An Control Method to Man-machine Systems with Brain Machine Interface

TOHRU KAWABE
Department of Computer Science
University of Tsukuba
Tennoudai 1-1-1, Tsukuba, 305-8573
JAPAN
kawabe@cs.tsukuba.ac.jp http://tk2.cs.tsukuba.ac.jp/ ~kawabe

Abstract: In this paper, a new control method to man machine systems with BMI (brain machine interface) is discussed. The man machine systems to support the paralyzed patients is especially targeted. Then, the following assumptions are put on the man-machine systems. In norml circumstances, the system is controlled automatically and the BMI is not worked. The BMI signals are only used for the emergency situation. It works as a trigger of the switch of control law. Since human's brain waves resulting from cerebral activity are considered to be effective triger signal of emergency situations in the man-machine systems. Under these assumptions, the new control method is proposed. The method based on the RHC (receding horizon control) and the adaptive DA converter is considered to effective for the system to which the switch of control law is indispensable. Some numerical examples are included to demonstrate the effectiveness of the proposed method.

Key–Words: Man-machine systems, EEG (Electrocorticogram), BMI (Brain machine interface), RHC (Receding horizon control), DA converter

1. Introduction

Recently, the various researches on man machine systems are actively done. Especially, the advanced man machine systems to support paralyzed patients, for examples, automatic wheel chair, car crusing system and so on, are studied aiming at practical use. In such systems, an important point is to combine 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). The brain waves resulting from cerebral a ctivity are used to support communication and control for patients whose communication abilities or movements are impaired because of paralysis but whose brain activity is otherwise normal. For examples, the case of patients with terminal amyotrophic lateral sclerosis (ALS) or spinal cord injury[1, 2] and so on. By interpreting the brain waves, output commands can be sent to the external world. Although reading commands from brain signals is difficult because of their sheer complexity, BMIs are now becoming a reality because of recent developments in physiological knowledge and information processing techniques. For example, EEG (electrocorticogram) based BMIs, which measure brain signals invasively through electrodes embedded inside the cranium, have been reported to have reached practical use[3]. Recent advances of technology about the BMI, there is possibility to be able to assist the automatic control of man-machine systems.

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. In this paper, a backward stepwise feature selection method based on the k-SVM(kernel support vector machines) [6] is used. This method has been already developed by our group [7]. It 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. Hence, by using the proposed method for man-machine systems, the signals for the quick and effective response in the emergent situation is expected to be generated.

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 [8, 9, 10] 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 [11]. 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 [11, 12]. 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 using the EEG based BMI, to realize the man machine systems for paralyzed patients, the RHC with the adaptive DA converter is developed in this paper. Some numerical examples are included to demonstrate the effectiveness of the proposed method.

2. Problem Formulation

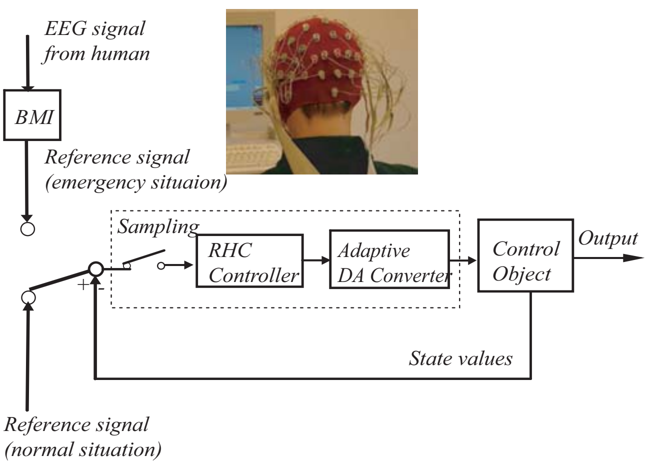

Fig. 1. The construction of targeted system

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 performance 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.

3. Outline of the EEG based BMI

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 [13] 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 [14] 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

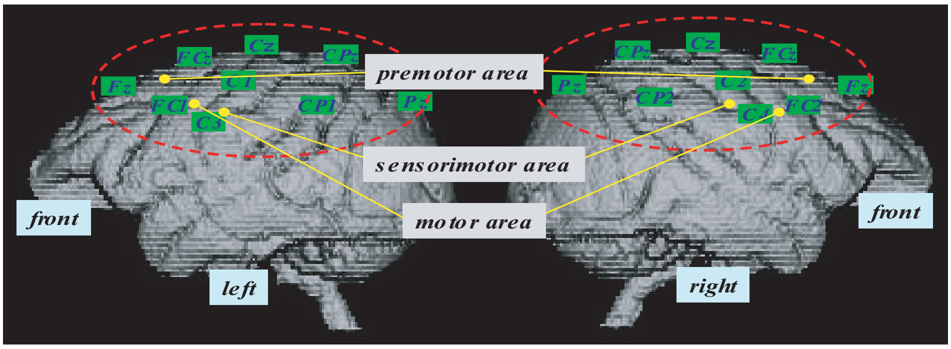

Fig. 2. Location of the EEG electrodes

(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 as shown in fig.2. 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 the current research results by our group[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 [8, 9, 10].

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 [15, 16].

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. 3 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.

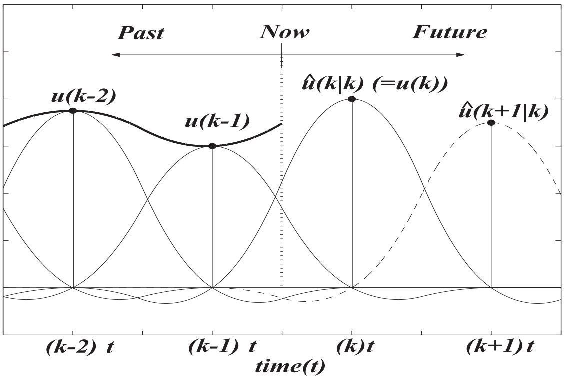

Fig. 3. Interpolation using predictive control inputs

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, It's considered 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, switching the spline functions optimally according to the system status in the adaptive DA converter is proposed. In this paper, the spline functions with the order $m = 0, 1, 2$ are used 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. 4.

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 the spline functions with the order $m = 0, 1, 2$ are only used.

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

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

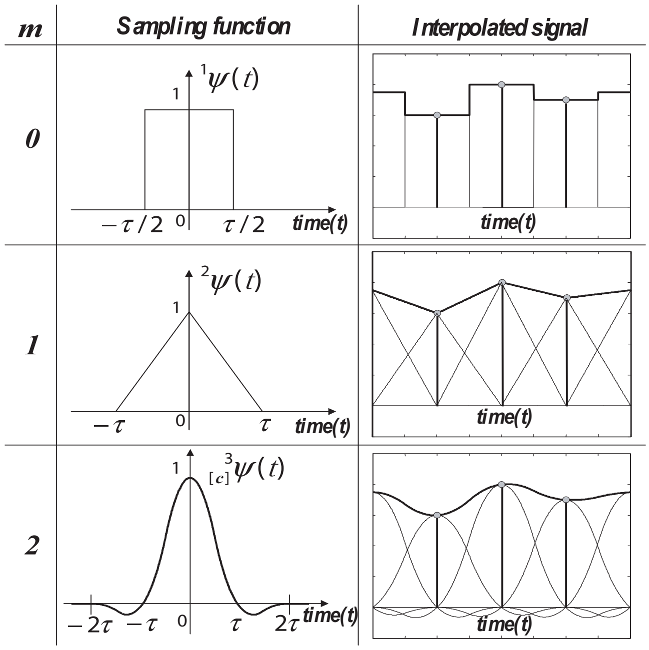

Fig. 4. Sampling functions and their interpolations ($m = 0, 1, 2$), (τ: sampling interval)

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. 5 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, it's obtained the fact that the most appropriate divided number of interval is $d = 5$ 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.

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, the algorithm to switch the spline sampling functions for the adaptive DA converter is summerized as follows,

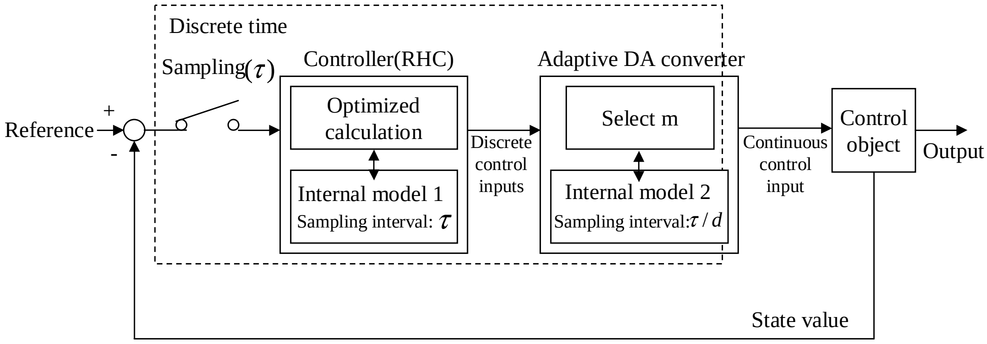

Fig. 6. Proposed RHC systems with adaptive DA converter.

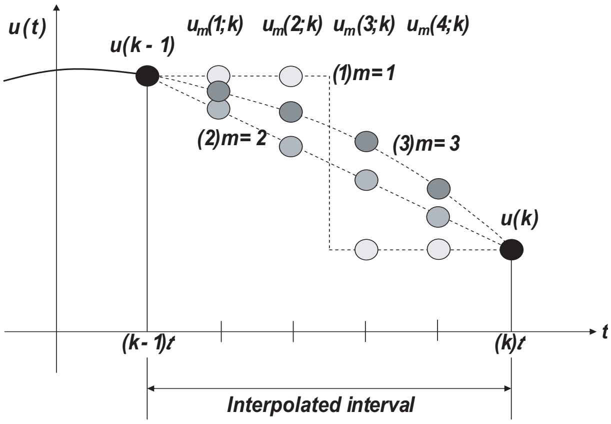

Fig. 5. Interpolation ways ($d = 5$)

(*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 using some optimization 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,

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

where Q_1 and R_1 are positive definite matrices.

Finally, the proposed RHC control parts of whole system is shown as fig. 6.

5. Numerical examples

In this section, to verify realizability of man machine systyems with EEG based BMI, two numerical examples are given to demonstrate the effectiveness of the proposed control method.

In examples, the following two methods are compared through a simulation.

1. LQ with zero-order hold (conventional).
2. Proposed method.

Simulation environments in following two examples are shown as table 1.

Table 1. Experimental environment.

CPU	Mobile Intel(R)Pentium(R)3 1.20GHz
Memory	512MB RAM
OS	Windows XP Home Edition
Software	MATLAB 7.0.1
Toolbox	Control System Toolbox 6.1 Symbolic Math Toolbox 3.1.1

5.1 Example 1

As first example, let's consider a control problem of the inverted pendulum. It's considered as a simple example of an automatic wheel-chaired system.

As fig.7 shows, inverted pendulum control problem is to control the wheel truck position without taking down the bar with weight.

The parameter M, m_g, and l in fig.7 mean the wheel truck mass, the weight mass, and the length of the bar respectively, and when the $O-XY$ coordinate system is defined like fig.5, the center of gravity point and the wheel truck position is defined as (x_G, y_G) and x_p. Moreover, the mass of the bar and the frictions are very tiny vanishingly.

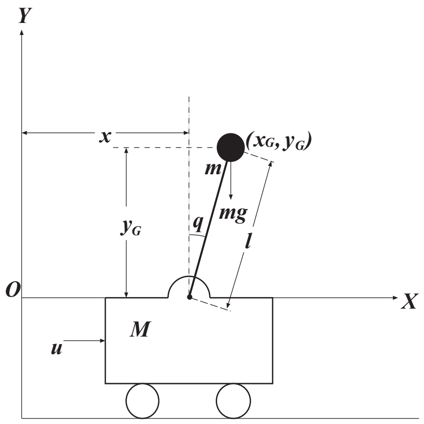

Fig. 7. Inverted pendulum model

Then, when the state values are taken as

$$x_1 = \theta, x_2 = \dot{\theta}, x_3 = x_p, x_4 = \dot{x_p} \tag{8}$$

the state space model is expressed as follows,

$$\frac{d}{dt}\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ \frac{M+m_g}{Ml}g & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ -\frac{m_g}{M}g & 0 & 0 & 0 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 \\ -\frac{1}{Ml} \\ 0 \\ \frac{1}{M} \end{bmatrix} u \tag{9}$$

$$y = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \tag{10}$$

5.1.1 Simulation results

Each parameter in the simulation is set as follows ,

$$\begin{cases} \text{wheel truck mass} : M = 2 \\ \text{weight mass} : m_g = 0.1 \\ \text{length of the bar} : l = 0.5 \\ \text{gravity acceleration} : g = 9.81 \\ \text{division number} : d = 5 \\ \text{sampling interval of controller} : \tau = 0.05s \\ \text{prediction horizon} : N = 70 \\ \mathrm{Q}, \mathrm{R}, \mathrm{P}, \mathrm{Q}_1, \mathrm{R}_1 \text{ are identity matrices.} \\ \text{weight for } m : w_1 = w_2 = w_3 = 1.0 \end{cases}$$

In proposed method, a discrete-time model is used for the RHC controller derived by a discretization assuming the interpolation of $m = 1$ sampling function. In addition, a discrete-time model of the adaptive DA converter is derived by a general discretization of the continuous-time model with the sampling interval $\tau/d = 0.01s$. In contrast, a discrete-time model of LQ controller in conventional one is derived by a general discretization with the sampling interval $\tau = 0.05s$.

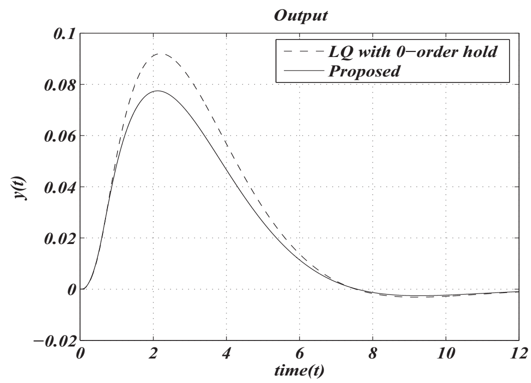

Fig. 8. Output responses

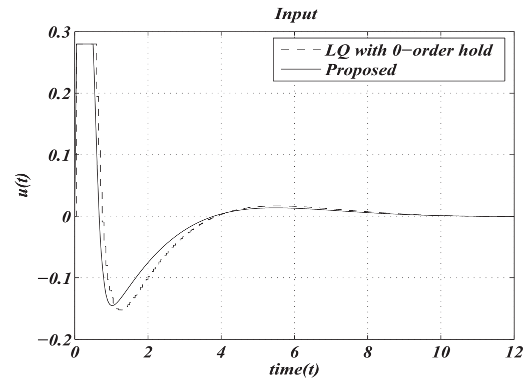

Fig. 9. Control input responses

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. Moreover, it's assumed that the control input is constrained as $-0.28 \le u(t) \le 0.28$. Besides, $0.02s$ time-delay is appended to the proposed method as waiting time for optimized calculation.

Now, figs.8 and 9 show simulation results from the initial system state $[0.01\ 0\ 0\ 0]^T$. Fig.8 shows the output responses of closed-loop systems and fig.9 shows the control input responses. As these figures show, it appears that the convergence to the equilibrium position in proposed method is faster than conventional one.

Next, let's check the influence that the change of reference input signal by EEG based BMI gives. Simulations start when the initial system state is set in equilibrium position $[0\,0\,0\,0]^T$. Then, the disturbance signal as virtual reference from BMI is added.

Fig.10 shows the added disturbance, and figs.11

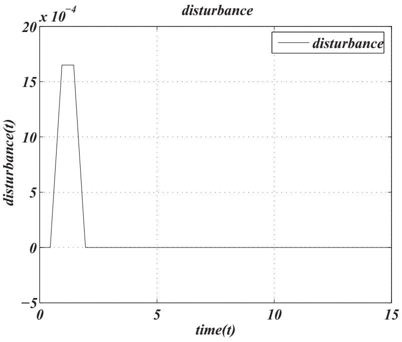

Fig. 10. Disturbance used in simulation

and 12 show the output responses of closed-loop systems change and control input responses respectively. As these figures show, the control performance of the proposed method is also better than conventional one.

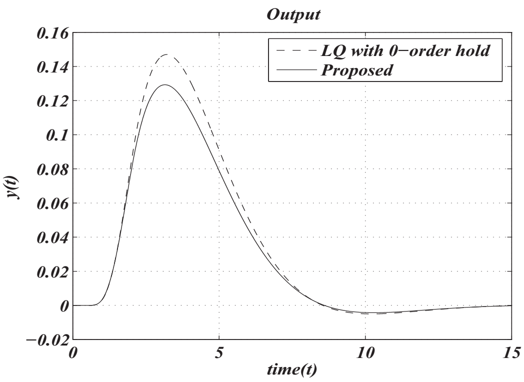

Fig. 11. Output responses

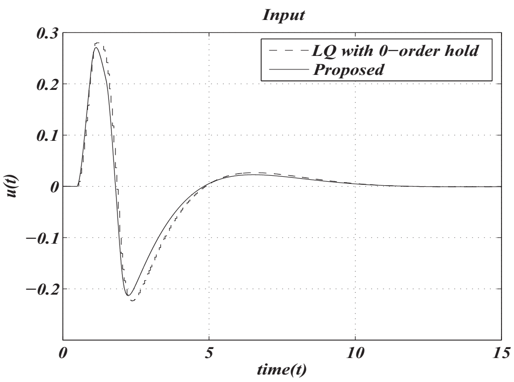

Fig. 12. Control input responses

From the comparison between the conventional method (LQ with zero-order hold) and the proposed one, there is no doubt about the effectiveness of the proposed. Moreover, please take notice that the tiny difference of control input causes a big influence for control performance in the case of the systems with relatively fast-moving dynamics like the inverted pendulum. Especially, in the case of the system for the physically handicapped person, it's critical point in safty.

5.2 Example 2

As another example, let's consider the simplified cmodel of car cruise control system for physically handicapped person as shown in fig. 13.

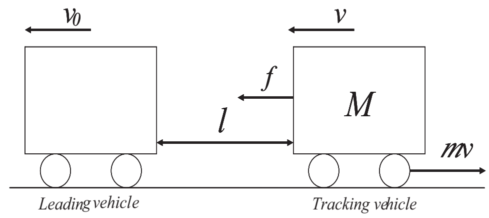

Fig. 13. Car cruising system

The state space model is expressed as follows,

$$\begin{cases} \frac{d}{dt}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} -\frac{\mu}{M} & 0 \\ -1 & 0 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{M} \\ 0 \end{bmatrix} f \\ y = \begin{bmatrix} 0 & 1 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} (= l) \end{cases} \tag{11}$$

5.2.1 Simulation results

Each parameter in the simulation is set as follows;

$$\begin{cases} \text{weightoftrackingcar} : M = 500 \\ \text{visocityconstant} : \mu = -5.0 \\ \text{division number} : d = 5 \\ \text{sampling interval of controller} : \tau = 0.05s \\ \text{prediction horizon} : N = 70 \\ \mathrm{Q}, \mathrm{R}, \mathrm{P}, \mathrm{Q}_1, \mathrm{R}_1 \text{ are identity matrices.} \end{cases}$$

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 100 and 300.

In the simulations, 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 $-0.28 \leq u(t) \leq 0.28$. Besides, 0.02s time-delay is appended to the proposed method as waiting time for optimized calculation.

Figs. 14 and 15 show 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.

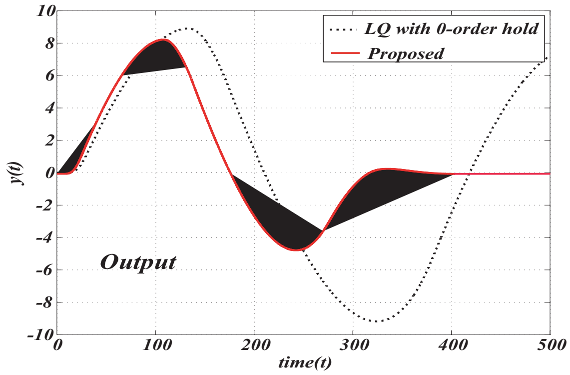

Fig. 14. Outputs responses

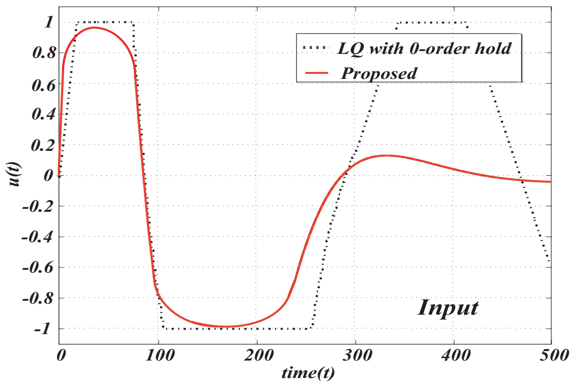

Fig. 15. Control input responses

Fig.16 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 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.

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. It can be said that it will become the first step to achievement of man-machine systems with EEG based BMI to support the physically handicapped person.

Some numerical examples have been given to demonstrate the effectiveness of the proposed method.

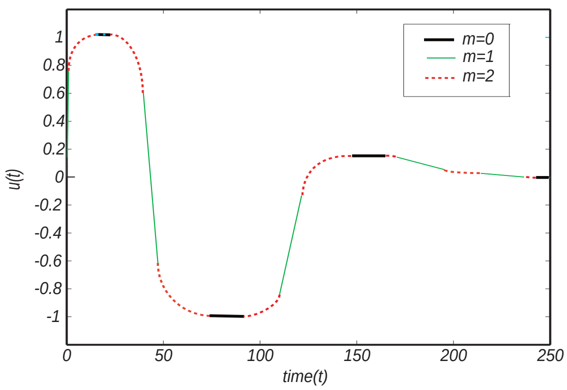

Fig. 16. Switching of the interpolation ways

By selecting the appropriate parameter m of the adaptive DA converter 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.

As future works, it's need to develop the selection method of the best sampling function according to the control objects and BMI signals. In addition, to make sure the effectiveness of the proposed method in various other man-machine systems is need.

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