On Adaptive Controller Design based on Many Parametric Models

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***Abstract*— In this paper, we consider a practical concept of designing discrete-time model based adaptive control system using many identification models and its implementation by special numerical processing hardware. The rapid progress of the multi-cores CPU and many-cores GPU in recent years, makes it possible to perform massively parallel computation in system identification and may change the adaptive controller design.**

I. Introduction

In the application of adaptive control technique based on the parametric model of the plant for real systems, it is very important and difficult to select the structure of the parametric model of the controlled process. If the assumed structure of the parametric model is not suitable for the real process, the performance of the adaptive control system becomes worse or the system may become unstable. For this problem, if the controlled process is identified based on many different types of parametric models with different order, different structure etc., we can select an optimal model for model-based control strategy suitable to the control objective in real-time.

In recent years, different types of the multi-model control system have been proposed. In these methods, Narendra and Balakrishnan [1] proposed an adaptive control system using switching and tuning algorithms and discussed the robustness and stability of the proposed control system. This method is one of the basic concepts for designing the multi-model based adaptive control systems and other researches in this field determined the extension and improvement of the concept [2].

However, in almost all papers, the number of the multiple models was implicitly assumed as not so large. This restricts the achieved performance for real application because the small number of models only covers narrow class of process characteristics. If the feasible number of the models for identification is very large, the models with same structure but with different initial parameters can be treated as independent models. In this case, one of the many models may improve the transient property of the adaptive control system.

Required calculation in the above controller structure is a massive task: A large number of parameters has to be updated with individual identification models. Despite the fact that recursive identification algorithms require significantly less computational effort compared with the batch processing, they are not favored for real time control.

However, now, we can get very powerful hardware for multi-model based adaptive control systems, which allows to perform massive numerical calculation for real-time applications. In former times, such an extensive calculation could only be realized using multiple DSPs, nowadays GPU (Graphic Processing Unit) is easily used.

Modern one GPU easily outperform current multi-DSPs by means of sheer floating-point performance. This is achieved by several hundred individual stream processors (SPs) on a single graphic chip.

Using the GPU for multiple model based identification and real-time controller design, the adaptive controller based on many models becomes feasible in real-time applications. Now, high-level programming interfaces (APIs), like NVIDIA's Compute Unified Device Architecture (CUDA) [3] and ATI's Stream technology [4], make the development of multi-model based adaptive controller programming easier.

In this paper a many-model based adaptive control system with closed loop identification and with adaptive control design after each switching operation is proposed.

First, the basic structure of the multi-model based adaptive controller is designed. Next, the identifier with many models with different adaptation algorithms is proposed. Moreover, the selecting function for the best model is mentioned. Finally, computer simulation results for plans with variable structure are included to illustrate the effectiveness of the proposed method.

II. Structure of the Control System

We consider a set of models $\{M_1, M_2, M_3 \ldots M_n\}$ and the set of the controllers $\{C_1, C_2, C_3 \ldots C_n\}$, corresponding the models as shown in Fig.1.

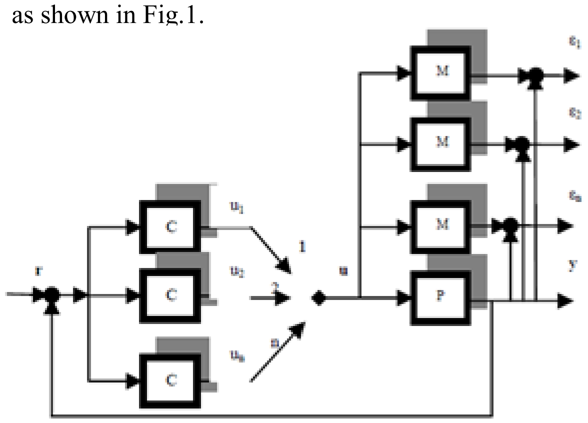

Fig.1 Many-Model based Adaptive Control System

In this figure, the input and output of the process P are u and y respectively, and r is the set point of the system. The structure of the M_i (i=1,2,... n) models are a priori assigned. For each model M_i, a model based controller C_i is designed in order to assure the control objectives (for example, the model reference strategy is adopted).

The most important task in the many-model based adaptive control system is to select one model included in the model sets that best describes the process around each operating condition.

In order to achieve this objective, the control system is constructed in two steps

A. *Control Step*

The model with the smallest error with respect to a performance criterion is chosen. After this procedure the control input u is calculated using the selected model based controller.

B. *Adaptation Step*

Using the independent adaptive algorithms for each model with different structure, the parameters of the model are adjusted by means of a recursive closed- loop identification. The controller is also updated according to the structure of the each model.

The many-model based control can be used without the adaptive mechanism, in this case the adaptation step being ignored. If the initial many models have wide range of parameters, one fixed model Mi that best approximates the process around the current operating condition, the controller Ci gives the sufficient performance.

III. MULTIPLE IDENTIFICATION MODELS OF UNKNOWN PLANT

Now, let us introduce the multiple models of the plant. Assuming that the plant can be modeled by many models with different structure.

$$A(z^{-1})y(k) = z^{-d}B(z^{-1})u(k) \qquad (1)$$

$$A(z^{-1}) = 1 + a_1 z^{-1} + \cdots + a_n z^{-n} \qquad (2)$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + \cdots + b_m z^{-m} \qquad (3)$$

where *y(k)* and *u(k)* denote the plant output and input respectively, and $A(z^{-1})$ and $B(z^{-1})$ are polynomials in the unit delay operator z^{-1} of degrees n and m.

The above model can be described as the following vector form and indexed by the structural numbers d, n and m.

$$y(k) = \theta^T(k)\varsigma(k-1) \qquad (4)$$

$$\theta(k) = [b_0(k), \cdots, b_m(k), a_1(k), \cdots, a_n(k)]^T \qquad (5)$$

$$\varsigma(k-1) = [u(k-d), \cdots, u(k-d-m), y(k-1), \cdots, y(k-n)]^T \qquad (6)$$

If the range of each structural numbers d, n, m is assigned as {1-10}, the total numbers of the model is equal to 10x10x10=1,000. This number is very large compared with the number of models in conventional multi-model based adaptive control system such as the Narendra's controller and the model sets can cover more wide range of characteristics of the unknown process.

Moreover, combining the following 'multiple rate interlaced adaptation algorithms', each model can describe periodically time-varying system.

$$\hat{\theta}(k) = \hat{\theta}(k-N) - \Gamma(k-N)\varsigma(k-1)\varepsilon(k) \qquad (7)$$

$$\varepsilon(k) = \frac{y(k) - \hat{\theta}^T(k-N)\varsigma(k-1)}{1 + \varsigma^T(k-1)\Gamma(k-N)\varsigma(k-1)} \qquad (8)$$

$$\Gamma(k) = \frac{1}{\lambda_1(k)}\left[\Gamma(k-N) - \frac{\lambda_2(k)\Gamma(k-N)\hat{f}(k-1)\hat{f}^T(k-1)\Gamma(k-N)}{\lambda_1(k) + \lambda_2(k)\varsigma^T(k-1)(k)\Gamma(k-N)\varsigma(k-1)}\right] \qquad (9)$$

Where $0 < \lambda_1(k) \le 1, 0 \le \lambda_2(k) < 2, \Gamma(0) = \Gamma^T(0) > 0$

If the parameter variation contains non-periodic components, the gain update scheme (9) should be modified as follows.

$$\Gamma'(k) = \left[\Gamma(k-N) - \frac{(\lambda_3(k)\Gamma(k-N)\hat{f}(k-1)\hat{f}^T(k-1)\Gamma(k-N))}{1 + \lambda_3(k)\varsigma^T(k-1)(k)\Gamma(k-N)\varsigma(k-1)}\right] \qquad (10)$$

$$\lambda_1(k) = \frac{tr\Gamma'(k)}{tr\Gamma(-1)}, \Gamma(k) = \frac{1}{\lambda_1(k)}\Gamma'(k), 0 < \lambda_3(k) < \infty$$

Moreover, if the parameters of the process are changed corresponding to the operating conditions but constant in each point, the following multiple algorithms are useful.

$$\hat{\theta}(k) = \hat{\theta}(k-N) - \Gamma(k-N)\varsigma(k-1)\varepsilon(k) - \sigma f(\hat{\theta}(k-N))\hat{\theta}(k-N),\ 0 < \sigma < 1 \qquad (11)$$

In the above algorithm, the function $f(\hat{\theta}(k-N)$ is selected as the value is equal to 0 for each operating condition.

In these algorithms, if the period N is assigned as {1-10} for all models mentioned above, the total number of model becomes 10x10x10x10=10,000 but it is feasible if the control system is implemented by newest GPU which has over 1,000 processing cores.

Combining the many models and multiple adaptation algorithms, the process is identified as the closed-loop manner as shown in Fig.2.

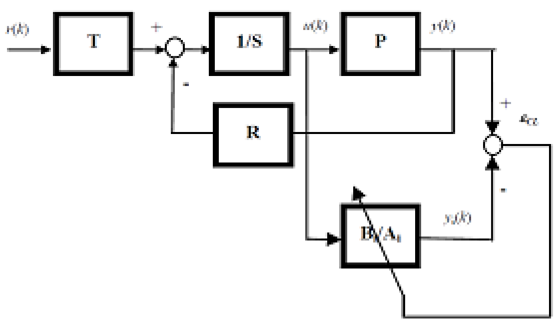

Fig. 2. Closed loop many model based identification

IV. STRATEGY OF MODEL SELECTION

The best model is selected basically based on the model-error at the k instant is defined as the difference between the output y of the process and the output y_i of the model M_i:

$$\varepsilon_i(k) = y(k) - y_i(k) \tag{12}$$

The example of performance criterion which can be used as selection rule is as follows:

$$J_i(k) = \alpha\varepsilon_i^2(k) + \beta\sum_{j=1}^{k} e^{-\lambda(k-j)} e_i^2(j) \tag{13}$$

where α>0 and β>0 are the weighting factor and the long term accuracy for the instantaneous measurements, respectively; λ>0 is the forgetting factor.

The choice of the α , β and λ parameters depends on the process.

The other criterions useful for model selection are the functions of the identification error and/or the variation of the estimated parameters.

$$\bar{e}_i(k) = \sum_{j=0}^{N_h-1} |\hat{e}_i(k-j)|/N_h \tag{14}$$

$$\bar{\theta}_{i,n}(k) = \sum_{m=0}^{N_h-1} \hat{\theta}_{i,n}(k-m)/N_h \tag{15}$$

$$\sigma_{i,n}(k) = \sum_{l=0}^{N_h-1} [\{\hat{\theta}_{i,n}(k-l) - \bar{\theta}_{i,n}(k)\}/\bar{\theta}_{i,n}(k)]^2/N_h \tag{16}$$

$$\bar{\sigma}_i(k) = \sum_{n=1}^{n_i} \sigma_{i,n}(k)/n_i \tag{17}$$

If the process has an explicit periodic varying parameters, the following criteria is useful.

$$J_{N_i}(k) = \left\|\hat{\theta}_i(k) - \hat{\theta}_i(k - N_i)\right\| \quad i = 1, \cdots, (N_{\max} - N_{\min}) + 1 \tag{18}$$

To determine the best model for control, the priority of each model which is decided to hold the stability of the control system is assigned according to other rules or criteria.

It seems that there are two different approaches for this procedure, one is a numerical approach and another is a heuristic approach. In the numerical approach, the priority of each model is determined based on some quantities which are introduced for supervision of parameter estimation

V. MODEL BASED CONTROLLER DESIGN

For each model M_i a controller C_i is designed that satisfies the desired performances. The controller C_i is computed using the polynomial based design with two degrees of freedom as shown in Fig.3.

The input $u(k)$ is calculated using the following equation.

$$u(k) = \frac{T(q^{-1})}{S(q^{-1})} r(k) - \frac{R(q^{-1})}{S(q^{-1})} y(k) \tag{19}$$

In this case, there exist unique polynomials $R(z^{-1})$ and $S(z^{-1})$, such that:

$$P_C(q^{-1}) = A(q^{-1})S(q^{-1}) + B(q^{-1})R(q^{-1}) \tag{20}$$

Where

– pair $(A(q^{-1}), B(q^{-1}))$ represents the process's model;
– $P_C(q^{-1})$ is the closed-loop characteristic polynomial.

The reference tracking performances are ensured by the choice of the $T(q^{-1})$ polynomial. For each model (A_i, B_i) a C_i control algorithm (R_i, S_i, T_i polynomials) will be computed respectively.

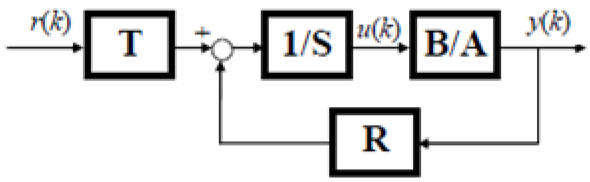

Fig. 3. Structure of Model Based Controller

VI. SIMULATOR BASED CONTROLLER DESIGN

In conventional adaptive control schemes, the control input which assures the nominal performance is solved based on the model based control equation such as Eq. (20).

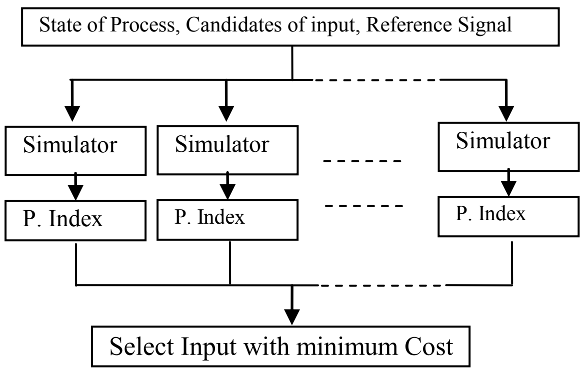

Fig.4 Parallel Simulation based Control Input Calculation

However, if the model is highly non-linear, it is very difficult to introduce the equation and to solve it. For this situation, we can solve the control problem based on many models. When we have obtained the accurate process model by using one of the non-linear model in the model sets, we can simulate the future behabiour of the process for many sets of input candidate using the same hardware which used in many model based identifications. After these many simulations, we can select the best input for control objective based on the performance index as shown in **Fig.4**.

This strategy is only feasible for the case of massive parallel or multi-core hardware like GPUs but it is reported that in some applications the performance of this kind of control system is superior to conventional method [10].

VII. SIMULATION RESULTS

In order to investigate the effectiveness of the multi model concept, computer simulations are performed for continuous time plants which abruptly change the structure. The adaptive control is performed in discrete time. The sampling period is set at 0.5 for all simulations described below.

The first example is the plant with variable order and dead time and without disturbance. The discrete time form of this plant is a minimum phase system for all time. The characteristics of the plant abruptly changes twice in this simulation.

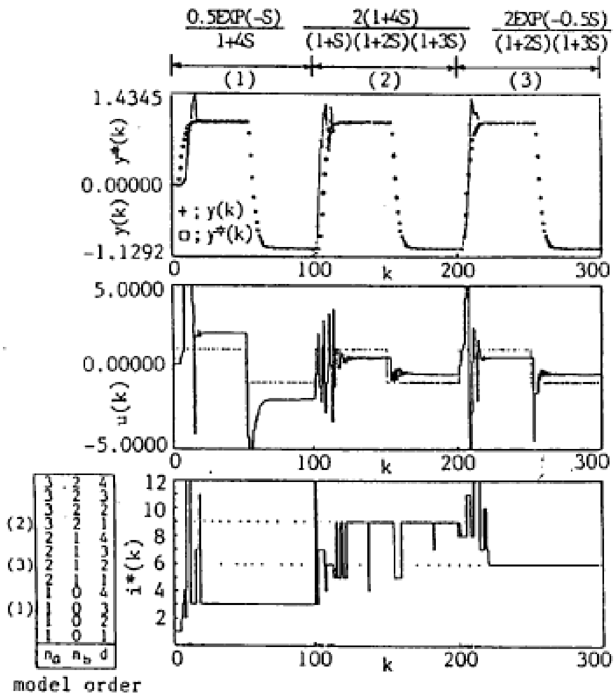

Fig.5 Simulation result for time-varying process

Figure 5 shows the control behaviour for this plant and the evolution of the selected plant model. In this simulation, the plant is simultaneously identified by twelve different models containing the true model of the plant. In Fig.4, the transfer function and the true model structure of the plant for each period are indicated. From this result, it is shown that for all changes of the plant, the on-line model selecting procedure can select the appropriate model after a short transient period.

The next example is the other plant with or without deterministic disturbance. The discrete time form of this plant is the non-minimum phase system. Figure 5 shows the results for this case. In this case, no unique identification model which completely agrees with the real plant.

However, in this case, the plant can be well controlled by the multiple identification models.

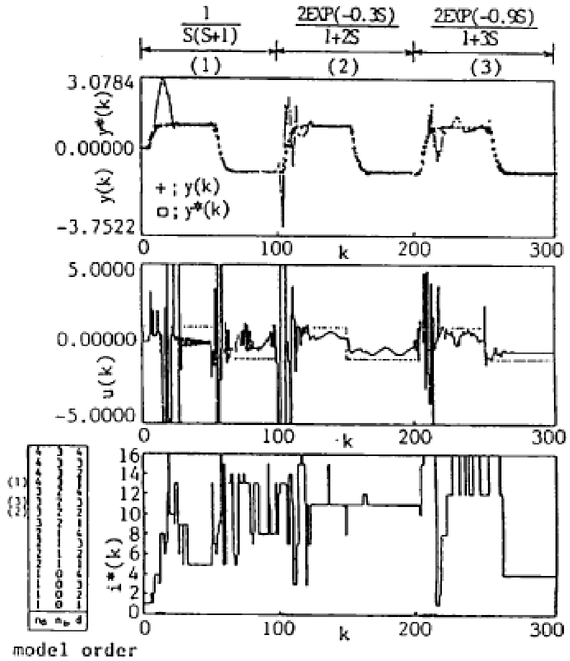

Fig.6 Simulation result for time-varying process with disturbance

The last example is the simulation result for unknown time varying system.

In this case, the process is described as the following equation $(d = 1, n = 2, m = 1)$

$$\left(1 + a_1(k)z^{-1} + a_2(k)z^{-2}\right)y(k) = \left(b_0(k) + b_1(k)z^{-1}\right)z^{-1}u(k)$$

In this case, the process is identified by multi models with multiple interlaced adaptation algorithms.

Figure 7,8,9 and 10 show the simulation results.

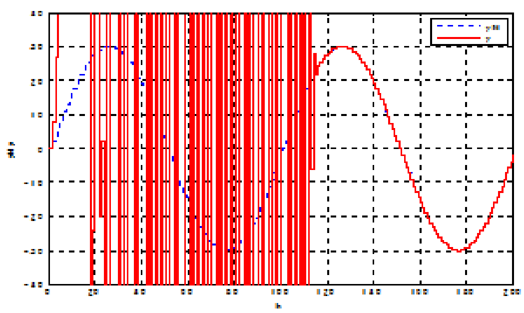

Fig.7 Simulation result of reference and plant output

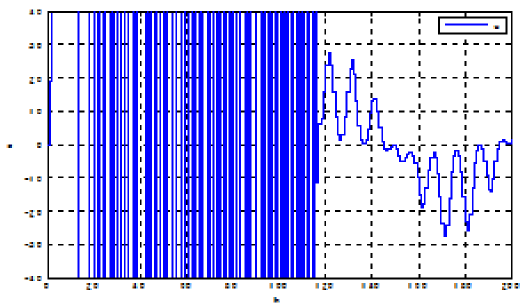

Fig.8 Simulation result of control input

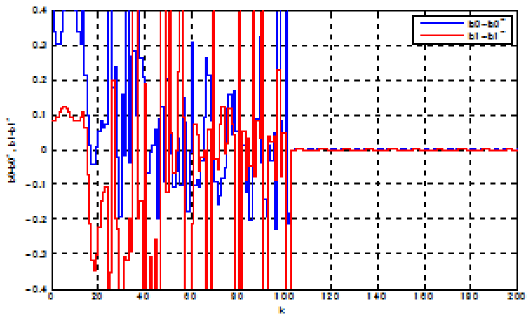

Fig.9 Trend of estimated parameter errors (input parameters)

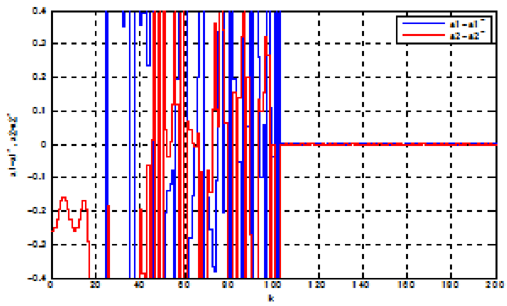

Fig.10 Trend of estimated parameter errors (output parameters)

VIII. Conclusion

We have proposed an adaptive control methodology using many identification models and selecting functions, especially implemented by parallel numerical processing hardware such as GPUs. The proposed adaptive control algorithm can work well for different types of plants when sufficient number of model set is available.

The method enables the application of the adaptive control system by knowing less a priori information about the real plant. Although the effectiveness of this method has been demonstrated for linear, time-varying, lumped parameter plants, it is clear that it can be readily applied to more wide class of plants. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions.

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