RHC method for application to BMI based systems

Abstract

Purpose - To present research in the area of control method for the man-machine systems with BMI (Brain machine interface). Concrete target system is, for instance, a car cruising system and so on.

Design/methodology/approach - The improved RHC (receding horizon control) method for the sampled-data systems and the adaptive DA converter which has the way to switch the sampling functions according to the system status are used. The feature selection method based on the k-SVM (kernel support vector machines) with the backward stepwise selection for the BMI signals are also used.

Findings - This paper proposes the new improved RHC method with the adaptive DA converter for the application of the BMI-based systems. The proposed method is illustlated as useful and efective method for the systems to which switch of control laws is indispensable by the simulations.

Research limitations/implications - Although the proposed method is effective for the BMI based-systems with switching of control laws, the more fast algorithm for RHC will be need to apply to the man-machine systems with the BMI in practical use.

Practical implications - The basic concept or framework of the proposed method can be used for the real man-machine systems with the BMI, for examples, car crusing systems, wheel-chaired systems and so on.

Originality/value - The paper contributes to the development of the new effective control method for the BMI-based man-machine systems.

Key-words Man-machine systems, BMI(Brain machine interface) Receding horizon control, Adaptive DA converter

Paper type Research paper

1. Introduction

In last few decades, RHC (Receding Horizon Control) has been widely accepted in the industries. The recent dramatic implovement of computer performance has made it possible to control the continuous-time objects by a discrete-time controller. Hence, the digital RHC method has been effective for various kinds of continuous-time objects. Such systems are so-called the sampled-data systems, and they are a kind of

haybrid sytems. In the standard RHC formulation, the current control action is obtained by solving a finite or infinite horizon quadratic cost problem at every sample time using the current state of the plant as the initial state (Garcia et al. (1989)). The RHC has some significant merits for applying to real systems. For examples, it's easy handling of constraints during the design and implementation of the controller (Bemporad and Morari (1999); Mayne et al. (2000)). Besides, it's flexibly correspond to the change of the situation of systems. Hence, it can be said that the RHC is the most suitable control method for man-machine systems with BMI (Brain Machine Interface).

On the other hand, recently, the various researches on man-machine systems are actively done. In the man-machine systems, an important point is to unite man's judgment, recognition, and the automatic control of the machine well. In this point, one of the key method is BMI. Although the BMI has been used to support to communicate for physically handicapped patients, for example, ALS (Amyotrophic Lateral Sclerosis) or spinal cord injury, and so on (Okuma (1999)), BMIs based on the EEG (Electroencephalogram) are now in the process of reaching practical use for man-machine systems owing to the recent developments in physiological knowledge and computer science technologies (Wolpaw (2002); Serruya et al. (2002)).

In this research, therefore, the EEG signals of brain waves are considered to use as the urgent evasion signals for man-machine systems. Generally, the EEG signals include redundant information that is unnecessary for decoding the commands and may also weaken the generalization performance of the classifier. To cope with this issue, Lal et al. (2004) proposed a search method of better combinations of EEG channels by using a feature selection technique called RFE (Recursive Feature Elimination). Millan et al. (2002) applied feature selection using decision trees to EEG data. We have also developed the feature selection method based on the k-SVM(kernel Support Vector Machines) (Vapnik (1998)) with the backward stepwise selection (Tanaka et al. (2006)) for the BMI. This method can remove unnecessary or redundant features of EEG signals and keep only effective features for the classification task as a way of improving accuracy and quickness.

The following assumptions are put on the man-machine systems targeted in this paper. In norml circumstances, the system is controlled automatically by using RHC method and the BMI is not worked. The BMI signals are used for the emergency situation. It works as a trigger for switching of control laws. The man-machine systems are usually modeled as the sampled-data control systems, since the systems are consisted of the discrete-time controller, namely computer, and continuous-time objects, like the car cruising system. In such systems, analog-to-digital(AD) and digital-to-analog (DA) conversion of signals are indispensable. In the DA conversion, the information about future sampling points is need. But, it's impossible to obtain them strictly. Then,

the zero-order hold has been used for the DA conversion on the assumption that the analog signals in each sampling interval are considered as constant values (Ackerman (1985)). But, to improve the performance of sampled-data control systems, it's very important to take account of the behavior of systems in the sampling intervals. This point is especially important for the system where the switch of the control laws is caused. On this issue, some notable methods to design the discrete-time controller for continuous-time objects with AD/DA conversion have been proposed by Ackerman (1985) and Yamamoto (1994). But, these methods are little complex and the aspect of improving the performance by adjusting the DA conversion is lacked. In this research, therefore, the method of the RHC with the adaptive DA converter which switches the sampling functions according to the system status is proposed. By using this method, we don't need to be forced to tolerate the long time-delay during the DA conversion to wait for getting the needable information. Therefore, the method is considered as suitable for man-machine systems to which switch of control laws is indispensable.

2. Problem Formulation

The target system is constructed with the RHC, the adaptive DA converter and the BMI as shown in fig. 1.

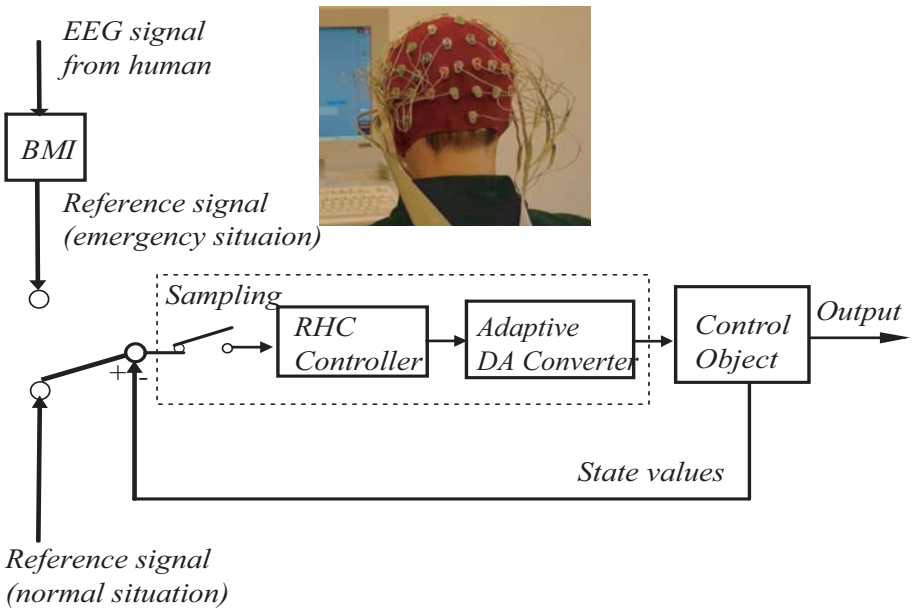

Figure 1. The construction of target system

The realization problem of this system is composed of two parts roughly separately. First one is how to construct the high perfomance controlled system in the presence of switching control laws between normal situation and the emergent situation. The

proposed method of the RHC controller with the adaptive DA converter for this issue will be presented in Chapter 3.

The other one is how to generate the reference signal with the high accuracy in the emergency situation by the EEG based BMI. Solution of this question will taken up concisely in Chapter 4.

3. RHC with adaptive DA converter

3.1 RHC

RHC is an online powerful control method which solves a finite horizon open-loop optimal problem with respect to each sampling frequency (Mayne et al. (2000)). Although RHC has been used in systems with relatively slow-moving dynamics such as petrochemical plants due to its big calculation amount, the recent advance of computer performance has made it possible to apply for the systems with relatively fast-moving dynamics.

Let's consider the finite-time constrained optimal control problem with the state space model as follows. The objective man-machine system can be moddeled as a discrete-time linear time-invariant model as:

$$x(k+1) = Ax(k) + Bu(k) \tag{3.1}$$

$$y(k) = Cx(k) \tag{3.2}$$

where $u(k) \in \boldsymbol{R}^1$, $x(k) \in \boldsymbol{R}^n$ and $y(k) \in \boldsymbol{R}^1$ mean control input, state values and observed output at step k respectively, and $A \in \boldsymbol{R}^{n\times n}$, $B \in \boldsymbol{R}^{n\times 1}$ and $C \in \boldsymbol{R}^{1\times n}$ are coefficient matrices.

Then the design problem is formulated as

$$\min_{\{u(k|k),\cdots,u(k+N-1|k)\}} J(k) = ||x(k+N|k)||_P^2 + \sum_{i=0}^{N-1} \left\{ ||x(k+i|k)||_Q^2 + ||u(k+i|k)||_R^2 \right\}$$

$$\text{subject to:} \quad u(k) \in \boldsymbol{U}, \quad x(k) \in \boldsymbol{X} \tag{3.3}$$

where P, Q and R are positive definite matrices, and N is the length of prediction horizon. $\boldsymbol{U}$ and $\boldsymbol{X}$ are constraints sets for inputs and states. Eq.(3.3) means constraint conditions for the control input and the state values. In practice, since this problem is equivalent to the quadratic programming problem, the optimal solution $\{\hat{u}(k|k), \cdots, \hat{u}(k+N-1|k)\}$ is easily solved. Then, only the first solution $\hat{u}(k|k)$ is used as a control input for control object at step k, and then, the current step goes on to next step. Several kinds of RHC method have been also proposed until now (Bemporad et al. (2002); Ohtsuka (2004); Kawabe and Hirata (2003)).

3.2 Interpolation using predictive control inputs

In RHC, the optimal control inputs $\{\hat{u}(k|k), \hat{u}(k+1|k), \cdots, \hat{u}(k+N-1|k)\}$ are calculated in each step, and only the first control input $\hat{u}(k|k)$ is used as a real control input. Therefore, we consider to use the other optimal control inputs $\{\hat{u}(k+1|k), \hat{u}(k+2|k), \cdots\}$ as virtual future sampling points. Actually, it is only necessary to use the optimal control inputs which are needed for interpolation according to the sampling function. Fig.2 shows this way using the 2nd order spline function for interpolations. Only $\hat{u}(k+1|k)$ is used as a virtual future sampling point in this case. By using the predictive control inputs for interpolation, it becomes possible to reduce the time-delay in the DA conversion, and the total time-delay to be needed is just only computation time of optimization in current step.

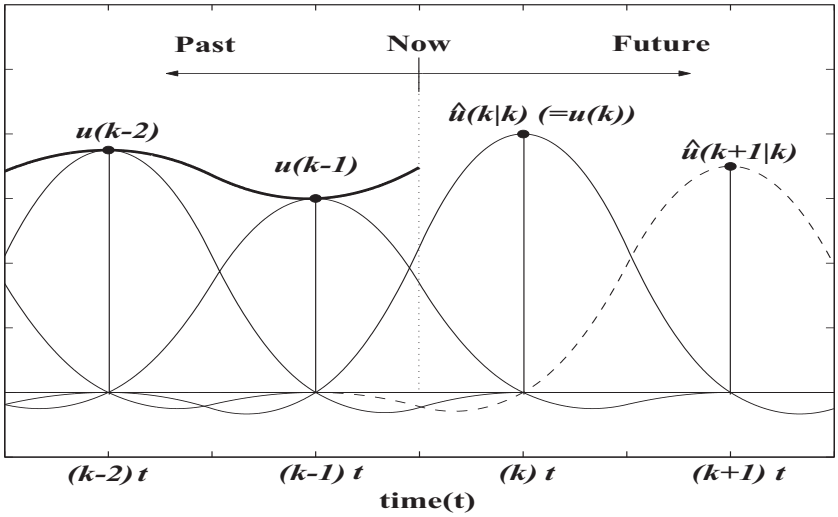

Figure 2. Interpolation based on 2nd order spline function using predictive future control inputs.

Of course, it needs to take account that there is a difference between virtual future sampling points and real sampling points like $\hat{u}(k+1|k) \neq u(k+1)$ in future step. However, we consider that this point is not a critical problem because the influence on interpolated waveform due to prediction error is not so big compared to the scale of prediction error. Although the differentiability of each sampling function is lost at sampling points, this also does not become a critical problem compared to the zero-order hold, and it is possible to keep a certain level of smoothness.

3.3 Adaptive DA converter

The spline functions provide various sampling functions with all kinfs of orders. Therefore, we consider switching the spline functions optimally according to the system status in the adaptive DA converter. In this paper, we use the spline functions with the order $m = 0, 1, 2$ as sampling functions. Namely, in the case of $m = 0$, the sampling function is equivalent to the staircase function. In the case of $m = 1$, it's the 1st order piecewise polynomial function, and in $m = 2$, 2nd order one as shown in fig. 3.

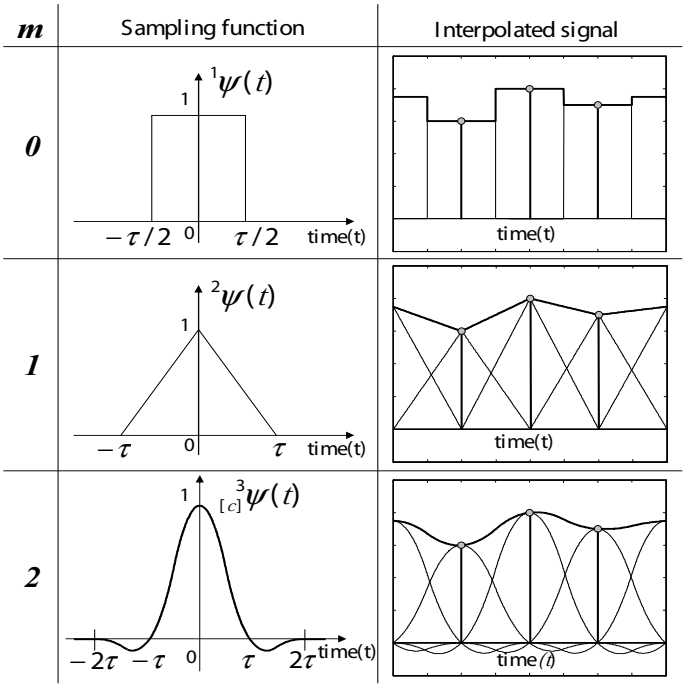

Figure 3. Sampling functions and their interpolations with $m = 1, 2, 3$ (τ is sampling interval).

Appropiate selecting the values of m according to the object, enables to deal with DA conversion flexibly and precisely in the interpolation operation. Although the interpolation is more precisely in the case of using the spline function with $m = 3$ or more, it's difficult to apply to fast-moving dynamic systems due to the bigger amount of calculation. Therefore we use only the spline functions with the order $m = 0, 1, 2$.

The interpolated signals in the closed-open interval $[k\tau, (k+1)\tau)$ using these sampling functions are obtained as follows,

$$u(t) = \sum_{l=k}^{k+1} \left\{ u(l) \cdot {}^{1,2}\psi(t - l\tau) \right\}, \quad (m = 0, 1)$$

$$u(t) = \sum_{l=k-1}^{k+2} \left\{ u(l) \cdot {}^{3}_{[c]}\psi(t - l\tau) \right\}, \quad (m = 2)$$

where $u(t)$ and $u(l)$ are analog signal and digital signal respectively, and τ is sampling interval.

The interval to be interpolated is also divided to d sections, and the dividing points $u_m(j;k), (j = 1, 2, \cdots, d-1)$ on interpolated waveforms are used for the selection of parameter m, that indicates the degree of spline sampling functions.

Fig. 4 shows the difference of the interpolation and dividing points according to the sampling function with $m = 0, 1, 2$ and $d = 5$.

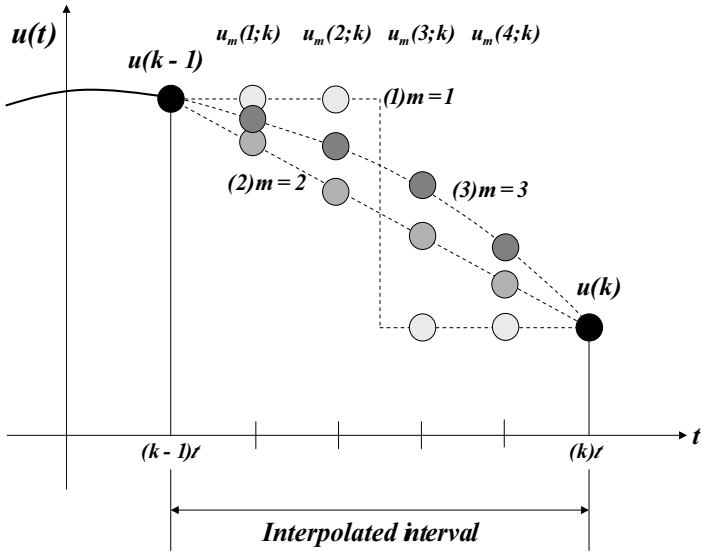

Figure 4. Illustlation of Interpolating way in the case of $d = 5$.

The calculation of the dividing points $u_m(j;k)$ as follows,

$$u_m(j;k) = \sum_{l=k-\alpha}^{k+\alpha-1} \left\{ u(l) \cdot {}^m\psi \left((k-1)\tau + \frac{\tau}{d} \cdot j - l\tau \right) \right\} \quad (j = 1, 2, \cdots, d-1) \quad (3.4)$$

where α is the number of samples which the sampling function needs for interpolation, and it is adjusted according to the sampling function.

From several test simulation results, we have obtained that it most appropriate to set the divided number of interval, $d = 5$ due to the trade-off of computation time and precision. If $d = 5$, the calculation amount in the adaptive DA converter is also vanishingly small compared to the calculation in RHC controller keeping a certain level of accuracy.

Then, we summarize the algorithm to switch the spline sampling functions for the adaptive DA converter as follows,

(*step1*) Set step $k = 0$.
(*step2*) The dividing points $u_m(j;k)$ are calculated.

(*step3*) The predicted state values $x_m(j+1;k)$ in this interval are calculated using internal model of DA converter and the dividing points $u_m(j;k)$.

(*step4*) If the interpolation wave exceeds the constrained conditions of control input due to the overshoot or undershoot, this m is excluded.

(*step5*) The evaluation values using evaluation function $J_m(k)$ are calculated in each m.

(*step6*) The parameter m whose evaluation value is the smallest is selected as an interpolation way in this interval, and then $k = k+1$ and go back to (*step1*).

From eq. 3.3, the evaluation function in (step 5) is described as

$$J_m(k) = \sum_{j=1}^{d-1} \left\{ ||x_m(j+1;k)||^2_{Q_1} + ||u_m(j;k)||^2_{R_1} \right\} \tag{3.5}$$

where Q_1 and R_1 are positive definite matrices.

Finally, the proposed RHC control parts of whole system is shown as fig. 5.

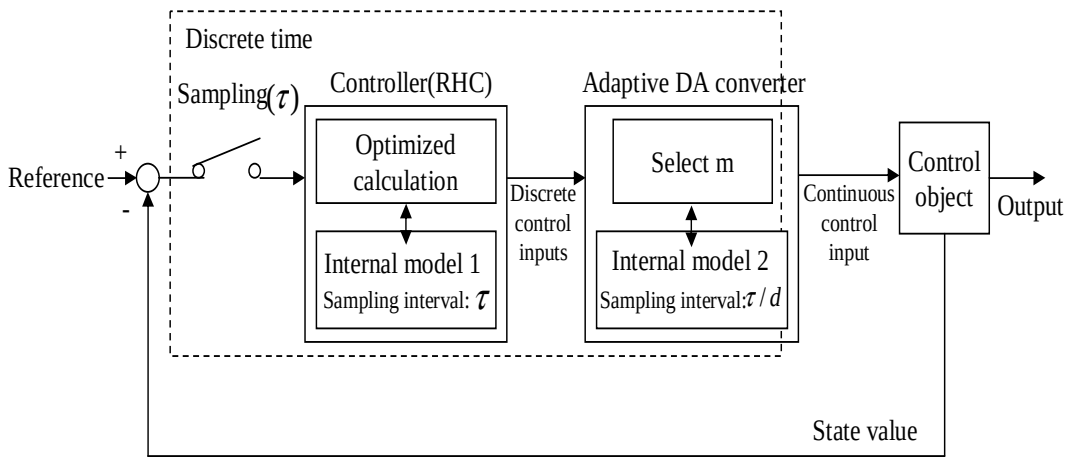

Figure 5. The controlled system part with proposed RHC controller and adaptive DA converter.

4. EEG based BMI

The EEG signal is used for the BMI in this research as I mentioned above. Since the EEG signals include both useful and unnecessary (or redundant) features, it is necessary to search for a combination of features that could improve the generalization performance of the classifier.

When the number of input features is large compared to the number of training samples, and uninformative or redundant features are included, several problems occur. Firstly, uninformative or redundant features may penalize the predictive power

of the classifier. Noisy features, in particular, reduce the generalization performance. Secondly, the computational load for the constructed classifier increases along with the number of input features considered. It is therefore reasonable to expect that online applications such as BCIs should benefit from a smaller set of features. Feature selection methods provide an answer to such problem.

The issue with feature selection methods, however, is how to find the best combination of features in a tractable manner. Evaluating all possible combinations might not be possible when the number of features is large. Several methods have been developed to obtain sub-optimal combinations. Wrapper feature selection methods such as forward stepwise selection and backward stepwise selection proposed by Kohavi and John (1997), for example, are simple but often used. The forward stepwise selection starts from a model with only one feature and best features in terms of generalization performance are added to the model one by one. Conversely, the backward stepwise selection method starts with a model including all features from which features are removed one by one until only one remains.

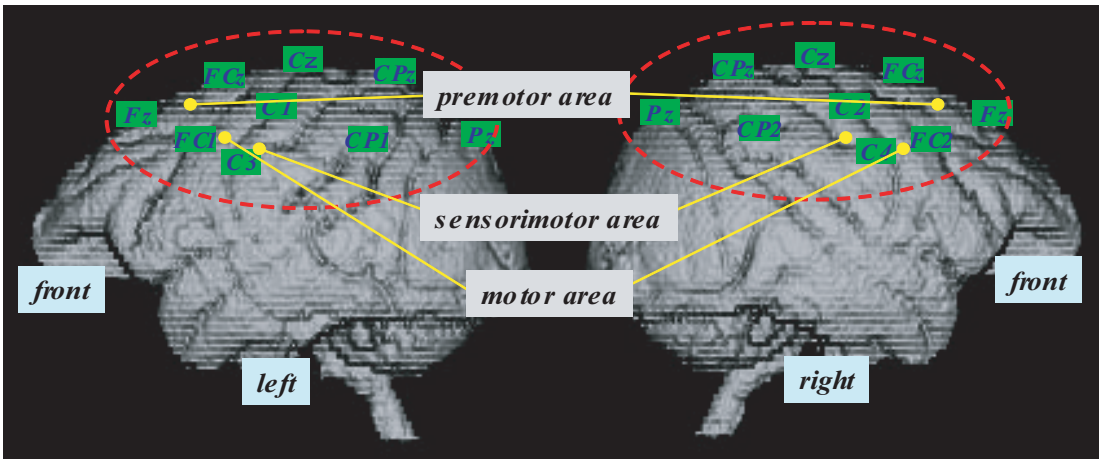

Figure 6. Location of the EEG electrodes in cerebrum

The method used in this research, therefore, is combined the backward stepwise selection with k-SVM proposed by Vapnik (1998). It's the nonlinear SVM by applying the '*kernel trick*'. By selecting an appropriate kernel function, suitable k-SVMs can be constructed for a given task. The backward stepwise selection is used to find the best possible combinations of features. For each combination of features, the parameters of k-SVMs were trained and the generalization performance of the constructed classifier (Duda et al. (2000)) was evaluated by 5-fold cross validation.

4.1 Closs validation

The most important issue with feature selection is how to evaluate the generalization performance of the constructed classifier. In this paper, the cross validation is employed.

It is a practical and well-known method to evaluate the generalization performance of a classifier (Duda et al. (2000)). This paper uses the K-fold cross validation method to evaluate the generalization performance of the classifiers trained using a combination of selected features. Cross validation method evaluate models dilectly. Firstly, the training samples are arbitrarily divided into K subsets. Next, one of the subsets is left out for evaluation and the parameters of the classifier are learned using the samples in the remaining $K-1$ subsets. The recognition rate corresponding to the subset left for evaluation is calculated using the trained classifier. Since there are K possibilities for how to leave out the subset for evaluation, the recognition rates of all K subsets are evaluated. Then, the final generalization performance is computed as the average of the recognition rate for the K subsets.

If there are N samples in the given training samples and K is equal to N, the method is called "leave-one-out". The "leave-one-out" method can evaluate the generalization performance of the classifier precisely, but at the expense of high calculation costs. In this paper, generalization performance had to be evaluated for a high number of combinations of features, and therefore a 5-fold cross validation method was employed.

4.2 Recognition Algorithm for BMI

The whole recognition algorithm of BMI is as follows:

Step A Evaluate the generalization performance of the classifier using all features by 5-fold cross validation.

Step B Eliminate one feature from the set of features and evaluate the generalization performance of the classifier using $N-1$ features by 5-fold cross validation. Since there are N possibilities to eliminate a feature from N features, repeat the evaluation N times for each possible feature combination.

Step C Select the feature combination with the best performance obtained from step [Step B], and repeat the elimination process [Step B].
In the event of a tie, select one combination randomly.

Step D Repeat [Step C] until all features are eliminated.

The combination of features that gives the largest evaluation value is considered the best (sub-optimal) combination of features.

4.3 Preliminary experiments of BMI

4.3.1 Experimental conditions

For investigating the possibility of the urgent evasion signals for man-machine systems, the following experiments of EEG-based BMI have been done. The multichannel EEG recordings used. Briefly, 64 electrodes were placed onto the head of the subject (a healthy right-handed man) at the standard locations of the 10-20 international system. The subject pressed a button by finger when danger is felt according to a stimulus, and continued pressing the button until the stimulus disappeared. EEG recordings made at 512Hz were epoched to the second before the subject actually released the button, i.e., the EEG data pertained to motor planning, rather than motor execution.

Since the urgent evasion signals are relevant to areas of the central part of the cerebrum cortex such as premotor cortex, motor cortex and sensorimotor cortex, EEG signals were recorded from 13 electrodes (Fz, FCz, FC1, FC2, Cz, C1, C2, C3, C4, CPz, CP1, CP2, Pz) as shown in fig. 6 (Fz, FCz, Cz, CPz and Pz are on the longitudinal fissure. Cz, C1, C2, C3, C4 are on the central sulcus). Physiological studies showed that both μ rhythms and β rhythms are related to the movements of the fingers (Okuma (1999)).

Accordingly μ rhythms are in the 8-13 Hz frequency band and β rhythms are in the 14-30 Hz frequency band, a 8-30Hz bandpass filter was applied to each electrode (Millan et al. (2002)). The power spectrum densities for each electrode was estimated using the Welch periodogram and was divided into 12 components with a 2Hz resolution. The resulting 156 features (13channels times 12 components) were used as the initial set of features for the classifier. The complete data set consisted of 700 samples acquired over 14 consecutive sessions (50 trials each) separated by a rest of a few minutes. For cross-validation purposes, the samples were randomly divided into a training data set with 500 samples, and a testing data set with 200 samples.

4.4 Experimental results

The solid line in fig. 7 shows the recognition rates obtained by 5-fold cross validation at each stage of the feature selection process. The dotted line indicates the recognition rate for the samples of testing set. As shown by the graph, the best recognition rate was obtained when 81 features were selected. Fig. 4.4 shows the selecter 81 features. With 81 features, the best recognition rate was 91.4%, which was 7.4% better than the recognition rate obtained with all 156 features (84.0%). Hence, we can say that the proposed feature selection method is effective in improving the generalization performance of EEG based BMI. Moreover, the prospect of practical use of the EEG based BMIs as the urgent evasion signals for man-machine systems seems to be good

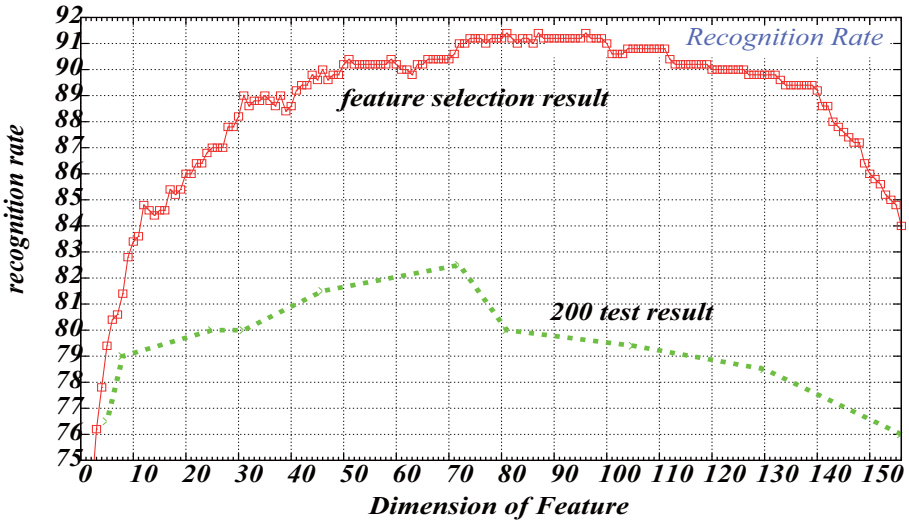

Figure 7. Recognition rates

enough.

From these results (Tanaka et al. (2006)), we can say that the proposed feature selection method is effective in improving the generalization performance of EEG based BMI. Moreover, the prospect of practical use of the EEG based BMIs as the urgent evasion signals for man-machine systems seems to be good enough.

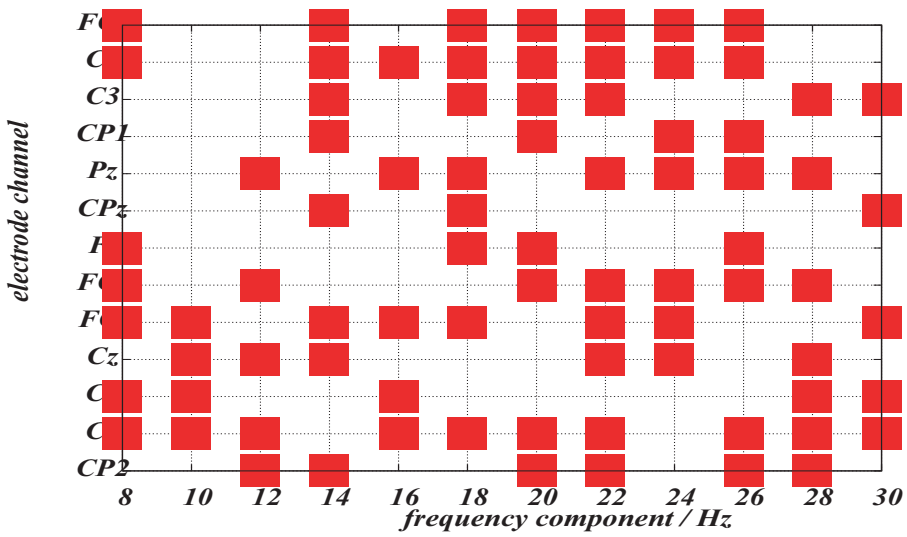

Figure 8. The selected 81 features

5. Numerical example

In this section, a numerical example is given to demonstrate the effectiveness of the proposed method. As the numerical example, let's consider the simplified car cruise control problem as shown in fig. 9.

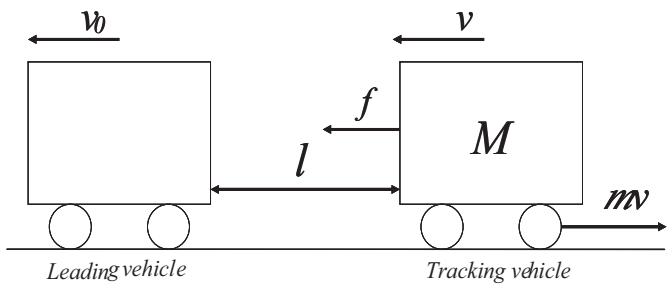

Figure 9. Simplified car cruise system model

The state space model is expressed as follows,

$$\begin{cases} \frac{d}{dt}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} -\frac{\mu}{M} & 0 \\ -1 & 0 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{M} \\ 0 \end{bmatrix} f \\ y = \begin{bmatrix} 0 & 1 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} (= l) \end{cases} \tag{5.6}$$

5.1 Simulation results

Each parameter in the simulation is set as follows;

$$\begin{cases} \text{weight of tracking car: } M = 500 \\ \text{viscosity constant: } \mu = -5.0 \\ \text{division number: } d = 54 \\ \text{sampling interval of controller: } \tau = 0.05s \\ \text{prediction horizon: } N = 704 \\ Q, R, Q_1, R_1 \text{ are identity matrices.} \\ \text{The switchings of signals is caused at time 300.} \end{cases}$$

Switch of signals means that the BMI signals is generated from human as the urgent evasion signals and the normal automatic control is switched to emargent one at time 300. Under this conditions, the following two methods are compared.

1. Conventional LQ and 0-order hold with the BMI.
2. Proposed method with the BMI.

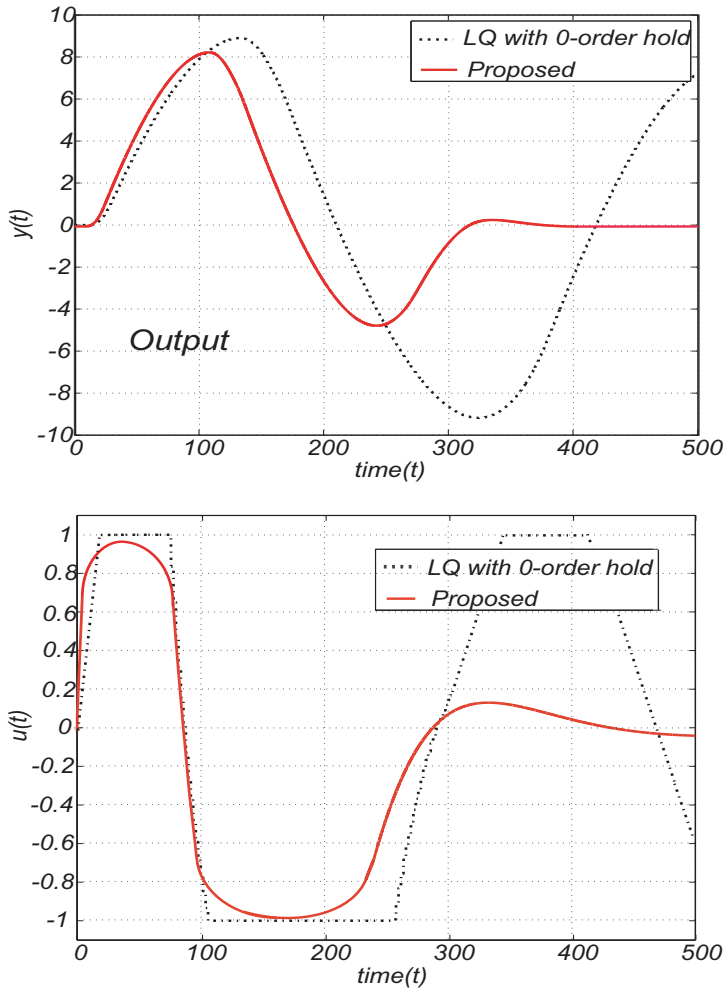

Figure 10. Time responses of systems; Upper:Output responses, Lower: control inputs responses

In this simulation, instead of a continuous-time model as a control object, a discrete-time model with the sampling interval $0.0005s$ is used, and the DA conversion means 100 times up-sampling. Furthermore, it's assumed the situation where control input is constrained as $-1.0 \leq u(t) \leq 1.0$. Besides, 0.02s time-delay is appended to the proposed method as waiting time for optimized calculation.

Fig. 10 shows the simulation results. From these, it can be easily see that the convergence to the equilibrium position in proposed method is faster than conventional one. So, we can say that the proposed method has good performance than the conventional one against the switching of control input.

Fig.11 shows the change of the parameter m. From this fig., the spline function with $m = 0$ (staircase function) is likely to be selected when the control input stays

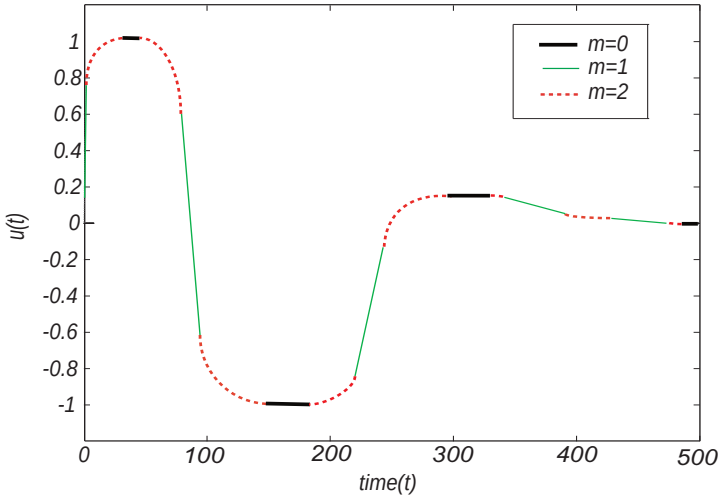

Figure 11. Illustration of Switching ways of sampling functions in the interpolation

flat, and the function with $m = 1$ (piecewise linear function) is selected when the control input changes rapidly. The function with $m = 2$ (piecewise quadratic function) is also likely to be selected when the control input changes smoothly.

In the case of the systems with fast-moving dynamics, the tiny difference of control input causes a big influence for the result. For this reason, by selecting the appropriate parameter m according to the system status, proposed method makes better control performance. If the sampling interval of the controller becomes longer, this tendency becomes much clearer. Therefore, it's considered the proposed method very efficient for the man-machine systems with switing signals.

6. Conclusion

In this paper a new RHC method with adaptive DA converter for EEG based BMI man-machine systems has been proposed. Some numerical examples have been given to demonstrate the effectiveness of the proposed method. It can be said that this result is the first step to achievement of man-machine systems with EEG based BMI to support the physically handicapped person.

As future works, it's need to develop the selection method of the best sampling function according to the control objects and BMI signals. Furthermore, the more fast algorithm for RHC will be need to apply to the man-machine systems with the BMI in practical use although the proposed method is effective for the BMI based-systems with switching of control laws. Therefore, to make sure the effectiveness of the proposed method in various other man-machine systems is need.

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