

Design of a Neural Controller using Multiobjective Optimization for Nonminimum Phase Systems

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Abstract

This paper presents a control architecture with a neural controller and a conventional linear controller for nonminimum phase systems. The objective is to minimize overall position errors as well as to maintain small undershooting. These attributes make it difficult to obtain the optimal solution which satisfied all individual objectives. Moreover, heuristic attempts of a proper combination of several objectives may produce a feasible solution but not necessarily optimal one. With the concept of Pareto optimality and evolutionary programming, we train the controller more effectively and obtain a valuable set of optimal solutions. According to the preference, we can easily determine the most suitable solution from a pool of optimal candidates.

1. Introduction

Artificial neural networks, known as good universal approximators, have been widely used as a computational tool to effectively learn unknown nonlinear functions[1]. They provide a complex solution easily from learning by examples without explicit programming. This makes them drawing much interest as a powerful tool in designing controllers of complex systems in control community. Practically industrial control systems makes mainly use of proportional-integral-derivative(PID) typed controllers in spite of many well-developed control theories. Although the controllers provide a simple structure and understandability, fine tuning of controller gains to guarantee good control performance still necessitates experts' sophisticated knowledge about both control theory and dynamic process of a specific system. It is well known that control of nonminimum phase systems is a difficult task because of their inherent tendency of unnatural undershooting. The systems having zeros or poles at the right-hand of an s-plane can be found in many industrial areas such as missile, plane, and power plant, etc. Early works on design of the controllers have been developed by many researchers[2],[3]. Even though they proposed efficient methods to find gains of a linear controller, their approaches are not capable of solving nonminimum zero phenomena like undershooting at the transient region because of the limitation of the linear controller. Widrow and Stearns[4] pro-

posed an (adaline-typed) adaptive controller for special cases of nonminimum phase systems under some relaxed assumptions. On the other hand, the unstable pole-zero cancellation method cannot be applied in the design of controllers of the systems because of an internal stability problem[5]. Park *et al.*[6] proposed a new control structure which consisted of a conventional PID typed controller and a supplementary nonlinear neural controller in parallel. To reduce the undershooting and shorten the settling time of the systems, they adopted evolutionary programming(EP) as an effective training algorithm of weight values of the neural network. EP has an advantage of a global evaluation without any differential information of output errors. It is generally impossible to train the controller with online because EP cannot utilize instant performance evaluation of the underlying controller. The cost function consisted of two conflict objectives, minimization of undershooting and overall position errors, and was defined with a weighted linear combination of two. The weighting factors were selected by trial and error.

Since there existed a tradeoff between small undershoot and fast rising time, it was not easy to obtain suitable factors in order to provide an (sub)optimal solution which satisfied individual objectives. The neural controller was trained with EP to optimize the prespecified cost function in the step response.

Although the proposed method of Park *et al.* alleviates the nonminimum phase phenomena and improves overall control performance to some degree, it does not guarantee real optimality. In general, for this kind of multiobjective problems, there exists a set of non-dominated, Pareto, solutions that present the optimal tradeoff relationship among objectives. Any solution in the Pareto set cannot improve all costs simultaneously[7]. Although there are many mathematical optimization procedures such as linear programming, integer programming, and nonlinear programming, the inherent parallel structure of EP provides some important advantages in multiobjective optimization such as easy handling of the Pareto optimal set[8]. We apply the concept of multiobjective technique(MO) to this problem to produce integrated optimization solutions and compare them with the previous solution found by the single EP approach.

This paper is organized as follows: Control structure and design methodology are briefly described in the following section. Also, to guarantee good control performance over

nonminimum phase phenomena, we devise a new cost function. In Section III, multiobjective evolutionary programming(MOEP) as a learning algorithm of the neural network is presented. The Pareto optimal sets on several nonminimum phase system are presented based on computer simulations in Section IV. Finally, several conclusions are made, and further research direction is suggested.

2.Design of a Neural Controller

The overall structure and the neural controller are shown in Fig.1 where the integrator is used to reduce the effect of the high frequency of the control output on the controlled system. The neural controller is designed to activate mainly in

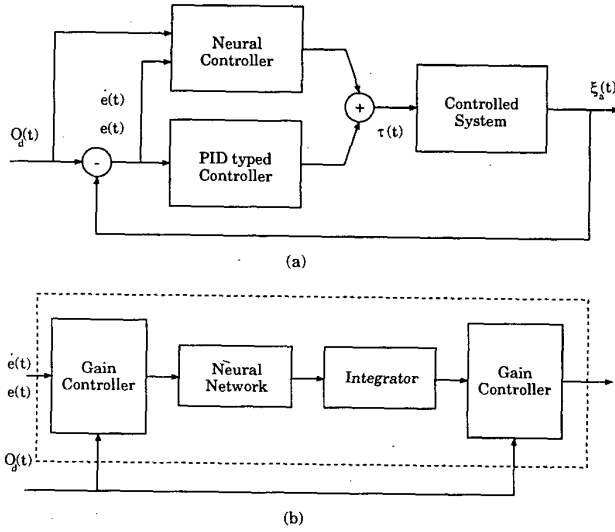


Figure 1: (a) Overall block diagram of the proposed controller. (b) Structure of the neural controller.

the undershoot regions where a PID typed controller does not give good performance. Analysis on the step response of the controlled system and its error curve provides proper physical quantities as an input of the neural controller. Undershoot phenomena appears when inequality (1) holds

$$\frac{de}{dt} \times e > 0. \quad (1)$$

Applying the product term of the error(e) and the error derivative($\frac{de}{dt}$) as one of inputs of the neural controller, we can dominantly activate the neural controller in undershooting regions.

The cost function in a design of the controller consists of two conflict objectives as shown in (2)–(5)

$$E_1 = E_{11} + E_{12}, \quad (2)$$

$$\begin{cases} E_{11} = |\min(\min_{0 \leq t \leq T} \xi_a(t), 0)| & \text{when } O_d(t) = 1, \\ E_{12} = |\max(\max_{0 \leq t \leq T} \xi_a(t)^{-1}, 0)| & \text{when } O_d(t) = 1, \end{cases}$$

$$E_2 = E_{21} + E_{22}, \quad (3)$$

$$\begin{cases} E_{21} = |\max(\max_{0 \leq t \leq T} \xi_a(t)^{-1}, 0)| & \text{when } O_d(t) = 0, \\ E_{22} = |\min(\min_{0 \leq t \leq T} \xi_a(t), 0)| & \text{when } O_d(t) = 0, \end{cases}$$

$$E_3 = \int_0^T (O_d(t) - \xi_a(t))^2 dt, \quad (4)$$

$$E_4 = \alpha \times (E_1 + E_2) + \beta \times E_3 \quad (5)$$

where $O_d(t)$ and $\xi_a(t)$ are the desired step response and the actual one, respectively. T is a training time interval, and α and β are the weighting factors. Equation (5) is a weighted linear combination of two different objectives: E_1 , E_2 , and E_3 are absolute magnitudes of undershooting(E_{11} , E_{21}) and overshooting(E_{12} , E_{22}) at each rising and falling period and the overall summation of squared position errors. This enables us to evaluate the extent to which each chromosome is suitable for the given criteria such as small undershooting and overshooting together with a minimization of overall position errors.

3.Multiobjective Optimization using EP

Since conventional training algorithms of a neuro-controller do not work well when the plant has nonminimum phase characteristics[9], We devise a training method with EP to improve global performance of the proposed controller for the given cost function of (5). EP is a stochastic search and optimization algorithm which uses concepts of evolution and natural selection[10]. It is based on a real number representation as a genotype. Its converging speed is relatively fast in finding near-optimal solutions. In addition, it has an advantage of finding an (sub)optimal solution fast without explicit mathematical formulations and gradient information, even when cost function is complicated and non convex. Due to such characteristics, EP has been successfully adopted as a parameter optimization tool for many real world applications. However, it is not easy to guarantee real optimality only with the original EP(OEP) approach.

Many real world problems involve multiple measures of performance, or objectives, which should be optimized simultaneously[7]. It is reasonable to treat them in point of multiobjective optimization. In general, such problems are optimized through a single objective formulation like a popular weighted-sum or constrained approach. However, weighting factors between objectives are not only difficult to determine but also seriously affect overall performance. The purpose of multiple optimization is to treat each objective independently and provides feasible solutions which cannot decrease all objectives simultaneously. The solutions are called non-dominated, and all feasible non-dominated solutions belong to Pareto optimal set(Pareto optimal frontier) as shown in Fig.2. We can divide the objective space

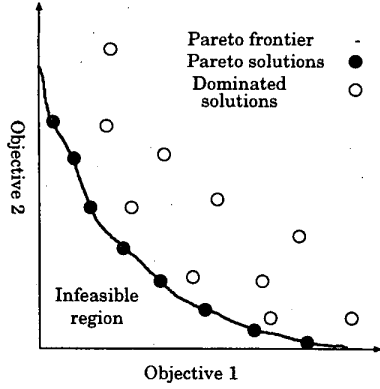


Figure 2: Pareto Optimal Set(frontier) when minimizing each objective.

into 3 regions: feasible, infeasible, and Pareto optimal frontier(surface). Therefore, the pareto frontier defines the optimal range of all objectives and the respective tradeoff. There has been much research related to multiobjective optimization and we adopt the Pareto-based niche and the sharing method as an optimization tool[11]. The Pareto-based techniques proposed by Goldberg have been a major research direction of MOEP[12]. In Pareto schemes, the fitness of an individual is defined in terms of rank. By assigning equal probability of reproduction to all non-dominated individuals in the population, they explicitly make use of the definition of Pareto optimality. The sharing method prevents solutions from concentrating on only one area of the pareto surface by penalizing members of the population that gather close together within a niche size. Although there exist many mathematical programming methods in dealing with multiobjective optimization techniques, EP provides important advantages in MO analysis: (1) its inherent parallel structure and (2) with carefully designed control parameters, chromosomes in the population can be directly converged to the set of the Pareto optimal solutions in a single run. A main difference between the single EP and the multiobjective EP(MOEP) is a selection strategy[13]. The latter selects non-dominated chromosomes with high probability from the population and uses a sharing function and niche concept to spread solutions uniformly over a wide solution region.

To adopt the concept of the multiobjective optimization, we reformulated the cost function of (5) with the two dimensional form in the objective space.

$$f(\omega) = (f_1(\omega), f_2(\omega)) \quad (6)$$

with $f_1(\omega) = E_1 + E_2$ and $f_2(\omega) = E_3$, where ω denotes a chromosome, i.e., weights of the neural controller. E_1 and E_2 are added together as the second component because they represent transient performance of undershooting and overshooting.

4. Simulations

We carried out computer simulations on the following two nonminimum phase systems to test the performance of the proposed control structure[6].

$$\frac{s-1}{s^2+7s+12} = \frac{s-1}{(s+3)(s+4)} \quad (7)$$

$$\frac{s-1}{s^2+1.7s-0.256} = \frac{s-1}{(s+2)(s-0.128)} \quad (8)$$

The first system has a nonminimum zero only and the second both nonminimum pole and zero. The sampling time of these systems are 0.05 sec. and 0.2 sec., respectively. As mentioned before, with only the PI controller, we cannot guarantee good performance and it is not easy to find out proper gains of the controller of the second system because of its inherent instability. We compared performance of the proposed controllers in OEP and MOEP approaches. As the inputs of the neural controller, we selected 6 components of $e(t)$, $e(t) - e(t-1)$, $e(t) * (e(t) - e(t-1))$ and each delayed value. We made use of 200 population for each approach. Figs.3 and 5 show the Pareto frontiers found by MOEP and a solution of OEP in the objective space. Although OEP provides faster convergent speed than MOEP, its solution is not a real optimal in the sense of multiobjective optimization. The solutions are far from the Pareto frontier and dominated. OEP may search a solution at a more complex landscape according to the weighting factors or end with premature convergence. And the convergent solution highly depends on the weighting factors or control parameters like mutation rate. Figs.4 and 6 show performance comparisons of each approach through the outputs of the controlled systems for each nonminimum phase system. Also, we can see the neural controller activate dominantly at the local region from Fig. 7. Table 1 provides final objective values of considered controllers for the given reference signals. Two solutions of MOEP 1 and 2 are non-dominated for each objective and can be chosen as the neural controller according to user's preference. Since MOEP provides a variety of optimal solutions and the compromise between them, user can easily select an solution pertinent to the final decision. Simulation results show that multiobjective optimization approach using EP is useful to effectively design the proposed neural controller.

5. Summary and Further Works

In this paper, we have proposed a parallel control architecture which consists of a conventional PID typed controller and a neural controller to control nonminimum phase systems. The nonlinear neural controller mainly activates to control the system in local operating region or local environment where the linear controller only cannot fulfill the given desired performance. The control objective is to minimize overall position errors as well as the undershooting simultaneously. Since this cost function causes a confliction between

Table 1: Performance Comparisons between two solutions(M1 and M2) of the Pareto frontier and a single solution of OEP. $E_{11} + E_{21}$ is the maximum magnitude of undershooting after falling and rising of the step response. System I and II are the controlled systems of (7) and (8), respectively.

	System I			System II		
	EP	M1	M2	EP	M1	M2
$F_1 \times 100$	12.6	8.0	3.9	20.8	13.6	7.6
F_2	144.4	142.2	173.6	36.5	34.8	39.9
$E_{11} + E_{21}$	4.0	4.0	1.9	6.6	5.0	3.6

each attribute, we cannot find the optimal solution which minimizes individual objectives simultaneously. Although EP can provide an optimal solution for the given weighted combination of the objectives, it may produce a dominated solution at the feasible region but not necessarily optimality because of the premature convergence. We have compared performance of a single EP and MOEP in a design of a neural controller for nonminimum phase systems. Computer simulations show that the MO technique using EP is very efficient in dealing with this kind of multiobjective problems. The proposed controller trained with MOEP provides a variety of optimal solutions which guarantee the successful improvement of the performance such as less undershooting and faster settling time. For a further work, it is necessary to develop a more effective cost function and MOEP algorithm.

6.Acknowledgment

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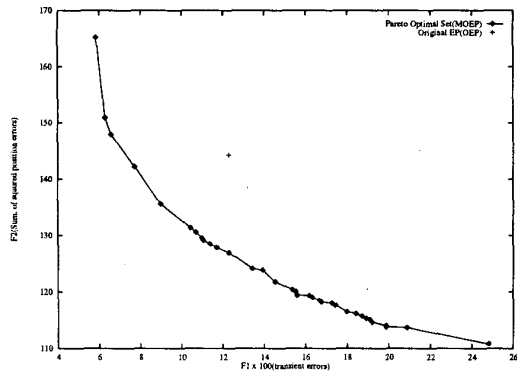


Figure 3: Pareto Optimal frontier found by MOEP and a solution of OEP for $\frac{s-1}{s^2+7s+12}$.

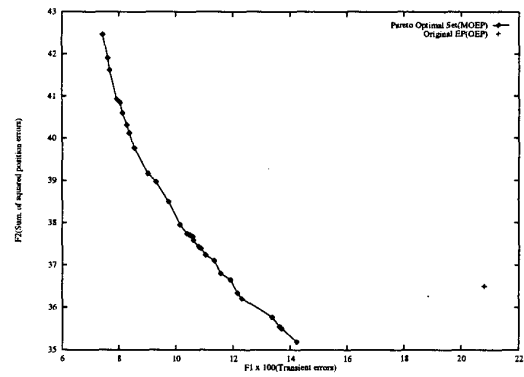


Figure 5: Pareto Optimal frontier found by MOEP and a solution of OEP for $\frac{s-1}{s^2+1.7s-0.256}$.

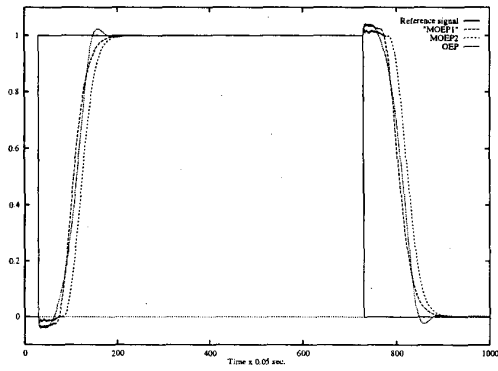


Figure 4: Performance of the proposed controller in OEP and MOEP. At OEP, the solution is obtained with $\alpha = 60$ and $\beta = 0.1$.

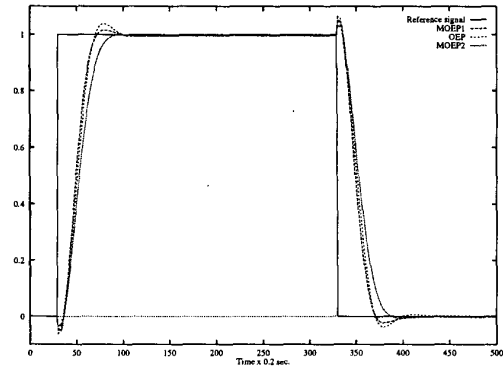


Figure 6: Performance of the proposed controller in OEP and MOEP. At OEP, the solution is obtained with $\alpha = 60$ and $\beta = 1$.

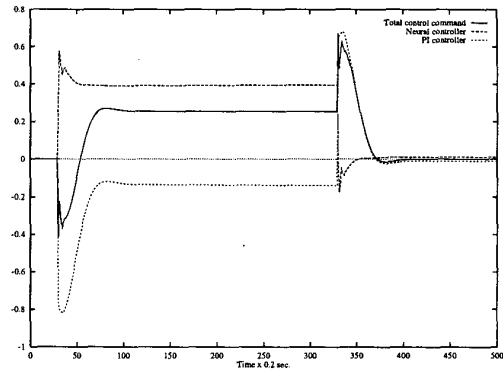


Figure 7: Torque profiles of the proposed controller when MOEP 1 is applied.