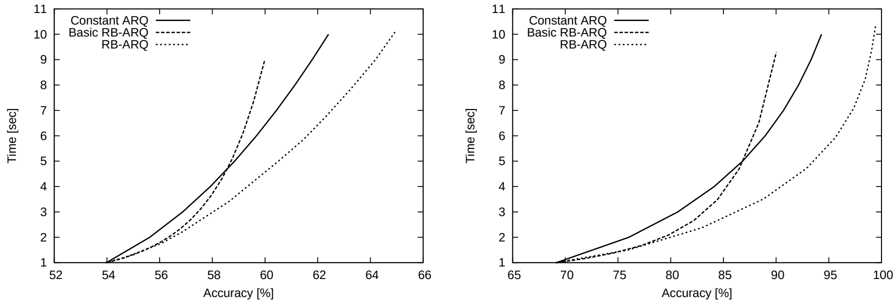
where $\boldsymbol{w} = \Sigma^{-1}(\boldsymbol{\mu}_0 - \boldsymbol{\mu}_1)$.

2.3 Comparison of Methods in Theoretical Value

The proposed method was compared with two possible methods. The first one can be called Constant ARQ requesting n times constantly regardless of the reliability. The second one can be called Basic RB-ARQ taking $\lambda^{(t)}$ obtained from (4).

$$\lambda_i^t = \ln \frac{Pr\left(u_i = 0|\boldsymbol{y}_i^t\right)}{Pr\left(u_i = 1|\boldsymbol{y}_i^t\right)} \tag{4}$$

Suppose both $f_0(\boldsymbol{y})$ and $f_1(\boldsymbol{y})$ obey p-dimensional Gaussian distributions with $\Sigma = \Sigma_0 = \Sigma_1$. Figure 2 describes the relationships between the accuracy and



(a) $d = 0.2$ (b) $d = 1$

Fig. 2. Comparison of Methods (Theoretical Value)

the transmission time (i.e. speed), comparing the proposed method (RB-ARQ) with the two methods mentioned above. The figure shows that the longer the transmission time is, the better the accuracy is. It also clearly shows that RB-ARQ is superior to the others in terms of both performances.

3 Experiments

3.1 Experimental Settings

According to the international 10-20 system [9], electrodes were places on Pz, and A2 as a reference. Then, EEGs were recorded with 1000 Hz sampling rate using Polymate AP216 manufactured by Degitex co, ltd. One trial consisted of 10-second measurement and 10-second break, and one run consisted of 12 trials. Four runs in one session, which were two runs for being relax called thought A and two runs for mental arithmetic called thought B, were performed by each subject. Six subjects in their early 20's participated in two sessions, however one session was excluded out of 12 sessions because of a lack of data. One dataset was 1-second EEG data; therefore 480 datasets were obtained for each session. The Fast Fourier Transform (FFT) was applied to the datasets and they were transformed into the band-power of alpha band (i.e. from 8 to 13 Hz).

3.2 Test of Fitness to Gaussian Distribution

In the proposed method, a band power of EEG is assumed to be normally distributed. In order to verify this assumption, the chi-square goodness of fit test was applied to the band power from 8 to 13 Hz, and the null hypothesis that it was normally distributed was not rejected at statistically significant level of 0.05. Figure 3 shows the histograms of a band power from 8 to 13 Hz when a subject

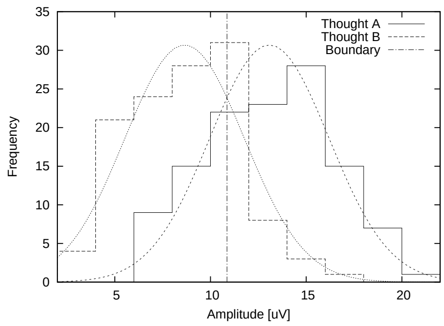


Fig. 3. Histogram of Band Power from 8 to 13 Hz

had thought A and B in his mind, and the Gaussian distributions corresponding to the data, respectively.

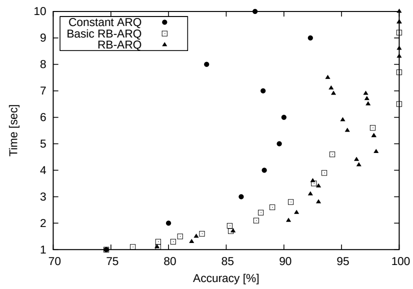
3.3 Application of RB-ARQ

The averages and variances were estimated using the first half 240 datasets (120 datasets from each thought) as training data (note that equal variances were assumed). Then, the rest 240 datasets were applied to the three methods as test data as follows:
Step 1 Set $l = i = t = 1$.
Step 2 Let x_l be the lth dataset and $\boldsymbol{y}_i^t$ be the received analog information of the ith information bit at time t corresponding to x_l
Step 3 Calculate λ_i^t based on (1a)
Step 4 If $|\lambda_i^t| < \lambda$, add 1 to both l and t, and go to step 2; otherwise go to the next step
Step 5 Estimate $\hat{u}_i$, add 1 to both i and l, substitute T_i (the transmission time for ith information bit) for t, t for one, and go to step 2
After these procedures, let N_{V} be the number of information bits, N_{C} be the number of them which fulfill $\hat{u}_i = u_i$. The accuracy and the transmission time are defined as follows:

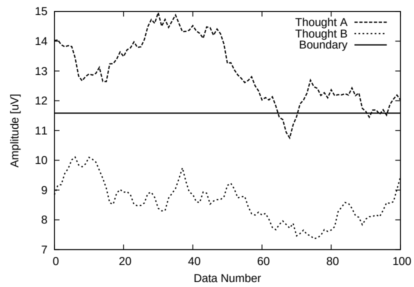
$$Accuracy[\%] = N_{\mathrm{C}}/N_{\mathrm{V}} \times 100, \tag{5}$$

$$Time[sec] = \sum_{i=1}^{N_{\mathrm{V}}} T_i/N_{\mathrm{V}}. \tag{6}$$

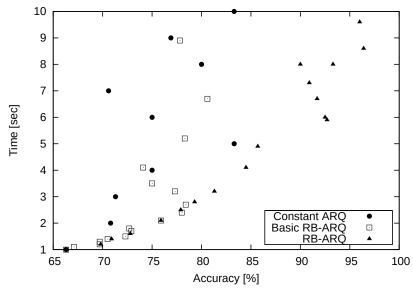
Figure 4 shows the relationships between the accuracies and the transmission times at certain λ (for RB-ARQ and Basic RB-ARQ) or n (for Constant ARQ) along with figures showing the 20 datasets' simple moving averages and the discrimination boundaries (i.e. λ_i^t=0).



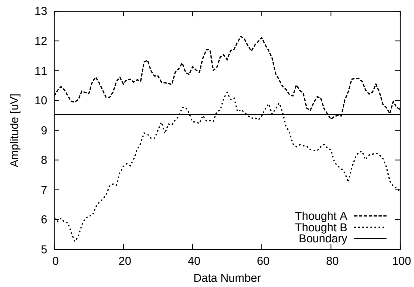
(a) Accuracy and Transmission Time (Subject A)



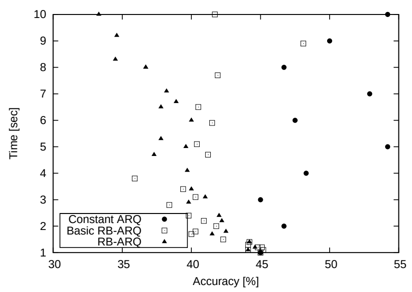
(b) Moving Average and Discriminant Line (Subject A)



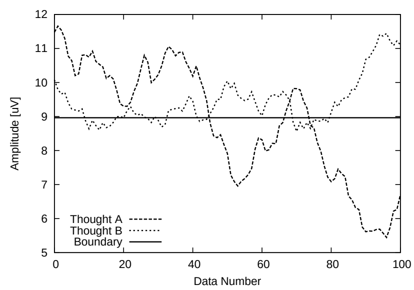
(c) Accuracy and Transmission Time (Subject B)



(d) Moving Average and Discriminant Line (Subject B)



(e) Accuracy and Transmission Time (Subject C)



(f) Moving Average and Discriminant Line (Subject C)

Fig. 4. Comparison of Methods (Experimental Value)

4 Discussions

Firstly, the test of fitness could not reject the null hypothesis that the data used in this experiment did not follow the Gaussian distribution; therefore, it is not unreasonable to employ the Gaussian distribution. However, it does not mean that the data follow it. To make the distribution more closed to the Gaussian, it might be better to use the logarithm of the band power [10].

Figure 4(a) shows a case where the performance of RB-ARQ was roughly equal to that of Basic RB-ARQ and both of them were superior to Constant ARQ. In this case, the assumption about distributions was reasonable because of the result of the fitness test and that the averages and the variance of learning data, $\mu_0 = 3.51, \mu_1 = 3.18, \sigma = 3.35$, were nearly equal to those of test data, $\mu_0 = 3.34, \mu_1 = 2.88, \sigma = 3.35$. RB-ARQ, therefore, should be superior to the other two methods theoretically as shown in Fig. 2.

Figure 4(c) shows another case where RB-ARQ was superior to the rest. According to Fig. 4(d), it can be seen that the moving average of thought B moved dynamically. The datasets from data sequence 0 to 20 could be classified correctly without combining datasets, in other words, requesting next dataset, because distances between the moving average and the boundary was large; requesting a certain number of datasets, Constant ARQ has a disadvantage in terms of transmission time in those datasets. Around data sequence 30 to 60, it was expected to discriminate them correctly by combining datasets because the moving average of thought B was close to the boundary; not combining datasets, Basic RB-ARQ has a disadvantage in terms of accuracy. On the other hand, RB-ARQ has an advantage especially when the moving average moves like this case because it classifies combined datasets based on the reliability, i.e. the distance from the boundary. Some methods which adjust the discrimination models since the optimal model would change as time passes because of the instability of EEGs [11, 12] have been proposed so far. These reports indicate that the proposed method could be improved by adjusting the averages or the variances in response to the changing EEGs.

Figure 4(e) also shows another case where Constant ARQ was superior to the others. Since the magnitude relation between averages of thought A and B in test data was different from that in learning data, accuracies were below 50 %. According to Fig. 4(f), the reverse of the magnitude relation is obvious especially after data sequence 80.

5 Summary

In this paper, BCIs were regarded as communications between users and computers based on Shannon's communication model, and a thought recognition method based on RB-ARQ was proposed in order to improve the speed and the accuracy simultaneously. Some simulations and experiments were performed, which showed that the proposed method was superior to other possible methods. In some of experiments, however, the average of the EEG's band power had changed through the experiment, which lowered the accuracies. A method which is adaptive to the changes, therefore, seems necessary to make the performance better.

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