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Reseach on low-cost sensorless semi-active suspension with Machine learning

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Suspension is an important chassis part which is vital to ride comfort. There are two types of suspension systems: conventional and semi-active suspension. Semi-active suspensions can control damping force and provide a higher level of ride comfort. However, it requires dedicated suspension sensors on all four wheels, which increases cost and tuning man-hours. Therefore, development of sensor value prediction technology based on CAN data has been promoting to achieve low cost sensorless semi-active suspension system. Fig.1 shows an overview of low cost Sensorless Semi-active Suspension system. This paper describes the suspension control method to replace the sensor function to the neural network by getting data from driving test of the vehicle with the acceleration sensor as a teacher data, and training.

The target of this estimation technique, sprung mass speed and piston speed, are time-series data that would conventionally be obtained from on-vehicle sensors. Therefore, we adopted a recurrent neural network RNN, which is considered suitable for predicting time-series data.

From the perspective of improving accuracy during training and validation with RNN, wheel speed, longitudinal acceleration, lateral acceleration, yaw rate, suspension control value and steering angle transmitted on the CAN were selected as input data used to estimate the sprung mass speed and piston speed.

Optimization of the RNN configuration, specifically with respect to the window width corresponding to the number of input layer elements, and the number of hidden layer elements, was performed. As a result, from the viewpoint of learning/estimation accuracy and circuit size, the window width was set to 0.5sec (= number of input layer elements 25/physical value) and the number of hidden layer elements to 50. Table5 provides a summary of the learning and validataion accuracy after optimization of RNN structure. The worst-case learning and estimation MAE for each of the four wheels in this configuration was 0.026m/sec, belo the target of 0.05m/sec. We also checked the output waveform of the RNN. Fig.8 shows an example of RNN output and sensor data. It was confirmed that the trend of the sensor output waveform was generally captured.

Based on the above, we believe that a sensorless semi-active suspension that replaces the sensor function with a neural network can be realized.

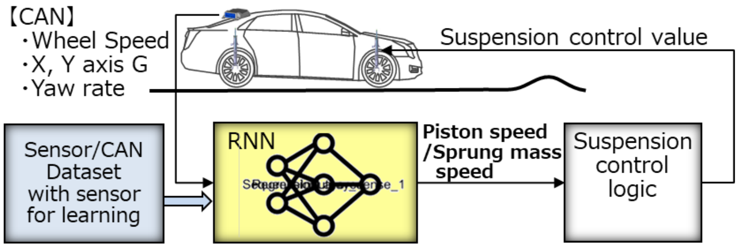

Fig.1 Overview of low cost Sensorless Semi-active Suspension system

Table5 Summary of learning and validation accuracy after optimization

Target	Wheel Position	Learning MAE	Validation MAE
Piston speed	FL	0.019m/sec	0.021m/sec
	FR	0.016m/sec	0.019m/sec
	RL	0.013m/sec	0.015m/sec
	RR	0.015m/sec	0.017m/sec
Sprung mass speed	FL	0.023m/sec	0.025m/sec
	FR	0.020m/sec	0.023m/sec
	RL	0.021m/sec	0.023m/sec
	RR	0.023m/sec	0.026m/sec

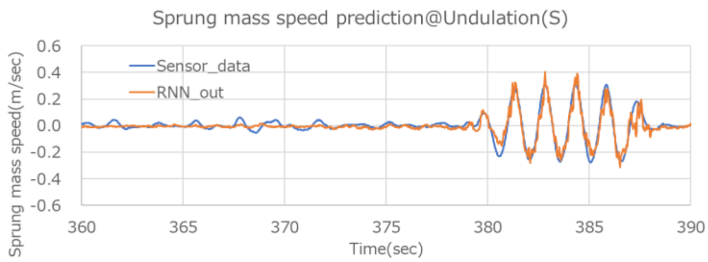

Fig.8 RNN output and sensor data on Undulation track