PosDI-Boosting: A Boosting Method by Fuzzy Data Interpolation for Brain-Computer Interface

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Abstract. Brain-computer interface (BCI) and brain-machine interface (BMI) technologies have recently entered the research limelight. In many such systems, external computers and machines are controlled by brain activity signals measured using near-infrared spectroscopy (NIRS) or electroencephalograph (EEG) devices. In this paper, we propose a new boosting algorithm for BCI using a possibilistic data interpolation scheme. In our model, interpolated data is generated around classification errors using membership function, and the class attribute is decided by a rule with three kinds of criterions. By using the interpolated data, the discriminated boundary is shown to control the external machine effectively. We verify our boosting method with some numerical examples in which NIRS data is assumed to detect from subjects, and discuss the results.

Keywords: Brain-Computer Interface, Boosting Algorithm, Possibilistic Data Interpolation.

1 Introduction

Recently, many papers on brain-computer interfaces (BCIs) have been published[1]. Brain activity signals are measured using near infra-red spectroscopy (NIRS) [2–4] and electroencephalographic (EEG) devices [5]. The classification model has been proposed to extract the discriminated boundaries in order to control an external machine and computer. However, the outer machine and computer are unable to follow dynamic changes because in particular the identified model is suitable to the brain prior-activity data. On the other hand, ensemble learning models [6–8] are applied to the pattern classification problems. AdaBoost [9, 10] is a remarkable boosting method[11, 12]. AdaBoost consists of multiple weak classifiers which are identified by assigning high weights to the misclassified data. The final output is determined using the result of a majority rule decision between the multiple weak classifiers. We have already proposed a boosting algorithm for brain computer interface as a discriminant model. We call the method pdi-Boosting (Probabilistic Data Interpolation-Boosting)[16–19] because interpolated data generate around misclassified data by a given probability density function.

In this paper, we propose a new boosting algorithm which interpolates data around misclassified data using a given membership function of fuzzy set. We call our method PosDI-Boosting (Possibilistic Data Interpolation-Boosting). Since PosDI-Boosting generates the interpolated data around the misclassified data by fuzzy sets, we can obtain a discriminant boundary with inherent robustness based on human rules. However, the interpolated data around the misclassified data are put as a class same as misclassified data. The class of interpolated data may not be necessarily put as the class same as the misclassified data. Thus, we propose a method to determine classes of interpolated data[20]. Three evaluation criterions, which are the evaluation of misclassified data, the evaluation of classification classes, and the evaluation of neighborhood classes, are defined, and the interpolated data is put as the class using the total evaluation formulated by three criterions. In AdaBoost, the discriminant curve is updated only by chosen individual data because Adaboost only updates the weight for the data. However, a discriminant curve of PosDI-Boosting draws a smoother trace by the whole number of data which generated around the misclassified data. Therefore, the recognition rate of PosDI-Boosting is better than AdaBoost.

First, we formulate the PosDI-Boosting algorithm. Second, we apply our method to an experiment in which brain activity is measured using a NIRS device to demonstrate the effectiveness of PosDI-Boosting. Finally, we propose an enhanced PosDI-Boosting algorithm and show the usefulness of our method by numerical examples which is easy issue to classify to two classes daringly to clarify characteristic difference between Adaboost and PosDI-Boosting.

2 Formulation of PosDI-Boosting

AdaBoost [9, 10] is an outstanding boosting method. In each iteration we select training data (TRD) from the set of misclassified data with high weights of over 50%, and then apply this data to a weak classifier in the consecutive iteration. After identifications are made by the weak classifier, the weights of the data are updated. After iterating the procedure sequentially, the final output is determined by majority rule decision of the multiple weak classifiers $M_1, M_2, \cdots, M_i, \cdots, M_L$, when the checking data (CHD) is given to these models.

A conceptual diagram of PosDI-Boosting is shown in Fig. 1. In the PosDI-Boosting algorithm, new data are interpolated around the misclassified data using a membership function of fuzzy set instead of the updating of the weights as in AdaBoost. Similar to AdaBoost, the final output is determined by a rule of majority decision using the multiple weak classifiers, when the checking data (CHD) is given to these models. However, the difference between AdaBoost and PosDI-Boosting is that the amount of data in PosDI-Boosting increases as compared to AdaBoost as shown in Fig. 2. Therefore, a discriminant curve of

PosDI-Boosting draws a smoother trace by the whole number of data which generated around the misclassified data. The recognition rate of PosDI-Boosting is better than AdaBoost.

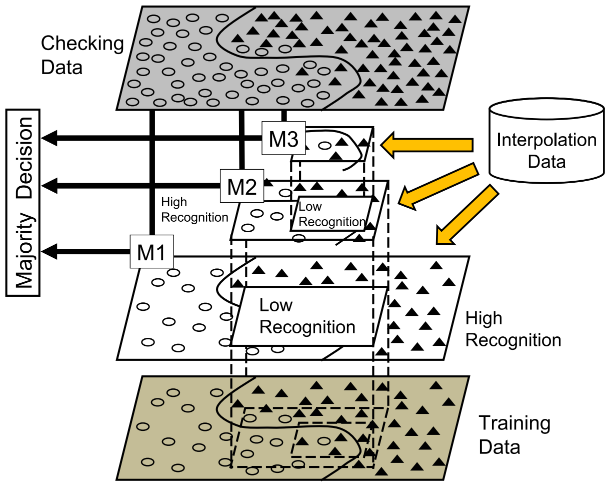

Fig. 1. Conceptual Diagram of PosDI-Boosting

We assume that the misclassified data is given as the d-th datum in TRD, and the j-th attribute of the d-th data is denoted by $x_j^F(d)$. The interpolated datum $x_j^{int}(d)$ is generated by a membership function $\mu_F(x_j)$ of fuzzy set F around the misclassified datum $x_j^F(d)$ when a level h, $0 \leq h \leq 1$ is given randomly.

$$x_j^{int}(d) = \{x_j \mid \mu_F(x_j) = h,\ \mu_F(x_j^F(d)) = 1\} \tag{1}$$

$$h \sim N(1,1), \qquad 0 \leq h \leq 1 \tag{2}$$

, where $x_j^F(d)$ is the center of the fuzzy set F

In general we choose L-function with the width c, and the normal distribution function with the standard deviation σ as a membership function $\mu_F(x_j)$ as follows:

$$\mu_F(x_j) = L(\frac{x_j - x_j^F(d)}{c}), \quad c \leq 0 \tag{3}$$

$$\mu_F(x_j) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{(x_j - x_j^F(d))^2}{2\sigma^2}) \tag{4}$$

As an example of $L(x)$-function, we usually adopt triangle membership function $L(x) = \max(0,\ 1 - |x|)$. We may also adopt a uniform distribution as

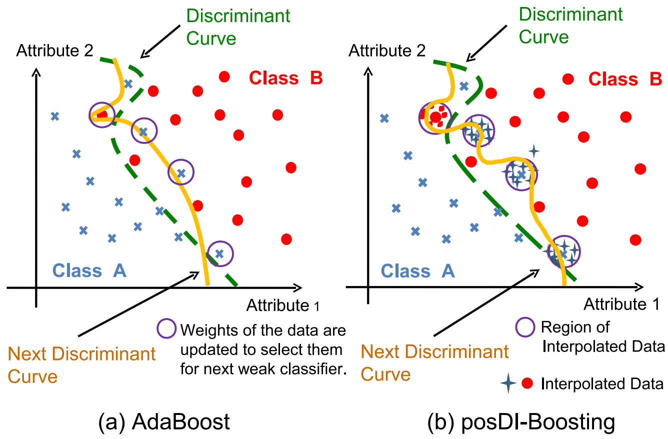

Fig. 2. Conceptual Difference between AdaBoost and PosDI-Boosting

follows:

$$\mu_F(x_j) = \begin{cases} \frac{1}{x_j^{max} - x_j^{min}} & ; \ x_j^{min} \leq x_j \leq x_j^{max} \\ 0 & ; \ x_j < x_j^{min} \ , \ x_j > x_j^{max} \end{cases} \tag{5}$$

where x_j^{max} and x_j^{min} are defined as

$$x_j^{min} = \frac{3x_j^F(d) + x_j(d-1)}{4} \tag{6}$$

$$x_j^{max} = \frac{3x_j^F(d) + x_j(d+1)}{4} \tag{7}$$

and $x_j(d-1)$ and $x_j(d+1)$ denote the $(d-1)$-th and the $(d+1)$-th datum, respectively.

We formulate the algorithm of PosDI-Boosting as follows:

Step 1 The brain activity data D of size W is divided into two data sets: the training data D^{TRD} with the size W^{TRD}, and the checking data D^{CHD} with the size W^{CHD}, where $W = W^{TRD} + W^{CHD}$. In addition, the interpolated data from D is denoted by D^{INT}.

Step 2 The training data D^{TRD} is given as input into the i-th weak classifier M_i. The recognition rate r_i^{TRD} is calculated and the result given as R_i.

Step 3 The d-th misclassified datum is selected from D^{TRD}. With this d-th datum, a new interpolated datum $x_j^{int}(d)$ is generated around $x_j^F(d)$ of the j-th attribute by the membership function $\mu_F(x_j)$ defined in equations (1) and (2), and this new datum $x_j^{int}(d)$ is saved to D^{INT}.

Step 4 Interpolated data are extracted from D^{INT} until the number of misclassified data are the same as the number of correctly classified data, where the number of interpolated data v satisfies

$$v \geq \frac{W}{2} - W^{TRD}(1 - r_i^{TRD}). \tag{8}$$

Step 5 Let θ be the threshold value and K is the number of iterations. The algorithm terminates when either one of the conditions $K = i,\ r_i^{CHD} \geq \theta$ or $i \geq K$ is satisfied.

Step 6 We apply D^{CHD} to $M_1,\ M_2,\ \cdots,\ M_i,\ \cdots,\ M_K$ to obtain the final discriminant result with recognition rate r_i^{CHD}.

Since new data are added around the misclassified data using a membership function, and in each successive iteration the weak classifier fits the misclassified data closer than in the previous iteration, the final result will more closely approximate the given data.

3 NIRS Signal Measurement Experiment of Calculation Task

As an application of PosDI-Boosting to NIRS measurement tasks, we performed the following experiment. We assigned subjects the task of performing a simple arithmetic calculation, and measured brain activity during the task using a NIRS device. We used the 2ch NIRS device (YN-502, Excel of Mechatronics Company, Tokyo, Japan). This device is able to measure the oxyhemoglobin (oxy-Hb) and deoxyhemoglobin (doxy-Hb) at two electrodes with the wavelength $770nm$ and $840nm$ with period $0.098s$. Our brain signal data sets consist of the above four attributes measurable by our NIRS device.

We gave a simple test consisting of arithmetic addition problems to our subjects as the experimental task. The test consisted of a simple addition problem that does not require carrying of decimals, similar to elementary school first grade level problems. We confirmed the ability of three subjects to perform the task, which is the subject's age, sex, dominant arm, health condition, and their ability to perform specific calculations before experiment. The experiment consisted of 5 trials that we called a set, and was 250 seconds in total. A trial is 50 seconds which consists of a 10 second pre-rest, a 10 second interval allotted for our simple arithmetic calculation test and 30 seconds of a post-task resting. We show the experiment protocol of the arithmetic calculation test in Figure 3. To serve as our three subjects, we selected one man and two women, and performed

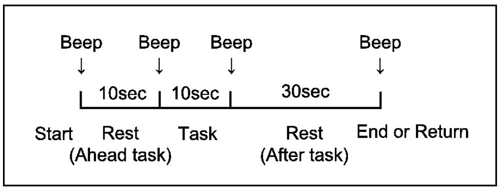

Fig. 3. Timing Protocol of Experiment

12 sets of trials with each subject extended over a period of several days. In the trials, we placed the two electrodes of the NIRS device on prefrontal areas F_{p1} and F_{p2} as described in the ten-twenty electrode system of the American Electroencephalographic Society. The discrete-valued data sets D of brain signals were created from a randomly selected 10 trials by each of the three subjects.

In Figures 4 and 5 we show the change in cerebral blood flow of subject A, which is the brain activity signal measured by NIRS equipment. Figure 4 shows the change in flow of oxy-Hb and doxy-Hb measured at the right side electrode, and Figure 5 shows that of the left side electrode. In Figure 5, we see that when the task is started at $10s$, the flow of oxy-Hb increases, and the flow of doxy-Hb decreases. After the task finishes at $20s$, both cerebral blood flow rates gradually return to the normal steady state.

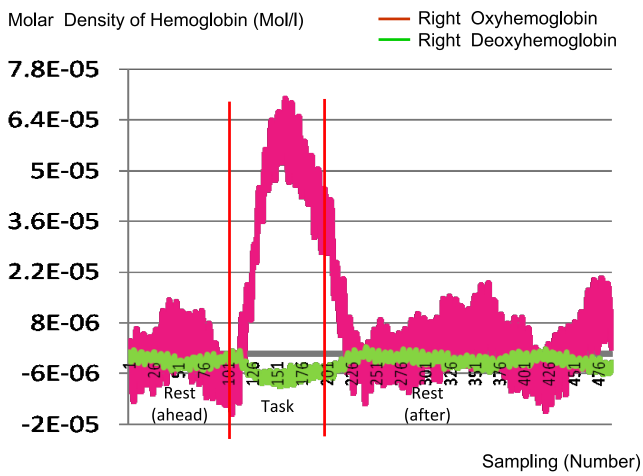

Fig. 4. Cerebral Blood Flow Change of Right Side Electrode

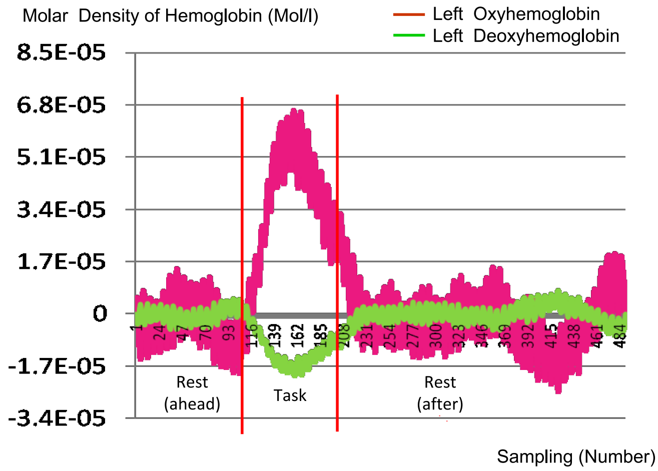

Fig. 5. Cerebral Blood Flow Change of Left Side Electrode

Next, we explain a model for cerebral blood flow changes using the PosDI-Boosting algorithm. We choose the uniform distribution to be the membership function $\mu_F(x_j)$, and we use REPTree as our weak classifier. The termination rule for the algorithm is set to be at iteration number $K = 3$. We set the size of data set D to be $W = 490$. However, we also set $W = W^{TRD} = W^{CHD} = 490$ and $D = D^{TRD} = D^{CHD}$ as we did not have ample data in this experiment.

First, we fed the data set D_1^{TRD} into the first weak classifier M_1 and obtained the recognition rate $r_1^{TRD} = r_1^{CHD} = 91.22\%$ as result R_1. The interpolated datum d_1 is randomly selected from D^{INT} and applied to the next weak classifier, until the number of the interpolated data becomes equal to the number of correctly identified data. The number of data points in D_2^{TRD} is $W_2^{TRD} = 894$ because the number of interpolated data in d_1 is 404.

In the next step, we input D_2^{TRD} into the second weak classifier M_2 and obtain the recognition rate $r_2^{CHD} = 92.24\%$ as result R_2. The recognition rate of M_3 is $r_3^{CHD} = 93.67\%$, and the algorithm stops running finished by the termination rule for $K = 3$.

From the three results R_1, R_2, and R_3 the majority rule yields a final result of 95.31% for the recognition rate. The number of interpolated data points as well as the recognition rates are summarized in Table 1.

Next, we discuss the recognition rates for the three individual subjects. We show that the average recognition rate for each step in Table 2. In the case of subject B, the recognition rate in the three consecutive steps are 93.69%, 93.47%, and 93.33%, respectively. However, the total recognition rate determined by the majority rule is 94.78%, higher by a full 1.0% than the recognition rates in the individual three steps. This phenomena is apparent in case of the other two

Table 1. Recognition Rates and Number of Interpolated Data

Model	Recognition Rate(%)	Interpolated Data (for next step)	TRD	CHD
M_1	91.22	404	490	490
M_2	92.24	414	894	490
M_3	93.67	428	904	490
PosDI-Boosting (TRD)	95.31			

subjects as well. The results are remarkable as the higher recognition rates in the total recognition rate show the effectiveness of PosDI-Boosting.

Table 2. Recognition Rate for Individual Subjects

Subjects	r_1^{CHD}(%)	r_2^{CHD}(%)	r_3^{CHD}(%)	Results(%)
A	90.33	90.29	90.51	91.04
B	93.69	93.47	93.33	94.78
C	92.13	88.37	88.01	94.16
Average	92.13	91.62	92.06	93.10

Finally, we compare PosDI-Boosting with REPTree and other conventional Boosting algorithms. The comparison results are summarized in Table 3. The comparison of PosDI-Boosting and REPTree, shows that the recognition rate of PosDI-Boosting is only 0.97% higher than that of REPTree on average for all three subjects. In addition, the recognition rate of PosDI-Boosting shows a significant difference ($p = 0.01616$) as compared with REPTree by the t-test with significance level 0.05%.

On the other hand, comparing PosDI-Boosting with the other boosting methods, AdaBoost and MultiBoost, the recognition rate of PosDI-Boosting is only 0.3% higher than that of AdaBoost, and 1.7% higher than that of MultiBoost in subject A. In subject A, the recognition rate of PosDI-Boosting is only 1.2% higher than MultiBoost, but the recognition rate became lower by a small 0.33% than for AdaBoost. Unfortunately, the recognition rate of PosDI-Boosting couldn't show a significant difference as compared with other boosting methods by the multiple comparison of Tukey method. However, the recognition rate of PosDI-Boosting shows a significant difference ($p = 0.0006860$) compared with MultiBoost by the t-test with significance level 0.05%. The recognition rate of PosDI-Boosting is only 0.56% higher than AdaBoost, but we could not show a significant difference ($p = 0.1578$) as compared to AdaBoost by the t-test with significance level 0.05%.

Table 3. Comparison of the Proposed and Existing Models

Subjects	PosDI-Boosting (%)	AdaBoost (%)	MultiBoost (%)	REPTree (%)
A	91.04	90.33	90.38	90.33
B	94.78	94.24	93.57	93.69
C	94.16	94.39	92.96	92.92
Average	93.10	92.54	92.14	92.13

As a result, we may conclude that recognition rates using PosDI-Boosting are higher than those of other Boosting methods. Therefore, the use of the proposed PosDI-Boosting algorithm is advantageous in practical BCI applications.

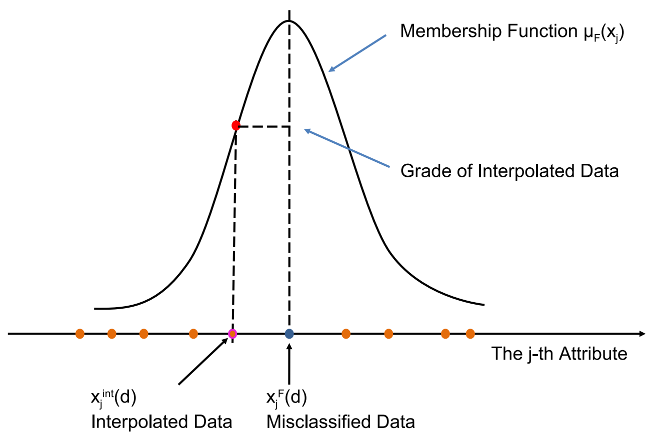

Fig. 6. Evaluation E_1

4 Enhanced PosDI-Boosting

The interpolated data around the misclassified data were put as a class same as misclassified data. However, the class of interpolated data may not be necessarily put as the class same as the misclassified data. Therefore we propose a new class decision method to decide the class of interpolated data. Assume that the interpolated datum $x_j^{int}(d)$ is generated from the misclassified datum $x_j^F(d)$. Three evaluation criterions, which are the evaluation of misclassified data E_1, the evaluation of classification classes E_2, and the evaluation of neighborhood classes E_3, is defined, and the interpolated data $x_j^{int}(d)$ is put as a class k^*.

(1) Evaluation of Misclassified Data

Evaluation E_{j1} is defined by the membership function $\mu_{E_1}(x_j^{int}(d))$, and that represents the dependence of the interpolated data to the misclassified data (See in Fig. 6). Evaluation E_{j1} shows that the dependence of the interpolated data to the misclassified data is high when E_{j1} of the interpolated data is large.

$$E_{j1}^k = \begin{cases} 1 - \mu_{E_1}(x_j^{int}(d)), & for \;\; k \in \{x_j^F(d)\} \\ \mu_{E_1}(x_j^{int}(d)), & for \;\; k \notin \{x_j^F(d)\} \end{cases} \tag{9}$$

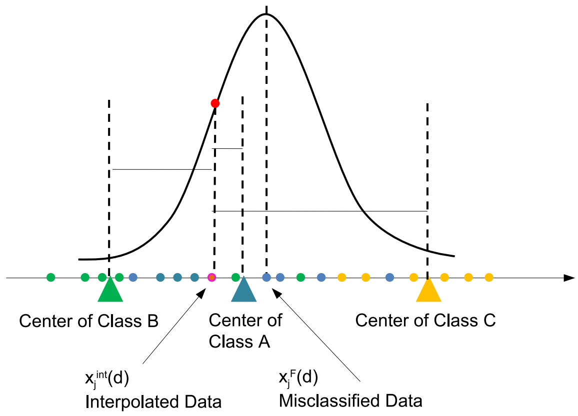

Fig. 7. Evaluation E_2

(2) Evaluation of Classification Classes

Evaluation E_{j2} is defined by distance between the interpolated data and the center of each classification class (See in Fig. 7). Evaluation E_{j2} shows that the dependence of the interpolated data to the classification class is high when E_{j2} of the interpolated data is small.

$$E_{j2}^k = \frac{|x_j^{int}(d) - x_c^k| - min_i|x_i^k - x_c^k|}{max_i|x_i^k - x_c^k| - min_i|x_i^k - x_c^k|}, \;\; for \;\; \forall i$$

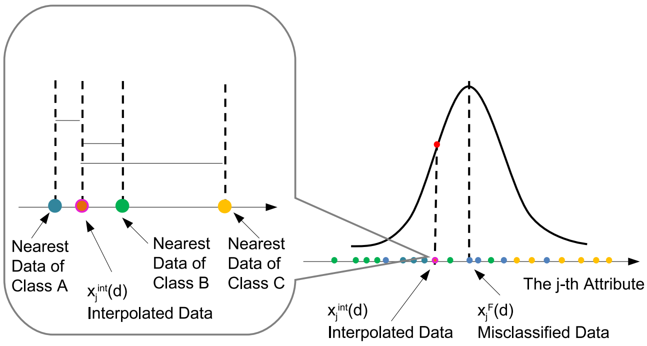

Fig. 8. Evaluation E_3

where, x_c^k is the center of the classification class k.

(3) Evaluation of Neighborhood Classes

Evaluation E_{j3} is defined by distance to data x_j^N which is the nearest to the interpolated datum in each classification class (See in Fig. 8). Evaluation E_{j3} shows that the dependence of the interpolated data to the neighborhood class is high when E_{j3} of the interpolated data is small.

$$E_{j3}^k = \frac{|x_j^N - x_j^{int}(d)| - min_i|x_i^k - x_j^{int}(d)|}{max_i|x_i^k - x_j^{int}(d)| - min_i|x_i^k - x_j^{int}(d)|}$$

$$for \ \ \forall i$$

The evaluation E_1 is large when interpolated datum is generated around the misclassified datum, and the evaluation E_2 is large when interpolated datum is generated around the center of the identification class. On the other hand, the evaluation of the class distribution around interpolated datum is calculated in evaluation E_3.

Evaluation E_j^k is calculated by the weighted summation of these three evaluation in each j attribute. The class of interpolated data $x_j^{int}(d)$ is defined as k^* where the total evaluation E^k of n attributes is minimized.

$$k^* = \{k| \min_k E^k = \min_k \sum_{j=1}^{n} E_j^k\} \quad (10)$$

$$E_j^k = w_1 E_{j1}^k + w_2 E_{j2}^k + w_3 E_{j3}^k \quad (11)$$

where, w_1, w_2, w_3 is weight at each evaluation, respectively.

We formulate the algorithm of enhanced PosDI-Boosting as follows:

Step 1 The brain activity data D of size W is divided into two data sets: the training data D^{TRD} with the size W^{TRD}, and the checking data D^{CHD} with the size W^{CHD}, where $W = W^{TRD} + W^{CHD}$. In addition, the interpolated data from D is denoted by D^{INT}.

Step 2 The training data D^{TRD} is given as input into the i-th weak classifier M_i. The recognition rate r_i^{TRD} is calculated and the result given as R_i.

Step 3 The d-th misclassified datum is selected from D^{TRD}. With this d-th datum, a new interpolated datum $x_j^{int}(d)$ is generated around $x_j^F(d)$ of the j-th attribute by the membership function $\mu_F(x_j)$ defined in equations (1) and (2).

Step 4 The class k^* of the interpolated datum $x_j^{int}(d)$ is distinguished by equations (10) and (11). This new datum $x_j^{int}(d)$ is saved to D^{INT}.

Step 5 Interpolated data are extracted from D^{INT} until the number of misclassified data are the same as the number of correctly classified data, where the number of interpolated data v satisfies.

Step 6 Let θ be the threshold value and K is the number of iterations. The algorithm terminates when either one of the conditions $K = i$, $r_i^{CHD} \geq \theta$ or $i \geq K$ is satisfied.

Step 7 We apply D^{CHD} to $M_1, M_2, \cdots, M_i, \cdots, M_K$ to obtain the final discriminant result with recognition rate r_i^{CHD}.

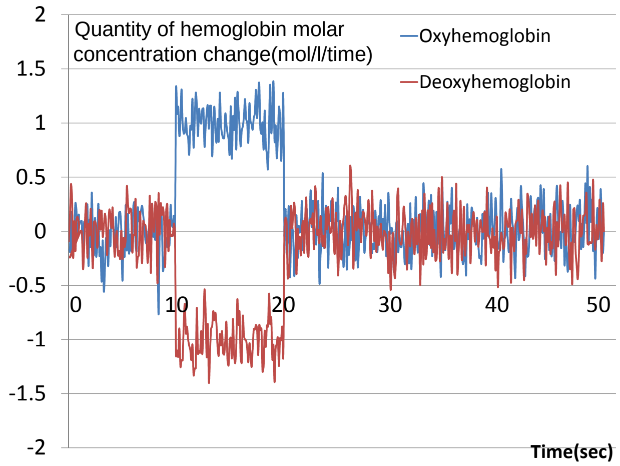

Fig. 9. Data of s=0.2

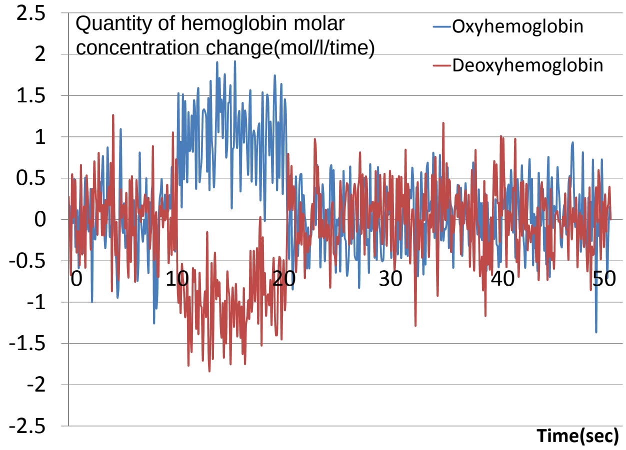

Fig. 10. Data of s=0.4

5 Evaluation of Enhanced PosDI-Boosting

We simulate examples of signals as two-cluster problem using numerical data to discuss the evaluation on enhanced PosDI-Boosting. We assume that brain activity signals of 490 are normalized to lie in the range $[0, 1]$ and $[-1, 0]$, and the value of the data corresponding to the steady state to be 0, and that to the activation state to be 1 or -1. We add four types of noise to the signals consisting of normally distributed random numbers with standard deviation s. We choose the normal distribution function to be the membership function $\mu_F(x_j)$, and we adopted REPTree as the weak classifier, which is a type of decision tree method. The termination rule for the algorithm is set to be at iteration number $K = 3$.

The four patterns are given in Fig. 9 to 12, respectively.

Weights: $w_1 = w_2 = w_3 = 1/3$
Standard deviation $\sigma = 0.0001$
Standard deviation $s = 0.2, 0.4, 0.6, 0.8$

We compare enhanced PosDI-Boosting with normal PosDI-Boosting, REPTree and other conventional Boosting algorithms, and we discuss the recognition rates at the different standard deviation. The comparison results are summarized in Table 4. We show that the average recognition rate is 10 times that of the disturbance data. In Table 4, the recognition rate of enhanced PosDI-Boosting is shown to be slightly higher than that of other methods with standard deviation s ranging from 0.2 to 0.8. The comparison of enhanced PosDI-Boosting and normal PosDI-Boosting, shows that the recognition rate of enhanced PosDI-Boosting is only 1.28% higher than that of normal PosDI-Boosting on average for all

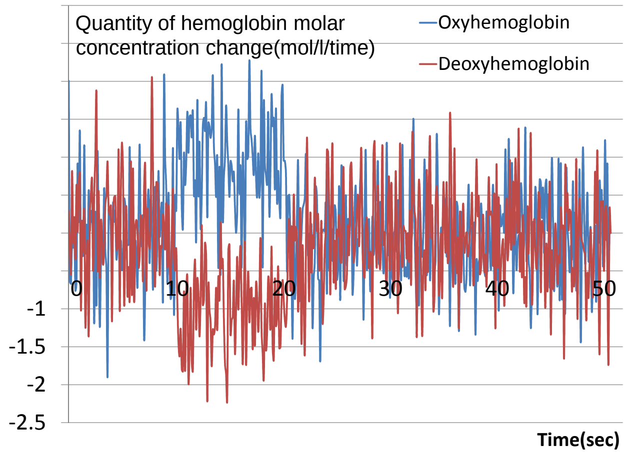

Fig. 11. Data of s=0.6

four patterns. In addition, comparing enhanced PosDI-Boosting with the other methods, AdaBoost, MultiBoost and REPTree, the recognition rate of enhanced PosDI-Boosting is only 0.58% higher than that of AdaBoost, 1.05% higher than that of MultiBoost and 2.53% higher than that of REPTree on average for all four patterns. Unfortunately, the recognition rate of enhanced PosDI-Boosting couldn't show a significant difference as compared with other boosting methods by the multiple comparison of Tukey method. However, the recognition rate of enhanced PosDI-Boosting shows a significant difference ($p = 0.000037$) as compared with normal PosDI-Boosting by the t-test with significance level 0.01%. Looking at these results, enhanced PosDI-Boosting is more accurate than other boosting methods even though the significance of enhanced PosDI-Boosting is not clear by a test.

At the stage $K = 1$ of the standard deviation $s = 0.8$, the number of all data became 866. Since the number of original data is 490, 376 as difference data are the interpolated data. The interpolated data which changed the class by new evaluation algorithm set off 67.0% of the total data. In those data, the interpolation data which were changed from the steady state "zero" to the activation state "one" were 73, and the interpolated data changed the steady state from the activation state were 181. We should notice that the recognition rate of PosDI-Boosting is having improved by the change of these classes more. Therefore, we conclude that the use of the proposed PosDI-Boosting algorithm is advantageous in practical BCI applications.

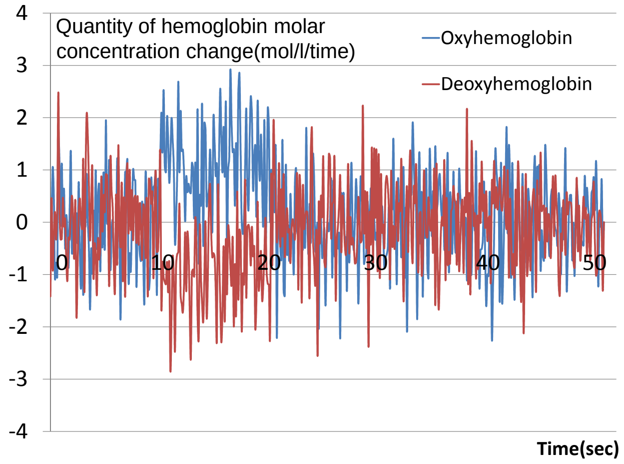

Fig. 12. Data of s=0.8

Table 4. Comparison of Enhanced pdi-Boosting with Other Methods

SD	Enhanced PosDI-Boosting (%)	PosDI-Boosting (Uniform) (%)	Ada Boost (%)	Multi Boost (%)	REP Tree (%)
0.2	99.81	99.63	99.80	99.76	99.37
0.4	97.32	96.18	96.57	94.84	97.14
0.6	92.65	90.05	91.22	91.22	92.41
0.8	88.78	87.69	88.63	88.55	88.33
Average	94.64	93.38	94.06	93.59	92.11

6 Conclusion

In this paper, we formulated a classification method based on a boosting algorithm using a possibilistic data interpolation scheme. We propose a new class decision method to decide the class of interpolated data. In addition, we showed our method in an experiment in which brain activity is measured using a NIRS device, and discussed the effectiveness of our new approach with numerical examples by comparing its performance to that of conventional boosting algorithms. In future work, we plan to discuss how to optimize the membership functions, and how to apply this method to a range of practical BCI problems.

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