Adaptive neural network automatic parking constrained control via anti-windup compensator

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Abstract
In this article, an adaptive proportional–integral–derivative–type neural network constrained control method based on radial basis function neural network model identifier is presented for automatic parking system. In the design process of the control method, the parameters of proportional–integral–derivative–type neural network controller can be adjusted online using the Jacobian information (the sensitivity of system output with respect to its input) of the controlled system. In this way, the proposed method will have a better adaptability. Meanwhile, we design a novel dynamic anti-windup compensation unit to solve the magnitude saturation and rate constraint problems of automatic parking system. The stability analysis based on Lyapunov function is given to prove the convergence of the proposed control algorithm. The final simulation results for automatic parking system show the effectiveness of the proposed method.

Keywords
Adaptive constrained control, neural network, anti-windup compensator, automatic parking

Introduction
Automatic parking system is a kind of intelligent parking assist system, which can make the vehicle automatically enter the parking space quickly and safely. It can identify the parking space by the ultrasonic sensor.¹,² Then, the automatic parking system generates the corresponding parking trajectory according to the relative position of the vehicle and the parking space. Finally, automatic parking controller automatically adjusts the steering wheel to complete the parking process.³

Compared with the manual parking process, automatic parking system has the advantages of simple operation, short parking time, and high safety. It successfully improves the intelligent level of the vehicle.⁴–⁶ In our daily life, the quantity of four-wheeled vehicles is reaching very large numbers. It causes the serious parking problems. Therefore, there are a lot of researches on automatic parking system.

In Liang et al.,⁷ a fuzzy control scheme is designed by adopting the fuzzy rules from the experience of driver parking. Its experimental results verify the feasibility of the scheme for automatic parking system. In Yang et al.,⁸ the variable universe adaptive fuzzy control scheme is proposed for automatic truck parking system. The authors verified the applicability of the proposed scheme through the simulation experiments. In Lin et al.,⁹ the automatic parking system is designed...
on the basis of multi-dimension fuzzy controllers. The proposed control scheme has good simulation results. However, the control rule base of fuzzy control scheme is complicated which can cause the redundancy between the rules. The kinematic model of vehicle can be established according to the distribution of parking space. Then, the automatic parking path tracking controller is designed to complete the tracking of the parking path.\(^\text{10}\) A self-organizing adaptive algorithm is proposed in Huang and Lin\(^\text{11}\) and Huang and Lee,\(^\text{12}\) which can make the automatic parking system have better robustness according to the simulation results. But there are some difficulties to put the simulation into practice. In Hou et al.,\(^\text{13}\) and Yan et al.,\(^\text{14}\) a model-free adaptive control (MFAC) algorithm is proposed for automatic car parking system. In the design process of the MFAC method, the model information of vehicle is not required to know which makes the proposed algorithm have a good adaptability to different types of vehicles. And the MFAC algorithm for automatic parking process is verified by the simulation experiment.

Neural network has strong ability of nonlinear fitting, self learning, and memory. At present, it has been applied in many fields due to the high robustness, such as signal processing, medicine, control system, pattern recognition, speech recognition, and much more areas. In Yang et al.,\(^\text{22}\) the adaptive radial basis function (RBF) neural network–enhanced controller is designed for the Baxter robot to achieve good control performance at dynamic level. Moreover, the authors improve the adaptive neural network by adopting the error transformation technique. And the proposed neural network control method has been verified by comparative experiments. In Yang et al.,\(^\text{23}\) the authors propose a novel neural control method by introducing the switching mechanism into the adaptive neural network controller to guarantee the global stability of closed-loop system. Moreover, the experiments on a robot show the effectiveness of proposed neural controller. Many theory analysis and applications verify the superiority of the neural network.\(^\text{15–18,24}\)

In this article, we propose an adaptive proportional–integral–derivative (PID)-type neural network constrained control method based on RBF for automatic parking system. The Jacobian information obtained from the results of RBF online identification can be used to adjust the parameters of PID-type neural network controller adaptively. In order to solve the problems of magnitude saturation and rate constraint, we design a dynamic anti-windup compensation unit to keep the control input in a safe range. After dynamic compensation, the control input is also consistent with the actual situation in automatic parking process. Finally, the simulation results for automatic parking system are given to verify the effectiveness of the proposed adaptive constrained control method.

### Automatic parking process problem description

There are three types of parking in our daily life (refer to Figure 1), including parallel parking, vertical parking, and oblique parking. This article focuses on the research of parallel parking system because the parallel parking is the most common situation.\(^\text{19}\)

#### Parking space detecting

The precondition of vehicle automatic parking is the detection of the parking space. In general, the automatic parking space detecting system is mainly composed of the ultrasonic sensors which are arranged on the side of the vehicle body. Here, we show the schematic diagram of the detecting process of parallel parking space as Figure 2. There are vehicles parked in the front and rear of the parking space. When the vehicle is moving forward for searching the parking space, the distance information can be detected by the ultrasonic sensor. If the sensor passes through the edge of vehicle body, the distance that detected by the sensor will change from \(d_1\) to \(d_2\). After the vehicle continues to move forward, the detected distance will have another change from \(d_2\) to \(d_1\). We can obtain the length of parking space \(L_s\) based on the vehicle velocity and the

![Figure 1. Types of parking: (a) parallel parking, (b) vertical parking, and (c) oblique parking.](image)

![Figure 2. Detecting process of parallel parking space.](image)
time interval of the two distance changes. Then, system identifies that the parking space is available when \( L_s \) is larger than the minimum available length of parking space \( L_{s_{\text{min}}} \). Otherwise, the car will keep moving forward to search another suitable parking space. After finishing the procedure of parking space detecting, the automatic parking system turns into the step of path planning.

**Path planning**

Path planning is one of the main strategies for automatic parking system. Based on the known parameters such as \( L_s, W_v, \) and \( L_v \), denoting the length of parking space, the vehicle width, and vehicle length, respectively, we show the curve of parallel parking path planning as Figure 3. From Figure 3, the process of parallel parking path planning contains four stages as follows:

1. The stage of backing the car in a straight line (refer to straight line \( Q_3Q_2 \)).
2. The stage of turning the steering wheel to the left (refer to arc segment \( Q_2Q_1 \)).
3. The stage of returning the steering wheel to turn the steering angle to zero (refer to straight line \( Q_1Q_0 \)).
4. Last stage is turning the steering wheel to the left (refer to arc segment \( Q_0O \)).

From the figure, we obtain the coordinates of \( Q_0, Q_2 \) and the angle \( \delta \) of straight line \( Q_1Q_0 \) through geometry calculation

\[
Q_0 : (R_1\sin\delta, R_1(1 - \cos\delta)) \tag{1}
\]

\[
Q_2 : ((R_1/\cos\delta - R_1 + d + W_v/2)/\tan\delta, d + W_v/2) \tag{2}
\]

\[
\tan\delta = \frac{W_v/2 + R_2\cos\delta - R_1(1 - \cos\delta)}{L_s - (R_1 + R_2)\sin\delta - \Delta d} \tag{3}
\]

where \( R_1 \) and \( R_2 \) denote the radius of circle \( O_1 \) and \( O_2 \), respectively. And \( R_2 = W_v/2 + \Delta d \). \( d \) and \( \Delta d \) denote the lateral distance and safe distance between the two cars (refer to Figure 3), respectively.

**Kinematic model of four-wheeled vehicle**

The four-wheeled vehicle model is shown in Figure 4. Generally, in the process of backing the car, the vehicle velocity is lower than 5 km/h, which ensures that the sideslip does not occur. Based on this precondition, we can obtain the kinematic model of four-wheeled vehicle as follows:

\[
\begin{align*}
\dot{x}_v &= u\cos\phi \\
\dot{y}_v &= u\sin\phi \\
\dot{\phi} &= \frac{u\tan\alpha}{L_w}
\end{align*}
\tag{4}
\]

in which \( x_v \) and \( y_v \) denote the horizontal and vertical coordinates of the center of rear wheel axle, respectively; \( u \) denotes the vehicle velocity; \( \alpha \) and \( \phi \) denote the steering angle and orientation angle of the vehicle, respectively; and \( L_w \) is the wheel base. Transform the kinematic model (4) into following discrete model by adopting the first-order Euler discretization method

\[
\begin{align*}
x_v(k + 1) &= x_v(k) + T_s u\cos(\phi(k)) \\
y_v(k + 1) &= y_v(k) + T_s u\sin(\phi(k)) \\
\phi(k + 1) &= \phi(k) + T_s u\tan(\alpha(k))/L_w
\end{align*}
\tag{5}
\]

in which \( T_s \) is the sampling time.

In the actual parking process, the control input \( \alpha(k) \) should satisfy the magnitude saturation and rate constraints because the steering angle cannot change too quickly in the short time interval. So the constrained conditions are given as follows:

\[
\alpha_{\text{min}} \leq \alpha(k) \leq \alpha_{\text{max}} \quad \dot{\alpha}_{\text{min}} \leq \dot{\alpha}(k) \leq \dot{\alpha}_{\text{max}} \tag{6}
\]

**Main results**

In this section, we propose an adaptive neural network constrained control algorithm based on RBF for automatic parking system. Main contributions consist of three parts: (1) RBF neural network for automatic parking identification, (2) put forward an adaptive
PID-type neural network constrained control method via anti-windup scheme, and (3) stability analysis of PID neural network based on Lyapunov function.

**RBF neural network for identification**

RBF neural network is a kind of three-layer feedforward network which has the advantage of fast learning speed. It can avoid local minimum problem because the mapping of the hidden layer space to the output layer space is linear. The RBF network structure is shown in Figure 5.

In the structure of RBF network, $X = [x_1, x_2, \ldots, x_n]^T$ denote the input vectors for the neural network. Choose the radial basis vectors for RBF network as $G = [g_1, g_2, \ldots, g_n, \ldots, g_m]^T$, where $g_j$ denote the Gaussian function which have the structure as following

$$g_j = \exp \left(-\frac{||X-F_j||^2}{2d_j^2}\right), j = 1, 2, \ldots, m$$

in which $F_j = [f_{j1}, f_{j2}, \ldots, f_{jm}]^T$, $i = 1, 2, \ldots, n$ denote the center vector of network node $j$. Define the base width vector of the network as $D = [d_1, d_2, \ldots, d_m]^T$, $d_j$ denote the base width parameters of node $j$ which are positive numbers. Define the weight vectors of neural network as $S = [s_1, s_2, \ldots, s_j, \ldots, s_m]^T$. Then, the positive output of identification network can be obtained as

$$\hat{\phi}(k) = s_1g_1 + s_2g_2 + \cdots + s_mg_m$$

Define the performance index function of identification network as

$$J = \left(\phi(k) - \hat{\phi}(k)\right)^2 / 2$$

We obtain the iterative algorithms of output weight vectors, node base width parameters, and node center using the gradient descent method

$$s_j(k) = s_j(k-1) + \eta(\phi(k) - \hat{\phi}(k))g_j + \kappa(s_j(k-1) - s_j(k-2))$$

where $\Delta s_j = \eta(\phi(k) - \hat{\phi}(k))s_jg_j \frac{||X-F_j||^2}{d_j^2}$

$$d_j(k) = d_j(k-1) + \eta\Delta d_j + \kappa(d_j(k-1) - d_j(k-2))$$

$$f_j(k) = f_j(k-1) + \eta\Delta f_j + \kappa(f_j(k-1) - f_j(k-2))$$

$
\Delta f_j = \eta(\phi(k) - \hat{\phi}(k))s_j \frac{x_j - f_j}{d_j^2}$

$\Delta d_j$ denote the center vector of network node $g_j$ and is designed as follows

$$\frac{\partial \phi(k)}{\partial \alpha(k)} = \frac{\partial \hat{\phi}(k)}{\partial \alpha(k)} = \sum_{j=1}^m s_jg_j \frac{f_j - x_1}{d_j^2}$$

**Adaptive PID-type neural network constrained controller design**

We choose the algorithm of the typical PID controller as follows

$$a_0(k) = \alpha(k-1) + k_p(e(k) - e(k-1)) + k_i e(k) + k_d(e(k) - 2e(k-1) + e(k-2))$$

where $k_p$, $k_i$, and $k_d$ denote the proportional, integral, and derivative parameters, respectively. $a_0(k)$ denotes the output of PID controller and $e(k) = \phi^*(k) - \phi(k)$ denotes the system tracking error. $\phi^*(k)$ and $\phi(k)$ denote the desired output of orientation angle of the vehicle and actual output of the controlled system, respectively. $\vartheta(k)$ denotes the compensation signal used to accommodate the desired trajectory $\phi^*(k)$ and is designed as follows

$$e(k) = \mu \vartheta(k-1) + \frac{\partial \hat{\phi}(k)}{\partial \alpha(k)}(a_0(k) - \alpha(k))$$

where $\mu$ is selected in the unit circle.

Consider the three-phase inputs of PID controller are

$$x_{c1}(k) = e(k) - e(k-1)$$

$$x_{c2}(k) = e(k)$$

$$x_{c3}(k) = e(k) - 2e(k-1) + e(k-2)$$

Therefore, the PID controller can be rewritten as follows

$$a_0(k) = \alpha(k-1) + k_{x_1}x_{c1}(k) + k_{x_2}x_{c2}(k) + k_{x_3}x_{c3}(k) = \alpha(k-1) + \sum_{j=1}^3 K_j x_{cj}(k)$$

where $K_j(k)$, $j = 1, 2, 3$ denote the parameters of PID controller. Generally, we can obtain the good tracking
effect by choosing the optimal PID parameters $K_j(k)$. However, because of the nonlinearity of automatic parking system, there exist difficulties to choose the optimal parameters. Therefore, we adopt the neural network to design the PID controller, and the weighting factors of neural network are related to the PID parameters. So that $K_j(k)$ can be adjusted online according to the outcomes of the neural network and RBF model identifier.

In order to ensure that the control input of automatic parking system is maintained in an acceptable range, we design an adaptive constrained controller as follows according to the constraint conditions (6)

$$
\alpha(t) = \text{Sat}\{\alpha(k - 1)
+ \text{Sat}\{\alpha_0(k) - \alpha(k - 1), T_s a_{\min}, T_s a_{\max}\}\},
$$

where $\text{Sat}(\cdot)$ function is described as follows

$$
\text{Sat}(x, x_L, x_H) = \begin{cases}
    x_H & x \geq x_H \\
    x & x_L < x < x_H \\
    x_L & x \leq x_L
\end{cases}
$$

We define the output of the first layer of the neural network and the output of the controller, respectively, as follows

$$
net_j = \sum_{i=1}^{3} o_{ij} \cdot x_{cj}(k)$$

$$
\alpha_0(k) = \alpha(k - 1) + \sum_{j=1}^{3} K_j(k) \cdot y(net_j)
$$

where $o_{ij} (i = 1, 2, 3, j = 1, 2, 3)$ denote the weights of input layer and hidden layer, $y(\cdot)$ denotes the nonlinear function of the hidden layer which has the structure as follows

$$
y(net_j) = \frac{1 - \exp^{-net_j}}{1 + \exp^{-net_j}}
$$

Therefore, we can get the derivative of above equation

$$
y'(net_j) = \frac{1}{2} \left(1 - y(net_j)\right)^2
$$

In order to obtain the parameters updating law of PID neural network, we define the performance index function as follows

$$
E(k) = \frac{1}{2} e(k)^2
$$

Then, the parameters of PID neural network can be adjusted by adopting the gradient descent method, and adjustment rules are as follows

$$
K_j(k + 1) = K_j(k) - \eta_b \frac{\partial E(k)}{\partial K_j(k)}
$$

$$
= K_j(k) - \eta_b \frac{\partial E(k)}{\partial o_0(k)} \frac{\partial o_0(k)}{\partial K_j(k)}
$$

$$
\simeq K_j(k) + \eta_b \left(\frac{\partial e(k)}{\partial o_0(k)}\right) y'(net_j)
$$

$$
o_{ij}(k + 1) = o_{ij}(k) - \eta_b \frac{\partial E(k)}{\partial o_{ij}(k)}
$$

$$
= o_{ij}(k) - \eta_b \frac{\partial E(k)}{\partial o_0(k)} \frac{\partial o_0(k)}{\partial o_{ij}(k)}
$$

$$
\simeq o_{ij}(k) + \eta_b \left(\frac{\partial E(k)}{\partial o_0(k)}\right) y'(net_j) x_{cj}(k)
$$

where $\eta_b$ denotes the parameter training rate.

**Stability analysis of PID-type neural network**

In view of equation (26), we can obtain

$$
\Delta o_{ij} = - \eta_b e(k) \frac{\partial e(k)}{\partial o_{ij}} \simeq \eta_b e(k) \frac{\partial e(k)}{\partial o_0} \frac{\partial o_0(k)}{\partial o_{ij}}
$$

where parameter $o_{ij}$ contains $K_j$ and $o_{ij} (i, j = 1, 2, 3)$. Following theorem is given to determine how the training rate $\eta_b$ is selected.

**Theorem.** Define $\theta_{b,\max} = \max_k \| \theta_b(k) \|$, where $\theta_b(k) = (\partial o_0)/(\partial o_b)$, and $\sigma_{e,\max} = \max_k \| \Delta e(k) \|$, where the training rate $\eta_b$ is selected as follows

$$
0 < \eta_b < \frac{2}{\sigma_{e,\max}^2 \theta_{b,\max}^2}
$$

The tracking error convergence can be guaranteed.

**Proof.** The discrete time Lyapunov function is defined as follows

$$
V_f(k) = \frac{e^2(k)}{2}
$$

Then, equation (29) can be transformed into the following form

$$
\Delta V_f(k) = V_f(k + 1) - V_f(k)
$$

$$
= \frac{1}{2} e^2(k + 1) - \frac{1}{2} e^2(k)
$$

$$
= e(k) + \frac{\Delta e(k)}{2} \Delta o_b + e(k)
$$

where

$$
e(k + 1) = \Delta e(k) + e(k) = \left(\frac{\partial e(k)}{\partial o_b}\right)^T \Delta o_b + e(k)
$$
In view of $(\partial e(k)) / \partial \omega_b = - (\partial \phi / \partial \alpha) (\partial \alpha_0 / \partial \omega_b)$, combining with equations (27) and (31), equation (30) can be rewritten as

\[
\Delta V_f(k) = \left[ e(k) + \frac{\Delta e(k)}{2} \right] \Delta e(k) \\
= \left( \frac{\partial e(k)}{\partial \omega_b} \right)^T \eta_b \cdot e(k) \cdot \frac{\partial \phi}{\partial \alpha} \cdot \frac{\partial \alpha_0}{\partial \omega_b} \left[ e(k) + \frac{\partial e(k)^2}{\partial \omega_b} \right] + \frac{1}{2} \left( \frac{\partial e(k)}{\partial \omega_b} \right)^T \eta_b e^2(k) \left( \frac{\partial \phi}{\partial \alpha} \right)^4 \left[ \frac{\partial \alpha_0}{\partial \omega_b} \right] \\
= - \frac{1}{2} \eta_b e^2(k) \left( \frac{\partial \phi}{\partial \alpha} \right)^2 \left[ \frac{\partial \alpha_0}{\partial \omega_b} \right]^2 \left[ 2 - \eta_b \left( \frac{\partial \phi}{\partial \alpha} \right)^2 \left[ \frac{\partial \alpha_0}{\partial \omega_b} \right] \right] \\
\leq - \frac{1}{2} \eta_b \left( \frac{\partial \phi}{\partial \alpha} \right)^2 \left[ \frac{\partial \alpha_0}{\partial \omega_b} \right]^2 \left[ 2 - \eta_b \sigma_{\max} \left[ \frac{\partial \alpha_0}{\partial \omega_b} \right] \right] e^2(k)
\]

Finally, we obtain $\Delta V_f(k) \leq 0$ by substituting equation (28) into equation (32). Therefore, when choosing the training rate $\eta_b$ as shown in equation (28), the tracking error convergence can be guaranteed.

To show a clear idea of the proposed adaptive neural network constrained control method based on RBF model identifier design procedures, we give a block diagram in Figure 6.

**Simulation results**

In this section, the simulation of automatic parking process is given to verify the effectiveness of the proposed adaptive neural network constrained control algorithm. The basic parameters (refer to Table 1) of parking space and Mercedes-Benz E-400 are selected for the simulation study.

As for the model identifier, six basis functions are used in RBF neural network. We choose the momentum factor and learning rate as $\kappa = 0.1$ and $\eta = 0.55$, respectively. After simulation test, the initial parameters $F_j(0)$, $d_j(0)$, and $S(0)$ of RBF neural network are obtained as follows

\[
F_j(0) = \begin{bmatrix} 0.001 & 0.001 & 0.001 & 0.001 & 0.001 & 0.001 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\ 1.2 & 1.2 & 1.2 & 1.2 & 1.2 & 1.2 \end{bmatrix}
\]

\[
d_j(0) = \begin{bmatrix} 7.15 & 7.15 & 7.15 & 7.15 & 7.15 & 7.15 \end{bmatrix}^T
\]

\[
S(0) = \begin{bmatrix} 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \end{bmatrix}^T
\]

The initial values of PID-type neural network parameters $K_i (i = 1, 2, 3)$ are selected as $K_1 = 25$, $K_2 = 0.7$, and $K_3 = 0.3$, respectively. And the learning rate of $K_j$ are selected as $\eta_{K_1} = 0.9$, $\eta_{K_2} = 0.09$, and $\eta_{K_3} = 0.09$, respectively. The learning rate of weight parameters $o_{ij}$ are chosen as $\eta_{o_{ij}} = 0.1$, $\eta_{o_{ij}} = 0.08$, and $\eta_{o_{ij}} = 0.15$, respectively. The initial values of the weights $o_{ij}$ for PID-type neural network are chosen as follows

\[
o_{ij}(0) = \begin{bmatrix} 1.45 & 1.34 & 9.9 \\ 0.006 & 0.08 & 0.9 \\ 1 & 1.15 & 0.57 \end{bmatrix}
\]

The response curves of PID-type neural network controller parameters and weight parameters estimation are shown in Figures 7 and 8, respectively. From Figures 7 and 8, we observe that the proposed method can tune the coefficients of PID-type controller.
Figure 7. Response curves of PID parameters.

Figure 8. Response curves of weight parameters estimation.
adaptively to obtain good control effect. The Jacobian information of the controlled system and the anti-windup compensation signal $e(k)$ are shown in Figure 9, which ensure that the control input is maintained within the constraints. During the whole parking process, the changes in orientation angle and steering angle are shown in Figures 10 and 11, respectively. From Figures 10 and 11, it can be seen that the two methods (proposed method and PID) can both track the target orientation angle of the vehicle in the automatic parking process. And the steering angle of the two methods is consistent with the change in the orientation angle. Moreover, the stable change in steering angle can make the front wheels not swing back and forth, which can guarantee a smooth parking process. According to the local magnification in Figures 10 and 11, we can see clearly that the proposed adaptive neural network constrained control method has better tracking effect and more quick response rate than traditional PID method.

**Figure 9.** Jacobian information and compensation signal $e(k)$.

**Figure 10.** The orientation angle of the vehicle.
Conclusion

In this article, an adaptive PID-type neural network constrained control method based on RBF model identifier is proposed for automatic parking system. The proposed method realizes the online identification of the automatic parking kinematic model by adopting the RBF neural network. Then, the Jacobian information of controlled system can be obtained for online parameters adjustment of the PID neural network controller. In order to solve the problems of magnitude saturation and rate constraint for automatic parking system, we design a dynamic anti-windup compensation unit to keep the control input in a safe range. Theoretically, the proposed method has good control performance due to the characteristic of inherently nonlinear time-varying. And it deserves to be mentioned that the proposed control method for automatic parking system is particularly effective in the case of inaccurate system model. The final simulation results have proved the better control effect and superiority of the proposed method. In the future work, the adaptive constrained nonlinear control approach for multi-input multi-output (MIMO) nonlinear system is the focus of our research.

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