A STUDY ON THE COMPUTER AIDED TESTING AND ADJUSTMENT SYSTEM UTILIZING ARTIFICIAL NEURAL NETWORK

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Abstract

In this paper, an implementation of neuro-controller with an application of artificial neural network for an adjustment and tuning process for the completed electronics devices is presented. Multi-layer neural network model is employed with the learning method of error back-propagation. For the intelligent control of adjustment and tuning process, the neural network emulator (NNE) and the neural network controller (NNC) are developed. Computer simulation reveals that the intelligent controllers designed can function very effectively as tools for computer aided adjustment system. The applications of the controllers to the real systems are also demonstrated.

1. INTRODUCTION

Application of artificial neural network to the control problems with an algorithmic form of computer control method has the practical merit of sustaining quality improvement and also robustness for the variation of control environment by virtue of its adaptive learning capability. Traditional techniques of controller design is based on the linearized or discretized model of plant under control in order to accomodate the control objectives. Therefore, robustness about the uncertainty of modelling error is to be restrictive and the extension of robustness is the object of intelligent control.

With the application of neural networks, the control problem can be now considered as a problem of pattern recognition, in which the patterns to be recognized are "change" signals that will be mapped into "action" signals for specified system performance. The intelligent controller should recognize and isolate patterns of change in real time and "learn" from experience to recognize change more quickly, even with incomplete data. The properties of pattern recognition and mapping with ever-improving self-organization and decision making are some of the potential advantages in using artificial neural networks for design and implementation of intelligent controllers[1].

The aim of control in adjustment and tuning process is to perform the adjustment of variable elements by operating rule for the measured waveform of testing point to fit in the predefined criteria. The adjustment and tuning process under control may be characterized as follow. At first, the initial values of variable element under adjustment differ on each product in the same model. And the extent of variation in input/output transfer function depends on the range of error in related elements. Furthermore, there is nonlinearity in input/output relation. Measurements of output waveform and automatic drive of variable element should be considered in the entire organization of computer aided adjustment system. Since the start/stop time of drive motor is fixed, it is desired that the intelligent control should be able to appropriately tackle the these characteristics within the limits of tolerence and to generate the minimum number of control signals to achieve successive control objectives. The present work is to focus on the application of artificial neural network to the development of the intelligent control of computer aided testing and adjustment system.

2. COMPUTER AIDED TESTING AND ADJUSTMENT SYSTEM

The computer aided testing and adjustment system of a SAMSUNG Electronics Co. (Fara WAT-CT1) is used in the present study. A hardware organization of the system is shown in Fig.1[2]. Variable coils of the electronic product under manipulation is adjusted automatically for the output waveform of testing point observed by oscilloscope in order to fit in the predefined criteria. In manual operation, adjustment criterion is determined by required time in complete adjustment within the predefined range. The value to be adjusted during the adjustment is inferred from a whole picture of oscilloscope. When this operation is to be automated in real time, it may not be proper to utilize the whole

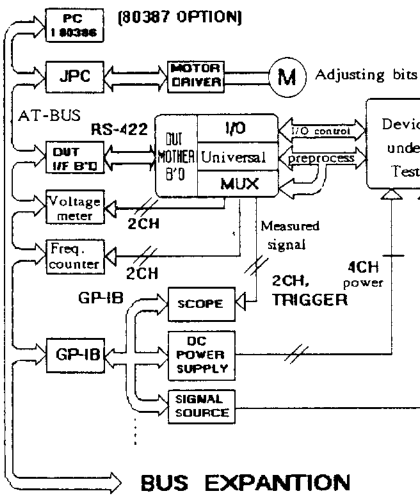
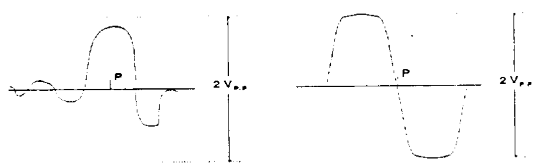


Fig.1 Hardware organization of computer aided testing and adjustment system

picture of oscilloscope and it is appropriate to use the computer control mathod. In the whole picture of oscilloscope, d.c. level of the point under observation in oscilloscope is merely assumed as the output of plant and automatic adjustment is carried out based on this value. The test for automatic adjustment using the system of Fig.1 is grouped into two parts. First, it is to adjust coil(a) automatically until the picture in FIg.2 from the oscilloscope of equivallent point(TP1) on chassis shows the desired shape indicating zero at point P. Fig.2(a) and (b) show the measured pictures at TP1 before and after adjustment of coil(a), respectively. Fig.3 shows the measured data at point P. Second, it is to adjust coil(b) automatically until the picture in Fig.4 from the oscilloscope of equivalent point(TP2) on chassis shows the desired shape, indicating that the value at point P is equal to that at point C. Fig.4(a) and (b) show the measured pictures at TP2 before and after adjustment of coil(b), respectively. Fig.5 shows the measured data at point P and point C. For the automated adjustment processes mentioned above, the facility which extracts the change in coil needed for adjustment with the measurement of their points is desired. And there are two additional points to be considered. The first is accidental error between coil and adjusting bit in the circumstance of reverse turn. The second is the irregularity of relation between the change of coil and the output values at corresponding point.



(a) before adjustment (b) after adjustment

Fig.2 Waveform of appropriate point(TP1) for process(A)

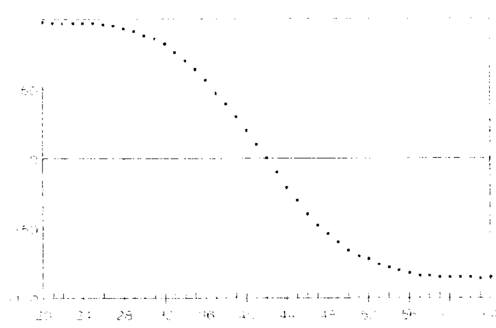
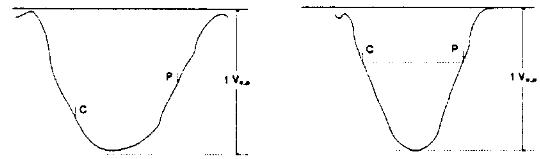


Fig.3 P point output variation of appropriate point(TP1) for process(A) by coil(a)



(a) before adjustment (b) after adjustment

Fig.4 Waveform of appropriate point(TP2) for process(B)

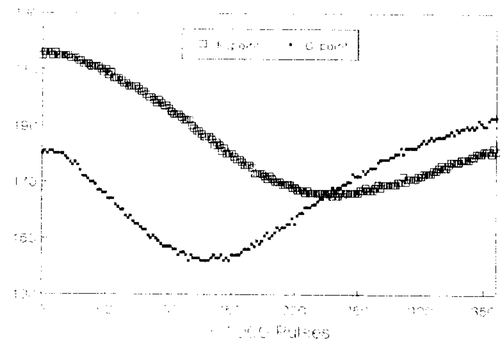


Fig.5 C_point and P_point output variation of appropriate point(TP2) for process(B) by coil(b)

3. UTILITY OF NEURAL NETWORK

The model dynamics in the relation between the change of coil and the output value at corresponding point is

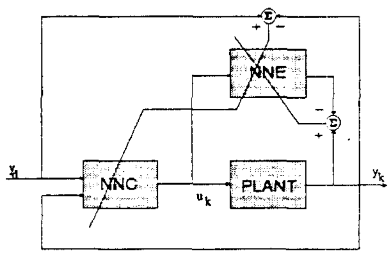


Fig.6 Control block diagram

characterized by nonlinear function f of eq.(1), where y_k is the output value of corresponding point at time k, and u_k is the change of coil at time k.

$$y_k = f(\Sigma_{i=0,k}u_i) \tag{1}$$

In order to adjust this process automatically, g function of eq.(3) which obtains the amount of change in coil for the minimization of loss function J_C in eq.(2) is required.

$$J_C = \tfrac{1}{2}(y_d - y_k)^2 \tag{2}$$

$$u_k = g(y_d, y_{k-1}) \tag{3}$$

where y_d and y_k are the desired and plant outputs of point P at time k.

The nonlinearity of f and g functions can be generated by multilayer neural network[3] through the learning algorithm of error back-propagation[4]. The proposed control system with artificial neural network for automated adjustment is shown in Fig.6, which includes the neural network emulator (NNE) as well as the neural network controller (NNC). The control system is composed of one input layer, one hidden layer of nonlinear sigmoidal output function, and one output layer with linear output function. The learning of NNE and NNC is carried out for two steps and initially off line.

3.1 Adaptation to environment

The NNE (neural network emulator) is described here. Information obtained from adjustment includes the initial output value, and the varied input value and corresponding output value at that time. The initial input value can be regarded as the change in environment. When either the inverse plant dynamics is known or the exact plant modelling is possible, the adaptive control technique for parameter estimation process can be employed as a control strategy with respect to the initial value of a parameter, which acts on the equations for plant model. However, in order to deal with the circumstances of input/output processing of the information about plant known as black box, with nonlinear characteristics and the least generating control command, an intelligent control with self-learning capability is more suitable than adaptive control. Therefore, the plant characteristics which enable to cope appropriately the random type of initial output value can be realized by means of neural network. The capability of neural network which reveals the same characteristics of plant is of considerable value in obtaining the plant Jacobian. In order to estimate plant using neural network, the network with two inputs and one output as given in eq.(4) can be used in process(A). Eq.(4) uses one control input and the plant output at the preceding step for plant model.

$$y_k = N_E^A[u_k, y_{k-1}] \tag{4}$$

One control input and two plant outputs at the preceding step are used by eq.(5) in plant modelling of process(B). The neural network of three inputs and two outputs is given by eq.(5).

$$[y^{11}_k, y^{12}_k] = N_E^B[u^1_k, y^{11}_{k-1}, y^{12}_{k-1}] \tag{5}$$

The advantages of neural network modelling are summarized as below:

1) Simple modelling of the plant with random initial value.
2) Backlash between adjusting tip and variable element is implemented easily by direct use of plant input and output signal in learning by the neural network.

In general, the long time for learning becomes a problem in real system application of neural network. However, the present study avoides it by reducing the amount of learning pertaining to automated adjustment process, which includes off line learning of plant dynamics for any chassis and on line learning with automated adjustment.

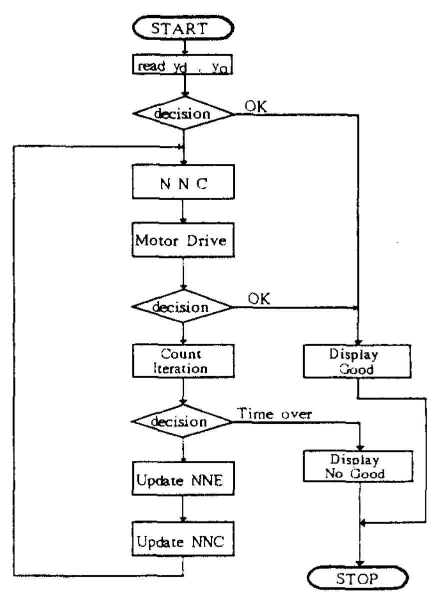


Fig.7 Flow chart for intelligent control

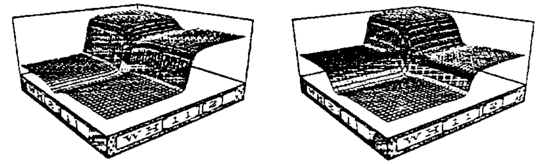
3.2 Decision making

The neural network controller (NNC) is described here. It can be regarded as a sequence of inference that generates new control command to adjust automatically for control action. Inference process includes the generation of a desired control command for attaining the predetermined objective and adapting the difference between the expected plant output and the one generated from control command. Therefore, by means of the neural network with the ability of pattern recognition and learning capability for control command generation and adaptation, the intelligent control for which the conventional control method expects its future solution can be obtained. Control command can be generated by modelling the inverse plant dynamics, the neural network controller (NNC) should learn the inverse plant dynamics. The off line learning of the inverse plant dynamics for any chassis by NNC will get its initial weights in automated adjustment. The off line learning of NNC is not able to adapt the environment of new chassis. The NNC in Fig.6 should have the capability of inference which adapts the difference between the expected output and plant output as in NNE. The characteristics of new chassis may be learned by NNC on line in the automated adjustment. In this case, teaching signal is needed and it is necessary to map the difference at plant output in terms of the difference at control command. For the Jacobian of the plant given, we can find the difference by considering the plant as a augmented layer of neural network[5]. Otherwise, we can use the method of back-propagation for the output error through the NNE without finding derivatives of plant. In process(A) the NNC of $u_k = N_C^A[y_k, y_{k-1}]$ and in process(B) the NNC of $u_k = N_C^B[y^1_{k-1}, y^2_{k-1}]$ can be organized. With off-line learning, these NNC are used with NNE in block diagram of Fig.6 with the flow chart shown in Fig.7.

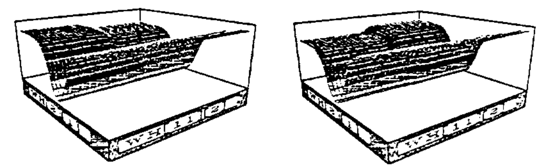
4. SIMULATION AND EXPERIMENT

4.1 Adaptation to environment

A random initial output of plant is considered as a change in environment. After modelling the plant under adjustment as in eq.(4) and (5), the transition of MSE(mean square error) in the plant output for 100 arbitrary selected input/output patterns is observed while learning is proceeded. In the plant model of eq.(4), the input/output patterns are selected based on data in Fig.3 and in the plant model of eq.(5), Fig.(5) is employed for selecting input/output patterns. In order to visualize the transition of MSE surface in weight space of learning by each neural network, MSE surface on any two weights in neural network is investigated. In this case, xy surface is composed of two weights and z axis represents MSE value at that point. As learning is proceeded, MSE value at the center of xy surface rerveals the more small value. In Fig.8 and 9, the MSE surfaces of

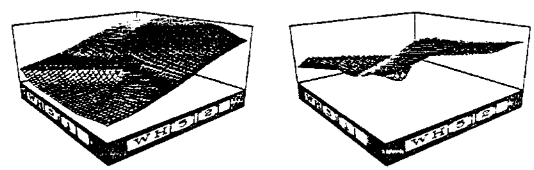


(a) Initial weights (b) After 50,000 iterations

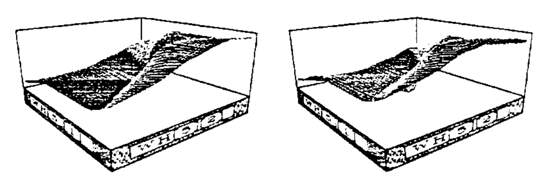


(c) After 200,000 iterations (d) After 300,000 iterations

Fig.8 Alteration of MSE surface through learning iterations in model of eq.(4)



(a) Initial weights (b) After 50,000 iterations



(c) After 200,000 iterations (d) After 300,000 iterations

Fig.9 Alteration of MSE surface through learning iterations in model of eq.(5)

Table 1. MSE value of NNE with iterations of learning

	Number of iterations for learning			
	initial	50,000	200,000	300,000
N_E^A	0.719591	0.325856	0.041018	0.036464
N_E^B	4.678664	0.168392	0.012781	0.007028

initial state with 50,000 iterations, 200,000 iterations and 300,000 iterations using eq.(4) and (5) are illustrated. Table 1 shows the value of MSE at each iteration for two neural network emulators.

4.2 Decision making

In order to generate the desired control command to achieve predetermined target in control block diagram of Fig.6, the NNC learned the inverse dynamics of plant. As discussed previously, for 100 arbitrary selected input/output patterns for any one plant, the values of MSE at each iterations for two NNCs are given in Table 2. With this initial off line learning of NNC and NNE, the on-line learning with automated adjustment is performed with the algorithm given in Fig.7 to adapt the plant dynamics. Fig.10 and 11 show the result of automated adjustment of process(A) and process(B) for 500 chassis that have different initial output value. Fig.10 shows that mean iteration number for adjustment is 3.222 while Fig.11 shows 4.104.

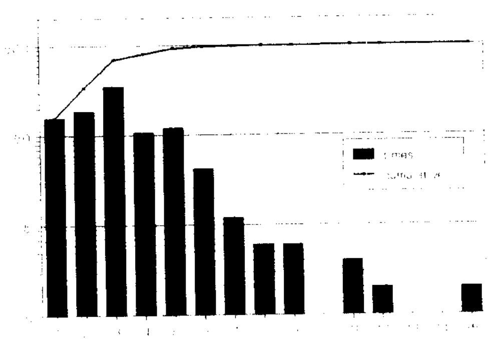


Fig 10 Number of iterations required for adjustment using the neural network for process(A)

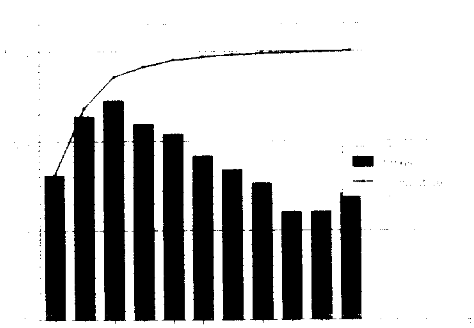


Fig.11 Number of iterations required for adjustment using the neural network for process(B)

Table 2. MSE value of NNC with iterations of learning

	Number of iterations for learning			
	initial	50,000	200,000	300,000
$N_C{}^A$	21.71775	0.042067	0.005601	0.002816
$N_C{}^B$	42.73894	0.349318	0.070409	0.060846

5. CONCLUSIONS

In this paper, a computer aided control of an adjustment process for the completed electronic devices by means of an application of artificial neural network is presented. Intelligent control required in automated adjustment is defined. Computer simulation, as well as the application to the real situation, is accomplished. The results obtained in this study are as below: (1) the plant under automated adjustment is modelled using NNE. (2) the initial plant output can be considered as a change in environment. (3) the backlash which is common in electric/mechanical system can be considered easily by intelligent control utilizing neural network. (4) the inference process of operator can be recognized by learning using neural network.

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