LTV-RBF Approach for Yaw Stability Control of Distributed Drive Electric Vehicles

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Abstract

This paper proposed a torque distribution strategy based on linear time-varying radial basis function (LTV-RBF) neural networks for yaw stability control of electric vehicles equipped with in-wheel motors. The desired yaw rate is calculated by the two-degree-of-freedom (2-DOF) bicycle dynamic model. The influence of the time-varying steering angle is considered for reducing the yaw rate error. To solve this problem, the constant connection weight of conventional RBF networks is converted into a time-varying variable which is used to track the reference trajectory and optimize the torque distribution. The torques of in-wheel motors are restricted in high efficiency range to improve the system energy efficiency. Simulation results of the proposed torque distribution strategy based on dSPACE simulator show that LTV-RBF networks can effectively track the reference yaw rate and stabilize the system.

Keywords: distributed drive electric vehicles, yaw stability control, linear time-varying radial basis function (LTV-RBF), torque distribution strategy

1. Introduction

With the rapid progress of control strategy, the distributed drive electric vehicles have ignited widespread interest because of the ability to control the wheel torque continuously and accurately [1]. Due to the complex conditions, the distributed drive electric vehicles with four independent in-wheel motors pose a challenge for torque distribution.

In recent years, a number of strategies were applied in this area, such as active front-wheel steering (AFS), direct yaw-moment control (DYC) and the combination of the them through differential braking. Wu proposed a controller based on AFS and DYC to figure out brake pressures and the range of active steering angle [2]. Shuai investigated the combined AFS and DYC for the steady-state response [3]. However, they were acceptable only for simple conditions. Zhai implemented three algorithm for torque distribution and the yaw rate error root mean square decreased by 75 percent [4]. As the variables to be controlled increase, the torque distribution control becomes complex. A lot of research aim at taking more variables into account, such as the time-varying steering angle. Alexander et al. proposed a linear time-varying model-based predictive controller (LTV-MPC) for an appropriate control performance by steering [5]. Radial basis function (RBF) neutral network is a kind of 3-layer forward network with single hidden layer and has powerful self-learning ability to bridge the input and the output [6]. Applying RBF NNs would improve learning speed of neutral network and be satisfied the requirements of real-time control and improve the accuracy and self-adaptability of the system effectively [7].

In this paper, a LTV-RBF controller is developed to improve the performance of yaw moment. In Section 2, a two-degree-of-freedom dynamic model of distributed electric drive vehicle is established. In Section 3, a LTV-RBF NNs is designed to distribute the acceptable optimal torque of each wheel. Section 4 presents the performance of proposed strategy based on dSPACE simulator.

2. Vehicle dynamic model

In this section, a two-degree-of-freedom dynamic model of distributed electric drive vehicle is established, as shown in Fig. 1. The dynamic equations that only consists of lateral and longitudinal movements can be expressed as follows.

\[
\begin{align*}
(\dot{\beta} + \gamma)mv_x &= F_d \cos \delta f + F_{ty} \\
I \dot{\gamma} &= a F_d \cos \delta f - b F_{ty}
\end{align*}
\]

where \(m\) is the vehicle mass, \(\beta\) is the sideslip angle of CG, \(\gamma\) is the vehicle yaw rate, \(a\) and \(b\) are longitudinal distances between the CG and the front-axle or rear-axle, \(\delta f\) is the steering angle of front wheels, \(I\) is vehicle yaw moment of inertia.

Tire sideslip angles are described as follows:
\[ \alpha_f = \beta - \delta_f + \frac{a \cdot \gamma}{v_r} \]
\[ \alpha_r = \beta - \frac{b \cdot \gamma}{v_r} \]  
\[ \alpha = \beta - \frac{b \cdot \gamma}{v_r} \]  

In (1)-(2), the dynamic equations can be expressed as follows:

\[ (\dot{\beta} + \gamma) mv_r = K_f \delta_f - (K_f + K_r) \beta - \frac{1}{v_r} (a K_f - b K_r) \gamma \]
\[ I_f \ddot{\delta}_f = a K_f \delta_f - (a K_f - b K_r) \beta - \frac{(a^2 K_f + b^2 K_r)}{v_r} \gamma \]  

The yaw rate and the sideslip angle can be simplified as follows [8]:

\[ \gamma = G_x \cdot \delta_f \]
\[ \beta = G_y \cdot \delta_f \]  

where \[ G_x = (1/(1 + A v_c^2)) \cdot (v_i / l), G_y = (1 - (m/l)) \cdot (a / b K_r) \cdot (v_i^2) / (1 + A v_c^2) \cdot (b / l) \]
\[ A = (m / l^3) \cdot ((a K_f - b K_r) / K_f K_r) \cdot 2 \]  

\[ \zeta = \frac{1}{2} m g b \]
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\[ \Sigma T_\text{req} = T_1 + T_2 + T_3 + T_4 \]  

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3. Yaw stability control algorithm

In this section, the yaw moment is generated from the driver input based on the MPC, the steering angle and the required torque. A LTV-RBF NNs is designed to calculate the acceptable optimal torque of each wheel. Fig. 2 shows the torque distribution strategy control system.

3.1 Control problem description

The key to achieve the vehicle yaw stability is to control the yaw rate and the sideslip angle of CG. Considering the friction coefficient of the wheel, the slip ratio of each tire should be controlled under 0.2. The method we adopted based on the combination of AFS and DYC to calculate the vehicle yaw moment and the front wheel active angle to track the yaw rate efficiently. Since the law of angle variation has been determined by the upper controller based on MPC [9], the torque distribution comes down to a linear time-varying problem.

3.2 Torque Distribution Strategy

The yaw moment \( M_z \) consists of two parts, the longitudinal yaw moment \( M_x \) and the lateral yaw moment \( M_y \). Only the \( M_y \) can be controlled by the longitudinal forces generated by four in-wheel motors. The lack of \( M_y \) may cause the oversteer or understeer. However, by adjusting the driving and braking torque, the vehicle lateral stability can be achieved [4]. The influence of the longitudinal force on the yaw moment is shown in Fig. 3. The total vehicle yaw moment can be simplified as follows:

\[ M_z = I_z \ddot{\gamma} = F_{x_1} \times (a \sin \delta f - l_i \cos \delta f) + F_{y_2} \times (a \sin \delta f + l_i \cos \delta f) + F_{x_3} \times (-l_i) + F_{y_3} \times l_i \]
\[ T_\text{req} = T_1 + T_2 + T_3 + T_4 \]  

When the vehicle steering angle is zero, the tires is only subjected to longitudinal forces which are determined by the vertical load. As the vehicle runs at a constant speed, the vertical load of the four wheel can be regarded as a constant. The torque caused by vertical load of each wheel is:

\[ T_i = T_2 = \frac{m g b}{2(a + b)} \cdot r \]
\[ T_i = T_4 = \frac{m g a}{2(a + b)} \cdot r \]  

When a time-varying steering angle is obtained, the two sides of in-wheel motors of the same axle have
different torque to generate the yaw moment. The longitudinal yaw moment $M_y$ is distributed to the four motors to track the desired yaw moment from the driver commands generated by MPC to achieve yaw stability. As the torque distribution of the distributed drive electric vehicles is a linear time-varying over-actuated system, the solution is infinite. LTV-RBF NNs is a reasonable algorithm to solve this situation due to its powerful self-learning ability and the connections between the inputs and outputs.

Radial basis function (RBF) neutral network is a kind of 3-layer forward network with single hidden layer. The input layer and the output layer of RBF networks are linear neurons, and the hidden layer transforms the input vector nonlinearly, and then outputs linearly through the output layer. The connection of the inputs and outputs based on Gaussian function is,

$$y = \sum_{i=1}^{j} \omega_i \exp\left(-\|x - \mu_i\|^2 / 2\sigma_i^2\right)$$  \hspace{1cm} (8)$$

The LTV-RBF network changes the constant connection weights of the network into time-varying variables, so that it can reflect the time-varying input-output relationship of the time-varying system, thus realizing the purpose of modeling the time-varying system. The LTV-RBF structure is shown in Fig. 4. The connection weights in the graph are time-varying. The input-output relationship of LTV-RBF networks can be expressed as:

$$y = \sum_{i=1}^{j} \omega_i(t) \exp\left(-\|x(t) - \mu_i\|^2 / 2\sigma_i^2\right)$$  \hspace{1cm} (9)$$

The inputs are time-varying steering angles and the desired yaw moment, the outputs are the torque of each wheel calculated by the LTV-RBF NNs. 5 neurons are chosen as hidden layer and have an appropriate performance.

### 4. Results and Discussion

In this section, the performance of the proposed strategy is tested based on dSPACE simulator. The parameters of the distributed drive electric vehicle are shown in Table 1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle Mass</td>
<td>1523 kg</td>
</tr>
<tr>
<td>Wheelbase</td>
<td>1.539 m</td>
</tr>
<tr>
<td>Vehicle Moment of Inertia</td>
<td>1558 Nm</td>
</tr>
<tr>
<td>Wheel radius</td>
<td>0.354 m</td>
</tr>
<tr>
<td>Distance from front axle to CG</td>
<td>1.016 m</td>
</tr>
<tr>
<td>Distance from front axle to CG</td>
<td>1.592 m</td>
</tr>
<tr>
<td>Dimensionless coefficient</td>
<td>0.3</td>
</tr>
<tr>
<td>Front area</td>
<td>1.95m²</td>
</tr>
<tr>
<td>Transmission ratio</td>
<td>7.1</td>
</tr>
<tr>
<td>Friction coefficient</td>
<td>0.01</td>
</tr>
</tbody>
</table>

This paper presents a constant longitudinal velocity 15 m/s with a sine steering input. The training samples of the LTV-RBF NNs were obtained from a large amount of experiments and the prediction accuracy is 0.023 with an iteration of 345.

Fig. 5 presents the comparison of the desired and actual yaw moment. The line is desired yaw moment and the dot line is actual yaw moment. The yaw moment is zero when the vehicle runs at a constant speed. Since $t=2.5$s, a time-varying steering angles are applied in the vehicle, the yaw moment changes with the input steering angles changes. The dot line is basically coincide with the line and has much less variation. Only at the area near the peak point, the output yaw moment is lower than the desired yaw moment.

Fig. 6, in which $T_1$, $T_2$, $T_3$ and $T_4$ mean the torque of left-front, right-left, left-rear and right-rear in-wheel motors respectively, shows that the torque distribution of four motors. When the yaw moment is zero, the torques in the same axle are the same and the front and rear axle torques are distributed based on the vertical load. When steering, two inside-motors have braking torques and the outside-motors have driving torques to ensure yaw stability. Meanwhile, the same sides motor torque of different axles is influenced by the different vertical load. Therefore, the proposed strategy can improve the yaw stability while considering the influence of the time-varying inputs.

![Figure 4 Structure of LTV-RBF](image-url)
5. Conclusion

Prior work has documented the accuracy of vehicle velocity prediction using a time-varying RBF NNs [10]. In this study, we employed LTV-RBF NNs to calculate the torque distribution of the distributed drive electric vehicles for stabilizing the yaw movement. The LTV-RBF NNs yaw moment predictors generally maintain the desired yaw moment with a time-varying steering input. Results show that the proposed strategy has an appropriate performance on vehicle yaw stability by controlling the four wheels torque generated by four in-wheel motors.

Acknowledgement

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Reference