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Application of Support Vector Machines to Reliability-Based Automatic Repeat Request for Brain-Computer Interfaces

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***Abstract*— A Brain-Computer Interface (BCI) is a system that could enable patients like those with Amyotrophic Lateral Sclerosis to control some equipment and to communicate with other people, and has been anticipated to be achieved. One of the problems in BCI research is a trade-off between speed and accuracy, and it is practically important to adjust those two performance measures effectively. So far the authors have considered BCIs as communications between users and computers, and have proposed an error control method, Reliability-Based Automatic Repeat reQuest (RB-ARQ). It has been shown that, with Linear Discriminant Analysis (LDA) as a classifier, RB-ARQ is more effective than other error control methods. In this paper, Support Vector Machines (SVMs), one of the most popular classifiers, are applied to RB-ARQ. A quantitative comparison showed that there was no significant difference between LDA and SVM. Also, it was demonstrated that RB-ARQ improved the accuracy from the one acquired by the top ranked methods in the BCI competition to 100 percents, with less loss of the speed.**

I. INTRODUCTION

Recently, a lot of researches on Brain-Computer Interfaces (BCIs) that record brain activities, discriminate the thoughts, and then enable patients like those with Amyotrophic Lateral Sclerosis (ALS) to control some equipment and to communicate with others have 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 because of its non-invasiveness and relatively small cost [1]. In fact, EEG-based BCIs have been researched well; for example, Thought Translations Device [2] and Graz-BCI [3]. The accuracy, however, is not always high since biological signals such as EEGs often 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], [4], [5]. It could be possible to say that high accuracy can be obtained in exchange for transmission speed in those methods; here seems to be a trade-off between accuracy and speed. Nonetheless, the importance of each of them would vary from one application to another; for instance, wheel chairs could not afford mis-controls, which might cause serious injuries; game controllers would require faster response times rather than accurate controls. Practically, it is important to adjust those two performance measures effectively. The purpose of this study, therefore, is to develop a BCI which accomplishes better accuracy with smaller time loss.

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In the field of data transmission, there are some error control methods; for instance, Automatic Repeat reQuest (ARQ), which asks the transmitter to repeat code words. In the last several years, Reliability-Based Hybrid ARQ (RB-HARQ) has been proposed [6], whose requests base upon the reliability of each bit in code words. It also has been reported that RB-HARQ can provide performance close to the channel capacity. BCIs, on the other hand, can be considered as communications between users and computers, and can be modeled using Shannon's communication model [7]. The authors have proposed Reliability-Based ARQ (RB-ARQ), customized RB-HARQ to be suitable for BCIs; and have shown that with Linear Discriminant Analysis (LDA) as a classifier, RB-ARQ is more effective than other error control methods [8]: Constant ARQ, combining multiple data to make a single prediction; and Basic RB-ARQ, using reliabilities as request criteria but not combining data. Support Vector Machines (SVMs) are one of the most popular classification methods along with LDA in BCIs [9]. Therefore they could possibly achieve better performance when applied to RB-ARQ. This paper applies one of the SVMs to error control methods, and compares it to LDA with different error control methods quantitatively.

As for the rest of this paper, RB-ARQ is briefly described in Section II; settings of experiments: data description, preprocessing and classification methods are explained in Section III; Section IV shows the experimental results, compares them to theoretical results, and discusses each of the differences among classification methods and error control ones with statistical figures; finally Section V makes conclusions.

II. RELIABILITY-BASED AUTOMATIC REPEAT REQUEST

Let K be a set of thoughts (e.g. motor imagery of left hand), and $\boldsymbol{x} \in \mathbb{R}^p$ be the preprocessed EEG data, belonging to $u \in K$. The likelihood of $\boldsymbol{x}$ being in $k \in K$ or the posterior probability is written as $P(k|\boldsymbol{x})$, and the label of $\boldsymbol{x}$ is predicted as follows:

$$\hat{u} = \arg\max_k P(k|\boldsymbol{x}), \tag{1}$$

where $\hat{u}$ denotes a predicted label. Note that $P(k|\boldsymbol{x})$ can be estimated in the case of SVMs, though primitive SVMs only predict class labels [11]. Let $X_T = \{\boldsymbol{x}_t | t = 1, 2, \ldots, T\}$ be a set of data at time T, $P(k|X_T)$ can be calculated as follows:

$$P(k|X_T) = \frac{\prod_t P(k|\boldsymbol{x}_t)}{\sum_{l \in K} \prod_t P(l|\boldsymbol{x}_t)}. \tag{2}$$

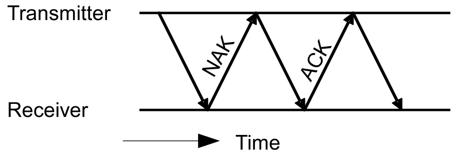

Fig. 1. Stop-and-wait ARQ. The receiver sends back a NAK when it detects an error, otherwise it sends an ACK.

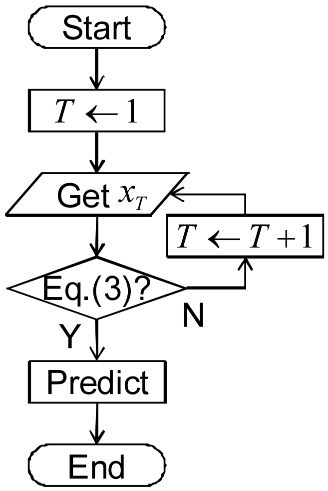

Fig. 2. Flow chart of request procedures: T denotes time. At each T, (3) is checked; if it holds, a prediction/classification is made, otherwise another set of data is requested.

The maximum of the posterior probability is equivalent to the probability of correct classification; thus, it can be seen as the reliability of data.

There exists three types of ARQ; the stop-and-wait ARQ is the simplest one [10], described in Fig. 1. On detecting an error, the receiver sends back a NAK (Not Acknowledge) message so that the transmitter sends the same data; otherwise the receiver sends an ACK (Acknowledge) message so that the transmitter sends the next data. The parity-check is one of the error detecting schemes, but it requires sending extra information to detect errors. RB-ARQ, however, utilizes solely the reliability as a criterion for the requests. In RB-ARQ, a user keeps thinking the same thought unless the following condition is satisfied (Fig. 2):

$$\max_k P(k|X_T) - \tau \geq 0, \tag{3}$$

where τ is a given threshold. On the other hand, Basic RB-ARQ employs the following condition instead of (3):

$$\max_k P(k|\boldsymbol{x}_T) - \tau \geq 0; \tag{4}$$

and the condition is "$T = n$" in the case of Constant ARQ, requesting n times constantly regardless of the reliability.

III. Experiment

A. Data Description

The data used in this experiment was the data set V in BCI Competition III[1] [12]. It contains EEG data recorded from three subjects, when they were doing one of three different mental tasks (i.e. three classes). Each data set of each subject includes four sessions: the first three as training data, and the last as test data. They are provided in two styles: raw EEG signals, and precomputed features; and the latter one was employed in this experiment. Every 62.5 msec (i.e. 16 Hz), the power spectral density (PSD) of the last second was estimated with a resolution of 2 Hz from 8-30 Hz for 8 channels (C3, Cz, C4, CP1, CP2, P3, Pz, and P4 [13]); therefore, the preprocessed data lied on 96 dimensional space. The number of the samples in one session was around 3,500.

B. Preprocessing

Considering a rule in the competition, which required us to make outputs of classifications every 0.5 sec (i.e. 2 Hz), the outputs were made longer than that in this experiment. To make sure this, consecutive 8 samples in the provided data were averaged; thus, the number of the averaged samples per session was around 440. For variable selection, Fisher's ratio was used as a criterion according to a method[2], which employed C-SVM and was ranked 2nd on the data set V; and five-hold cross validation with LDA as a classifier was conducted.

C. Classification

Two methods were examined: LDA and ν-SVM, as the $\nu \in [0, 1]$ parameter in ν-SVM is easier to deal with than the $C \in [0, \infty)$ parameter in C-SVM [14]. As for LDA, the prior probabilities were set as one-third for each class. As for ν-SVM, the ν parameter was determined by five-hold cross validation; the Gaussian radial basis function (5) with the γ estimated by training data [15] was used; and the second approach in [11] was utilized for the post probability estimation.

$$k(x, x') = \exp(-\gamma||x - x'||^2) \tag{5}$$

IV. Results and Discussion

Table I shows the excerpt from the competition results, ranked the 1st to the 3rd out of twenty contributions; and the results, labeled LDA and SVM, obtained from the implementations of the algorithm described above without error controls. Since RB-ARQ is an error control method, it can be combined with any classifier. Now that good classifiers that are well competitive with the top three are available, it can be demonstrated that RB-ARQ further improves accuracy more effectively compared with the conventional methods.

[1]available from `http://ida.first.fhg.de/projects/bci/competition_iii/` (accessed April 20th, 2009)

[2]`http://ida.first.fhg.de/projects/bci/competition_iii/results/martigny/XiangLiao_desc.htm`, (accessed April 20th, 2009)

TABLE I

CLASSIFICATION ACCURACY WITHOUT ERROR CONTROLS [%]

	Sub 1	Sub 2	Sub 3	AVG
1st	79.60	70.31	56.02	68.65
2nd	78.08	71.66	55.73	68.50
3rd	77.85	66.36	53.44	65.90
LDA	77.40	67.74	52.29	65.81
SVM	77.40	67.28	54.59	66.42

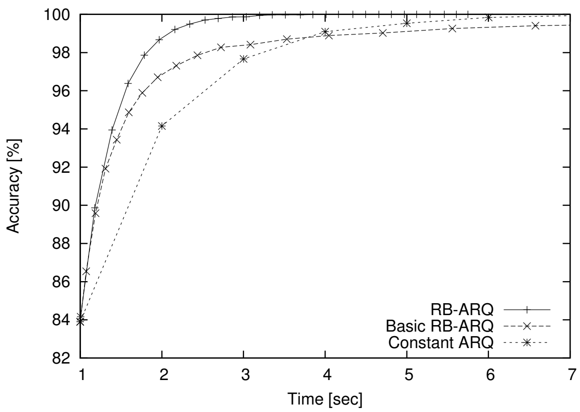

Fig. 3. Theoretical relationships between accuracy and time, obtained from artificially created Gaussian data. A plotted point represents the relationship using a certain τ (RB-ARQ and Basic RB-ARQ) or n (Constant ARQ).

Figure 3 shows the theoretical relationships between the accuracy (6) and the averaged time used for one classification (7) when data are Gaussian and are classified by LDA, comparing the three error control methods [16].

$$\text{Accuracy} = \frac{\text{number of correct classifications}}{\text{number of classifications}} \tag{6}$$

$$\text{Time} = \frac{\text{number of averaged samples}}{\text{number of classifications}} \times 0.5 \tag{7}$$

The more closed to the top-left a plotted point is, the better performance is in terms of accuracy and time; thus, the plotted series rising sharply and remaining at the top is better. Figure 4 shows the experimental relationships of them with SVM as a classifier. Some common features can be seen amongst Fig. 3 and 4; for example, RB-ARQ and Basic RB-ARQ were better than Constant ARQ at high speed (i.e., around 0.5 to 2 seconds), RB-ARQ and Constant ARQ were superior to Basic RB-ARQ at lower speed. It can be said that SVMs applied to error control methods improved accuracy in exchange for speed, and that RB-ARQ performed the best even with SVMs. Moreover, it would be practically necessary to attain 100% of correct classification. According to Fig. 4 (a) and (b), RB-ARQ achieved it at half of the time when Constant ARQ did (Basic RB-ARQ never did within the time-window). This tells that RB-ARQ is greatly useful for such applications that requires much accuracy like wheel chair controls.

In order for the performance to be compared quantitatively, the area under each series ranged from 0.5 to 15 seconds was calculated by the simple trapezoidal rule. Table II and III show the calculated areas, and the three-way analysis of variance (ANOVA) table, respectively. As seen in Table II, RB-ARQ was better than the other methods, meaning that its average performance in the time interval was good. Also, Table III tells that there were statistically significant differences ($\alpha = 0.05$) among both subjects and error control methods, while no difference between LDA and SVM. However, owing to its ease of implementation and less computational cost, LDA is more suitable for error control methods. Additionally, Table IV shows the result of the Tukey's test among error control methods at the significant level $\alpha = 0.05$, telling that unlike the other pairs there was no significant difference in the pair of RB-ARQ and Basic RB-ARQ at $\alpha = 0.05$. The reason for this would be the lack of samples to be statistically significantly different; and moreover, the differences among those pairs partly depend on the time interval for the area calculation, according to Fig. 3.

TABLE II

AREA UNDER THE PLOTTED SERIES [SEC]

	Sub 1		Sub 2		Sub 3	
	LDA	SVM	LDA	SVM	LDA	SVM
RB-ARQ	14.38	14.38	13.95	14.03	12.73	12.91
Basic RB-ARQ	14.12	13.86	12.72	12.75	12.02	12.02
Constant ARQ	13.75	13.79	11.87	12.73	9.74	10.19

TABLE III

THREE-WAY ANALYSIS OF VARIANCE TEST

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Classifiers	1	0.11	0.11	0.34	5.69E-1
Subjects	2	18.07	9.03	29.22	2.44E-5
Error controls	2	8.87	4.44	14.35	6.57E-4
Residuals	12	3.71	0.31		

TABLE IV

TUKEY'S TEST AMONG ERROR CONTROL METHODS

	diff	lwr	upr	P value
Constant ARQ / Basic RB-ARQ	-0.90	-1.76	-0.05	3.83E-2
RB-ARQ / Basic RB-ARQ	0.81	-0.04	1.67	6.29E-2
RB-ARQ / Constant ARQ	1.72	0.86	2.58	4.67E-4

V. CONCLUSIONS

Reliability-Based Automatic Repeat reQuest (RB-ARQ) is an error control method designed for Brain-Computer Interfaces (BCIs) by the authors. In this paper, one of the Support Vector Machines (SVMs) was applied to RB-ARQ and compared to LDA, using one of the datasets from the BCI competition. The experimental results have shown that there was no significant difference between LDA and SVM; however, LDA is more suitable for error control methods due to its advantages such as its ease of implementation and less computational cost. The results have also shown that RB-ARQ improved the accuracy from the one acquired by the top ranked methods in the BCI competition to 100 percents, with less loss of the speed. And RB-ARQ has been quantitatively shown to be more effective than the other error control methods available for BCIs. In future works, C-SVM, another variation of SVMs, will be applied to RB-ARQ; and other kernel functions in SVMs will be investigated.

In addition to improving the algorithm, RB-ARQ will be implemented to actual BCIs in order to evaluate its practical usefulness.

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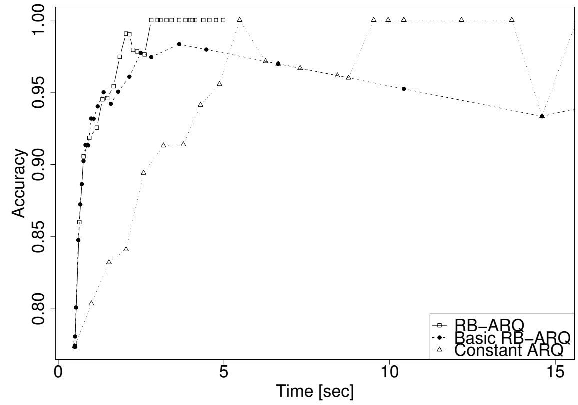
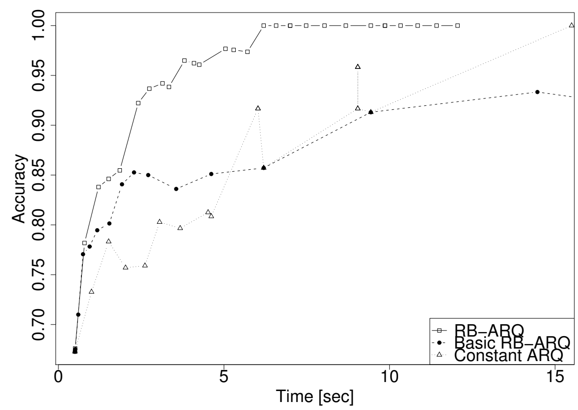


(a) Subject 1



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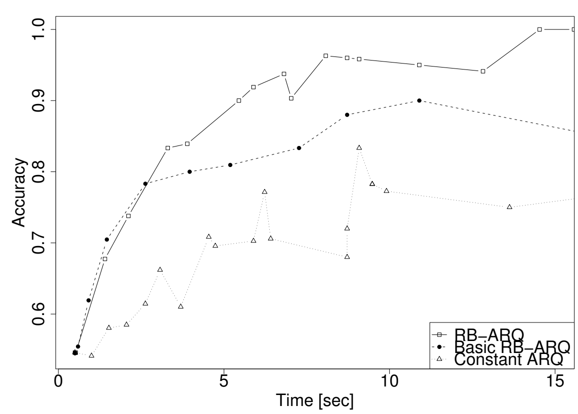

(c) Subject 3

Fig. 4. Comparison of error control methods. A plotted point represents the relationship using a certain τ (RB-ARQ and Basic RB-ARQ) or n (Constant ARQ). Note that, in the cases of Basic RB-ARQ and RB-ARQ, the resolution of plot series depends on the selection of τ and the density of the posterior probability.