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An application of a smart control suspension system for a passenger car based on soft computing

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Abstract

A mathematical model-based design methodology for a robust intelligent semi-active suspension control system for passenger cars based on stochastic simulation and soft computing was developed. A globally optimized teaching signal for damper control was generated by a genetic algorithm, the fitness function of which is set to satisfy conflicting requirements such as riding comfort and stability of the car body.

Proper selection of the input signals for the fuzzy controller achieved accurate and robust control, making it possible to reduce the number of sensors.

The knowledge base is optimized for various kinds of stochastic road signals on a computer without carrying out actual field tests.

1 INTRODUCTION

Various kinds of methods have been proposed for semi-active suspension systems that control only the damping force of the vehicle suspension. Using classical control algorithms one can adjust the transfer function of the suspension system with fewer numbers of sensors but not the vehicle attitude. On the other hand, modern control algorithms are very effective for controlling the vehicle attitude, but many sensors are required to get sufficient information about the vehicle condition.

Design methodology for a fuzzy controller using genetic algorithms that optimizes only the membership functions[1) was begun originally by Karr. Hashiyama et al. expanded the function of genetic algorithms to find control rules[2),3)], and the algorithms they developed are based on the skyhook control of Karnopp[4)] with some original additions.

Hagiwara et al. presented an idea for a method to create a knowledge base that is completely self-organized according to only fitness functions without any other predefined rule base[5)].

This paper presents a design method for a smart control system with a reduced number of sensors that does not reduce the performance of the fuzzy controller. Applying the above-mentioned method, rich information from the sensor signals is extracted and an effective knowledge base is created consequently, realizing both good riding comfort and stability.

Two cases are compared in this paper. One uses seven sensors to detect car body movement and the damper stroke. The other uses only one sensor with information supplementation by means of a knowledge base. The result is evaluated by computer simulation and field tests.

2 GENERATION OF THE TEACHING SIGNAL

2.1 Mathematical vehicle model and equation of motion

In order to make it possible to represent non-linear movement, a mathematical vehicle model (**Fig. 1**) is formulated using four local coordinates for each suspension and three for the vehicle body, totaling 19 local coordinates. Equations of motion are derived by Lagrange's approach. Each variable and a part of the equation are represented as follows:

- $\ddot{Z}_0$: Heave acceleration
- $\ddot{\beta}$: Pitch angular acceleration
- $\ddot{\alpha}$: Roll angular acceleration
- $\ddot{\theta}_n$: Angular acceleration of lower arm in relation to the body frame
- $\ddot{\eta}_n$: Angular acceleration of damper axis in relation to the body frame
- $\ddot{Z}_{6n}$: Damper stroke acceleration
- $\ddot{Z}_{12n}$: Tire deflection acceleration
- $\lambda_{1n} \sim \lambda_{3n}$: Lagrangian multipliers

Where suffix 'n' indicates the position of the wheels.

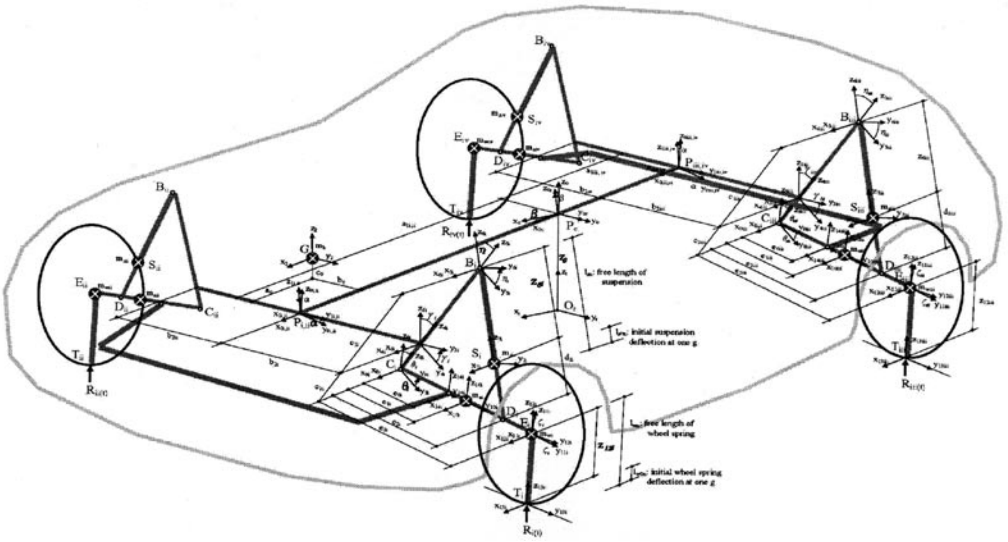

fig.1 A full car model

$$\ddot{z}_0 = \lambda_{3n} - g - \frac{\begin{array}{l} m_b(\cos\beta\,((b_0\cos\alpha - c_0\sin\alpha)\ddot{\alpha} - (b_0\sin\alpha + c_0\cos\alpha)(\dot{\alpha}^2 - \dot{\beta}^2) - (\alpha_0 + \alpha_1)\ddot{\beta}) + \sin\beta\,((\alpha_0 + \alpha_1)\dot{\beta}^2 - (b_0\sin\alpha + c_0\cos\alpha)\ddot{\beta}) \\ +m_{sn}(\cos(\alpha + \gamma_n + \eta_n)(\ddot{z}_{6n} - (\dot{\alpha} + \dot{\eta}_n)^2) - \sin(\alpha + \gamma_n + \eta_n)(2(\dot{\alpha} + \dot{\eta}_n)\dot{z}_{6n} + (\ddot{\alpha} + \ddot{\eta}_n)z_{6n})) \\ +m_{aw1n}((\ddot{\alpha} + \ddot{\theta}_n)\cos(\alpha + \gamma_n + \theta_n) - (\dot{\alpha} + \dot{\theta}_n)^2\sin(\alpha + \gamma_n + \theta_n)) \\ -m_{sawcn}(\ddot{\alpha}\sin(\alpha + \gamma_n) + \dot{\alpha}^2\cos(\alpha + \gamma_n)) + m_{sawbn}(\ddot{\alpha}\cos\alpha - \dot{\alpha}^2\sin\alpha) - \ddot{\beta}\,m_{sawan})\cos\beta \\ -2\dot{\beta}\,(\dot{z}_{6n}m_{sn}\cos(\alpha + \gamma_n + \eta_n) - (\dot{\alpha} + \dot{\eta}_n)z_{6n}m_{sn}\sin(\alpha + \gamma_n + \eta_n) + (\dot{\alpha} + \dot{\theta}_n)m_{aw1n}\cos(\alpha + \gamma_n + \theta_n) \\ -\dot{\alpha}\,m_{sawcn}\sin(\alpha + \gamma_n) + \dot{\alpha}\,m_{sawbn}\cos\alpha - \dot{\beta}\,m_{sawan}/2)\sin\beta \\ -(\ddot{\beta}\sin\beta + \dot{\beta}^2\cos\beta)(m_{aw1n}\sin(\alpha + \gamma_n + \theta_n) + z_{6n}m_{sn}\cos(\alpha + \gamma_n + \eta_n) + m_{sawcn}\cos(\alpha + \gamma_n) + m_{sawbn}\sin\alpha) \end{array}}{m_b + m_{sn} + m_{an} + m_{wn}}$$

. . . Where m_{xxx} represents mass of each element or grouped elements.

Principal parameters for the test vehicle are shown in Table 1 and the characteristics of the variable dampers in Fig. 2. The valve of the damper is controlled by a stepper motor with nine steps from the softest position to the hardest. It takes 7.5ms to make one step shift.

Table.1 Principal vehicle parameters

Parameter	Front	Rear	Unit
Mb: Body mass	1594		kg
Ms: Suspension mass	3.9	5.6	kg
Ma: Lower arm mass	4.4	6.6	kg
Mw: Wheel mass	28.3	37	kg
Ks: Suspension spring constant	50000	45000	N/m
Kw: Tire spring constant	191300	131300	N/m
Cw: Tire damping coefficient	100	100	Ns/m
Kz: Torsion bar spring constant	26300	14300	N/m
Ibx: Body roll moment of inertia	431		kgm^2
Iby: Body pitch moment of inertia	1552		kgm^2
a_l: Wheel base	2.78		m

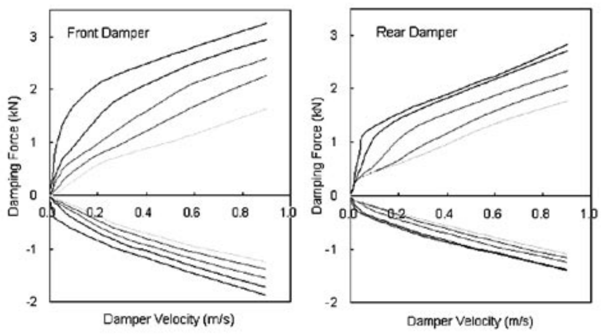

fig.2 Characteristics of the variable dampers

2.2 Road signal

Measured road profile data are differentiated and used as input velocity signals for each wheel (Fig. 3). We call this road "the teaching signal road."

Signals for the rear wheels are delayed for 200ms, which corresponds with the time difference between the front wheels and the rear at a vehicle speed of 50km/h.

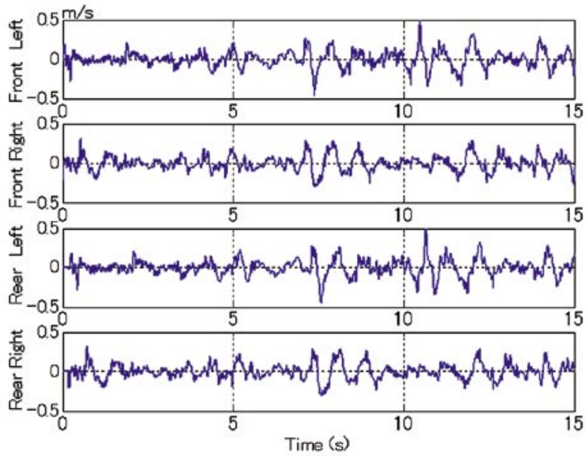

fig.3 Road signals

2.3 Set-up of the fitness function

The behavior of the car body is often discussed from standpoint of acceleration and jerk. However, these two factors alone are not sufficient when considering control of both vehicle stability and riding comfort. The stability is dominated mainly by a low frequency component around 1Hz and the comfort by one above 4 or 5Hz. The three axes of heave, pitch and roll also have to be considered.

Here, the following fitness function FF is set to reduce the low frequency component of pitch angular acceleration to get better stability and the high frequency components of heave acceleration to get better riding comfort.

$$FF = |A_p(1)| + |A_h(5)| + |A_h(9)| + |A_h(12)| + |A_h(13)|$$

This exhibits the amplitude of the 1Hz pitch angular acceleration, the 5Hz component of the heave acceleration, and so on. These frequency components were selected in the order of largest vibration value appearing on the test vehicle in actual running tests.

2.4 Teaching signal generation by Genetic Algorithm

Based on the equations of motion, a Simulink model is formulated (**Fig. 5**) and used in the teaching signal generation (**Fig. 6**).

With the road signal and damping coefficients for the four dampers being supplied, the Simulink model calculates the motion of the car and suspension. The genetic algorithm searches out the best damping coefficients for the dampers that minimize the fitness function every 7.5ms. This job takes about two days working on a 1GHz PC. A series of such damping coefficients are stored as teaching signals (**Fig. 7**).

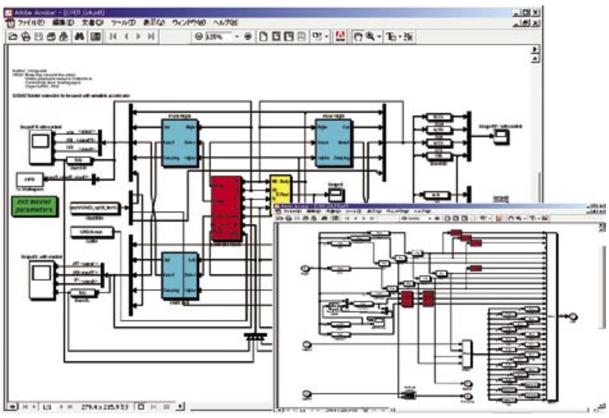

fig.5　Simulink Model of Car and Suspension

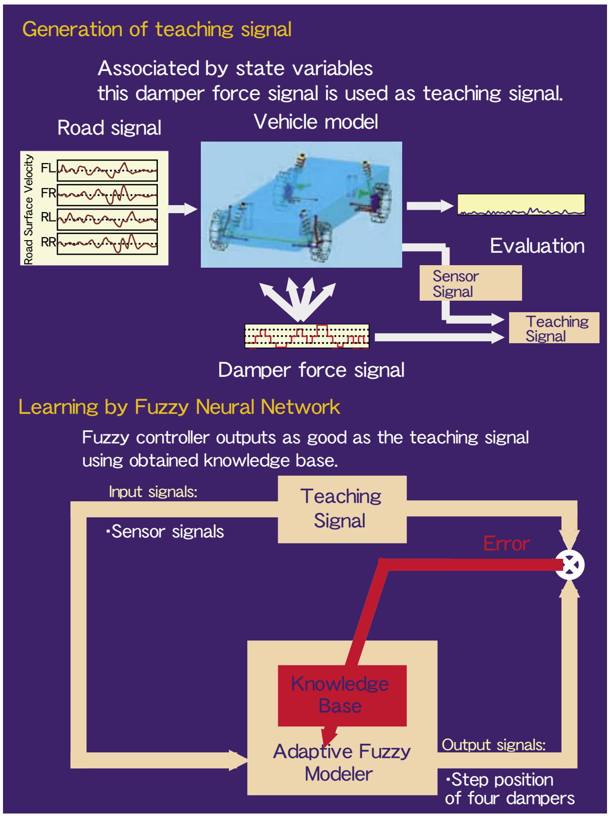

fig.4　Teaching signal generation and learning

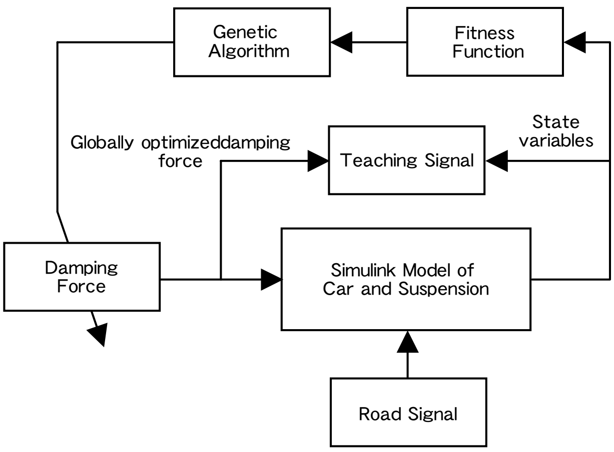

fig.6　Teaching signal generation scheme

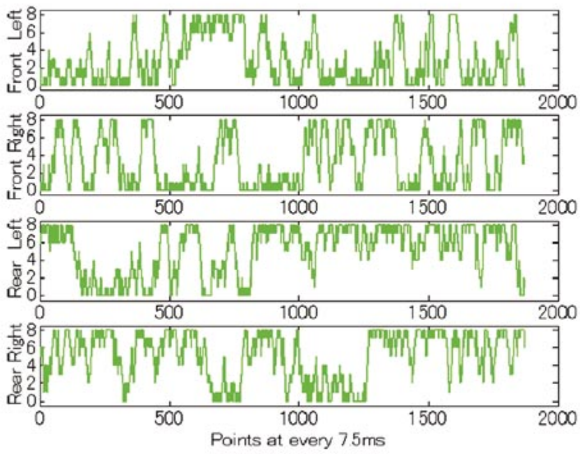

fig.7　Teaching signals

3 LEARNING BY FUZZY NEURAL NETWORK (FNN)

3.1 Structure of the FNN

The Adaptive Fuzzy Modeller of STMicroelectronics[6] is used for learning.

This program builds the rules through unsupervised learning on a Winner-Take-All Fuzzy Associative Memory neural network. The tuning of the position and the shape of each input/output membership function is carried out by Supervised Learning on a multilayer Backward-propagation Fuzzy Associative Memory neural network. The fuzzy model is of Zero-order Sugeno type.

3.2 Learning process of the seven-sensor system

Since the damping force is a non-linear function of the damper velocity, seven kinds of signal sources are thought to be necessary to control the body movement along three axes with the four independent dampers acting as actuators. In this case, three body acceleration signals of heave, pitch and roll and four damper velocity signals are used as input for fuzzy inference (Fig. 8, 9).

The knowledge base is obtained by learning from the teaching signal generated by the genetic algorithm described in 2.4. Fig.10 shows the inference simulation created from the knowledge base as compared with the teaching signal.

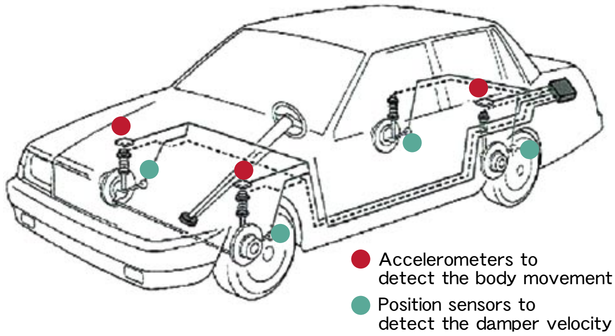

fig.8 Sensor layout of the seven-sensor system

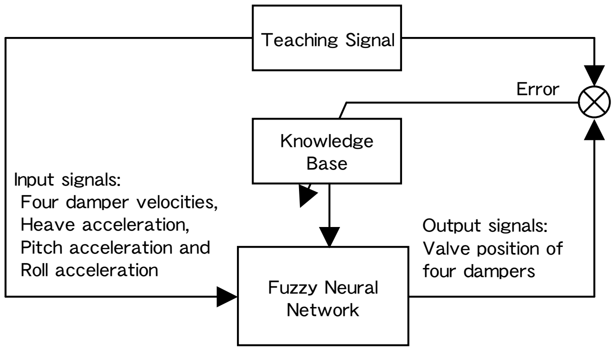

fig.9 Learning scheme of the seven-sensor system

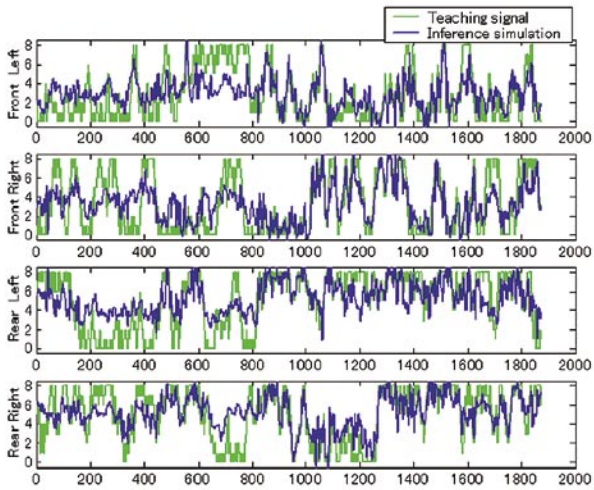

fig.10 Learning results of the seven-sensor system

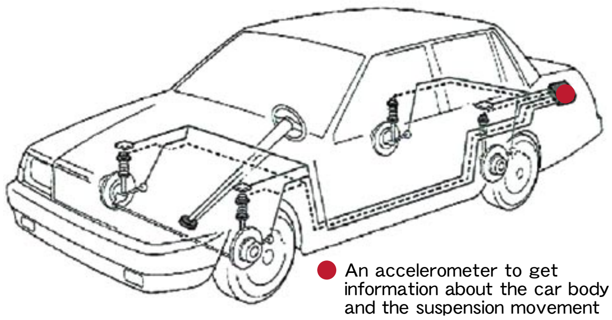

fig.11 Sensor layout of the single-sensor system

3.3 Learning process of the single-sensor system

The movements of heave, pitch and roll of the car body are in the mode of coupled vibration and are closely related to each other. Vertical translation motion induces pitching and rolling motion. Therefore, it is believed that the latter two movements can be estimated by observing the movement of heave. It is also expected that the heave signal should contain certain information about the wheel movement. In this case, attempts are made to extract several kinds of information from the heave acceleration signal through filters (**Fig. 11, 12, 13**).

The heave acceleration signal is filtered through a low pass filter for noise canceling and applied to the FNN as input 1. It is transferred to the velocity signal through an integrator and applied as input 2. Next, information about the movement in the frequency range around the natural frequency of the car body is extracted by a band pass filter for input 3. The frequency components above 5Hz, which affect the degree of annoyance from vibration including wheel hops, and the amplitude of 1Hz, which is extracted by FFT to represent road roughness, are applied as inputs 4 and 5, respectively.

The same teaching signal is used for learning as is used with the seven-sensor system. **Fig. 14** shows the inference simulation created from the knowledge base as compared with the teaching signal.

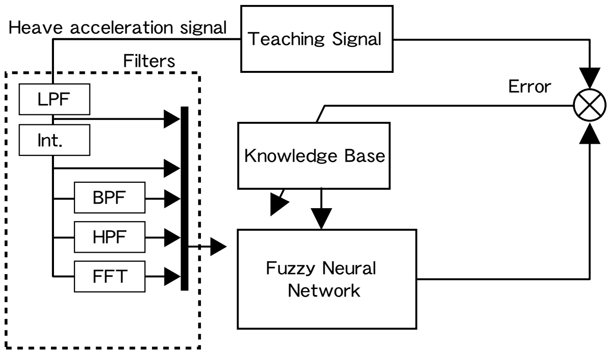

fig.12 Learning scheme of the single-sensor system

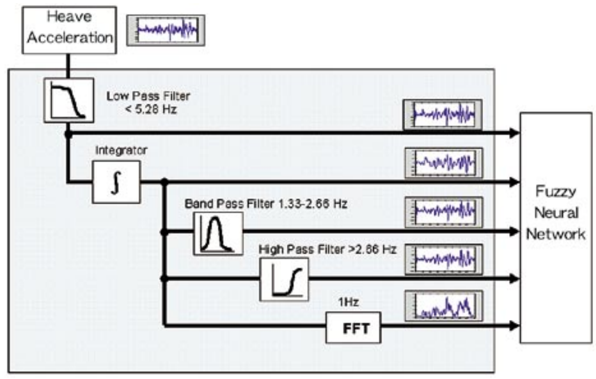

fig.13 Filter block layout

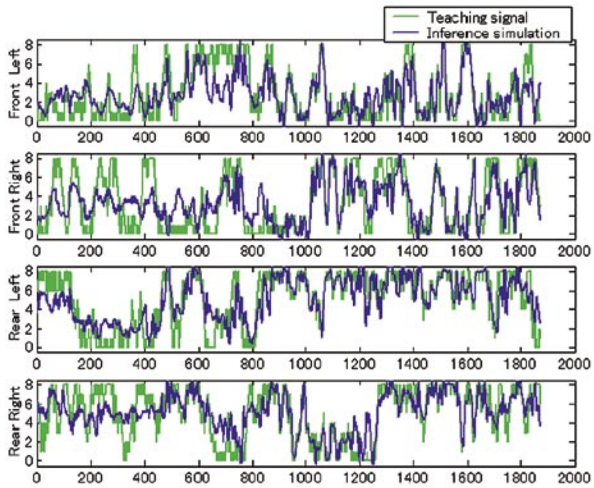

fig.14 Learning results of the single-sensor system

Table.2 Modeling parameters and learning result

Fuzzy system		Seven- sensor	Single-sensor
Modeling parameters	Antecedent number	7	5
	Consequent number	4	4
	Fuzzy set number	4	5
	Inference method	Product	Product
	Antecedent shape	Gaussian	Gaussian
Learning result	Rule number	333	248
	Error	6.526	5.457

Fuzzy modeling parameters and the results of learning are shown in Table 2.

4 EVALUATION OF THE KNOWLEDGE BASE

4.1 Simulation by means of Simulink model

Simulation is carried out on the same Simulink model that is used for teaching signal generation (Fig. 6), except that the damping coefficients are controlled by a fuzzy controller (Fig. 15).

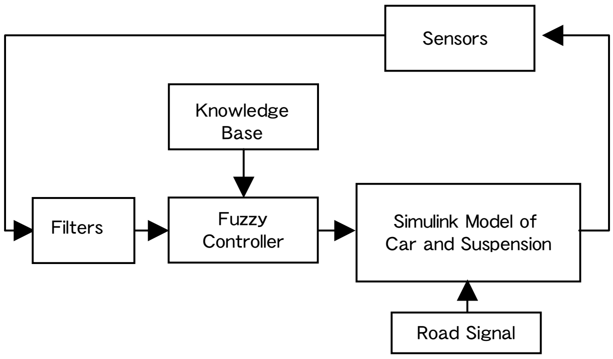

fig.15 Fuzzy control simulation

Both of the simulation results from the seven-sensor and single-sensor systems are shown in Fig. 16. Simulation results without control are also added in the figure for comparison. Hard damping means that the damping coefficient is kept at the maximum position, as is shown in Fig. 2, and for soft damping, vice versa.

The figure consists of three groups, heave, pitch and roll. The lower raw data for each group shows accumulated amplitude to make it easy to distinguish the difference between lines while the upper raw data shows the time history of the amplitude itself.

In order to investigate the robustness of the knowledge base, another simulation is carried out (Fig. 16) with stochastic road signals that have different characteristics from the teaching signal road.

4.2 Evaluation based on field tests

The field test was carried out with the single-sensor system and with fixed damping coefficients on the teaching signal road (Fig. 18).

The test conditions were almost the same as the simulation except that the road profile had changed after the road signal measurement and that the signal of the accelerometer on the vehicle body contained more high frequency components than this simulation.

Another field test on a different road from the teaching signal road was carried out to investigate the robustness (Fig. 19).

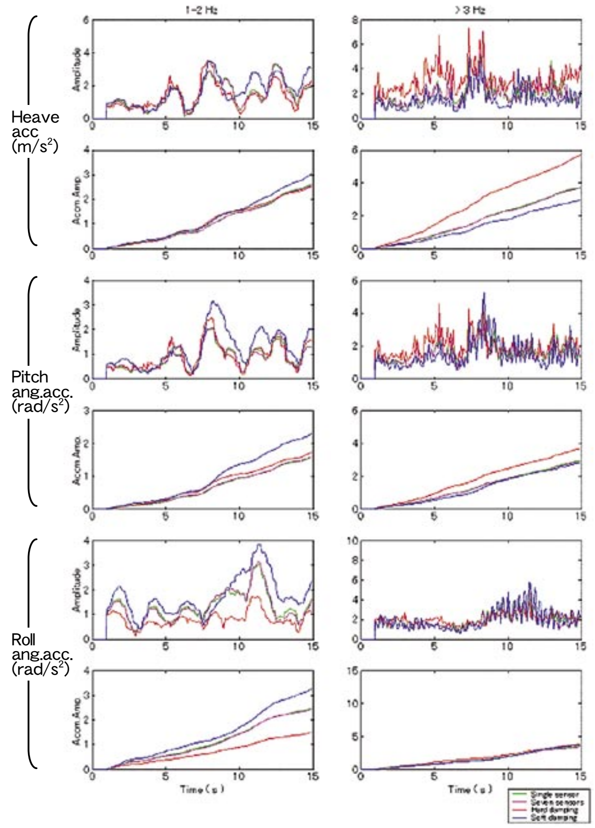

fig.16　Simulation on the teaching signal road

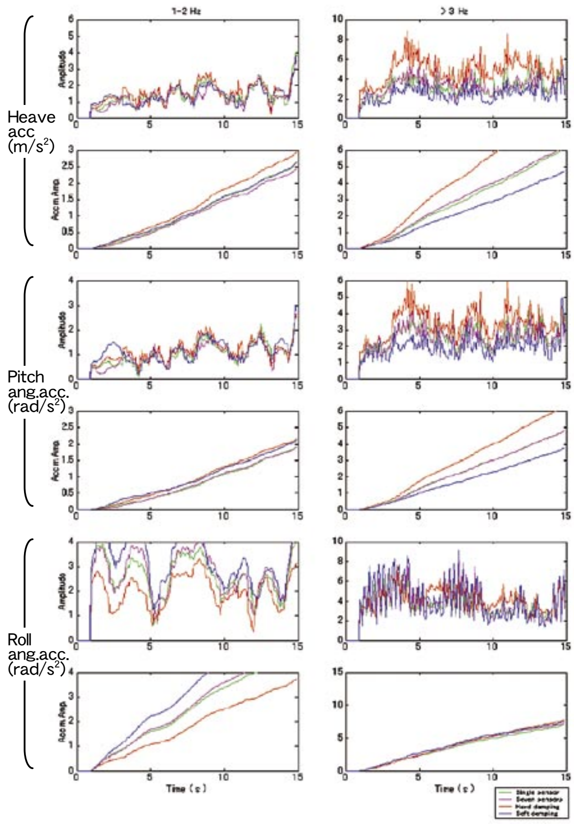

fig.17　Simulation on another road

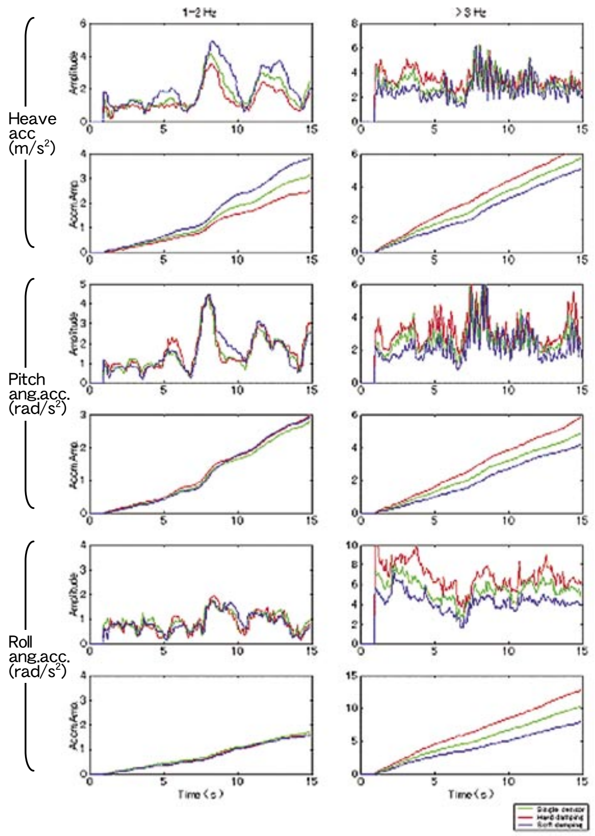

fig.18　Field test on the teaching signal road

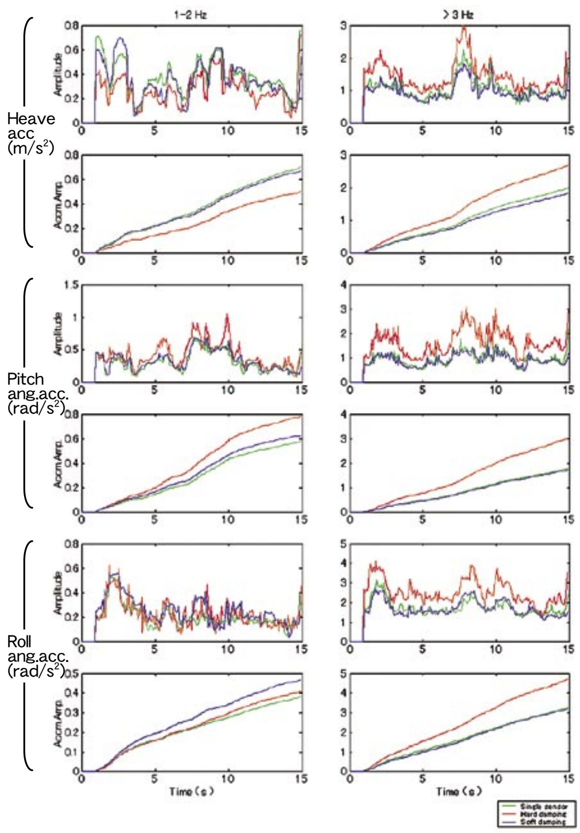

fig.19　Field test on another road

5 CONSIDERATIONS

The learning results show that the error of the single-sensor system is smaller even though it has a smaller number of rules (**Table 2**), which is also found on the inference simulation (**Fig. 13, 14**). This is explained by the fact that the former system could create a better knowledge base thanks to the properly selected input signals.

In other words, the filters used for processing the input signals in the single-sensor system are believed to have been skillfully extracted from the various elements of the vehicle's vertical accelleration signals to provide the necessary information for control purposes. For this reason, if there are changes in factors like vehicle weight, the characteristics of these filters will also have to be changed. This means that measures will have to be taken in this regard when applying the system to a specific vehicle, and we will go on to investigate this process in the future.

The simulation shows no big difference in the control performance of the fuzzy controller with these knowledge bases as long as the road signal of the teaching signal road is applied (**Fig. 16**). Low frequency components of pitch movement are well reduced as intended by the fitness function, though the high frequency components of heave are insufficient.

However, the single-sensor system shows a slight advantage on different roads because of its robustness (**Fig. 17**). Every intended part of the frequency component by the fitness function is better reduced than with the seven-sensor system.

The single-sensor system shows a similar control performance on the field test (**Fig. 18**) as the simulation. It works well even on other roads (**Fig. 19**), which means that the knowledge base has learnt important information about the characteristics of the vehicle behavior and, thus, the fuzzy system can extract it properly from the single signal source of the heave acceleration.

6 CONCLUSIONS

A model-based design methodology for a robust intelligent semi-active suspension control system based on soft computing was applied to a passenger car with the following results:

(1) A globally optimized teaching signal for damper control was generated by a genetic algorithm, the fitness function of which was set to satisfy the conflicting requirements of riding comfort and stability of the car body.

(2) A fuzzy controller realized accurate and robust control with properly selected input

signals that are provided by a single accelerometer through appropriate filters.

(3) It was shown that the knowledge base can be optimized for various kinds of stochastic road signals on a computer alone, without carrying out actual field tests.

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