Development and Implementation of Brushless DC Motor Controllers Based on Intelligent Control

Jin-Hyun Park and Young-Kiu Choi

Abstract

This paper proposes an intelligent controller for brushless DC motor and load with unknown nonlinear dynamics. The proposed intelligent control system consists of a plant identifier and PID controller with varying gains. The identifier is constructed using an Auto Regressive Moving Average(ARMA) model. In order to tune the parameters of the identifer and the gains of the PID controller efficiently, we also propose a modified Evolution Strategy. Experimental results show that the proposed intelligent controller for brushless DC motor has good control performance under unknown disturbance.

I. Introduction

Evolutionary Algorithms(EAs) have become a very attractive way to search algorithms which imitate the principles of natural evolution as a method to solve parameter optimization problems[1, 2]. EAs have low possibility to be stuck on the local optimum points. Also, EAs do not require conditions such as continuities and derivatives, which are essential to the conventional hill climbing methods[1].

Evolution Strategy(ES), a kind of EAs, was developed at the Technical University of Berlin(TUB) in Germany by Rechenberg and Schwefel in the 1960s. Early ES may be recognized as evolutionary programs where a floating point number representation is used, with the mutation being the only recombination operator[2, 3]. Recently, it has been applied to various optimization problems.

ES is outstanding in finding the optimum points, but the search space is mainly confined within the region specified by the given standard deviation[2, 4].

If the standard deviation is large then the ES looks like a random search with no direction. If the standard deviation is small then the ES requires a very long search time for convergence. To resolve this problem, Rechenberg proposed a "1/5 success rule" [5], but it is not certain whether the 1/5 success rule has some advantages over the ES with constant standard deviation or not. In this paper, we propose a modified ES that adjusts standard deviation according to the shape of the fitness functions. If the fitness function is steep then the standard deviation should be small enough to make a precise search. If the fitness function is flat then the standard deviation may be increased to accelerate the search. Therefore, the proposed ES overcome the problems : the ES looks like a random search in case of the large standard deviation and requires long search time for convergence in case of the small standard deviation.

On the other hand, EAs have been successfully applied to various fields related with optimization such as the parameter tuning for control system[6-12]. But in the studies related with tuning the control parameters, the optimal control parameters are selected from the viewpoint of iterative or off-line experiments, therefore there can be a problem for the real time control. That is, it is difficult for the control system to deal quickly with a sudden disturbance or a change of plant parameters. We suggest an on-line intelligent controller using the modified ES.

The intelligent control system consists of plant identification part and PID controller with varying gains. The plant identification part composed of the Auto Regressive Moving Average (ARMA) model, is tuned in the on-line sense using the modified ES to reflect sudden disturbances and changes of plant parameters. Based on the identified plant parameters, we can find parameters of the PID controller with the most appropriate characteristics by using the modified ES.

Genetic Algorithm(GA)[9-12] may be used for tuning the ARMA model parameters and control parameters, although, it makes more drastic changes in parameter space than the ES, thus making control behavior less smooth. Also, the GA usually takes longer convergence time than the ES[2], hence the GA is less favorable than the ES to on-line control schemes. As a result, we make use of the ES for tuning operation.

Finally, real experimental results for the brushless DC motor and unknown nonlinear load show that under unknown distur-

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bance the proposed intelligent controller has better performance than the conventional PID controller with constant control gains.

II. Modified Evolution Strategy

Rechenberg and Schwefel introduced the ES as a simulating evolution to optimize functions[5]. Conventionally, the genetic operator used in the ES is a mutation. The individual is represented as a pair of float-valued vectors (x, σ). The first vector x denotes a point in the search space and the second vector σ designates standard deviation. The mutation operation is realized by the following equation.

$$x' = x + N(0, \sigma) \tag{1}$$

where $N(0, \sigma)$ is a vector of independent random Gaussian numbers with a mean of zero and standard deviation σ.

The offspring x' replaces its parent x if it has better fitness and all constraints are satisfied.

In the ES operation, the standard deviation σ plays an important role. If σ is large then the ES looks like a random search so that it has no direction, whereas if σ is small then the ES requires a very long search time for convergence. To resolve this problem, Rechenberg proposed a "1/5 success rule" [5]. The rule is applied to every l generations to have a new standard deviation σ' as follows.

$$\sigma' = \begin{cases} \delta\sigma & \text{if } P_s < 1/5 \\ \frac{1}{\delta}\sigma & \text{if } P_s > 1/5 \\ \sigma & \text{if } P_s = 1/5 \end{cases} \tag{2}$$

where P_s is the success ratio of the mutation operator during the last l generations, and $\delta > 1$ is the increase rate for the standard deviation.

It is not certain whether the 1/5 success rule has some advantages over the ES with constant standard deviation or not. So, in this paper, we propose a modified ES that adjusts standard deviation σ according to the shape of the fitness functions. If the fitness function is steep then the standard deviation σ whose role is similar to the step size, should be small enough to make a precise search. If the fitness function is flat then σ may be increased to accelerate the search. The following equations describe the proposed method.

$$\alpha = \frac{C}{f_{best} - f_{avg}} \tag{3}$$

where f_{best} and f_{avg} are the best and average fitnesses, respectively. C is a constant vector.

$$\sigma = \begin{cases} \alpha & \text{if } \alpha < \sigma_{max} \\ \sigma_{max} & \text{if } \alpha \geq \sigma_{max} \end{cases} \tag{4}$$

where σ_{max} is the maximum standard deviation.

Then the proposed ES overcome the problems : the ES looks like a random search in case of the large σ and requires long search time for convergence in case of the small σ.

III. Plant Identification and Control Parameters Tuning

In order to get the control action, first we do an on-line identification of the plant by using the ARMA model and then have an on-line tuning of the control parameters. This process repeats every sampling period. In order to tune the ARMA model parameters and control parameters the GA may be used, but it will make more drastic changes in parameter space than the ES, so the control behavior may not be smooth. The GA, also usually takes a longer convergence time than the ES[2]. As a result, the GA is less favorable than the ES to on-line control scheme. So we make use of the modified ES for tuning operation.

The ARMA model is represented as[13]

$$\begin{aligned} y(k) = {} & a_1 y(k-1) + a_2 y(k-2) + \cdots + a_n y(k-n) \\ & + b_1 u(k-1) + b_2 u(k-2) + \cdots + b_m u(k-m) \end{aligned} \tag{5}$$

where y(k) is the output and u(k) is the input at the k-th time step. n and m are constants.

The ARMA model parameters are constructed into a vector which is called an individual for the ES, and we find optimum parameters using the modified ES every sampling time. Fig. 1 illustrates the individual of the ARMA model parameters.

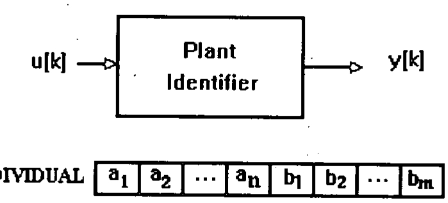

Fig. 1. Construction of the individual for the plant identification.

The ARMA model parameters are tuned with the input and output data of the actual plant from the past N-th step to the present step. Since the above tuning process is repeated every sampling time, the effects of the disturbances and the parameter variations of the plant can be well compensated, so that we can have a high adaptive control performance.

The fitness function for the plant identifier is represented as an inverse of summation of the squared output errors as follows.

$$f(x) = \frac{1}{1 + \sum_{i=k-N}^{k} e_x^2(i)} \tag{6}$$

where f(x) is the fitness function for the individual x which is a vector of ARMA model parameters. $e_x(i)$ is considered as the identification error at the i-th time step. k means the present time step. N is the number of the past data for fitness function.

The best identified plant model is used to compute the fitness of the controller. The controller has PID control structure which is simple and widely used. The control input of the plant is

$$u(k)=K_p e(k)+K_i T_s \sum_{i=0}^{k} e(k)+\frac{K_d}{T_s}[e(k)-e(k-1)] \qquad (7)$$

where T_s is sampling time. e(k) means the tracking error between the desired output $y_d(k)$ and actual output y(k), that is, e(k) = $y_d(k)$-y(k). K_p, K_i and K_d are the proportional, integral and derivative gains, respectively.

The gains of PID controller are packed into an individual as shown in Fig. 2 and are adjusted by the use of the identified plant model and the modified ES.

With the identified plant model, output predictions up to the future M-th time step can be made. Then we can compute the tracking errors up to the future M-th time step using the predicted outputs, since we have the desired output trajectory.

The fitness function for the controller is given as

$$g(\omega) = \frac{1}{1+\sum_{j=k}^{k+M} \varepsilon_{\omega}^{2}(j)} \qquad (8)$$

where $g(\omega)$ is the fitness function for the individual ω being a vector of PID control gains. $\varepsilon_{\omega}(j)$ is the predicted tracking error at the j-th time step. k is the present time step. M is the number of the predicted tracking errors.

Using the modified ES, the best individual can be found and used as the actual control gains. Fig. 3 depicts the configuration of the overall system. As explained earlier, we repeat the tuning operation for the parameters of the identifier(ARMA model) and PID controller gains every sampling time.

If the plant specifications are changed, the parameters of the identifier are adjusted to minimize the identification errors, so that the adjusted identifier will represent the changed plant. Based on the adjusted identifier, the PID controller gains are changed to minimize the tracking errors. Hence we can get the adaptive control performance.

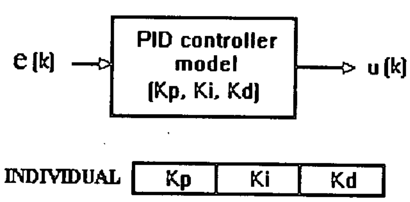

Fig. 2. Construction of the individual for the PID controller.

Ⅳ. Experimental Results

We apply the proposed algorithm to on-line velocity control of the brushless DC motor and show the propriety and usefulness of

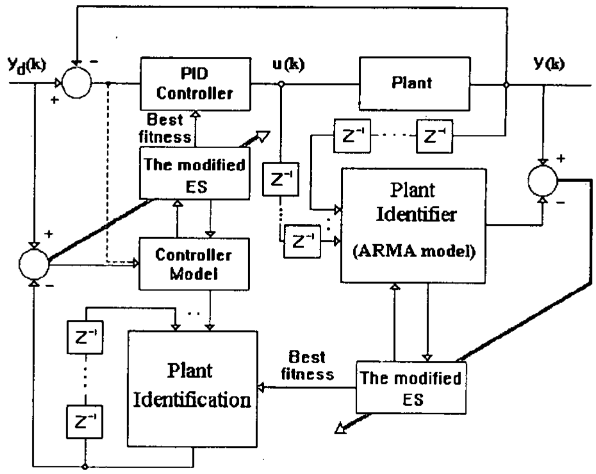

Fig. 3. Configuration of the proposed intelligent control system.

the control scheme. We execute the proposed algorithm by using a DSP board(TMS320C40) based on IBM PC 486-DX-66. The rated output of the brushless DC servo motor is 200W. And theload is a fan with unknown nonlinear characteristics. The sampling time Ts is 10m seconds. The hardware configuration for the control of the brushless DC motor is shown in Fig. 4. And the specifications of the brushless DC motor and load are given in Table 1.

In this study, we set n and m in the ARMA model (5) to be 3. The ranges of the PID controller gains are assumed to be Kp ∈[0, 0.2], Ki∈[0, 0.2] and Kd∈[0, 0.02]. The parameters of the modified ES for real experiments are as follows.

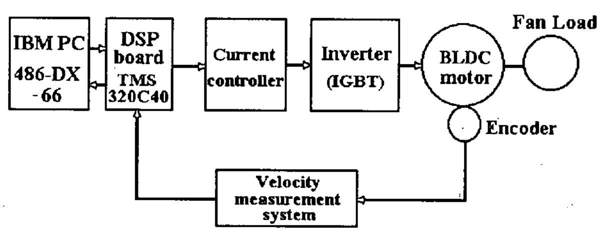

Fig. 4. The hardware configuration for the control of brushless DC motor.

Table 1. Specifications of brushless DC motor and load.

Brushless DC motor	Value
Rated Output(W)	200
Rated Torque(Nm)	0.65
Rated Speed(rpm)	3000
Shaft Inertia($\times 10^3$kgfcms^2)	1.7
Rated Voltage(V)	75
Rated Current(A)	3.3
Armature Resistor(Ω)	1.42
Torque Constant(Nm/A)	0.2156
Load	Unknown Nonlinear Fan

1. Parameters for the Plant Identification

- Population size : 26
- Maximum standard deviation σ_{max} : [0.01 0.01 0.01 0.01 0.01 0.01]
- Constant vector C in (3) : [0.01 0.01 0.01 0.01 0.01 0.01]
- Individual type : 6-dimensional real vector
- N (Number of the past data) : 5

2. Parameters for the Controller Tuning

- Population size : 26
- Maximum standard deviation σ_{max} : $[6.52*10^{-3}\ \ 6.52*10^{-3}\ \ 6.52*10^{-4}]$
- Constant vector C in (3) : $[6.52*10^{-3}\ \ 6.52*10^{-3}\ \ 6.52*10^{-4}]$
- Individual type : 3-dimensional real vector
- M (Number of the predicted data) : 5

Fig. 5 describes the velocity tracking performances for the proposed intelligent controllers based on the modified ES, 1/5 success rule ES, and constant standard deviation ES under the desired trajectory of a rectangular shape whose magnitudes are +800 and -800 rpm.

The initial PID gains Kp, Ki and Kd are 0.0038, 0.003 and 0.000001, respectively. The initial ARMA model parameters areselected to be [0 0 0 0 0 0]. From Fig. 5, we can find that the performance of the constant standard deviation ES is the worst, whereas that of the modified ES is the best. Although after 10 seconds the performance of the 1/5 success rule ES is almost the same as that of the modified ES, the tracking error of the 1/5 success rule ES is larger compared to that of the modified ES in the initial phase. So it is reasonable to use the modified ES as the parameter tuning algorithm for the proposed intelligent controller.

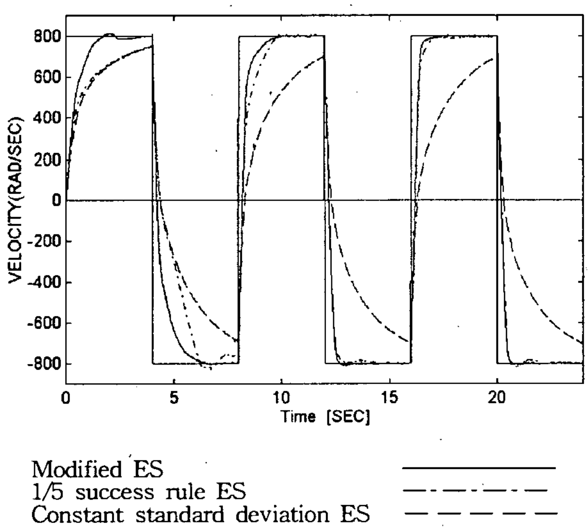

Fig. 5. Comparison of tracking velocities for the proposed intelligent controllers based on the modified ES, 1/5 success rule ES, and constant standard deviation ES.

To see the adaptability of the proposed control method to the unknown disturbance, we imposed a constant disturbance of 0.646 Nm on the plant from 8 seconds to 32 seconds. Fig. 6 illustrates the performances of 2 controllers : the proposed controller with the modified ES, and the conventional constant PID controller. The trends of controller gains are shown in Fig. 7. The control gains of the constant PID controller Kp, Ki and Kd are 0.017, 0.0135 and 0.000001, respectively. These gains were chosen as the approximations to those of the proposed intelligent controller without disturbance. From 8 seconds to 32 seconds, the control performance of the constant PID controller has deteriorated since

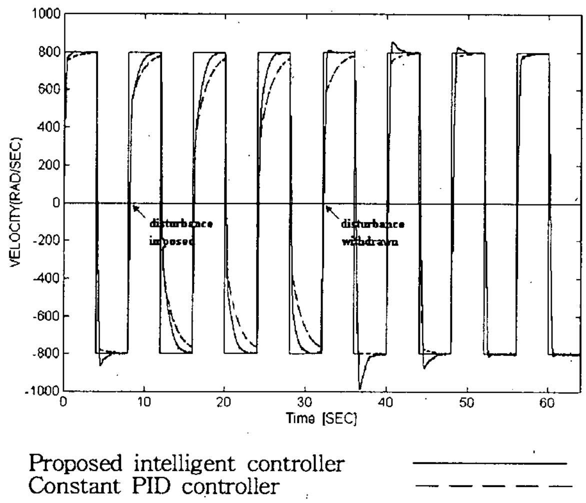

Fig. 6. Tracking velocities for the proposed intelligent controller based on the modified ES, and constant PID controller under the disturbance of 0.646 Nm.

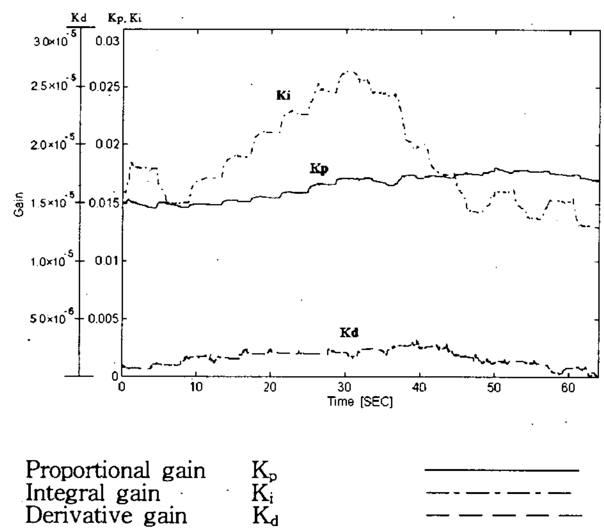

Fig. 7. Gain trends of the proposed intelligent controller based on the modified ES under the disturbance of 0.646 Nm.

the applied disturbance changes the characteristics of the plant, however, the proposed method has gradually improved tracking performance. When the disturbance is imposed at 8 seconds, the control gains are not large enough to handle the disturbance, therefore, the tracking error is increased. However, as time goes by, the identifier is adjusted to reflect the effects of the disturbance so that the controller gains are gradually increased. As the result, the tracking error becomes decreased. When the disturbance is withdrawn at 32 seconds, the control gains are regarded to be excessive so we have some overshoots. Gradually the gains become decreased through the tuning process. Experimental results show that the proposed control method has the adaptability to the unknown system with disturbance, and the proposed modified ES is more efficient than the conventional ES with 1/5 success rule or constant standard deviation.

V. Conclusions

In this paper, we effectively have applied the ES to intelligent control for a nonlinear dynamic system. For this purpose, we modified the ES to improve the convergence property, and we achieved intelligent control system where the modified ES is used as the tuning algorithm for the plant identifier and controller.

Real experimental results for brushless DC motor and unknown nonlinear load have found that the proposed intelligent control system changes its control parameters adaptively and show adaptable performance under the changing circumstances of the system.

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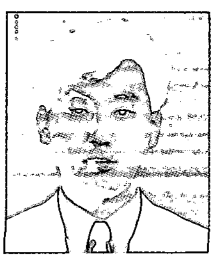

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