A Control Method with Brain Machine Interface for Man-machine Systems

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Abstract: In this paper, the control aspects of man-machine systems with BMI (Brain machine interface), for example, car cruising systems and so on, are discussed. In norml circumstances, the system is controlled automatically 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. On the assumption of combining with the EEG (Electroencephalogram) based BMI, new Receding Horizon Control (RHC) approach with the adaptive DA converter is proposed. Some numerical examples are included to demonstrate the effectiveness of the proposed method.

Key–Words: Man-machine systems, BMI (Brain machine interface), RHC (Receding horizon control), Adaptive DA converter, Car cruising system

1 Introduction

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 (Brain Machine Interface). Since the brain waves resulting from cerebral a ctivity are used in the BMI, it has been usually used to support to communicate for physically handicapped patients, for example, amyotrophic lateral sclerosis (ALS) or spinal cord injury, and so on [1]. But, recent advance of technology about the BMI, there is possibility to be able to assist the automatic control of man-machine systems. Although recognizing the brain signals is difficult due to their complexity, 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 [2, 3].

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. [4] proposed a search method of better combinations of EEG channels by using a feature selection technique called Recursive Feature Elimination (RFE). Millan et al. [5] 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) [6] with the backward stepwise selection [7] 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.

On the other hand, in normal circumstances, the man-machine systems are controlled automatically. In consideration of the easiness of the switching of control laws between the emergent situaion and the normal situation in the man-machine systems, the Receding Horizon Control (RHC) method is most suitable. The RHC can flexibly correspond to the change of the situation of systems. However, 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 [8]. 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 [8, 9]. 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.

Hence, on the assumption of combining with the EEG (Electroencephalogram) based BMI method, new Receding Horizon Control (RHC) approach with the adaptive DA converter is proposedto control the man-machine systems. Some numerical examples are included to demonstrate the effectiveness of the proposed method.

2 Problem Formulation

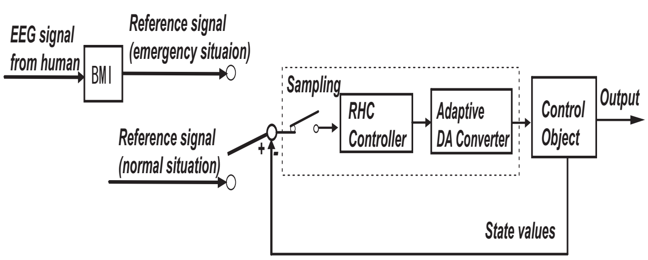

Fig. 1: The construction of targeted system

The targeted system is constructed with the RHC, the adaptive DA converter and the BMI as shown in fig. 1. The realization problem of this system is composed of two parts roughly separately. First one is how to generate the reference signal with the high accuracy in the emergency situation by the EEG based BMI. As mentioned above, The already developed method [7] is employed to solve this question. The outline of this method will taken up concisely in Chapter 3.

The other 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 4.

Fig. 2: EEG

3 Outline of the EEG based BMI

The EEG signal is used for the BMI as shown in fig. 2. 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.

The method used in this research is combined the backward stepwise selection with k-SVM [6]. 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 [10] 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 [11] was evaluated by 5-fold cross validation. The whole algorithm 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.

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 [1], EEG signals were recorded from 13 electrodes

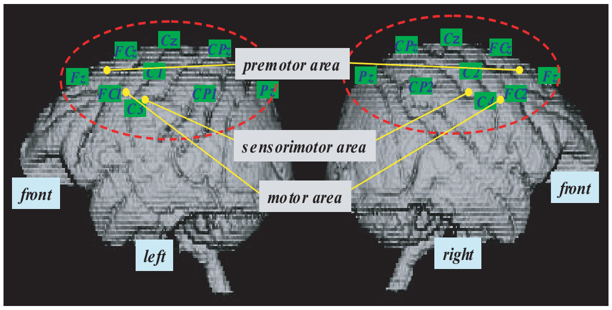

Fig. 3: Location of the EEG electrodes

(Fz, FCz, FC1, FC2, Cz, C1, C2, C3, C4, CPz, CP1, CP2, Pz) as shown in fig. 3 (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 [1].

Since 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 [5]. The power spectrum densities for each electrode was estimated using the Welch periodogram [5] 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.

By our current research results[7], 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.

4 RHC with adaptive DA converter

4.1 RHC (receding horizon control)

Let's consider a discrete-time model for man-machine systems in normal circumstances as follows,

$$x(k+1) = Ax(k) + Bu(k) \tag{1}$$
$$y(k) = Cx(k) \tag{2}$$

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.

RHC is an online powerful control method which solves a finite horizon open-loop optimal problem with respect to each sampling frequency [12, 13].

Let's consider the finite-time constrained optimal control problem with the state space model as follows,

$$\min_{\{u(k|k),\cdots,u(k+N-1|k)\}} J(k) = ||x(k+N|k)||_P^2 + \sum_{i=0}^{N-1} \left\{ ||x(k+i|k)||_Q^2 + ||u(k+i|k)||_R^2 \right\} \tag{3}$$

subject to:

$$u(k) \in \boldsymbol{U}, \quad x(k) \in \boldsymbol{X} \tag{4}$$

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.(4) 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 [14, 15].

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 can 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.

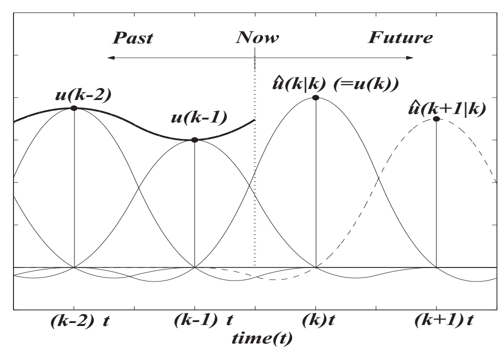

Fig. 4: Interpolation by using predictive future control inputs

Fig. 4 shows interpolation ways using the 2nd order spline function. 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.

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.

4.2 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. 5.

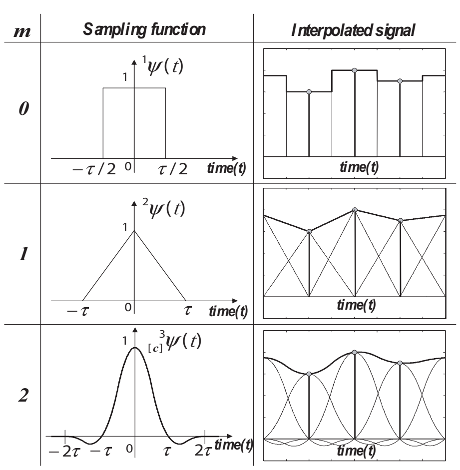

Fig. 5: Sampling functions and their interpolations ($m = 0, 1, 2$), (τ: sampling interval)

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,

$$
\begin{aligned}
u(t) &= \sum_{l=k}^{k+1} \left\{ u(l) \cdot {}^{1,2}\psi(t - l\tau) \right\}, \quad (m = 0, 1) \\
u(t) &= \sum_{l=k-1}^{k+2} \left\{ u(l) \cdot {}^{3}_{[c]}\psi(t - l\tau) \right\}, \quad (m = 2)
\end{aligned} \tag{5}
$$

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

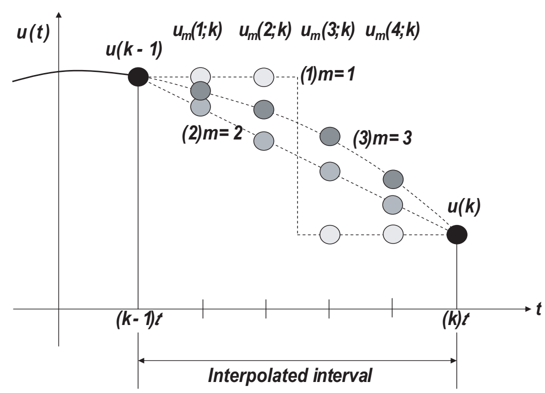

Fig. 6: Interpolation ways ($d = 5$)

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

$$
u_m(j;k) = \sum_{l=k-\alpha}^{k+\alpha-1} \left\{ u(l) \cdot {}^{m}\psi\left((k-1)\tau + \frac{\tau}{d} \cdot j - l\tau \right) \right\} \quad (j = 1, 2, \cdots, d-1) \tag{6}
$$

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

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 by using dividing genetic computation method 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*).

In this paper, the evaluation function in (step 5) is used as follows,

$$J_m(k) = \sum_{j=1}^{d-1} \left\{ ||x_m(j+1;k)||^2_{Q_1} + ||u_m(j;k)||^2_{R_1} \right\} \tag{7}$$

where Q_1 and R_1 are positive definite matrices.

5 Numerical examples

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. 7.

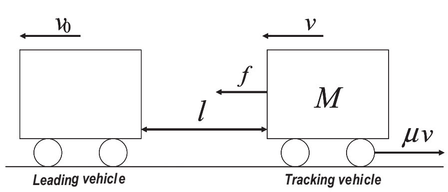

Fig. 7: Car cruise system

The state space model is expressed as follows,

$$\begin{cases} \frac{d}{dt}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} -\frac{\mu}{M} & 0 \\ -1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{M} \\ 0 \end{bmatrix} f \\ y = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} (= l) \end{cases} \tag{8}$$

5.1 Simulation results

Each parameter in the simulation is set as follows;

$$\begin{cases} \mathrm{weight of tracking car} : M = 500 \\ \mathrm{visocity constant} : \mu = -5.0 \\ \mathrm{division\ number} : d = 5 \\ \mathrm{sampling\ interval\ of\ controller} : \tau = 0.05s \\ \mathrm{prediction\ horizon} : N = 70 \\ \mathrm{Q, R, P, Q_1, R_1\ are\ identity\ matrices.} \end{cases}$$

Moreover, the following three methods are compared.

1. Conventional LQ used 0-order hold with the BMI.
2. RHC used 0-order hold with the BMI.
3. Proposed method with the BMI.

In this simulation, instead of a continuous-time model as a control object, we use a discrete-time model with the sampling interval $0.0005s$, and the DA conversion means 100 times up-sampling. Moreover, we assume the situation where control input is constrained as $-0.28 \leq u(t) \leq 0.28$. Besides, 0.02s time-delay is appended to the proposed method as waiting time for optimized calculation.

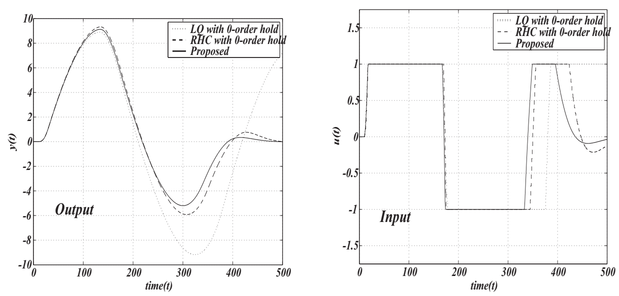

Fig. 8: Outputs and control inputs responses

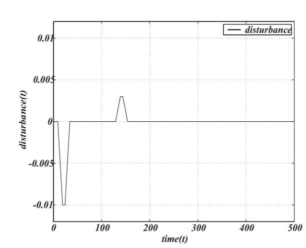

Fig. 9: Disturbance signal

Fig. 8 shows the simulation results with the disturbance shown in fig. 9. When the disturbance happend, the BMI signals is generated from human as the urgent evasion signals and the normal automatic control is switched to emargent one.

Moreover, fig.10 shows the change of the parameter m. From these figs., we can easily see that

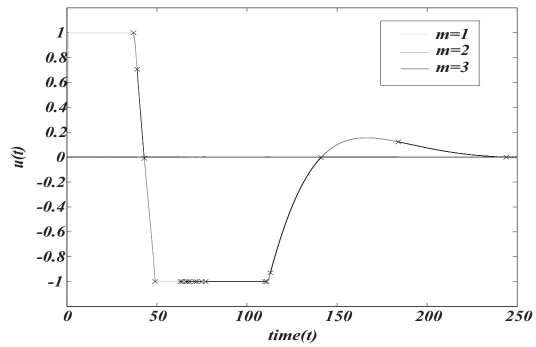

Fig. 10: Switching of the interpolation ways

the convergence to the equilibrium position in proposed method is faster than conventional one. Furthermore, the spline function with $m = 0$ (staircase function) is likely to be selected when the control input stays 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.

From these results, we can easily see that the convergence to the equilibrium position in proposed method is faster than conventional one. From the comparison between RHC with zero-order hold and proposed method, there is no doubt about the effectiveness of the proposed method. In the case of the systems with relatively 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, we think the proposed method is efficient for any other general man-machine systems.

So, we can say that the proposed method has good performance than the conventional methods.

6 Conclusion

In this paper, control aspects of RHC with BMI for man-machine systems have been discussed. From simulation results, we can recognize that the proposed method has good performace.

As future works, we need to develop the selection method of the best sampling function according to the control objects. In addition, we need to make sure the effectiveness of the proposed method in various other man-machine systems.

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