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A Biologically Inspired Adaptive Nonlinear Control Strategy for Applications to Powertrain Control

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Abstract*— In this paper, an adaptive nonlinear control strategy derived from a biological control system is developed and its applications to the automotive engine are presented. The biological adaptive nonlinear control strategy inspired by the functions of baroreceptor reflex is realized by a parallel controller. The controller consists of a linear controller and a nonlinear controller that interact via a reciprocal lateral inhibitory mechanism. The linear controller design is based on a PID controller, while the nonlinear controller is constructed from neural networks which are updated online. In order to provide superior control performances, the controller must be robust to external unknown disturbances, un-modeled dynamics and plant uncertainties and also be able to perform well under a wide range of operating conditions. In the linear operating region, the linear controller takes control. If the controlled process is far away from the linear regime or is disturbed by the noise, the output of linear controller may be inappropriate, and therefore the nonlinear controller is activated to compensate for the inadequacy of the linear controller in a dynamic environment and in the presence of distances and process parameter variations. These situations can be addressed by adjusting the amount of lateral inhibition and learning the characteristics of the controlled system such that desirable controller outputs are produced in any particular operating region. The novelty of the biological adaptive nonlinear control strategy is that each controller modulates the other controller via the reciprocal lateral inhibitory connections. The good transient performance, computational efficiency, real-time adaptability and superior learning ability are illustrated through extensive numerical simulations for engine torque management driven by the biological adaptive nonlinear control strategy.

I. INTRODUCTION AND BACKGROUND

Biological processes have evolved sophisticated mechanisms for solving difficult control problems with precise control abilities, robust stability and strong fault tolerance. By analyzing and understanding these natural systems, it is possible that principles can be derived which are applicable to general control systems. The methodologies based on the inspiration of some biological mechanism include: Artificial Neural Network (ANN), Genetic Algorithm (GA), Artificial Immune System (AIS), etc. The ANN, GA and AIS have been researched for quite a long time by many researchers and are being widely employed ([1], [2], [4], [7], [8], [10], [14]). However, due to the high complexity and the scarce cognition of biological prototype, there are still many open problems under consideration, such as the processing mechanism of the each part of the brain. Even so, it is believed that control techniques derived from biological systems offer great potential for solving complex and nonlinear problems in the modern field of control.

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The peripheral autonomic nervous system functions in a dynamic balance aiming at homeostasis. It is divided into two nervous systems: the parasympathetic nervous system and the sympathetic nervous system ([19]).

The sympathetic system originates from the thoracic and upper lumbar spinal segments, while the parasympathetic system originates from the brain stem and sacral spinal cord. Both systems are efferent and consist of a chain of preganglionic and postganglionic neurons, which are synaptically connected in peripheral autonomic ganglia. Sympathetic ganglia are situated remote from the target organs and organized bilaterally in the sympathetic chains and in the prevertebral ganglia. Parasympathetic ganglia are situated close to the target organs. Stimulation of sympathetic neurons produces many distinct effector responses elicited from a variety of cell and tissue types including blood vessels, heart, exocrine epithelia, etc., while stimulation of parasympathetic neurons leads to activation of most exocrine glands, pacemaker and atria of the heart, and some other target cells ([11]).

The baroreflex is responsible for short-term regulation of arterial blood pressure ([16])though recent research in ([18]) point out that baroreceptors are also important for the regulation of long-term mean arterial blood pressure. It provides a negative feedback loop in which an elevated blood pressure reflexively causes blood pressure to decrease; similarly, decreased blood pressure depresses the baroreflex, causing blood pressure to rise.

Regulation of arterial blood pressure by baroreceptor reflex would be regarded as tracking a desired curve or value. When blood pressure rises, the carotid and aortic sinuses are distended, resulting in stretch and therefore activation of the baroreceptors. Active baroreceptors fire action potentials that are relayed to the nucleus of the tractus solitarius (NTS), which uses frequency as a measure of blood pressure. The increased activation of the NTS inhibits the vasomotor center and stimulates the vagal nuclei. The end result of baroreceptor activation is inhibition of the sympathetic nervous system and activation of the parasympathetic nervous system. Sympathetic inhibition leads to a reduction of total peripheral resistance and cardiac output via increased contractility of the heart, heart rate, and arterial vasoconstriction, which tends to decrease blood pressure. At the same time, parasympathetic activation leads to a decreased cardiac output via decrease in contractility and heart rate, resulting in a tendency to decrease blood pressure.

By coupling sympathetic inhibition and parasympathetic

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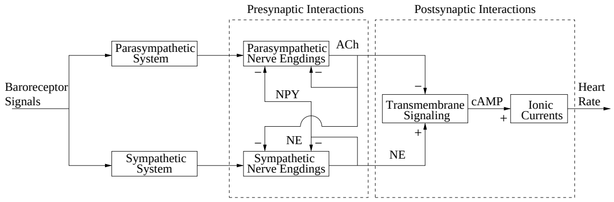

Fig. 1. Parasympathetic and sympathetic manipulation of heart rate

activation, the baroreflex maximizes blood pressure reduction. Sympathetic inhibition leads to a drop in peripheral resistance, while parasympathetic activation leads to a depressed heart rate and contractility. The combined effects will dramatically decrease blood pressure to the normal level. Similarly, sympathetic activation with parasympathetic inhibition allows the baroreflex to elevate blood pressure to the desired level.

A particularly distinctive feature of the baroreflex is the interactions that occur between the parasympathetic and sympathetic systems at the level of the cardiac pacemaker cells ([12], [13]). A simplified representation is shown in Figure 2. The two controllers adjust heart rate by releasing neurotransmitters from nerve fibers. Acetylcholine (ACh) is released from parasympathetic nerve endings, while norepinephrine (NE) and neuropeptide Y (NPY) are released from sympathetic nerve endings. ACh and NE bind to receptors on the surface of cardiac pacemaker cells, thereby altering the production of second messenger cyclic AMP (cAMP). cAMP affects heart rate by modulating ionic currents in pacemaker cells. Note that the overall effects of the sympathetic and parasympathetic systems on heart rate are facilitatory and inhibitory, respectively.

Complex interactions occur before and after the synapses between the nerve endings and the cardiac cells. Presynaptically, ACh inhibits the release of NE from sympathetic nerves, while NPY inhibits the release of ACh from parasympathetic nerves. Postsynaptically, ACh inhibits the production of CAMP and therefore diminishes the heart rate response to a given level of NE. In addition, parasympathetic nerves have ACh autoreceptors which subserve a negative feedback function; analogous NE autoreceptors are present in sympathetic nerves. This inhibition mechanism depicted in Figure 2 is present in other biological control systems, including the vestibulo-ocular reflex (VOR) ([17]) and the auditory system ([15]).

The regulation by reciprocal lateral inhibition of sympathetic and parasympathetic nervous systems exhibit the following interesting control characteristics:

1) The sympathetic and parasympathetic nervous systems have opposite effects.
2) The effects of the parasympathetic nervous system are considerably faster than those of the sympathetic nervous system.
3) The parasympathetic nervous system is employed only for dynamic control, while the sympathetic nervous system is used primarily for steady-state control.
4) The effects of the two nervous systems do not sum linearly due to complex interactions which occur in both the autonomic nervous system and the heart itself.

This body's homeostatic mechanisms and characteristics for maintaining blood pressure at the desired value showed superior performances in the highly complex cardiovascular system, which proves baroreceptor reflex is an adaptive, nonlinear, multivariable control system. Thus, it is potentially suitable to develop an effective control strategy based on the mechanism of baroreceptor reflex for the control of such nonlinear dynamic processes as engine torque and air-fuel ratio generation processes.

II. ADAPTIVE NONLINEAR CONTROL STRATEGY

From the optimal control views, the role of parasympathetic nervous system is to refine the performances of the sympathetic nervous system by discovering optimal corrections to be added to the output of whole neural control system.

The proposed adaptive nonlinear control strategy (ANCS) derived from a biological control system consists of a linear controller and a nonlinear controller which interact via a reciprocal lateral inhibitory mechanism as shown in Figure 3, where Y is the control output, U is the control command, Y_{sp} is the target. The control system has three components: a linear controller, an adaptive nonlinear controller, and a summation that produces U from the outputs of the two parallel controllers (U_1, U_2). By analogy to the baroreflex, the linear controller plays role of the parasympathetic system, the nonlinear controller plays the role of the sympathetic system, and the summation represents the postsynaptic interactions. Note that each controller modulates the other controller via reciprocal lateral inhibitory connections.

The control output of the linear controller to the nonlinear controller is regarded as a complex expression of the error of the controlled plant in the way that includes the integral of the errors, the derivative of the errors and the proportional error. These three terms represent the whole history of errors, the nonlinear trend of the change of the error and the current error, respectively. Using error information provided, the nonlinear controller would, in a sense, see the possible situation of the system and know the compensation will be input to the controlled plant by the other controller. In this way, the nonlinear controller learns the characteristics of the plant and adjusts itself according to the other linear controller. What's more, in the nonlinear operating regions or the situation with disturbance, the linear controller may be inappropriate, and therefore, the nonlinear controller is added to compensate the insufficiency of the linear controller and the dynamic environment such as the parameter variations of the process and disturbances. These situations can be addressed by adjusting the amount of lateral inhibition and learning the characteristics of the controlled system such that desirable controller outputs are produced in particular operating regions.

The linear controller learns the action of the other controller by watching an input from the nonlinear controller. The adjustable parameter attached to this input increases the degree of freedom of the linear fixed controller.

By coupling linear controller and nonlinear controller, the whole controller adjusts the output of the controlled plant.

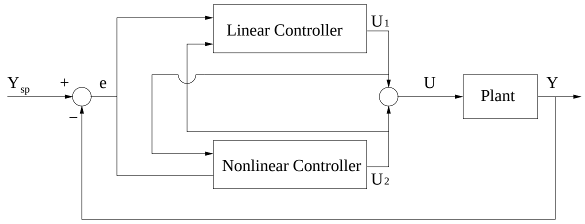

Fig. 2. Biological Inspired Control System

The linear controller leads to a basic control output, while the nonlinear controller refines the performances of the linear controller. The combined effects will dramatically increase the systems learning ability and adjustability to the noisy environment.

A. Linear Controller Design

The possible linear controller would be a proportional-integral-derivative controller (PID controller). The PID controller is a generic control loop feedback mechanism widely used in industrial control systems. The PID controller attempts to correct the error between a measured process variable and a desired setpoint by calculating and then outputting a corrective action that can adjust the process accordingly.

The PID controller algorithm involves three separate parameters; the Proportional, the Integral and Derivative gains. The Proportional gain determines the reaction to the current error, the Integral determines the reaction based on the sum of recent errors and the Derivative determines the reaction to the rate at which the error has been changing.

The general form of the PID controller in the time domain is:

$$U_{pid} = K_p e(t) + K_i \int e(t)dt + K_d \dot{e}(t) \quad (1)$$

where $e(t)$ is tracking error between the target and the actual output of the controlled plant, K_p is proportional gain, K_i is integral gain and K_d is derivative gain. By tuning the three gains in the PID controller algorithm, the PID can provide control action designed for specific process requirements.

The modulatory effect of the nonlinear controller is incorporated by adding an interaction term to the linear PID controller. The form of the PID controller with reciporcal lateral impact is:

$$U_1 = U_{pid} + K_1 U_2 \quad (2)$$

where U_2 is the control output of the nonlinear controller, K_1 is a lateral impact weight which determine the amount of the lateral impact from nonlinear controller.

B. Nonlinear Controller Design

The nonlinear controller is designed without the aid of an explicit dynamic model. The motivation for this approach is that nonlinear models are much more difficult to obtain than linear models. The controller could be chosen to have the following form:

$$U_2 = f(e, \dot{e}) + K_2 U_1 \quad (3)$$

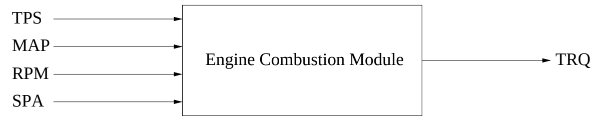

Fig. 3. The model structure of the test engine

where $f(e, \dot{e})$ represents a neural network which would be chosen according to the specific control goal and K_2 is another lateral impact weight which determine the amount of the lateral impact from linear PID controller.

The control law from equation (4) would be represented as:

$$U_2 = y^T(e, \dot{e})\omega + K_2 U_1 \quad (4)$$

where $y^T(e, \dot{e})$ is the regressor vector and ω is the vector of nonlinear controller parameters. The objective is to adapt the nonlinear parameters (ω) and lateral impact weight (K_1, K_2) such that the system output matches the target.

III. SIMULATION RESULTS OF ANCS OF A V8 ENGINE

A. Engine Description

A test vehicle with a V8 engine and 4-speed automatic transmission is instrumented with engine and transmission torque sensors, wide-range air-fuel ratio sensors in the exhaust pipe located before and after the catalyst on each bank, as well as exhaust gas pressure and temperature sensors. The vehicle is equipped with a dSpace rapid phototyping controller for data collection and controller implementation. Data is collected at each engine event under various driving conditions, such as Federal Test Procedure (FTP cycles), as well as more aggressive driving patterns, for a length of about 95,000 samples during each test. The engine is run under closed-loop fuel control using switching-type oxygen sensors. The dSpace is interfaced with the powertrain control module (PCM) in a by-pass model.

B. Control Objectives

The objective of the present engine controller is to provide control signals so that torque generated by the engine will track the torque measurement as in the data. The measured values in the data are obtained using the commercial engine controller under warmup conditions. Based on the data collected we use the neruo-sliding mode controller to generate control signal TPS (throttle position) with the goal of producing exactly the same torque as in the data set. That is to say, we keep our system in the same requirements as the data collected and build a controller that provides control signal which achieve the torque performance of the engine. The performance is defined as variations of the torque generated from the measured values in the data set.

C. Engine Model

We consider a model of the test engine shown as in Figure 4: The model structure chosen here is compatible with the

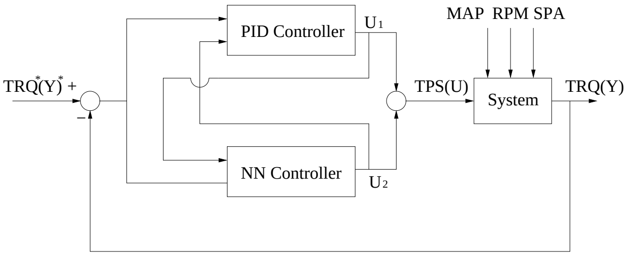

Fig. 4. The proposed control system

mathematical engine model developed by Dobner [5], [6] and others.

The engine model is constructed by a two-layers feedforward neural network with four inputs: TPS, MAP (manifold pressure), RPM (engine speed) and SPA (spark advance) where TPS is the control signal and the other three inputs are reference signals. In this structure, the output variable is the measured engine torque (TRQ).

D. Control Algorithm

The structure of the torque control system is shown in Figure 5. The control system consists of three components: a linear controller, an adaptive nonlinear controller, and a summation that produces TPS, command signal, from the outputs of the two parallel controllers (U_1, U_2). By analogy to the baroreflex, the linear controller plays role of the parasympathetic system, the nonlinear controller plays the role of the sympathetic system, and the summation represents the post-synaptic interactions. In Figure 5, TRQ* is the desired TRQ to be tracked by the parallel biologically inspired controllers system, TPS is the command signal which is formed by the sum of U_1 and U_2. The two controllers interact via reciprocal lateral inhibitory connections, that is, U_1, the output of PID controller, is one of inputs of neural network controller while U_2, the output of neural network controller, is incorporated in the PID controller. The idea of coupling controller is the tracking error of the system is asymptotically convergent to zero by two linear and nonlinear controller cooperating with each other using the feedback control output of the each controller. When the error of the system is zero, since the input of the PID controller from the NN controller is not zero, the output of the PID controller will not be zero either. The same rule applies to the NN controller. In this way, the system is controlled to track the desired TRQ in the normal situation. When there is disturbance in the system, the PID controller and NN controller will cooperate with each other to pull the disturbed system back to the normal situation. The linear PID controller could take the following form:

$$U_1 = K_p e(t) + K_i \int e(t)dt + K_d \dot{e}(t) + K_1 U_2 \qquad (5)$$

where $e(t) = Y^*(t) - Y(t)(TRQ^*(t) - TRQ(t))$ and K_p, K_i, K_d, K_1 are proportional gain, integral gain, derivative gain and lateral impact weight respectively. The lateral impact weight K_1 is tuned by adaptive learning algorithm.

The nonlinear controller would have the following form:

$$U_2 = f(e, \dot{e}, U_1) \qquad (6)$$

where $f(e, \dot{e}, U_1)$ represents a feedforward neural network with inputs: the error, the derivative of the error and the control output of the PID controller. Here, the control output of the PID controller is incorporated into the neural network with more parameters to be tuned which have the same effect as equation (4).

The weight adaption of the adaptive nonlinear control strategy is based on a minimization of the cost function as follows:

$$E = \frac{1}{2}(Y^* - Y)^2 = \frac{1}{2}\zeta^2 \qquad (7)$$

where $\zeta = Y^* - Y$.

The Levenberg-Marquardt (L-M) algorithm is used to update the weights of feedforward neural network instead of the backpropagation algorithm which is a steepest descent algorithm. The selection of L-M algorithm is based on the fact that the L-M algorithm is widely accepted as the most efficient one in the sense of realization accuracy for nonlinear least squares [9].

The formula for updating neural network weights is given as follows:

$$\triangle W = [J^T(W)J(W) + \mu I]^{-1} J^T(W)\zeta \qquad (8)$$

where the parameter μ is adjustable and $J(W)$ is the Jacobian matrix. μ is multiplied by some factor β whenever a step would result in an increased E. When a step reduces E, μ is divided by β. By adjusting μ in this way, the search direction interpolates between the gradient and the Gaussian-Newton direction. That is the reason that the rate of convergence is satisfactory. Jacobian matrix $J(W)$ can be expressed as follows:

$$J(W) = \left[\frac{\partial \zeta}{\partial W_1} \quad \frac{\partial \zeta}{\partial W_2} \quad \cdots \quad \frac{\partial \zeta}{\partial W_n}\right]^T. \qquad (9)$$

From equation (7),

$$\frac{\partial \zeta}{\partial W_i} = \frac{\partial (Y^* - Y)}{\partial W_i} = -\frac{\partial Y}{\partial U}\frac{\partial U_2}{\partial W_i}. \qquad (10)$$

where $U = U_1 + U_2$. $\frac{\partial U_2}{\partial W_i}$ could be easily calculated using the standard backpropagation algorithm. Thus, the Jacobian matrix can be computed by (10).

The formula for updating lateral weight K_1 to minimize E in the direction of the negative gradient is given as follows :

$$\begin{aligned}\triangle K_1 &= -\mu \frac{\partial E}{\partial K} \\ &= \mu e \frac{\partial Y}{\partial K} \\ &= \mu e \frac{\partial Y}{\partial U}\frac{\partial U}{\partial K} \\ &= \mu e \frac{\partial Y}{\partial U}\frac{\partial U}{\partial U_1}\frac{\partial U_1}{\partial K} \\ &= \mu e \frac{\partial Y}{\partial U}\frac{\partial U_1}{\partial K} \qquad (11)\end{aligned}$$

where μ is the learning rate.

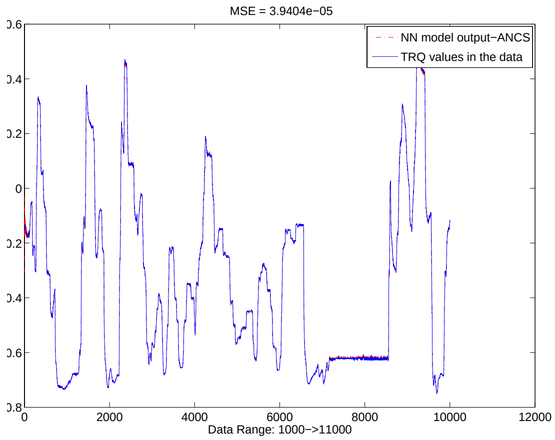

Fig. 5. ANCS control effect

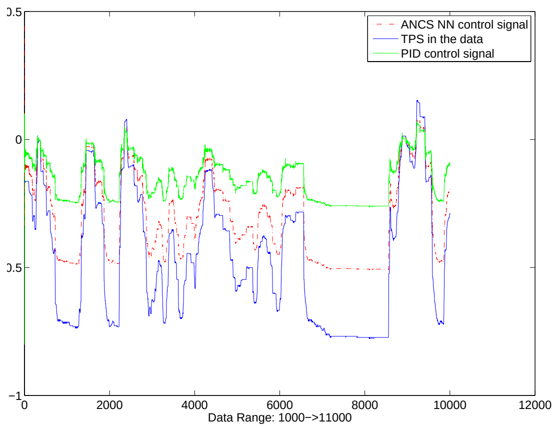

Fig. 6. The output of PID control, NN control and TPS in the data

From (4),

$$\frac{\partial U_1}{\partial K} = U_2 \tag{12}$$

That is, the change of lateral impact weight is:

$$\triangle K_1 = \mu e \frac{\partial Y}{\partial U} U_2 \tag{13}$$

Since the module of the engine TRQ is represented by a neural network, according to the backpropagation algorithm, $\frac{\partial Y}{\partial U}$ could be derived easily for updating weights of the algorithm.

E. Simulation Results

The results of the experimental studies are shown in this section:

The data range for the training part of the control algorithm on the TRQ control is from 1000 to 11000 from the data set without any special purpose for the selection. Figure 6 is the output (TRQ) of the engine using adaptive nonlinear control strategy compared to the TRQ data in the data set. From the figure 6, we can see that the TRQ controlled by the adaptive nonlinear controller tracks the TRQ measurement in the data set very well. All variables in our simulation displays were transformed into the range of $\{-1, 1\}$ by $(2x - x_{\max} - x_{\min})/(x_{\max} - x_{\min})$ where $x_{\max}$ and $x_{\min}$ are the max and min values of the variable x.

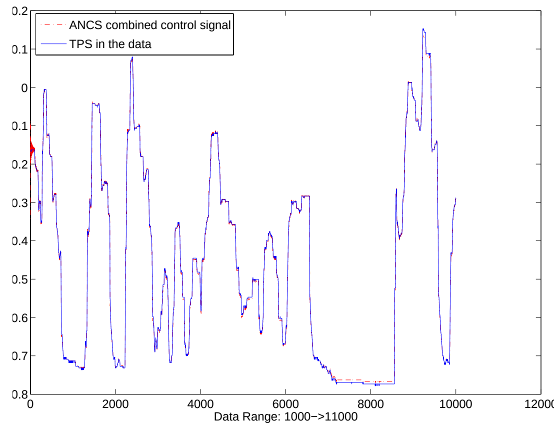

Fig. 7. The combined output of PID control and NN control and TPS in the data

Figure 7 is the output of the PID controller and neural network controller compared to the TPS in the data. Figure 8 is the combined control to the engine compared to TPS in the data. From the figure 8, we can see that the combined control output of controllers is very close to the TPS measurement in the data set. From figure 7 and 8, we can see that the neural network and PID controller interact with each other all the time. When there is disturbance in the system, the PID controller and neural network controller cooperate with each other to pull the disturbed system back to the normal situation.

The data range for the validation part of the control algorithm on the TRQ control is from 21000 to 31000 from the data set without any special purpose for the selection. Figure 9,10 and 11 are the results from which we can say that the control effect is pretty good. We can also see that the neural network and PID controller cooperate with each other all the time.

F. Discussions

From the Figures, we can see that the role of neural controller is to refine the performance of the linear PID controller by discovering optimal corrections to be added to the linear controllers output, which bears an analogy with the mechanism of the baroreceptor reflex to regulate arterial blood pressure. When there is a deviation of the states of the system, the neural controller takes actions to pull the systems back to the normal conditions.

We do not have to choose the parameters of PID controller by trial and error which is a very time-consuming task. In

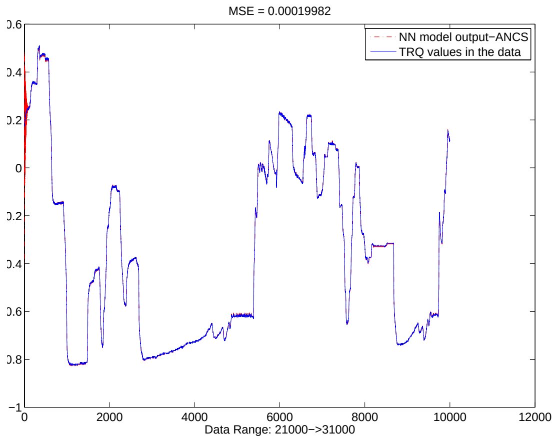

Fig. 8. ANCS control effect

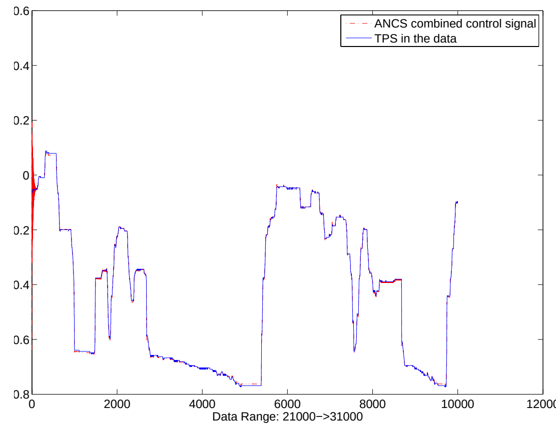

Fig. 10. The combined output of PID control and NN control and TPS in the data

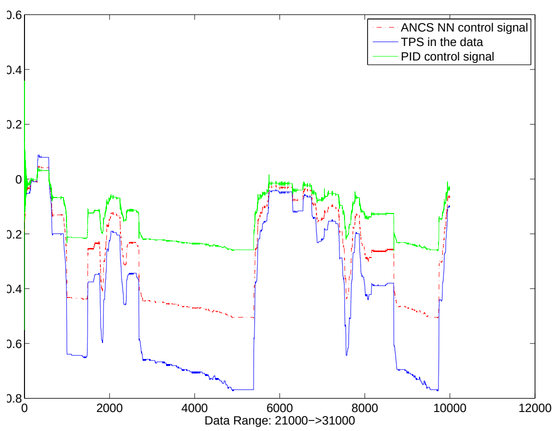

Fig. 9. The output of PID control, NN control and TPS in the data

fact, the corrections produced by the neural controller will compensate the insufficiency of the PID controller, plant-model mismatches and disturbances from the environment.

Compared to the method of neuro-sliding mode control, the training speed is almost the same, but the tracking effect of control is better. It just took only 15 steps (about 1 minute) to get very good results using L-M training algorithm. While using backpropagation (delta training rule), it took around 2 hours steps to make MSE below 0.0004 during the training. Considering the speed, the adaptive nonlinear control strategy can be a good candidate used for the online learning control.

The tuning of the parameters (the gains of the proportional, integral and derivative terms) of PID controller is a very time-consuming task. If the PID controller parameters are chosen incorrectly, the controlled process input can be unstable, i.e. its output diverges, with or without oscillation, and is limited only by saturation or mechanical breakage. In our control strategy, the parameters are selected as $K_p = 1.6$, $K_i = 0$ and $K_d = -0.48$ without any special purpose for the selection. The other random selections of PID parameters are $K_p = 0.6$, $K_i = 0.12$ and $K_d = 0.18$ also produced good results, though the selection of the PID parameters may warrant further investigations and can be the subject of a separate study.

IV. CONCLUSIONS

Our research results have indicated that the method of adaptive nonlinear control strategy is an effective approach for engine control. The parallel controllers inspired by the functions of baroreceptor reflex consist of a linear controller and a nonlinear controller that interact via a reciprocal lateral inhibitory mechanism. The linear controller design is based on a PID controller, while the nonlinear controller is constructed from neural network that are updated online. The nonlinear controller is designed without the aid of an explicit dynamic model. In the linear operating region, the PID controller takes control. If the controlled process is far away from linear regime or is disturbed by the noises, the output of linear controller may be inappropriate, and therefore, the nonlinear controller is added to compensate for the inadequacy of the linear controller and the dynamic environment as process parameter variations and disturbances. These situations can be addressed by adjusting the amount of lateral inhibition and learning the characteristics of the controlled system such that desirable controller outputs are produced in particular operating regions. From these two controllers, the objective of tracking the desired torque could be realized.

The following advantages are observed in the experiments:

1) Computational efficiency, suitable for real-time implementation.
2) Real-time adaptability, insensitive to the changing characteristics of the controlled plant or the noisy environment.
3) Superior learning ability, even in the situation of a very poor linear controller.
4) No prior knowledge of the controlled plant needed.

5) Control and learning are done simultaneously.
6) No need to tune the parameters of PID controller by trails and errors which is a very time-consuming task.

In the future, we will also apply the method to the problem of air-fuel ratio control in an internal combustion engine.

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