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ADAPTIVE NEURAL NETWORK BASED FUZZY CONTROL FOR A SMART IDLE STOP AND GO VEHICLE CONTROL SYSTEM

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ABSTRACT−Idle stop and go (ISG) is a low cost but very effective technology to improve fuel efficiency and reduce engine emissions by preventing unnecessary engine idling. In this study, a new method is developed to improve the performance of conventional ISG by monitoring traffic conditions. To estimate frontal traffic conditions, an ultra-sonic ranging sensor is employed. Several fuzzy logic algorithms are developed to determine whether the engine idling is on or off. The algorithms are evaluated experimentally using various data gathered in real areas with traffic congestion. The evaluation results show that the method developed can reduce the chance of false application of ISG significantly while improving fuel efficiency up to 15%.

KEY WORDS : Idle stop and go system, Fuzzy inference system, Clustering, Adaptive network fuzzy inference system, Hybrid method

NOMENCLATURE

ACC : adaptive cruise control
AISG : adaptive idle stop and go
CL : close
FLC : fuzzy logic control
FN : fuzzy neural network control
FR : far
FS : fast
HV : host vehicle
ISG : idle stop and go
MB : maybe
MD : medium
NH : negative high
NL : negative low
OF : off
ON : on
PF : probably off
PH : positive high
PL : positive low
PN : probably on
SL : slow
SRB : simple rule based control
TV : target(frontal) vehicle
VC : very close
VF : very far/fast
VS : very slow
ZR : zero

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1. INTRODUCTION

Due to current and projected rises in oil prices, vehicle fuel efficiency has become an issue of paramount importance to drivers, to the extent that it is now thought of as a key factor in comparing vehicle performance. According to a study on ending idling by Yoshitaka Motoda, idling while driving accounts for over 50% of the total stop time for vehicles (Motoda and Taniguchi, 2003). In urban areas, where vehicle concentrations are especially high, numerous vehicles are moving slowly or stopped due to traffic congestion. Moreover, complicated traffic signal systems compel drivers to spend a substantial amount of time waiting for signal changes, during which time the engine is left idling. In idling mode, the engine burns fuel at a slightly higher rate than the stoichiometric air-fuel ratio to ensure combustion stability.

Thus, fuel is wasted even when the car is not in fact running. Accordingly, automobile manufacturers around the world are focusing on achieving dramatic improvements in fuel economy as the highest priority in next-generation automotive engineering. These companies are working to develop technologies that not only contribute to the preservation of the natural environment but also prepare them for future increases in the price of oil. Among such technologies, idle stop and go (ISG) is garnering particular attention as the most vital and promising technology.

The existing ISG control system turns the engine on and off automatically depending on the host vehicle information only, such as engine speed, vehicle speed, gear position, clutch pedal, and brake pedal. Hence, it fails to adequately reflect traffic flow in congested areas and ends up unnecessarily repeating the engine on/off cycle, which not only wastes fuel but can also be uncomfortable for the driver as well. Therefore, it is difficult to operate ISG optimally in various traffic conditions. To solve this problem, other sensors such as a radar sensors or ultrasonic sensors are exploited. The sensors provide the information about the behavior of the preceding vehicle, and the current traffic condition is estimated accordingly using that information. In the case of adaptive cruise control (ACC), a radar sensor signal is already used to adjust the vehicle speed automatically for the maintenance of a suitable headway distance between the host vehicle and the proceeding vehicle in the same Lane (Crosse, 2000; Scenarios and Evaluation Framework for City Case Studies, 2002; Serafin, 1996). This principle can be applied similarly to the ISG system.

In this study, a new concept ISG system, Adaptive idle stop and go (AISG), is proposed. It uses the information of the preceding vehicle and that of the host vehicle. A low cost ultrasonic sensor is used in place of a costly radar sensor because the inter vehicle range is very short and the vehicle speed is very low in congested areas. Ultrasonic sensors are known to work reasonably well in these conditions. These sensors measure the appropriate headway distance between the host vehicle and a preceding vehicle in the same lane, use this information to determine the acceleration of the target (preceding) vehicle and finally apply the information as inputs to the idling stop controller. A neural network based fuzzy control algorithm is developed to control the AISG system (Takagi and Sugeno, 1985; Zadeh, 1965; Mamdani *et al*., 1974; Sugeno *et al*., 1989, 1995; Sugeno, 1985). It is a proper scheme to be applied in this control system because it is extremely difficult to model the traffic conditions and the resulting driver response mathematically. The performance of the AISG control algorithm developed is verified using various experimental data gathered in real areas with traffic congestion.

The organization of this study is as follows. Section 2 discusses the analysis of the experiment data. Section 3 describes several proposed AISG control algorithms. Section 4 evaluates the performance of the developed algorithms.

2. ANALYSIS OF EXPERIMENTAL DATA

A series of experiments was conducted to obtain travel related data in a real area with traffic congestion. The system configuration of the test vehicle is shown in Figure 1. An ultrasonic ranging sensor is used to measure the distance between the preceding vehicle and the host ve-hicle and the host vehicle. A dSPACE MicroAutoBox 1403 is used for data acquisition.

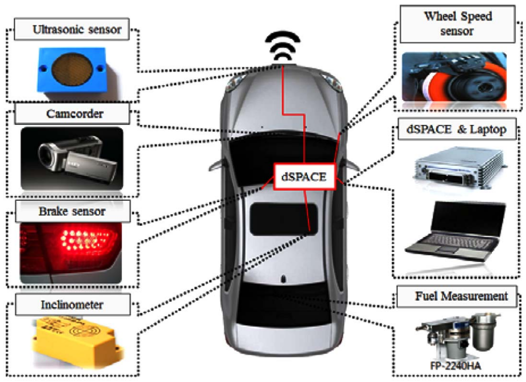


Figure 1. System configuration of the test vehicle.

The experiment was performed to measure the engine idling time in a real area with traffic congestion. The test driving condition is shown in Table 1. The total driving distance is 9.8 km, and the driving time is 66 minutes. The total fuel consumption is 1624.33 ml. Because the idling fuel consumption rate of the test vehicle is 13.87 ml/min, the total fuel consumption due to idling is 291.3 ml. The total idling time while driving is 24 minutes, and the number of idling events is 46. Figure 2 shows the portion of idling time for each 1 minute driving time interval.

Considering the extra fuel consumption associated with the restarting of an engine, the real fuel saving due to the idling stop is calculated by the formula shown in (1).

$$F_s = F_i \cdot T_i - F_r \cdot T_r$$
$$F_e = F_s / F_t \tag{1}$$

where, F_s is the saved fuel consumption [cc], F_i is the fuel consumption during idling [cc/s], T_i is the idling stop period [s], F_r is the extra fuel consumption for restarting an engine [cc], T_r is the engine restarting time [s], F_e is the fuel efficiency improvement [%], and F_t is the total fuel

Table 1. Test driving conditions in the area with traffic congestion.

TEST DRIVING DATA		IDLING DATA	
Test time	14:40~14:45 (66 min)	Total idling time	24 min
Test place	Gangnam main street	Fuel consumption	13.87 ml/min
Driving distance	9.8 km	Idling fuel consumption	291.3CC (18%)
Fuel consumption	1624.33cc		

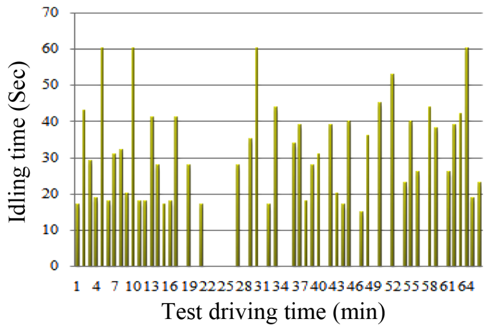


Figure 2. ISG engine idling analysis.

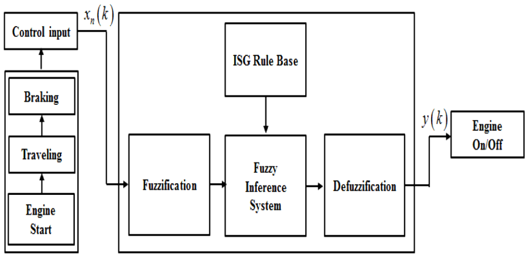


Figure 3. Schematic of an expert knowledge-based ISG fuzzy controller.

consumption [cc].

The evaluation result confirms that fuel efficiency can be improved up to 18% if an ISG system is implemented ideally.

Instead of using virtual simulation data, this study uses vehicle data gathered from actual congested areas for controller design. Basic ISG fuzzy control rules are established using these data. The fuzzy controller is integrated with a neural network and then optimized. The details of the controller design are discussed in the following section. Figure 3 shows the overall schematic diagram of the ISG control system.

3. DESIGN OF IDLE STOP AND GO CONTROL SYSTEMS

In this section, the design of ISG systems is described. The overall structure of the ISG controller is shown in Figure 4. An expert knowledge-based control system and a neural network based fuzzy control system are designed to turn the vehicle engine on or off.

3.1. Design of a Simple Rule-based ISG Fuzzy Controller

The ISG system is usually equipped on hybrid cars. A simple rule-based ISG system is designed for the purpose of comparison with the performance of the proposed advanced control system. The rules are as follows. They are used in an existing mass production hybrid car.

- Velocity (Host vehicle)

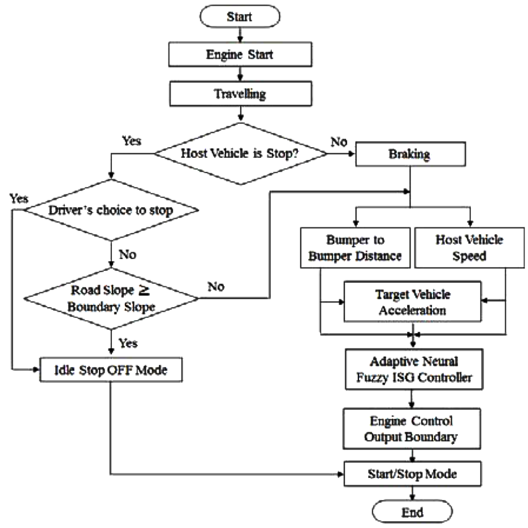


Figure 4. ISG engine on/off controller schematic.

If the velocity is faster than 1.67 m/s, then the engine must be turned on.

Otherwise, the engine must be turned off.

- Distance (between the host and preceding vehicle)

If the distance is further than 2 m, then the engine must be turned on.

Otherwise, the engine must be turned off.

3.2. Design of an Expert Knowledge-based ISG Fuzzy Controller

Fuzzy control is abstract and nonspecialized. It considers only input and output variables, and it does not require any knowledge of the mathematical model of the processes involved. The relationship between the input and output variables is expressed in sentences that closely mimic human thinking (Naranjo *et al*., 2003). Therefore, as the first stage in achieving human-like engine control in traffic congested areas, an expert knowledge-based, simple rule based ISG fuzzy controller is implemented.

Fuzzy control derives a control algorithm using only general knowledge about the plant and relies not on mathematical modeling but on control rules to execute an algorithm based on fuzzy inference. Therefore, the algorithm for determining the appropriate input to the plant from among the inputs entering the controller is expressed not as a single mathematical formula, as is true of conventional control methods, but as linguistic definitions specific to each case. That is, the control algorithm is expressed as if-then control rules for each case, and these rules manifestly display control characteristics based on expert knowledge.

Input variables $x_n(k)$ for the fuzzy controller consist of the relative distance $x_1(k)$, host vehicle speed $x_2(k)$, and target vehicle acceleration $x_3(k)$. The output $y(k)$ signifies the output of the fuzzy controller. These three input

Table 2. Linguistic variables for the ISG system.

Distance	VC	CL	MD	FR	VF
[m]	1	1.5	2	2.5	3
Speed	VS	SL	MD	FS	VF
[m/s]	0.56	1.12	1.67	2.22	2.78
FV's Acceleration	NH	NL	ZR	PL	PH
[m/s^2]	-0.6	-0.3	0	0.3	0.6
Engine	OF	PF	MB	PN	ON
[w.f]	0.1	0.3	0.9	0.6	0

variables, which enable judgment of the engine idling situation through analysis of collected traffic condition data, are combined with expert knowledge and used to propose a total of 125 control rules for idle stops. The input-output relationship is determined as fuzzy rules using the input variables and then applied to the fuzzy inference system.

In this paper, we consider a fuzzy system with a basic configuration, as shown in Figure 3. There are four principal elements in this fuzzy system: fuzzifier, fuzzy rule base, fuzzy inference system, and defuzzifier. We consider multi-input, single-output systems:

$U \subset R^n \rightarrow R$, where U is compact.

The fuzzifier performs a mapping from the observed crisp input space $U \subset R^n$ to the fuzzy sets defined in U, where a fuzzy set defined in U is characterized by a membership function $\mu_F: U \rightarrow [0,1]$ and is labeled by a linguistic term F such as "close," "medium," "far" or "very close." The most commonly used fuzzifier is the singleton fuzzifier, which maps $x \in U$ into a fuzzy set A_x in U with $\mu_{A_x}(x) = 1$ and $\mu_{A_x}(x') = 0$ for all $x' \in U$ with $x' \neq x$.

For a short description of our fuzzy controller, consider the case where the fuzzy rule base consists of 125 rules in the following form:

$$R_j: If\ x_1\ is\ A_1^j\ and\ x_2\ is\ A_2^j \\ and\ x_3\ is\ A_3^j, THEN\ y\ is\ B^j \tag{2}$$

where $j = 1, 2, \ldots, 125$, $x_i (i = 1, 2, 3)$ are the input variables to the ISG fuzzy system, y is the output variable of the fuzzy system, and A_i^j and B^j are linguistic terms characterized by fuzzy membership functions $\mu_{A_i^j}(x_i)$ and $\mu_{B^j}(y)$, respectively.

To give a more specific example,

IF Relative Distance x_1 (k) is VC, and
Host Vehicle Speed x_2 (k) is VS, and
Target Vehicle Acceleration x_3 (k) is NH,
THEN Engine $y(x)$ is OFF.

The set of ISG fuzzy systems with a singleton fuzzifier, product inference, centroid defuzzifier, and Gaussian membership function consists of all functions of the form:

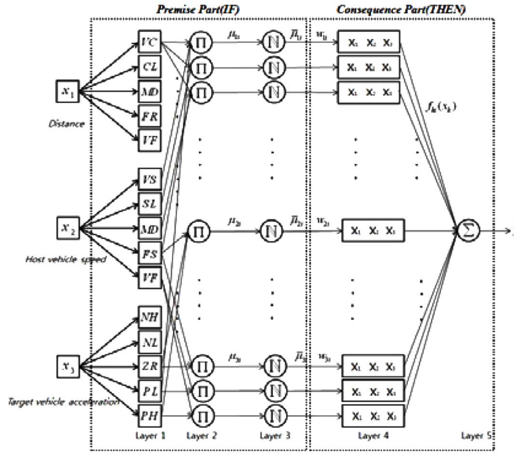


Figure 5. Structure of ISG fuzzy inference system (expert knowledge based).

$$f(x) = \frac{\sum_{j=1}^{5} \bar{y}^j \left(\prod_{i=1}^{3} \mu_{A_i^j}(x_i) \right)}{\sum_{j=1}^{5} \left(\prod_{i=1}^{3} \mu_{A_i^j}(x_i) \right)} \tag{3}$$

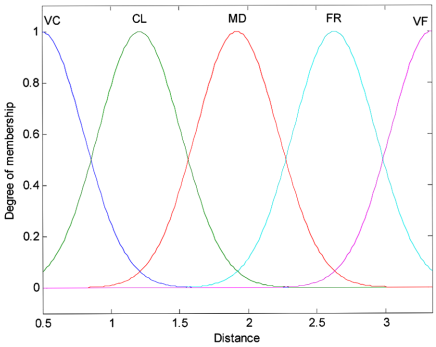
where $f: U \subset R^n \rightarrow R, x = (x_1, x_2, x_3) \in U: \mu_{A_i^j}(x_i)$ is the Gaussian membership function, defined by

$$\mu_{A_i^j}(x_i) = a_i^j\ exp\left[-\frac{1}{2} \left(\frac{x_i - \bar{x}_i}{\sigma_i^j} \right)^2 \right] \tag{4}$$

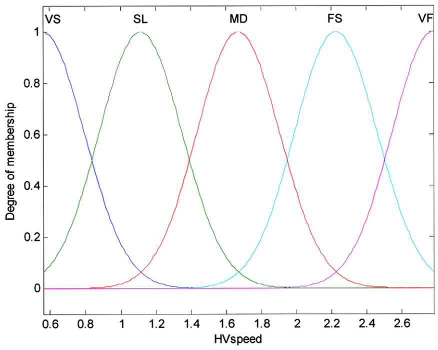
where a_i^j, $\bar{x}_i^j$ and σ_i^j are real-valued parameters with $0 < a_i^j \leq 1$ and $\bar{y}^j$ is the point in the output space R at which $\mu_{B^j}(y)$ achieves its maximum value. Clearly, (3) is obtained by a centroid defuzzifier.

The structure of the fuzzy inference system developed using the 125 expert knowledge-based ISG fuzzy control rules, Gaussian membership function, product operator, and centroid defuzzifier described above is shown in Figure 5. The linguistic variables and membership functions for each linguistic variable are illustrated in Table 2 and Figure 6. The relationship between the respective variables can be ascertained from Figure 7.

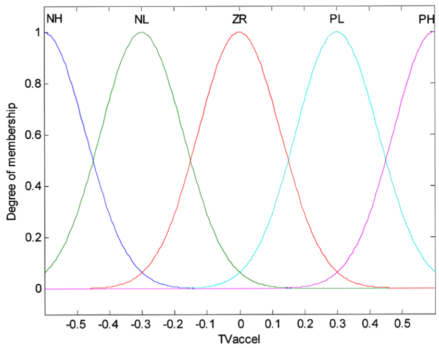
However, simple ISG fuzzy control based on expert knowledge cannot be optimized for all driving conditions and thus requires supplementation. To do so, necessary sensors and other equipment are installed on the test vehicle. The host vehicle and preceding vehicle data are entered into the ISG fuzzy controller as input. The resulting output value of 0.5 or higher signifies "engine on," and a value of less than 0.5 signifies "engine off." However, in the case of certain road congestion conditions, the data values can change dramatically due to the sensor noise itself, the occurrence of vehicle cut-in or cut-out, etc.



(a) Distance

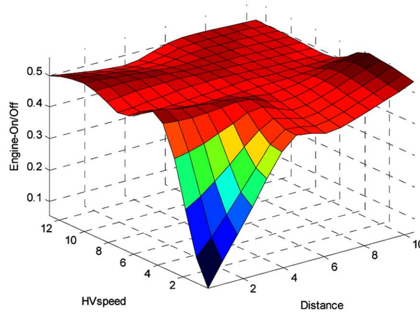


(b) Host vehicle speed

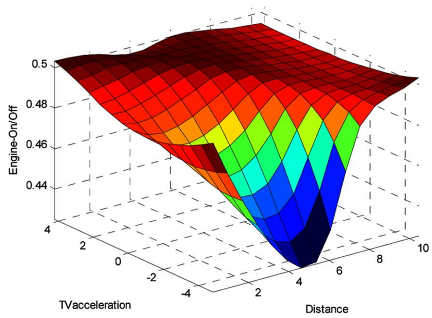


(c) Target vehicle acceleration

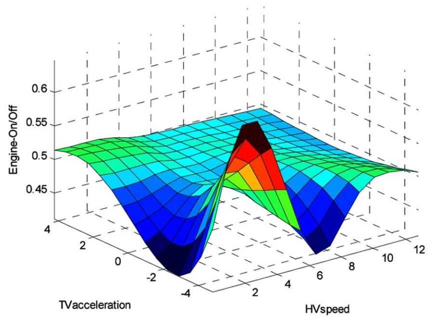
Figure 6. ISG fuzzy membership function partition (expert knowledge-based).



(a) Surface of distance and host vehicle speed



(b) Surface of distance and target vehicle acceleration



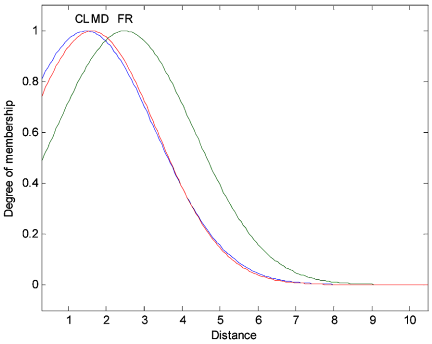
(c) Surface of host vehicle speed and target vehicle acceleration

Figure 7. ISG surface between variables (expert knowledge-based).

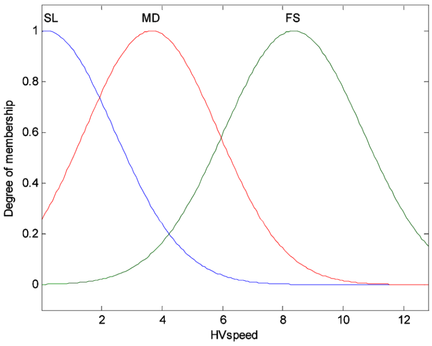
Consequently, if the output varies frequently around the 0.5 threshold, the engine may be turned on and off constantly. This problem is resolved by debouncing via the definition of an upper boundary and a lower boundary separately. These boundary values are optimized by applying the collected traffic condition data to the controller developed through off-line simulations.

3.3. Design of an Adaptive Neural Network-based Fuzzy ISG Controller

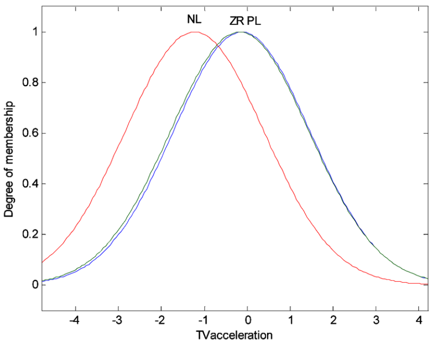
The expert knowledge-based fuzzy inference system represents the intuition of the driver in judging traffic conditions but poses difficulties in the structuring of membership functions and adjustment of variables. It also expends too much time calculating numerous rules, which makes it unfeasible for real-time application in actual vehicles. Therefore, the fuzzy inference system is restructured to achieve enhanced performance by applying fuzzy clustering and a neural network hybrid method to the training data composed of the results of the expert knowledge-based fuzzy inference system. It can be seen that the restructured controller, developed by clustering the expert knowledge based fuzzy output values found with the 125 control rules, tracks the performance of the expert knowledge-based fuzzy controller fairly well.



(a) Distance

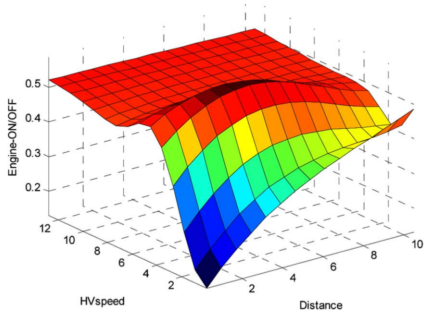


(b) Host vehicle speed

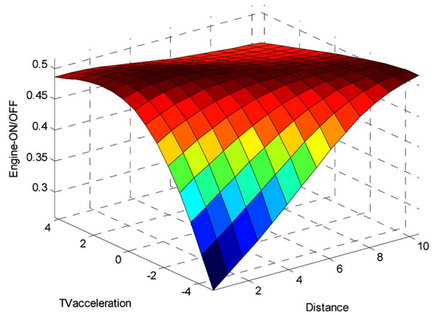


(c) Target vehicle acceleration

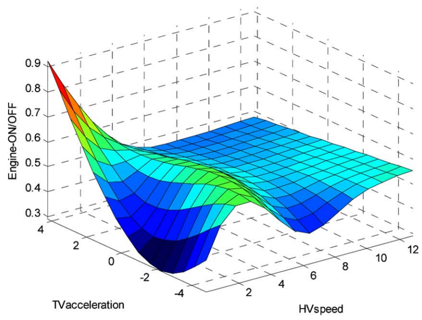
Figure 8. Membership function partition of the adaptive neural fuzzy ISG controller.



(a) Surface of distance and host vehicle speed



(b) Surface of distance and target vehicle acceleration



(c) Surface of host vehicle speed and target vehicle acceleration

Figure 9. ISG surface between variables (adaptive neural fuzzy ISG controller).

Fuzzy clustering is the process of partitioning data so that data belonging to the same cluster have high similarity and data belonging to disparate sets have little similarity. Typically, the purpose of fuzzy clustering is to compress data or to extract data characteristics. Data generated in everyday situations often harbor ambiguity due to observation error, uncertainty, subjective judgment, and so on. One effective way to express such ambiguity is to use fuzzy sets (Wang, 1996). Fuzzy c-means (FCM), currently in general use, was proposed by Jim Bezdek as a way to supplement the existing method of clustering; according to this method, each piece of data is clustered according to its degree of membership in the relevant cluster. (Bezdek, 1973, 1981; Bezdek *et al*., 1999) However, because it is impossible to determine a clear basis for how many clusters should be formed as a data group using the collected driving information data, this study applies subtractive clustering instead. Subtractive clustering as carried out by Matlab/Simulink is a one-pass algorithm for predicting the number of clusters and the cluster centers of data sets. It is characterized by fast convergence speed and used for initializing the model identification method and iterative optimization-based clustering method.

The training data are composed of the input/output data pairs acquired using the expert knowledge-based ISG fuzzy controller. The data are then used to restructure the controller in the following order:

(1) Find centers/widths of membership functions by self-organized clustering.
(2) Find fuzzy logic rules by competitive learning.
(3) Eliminate rules.
(4) Combine rules.
(5) Find the optimal membership functions by the hybrid learning method.

To compensate for errors in the controller output, the neural network hybrid method presented is composed of the combination of least square method and error back-propagation. The least square error is expressed as shown in (5).

$$E=\frac{1}{2}\sum_{i\mu}(\zeta_i^{\mu}-y_i^{\mu})^2, i=1,2,\dots,m \tag{5}$$

where ζ_i is the target value, y_i the inference result values, i the output node, and μ the input pattern. Hence, using the hybrid method, if the error falls below a certain specified value, learning is completed.

In the Adaptive Neural Fuzzy ISG Controller, restructured using clustering and the neural network hybrid method, the 125 control rules are reduced to 27 rules. The restructured membership functions and fuzzy rules for the respective input variables are as shown in Figure 8 and Figure 9.

4. CONTROL ALGORITHM EVALUATION

To demonstrate the performance of the proposed expert knowledge-based ISG fuzzy inference system, the ISG

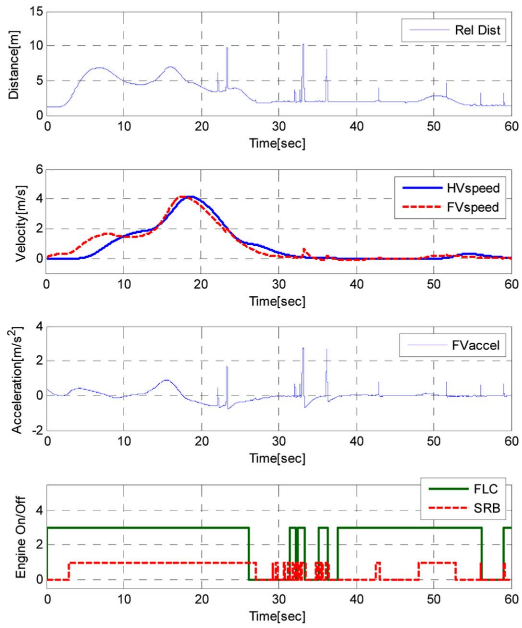


Figure 10. ISG engine on/off control results : Case 1 (60 seconds).

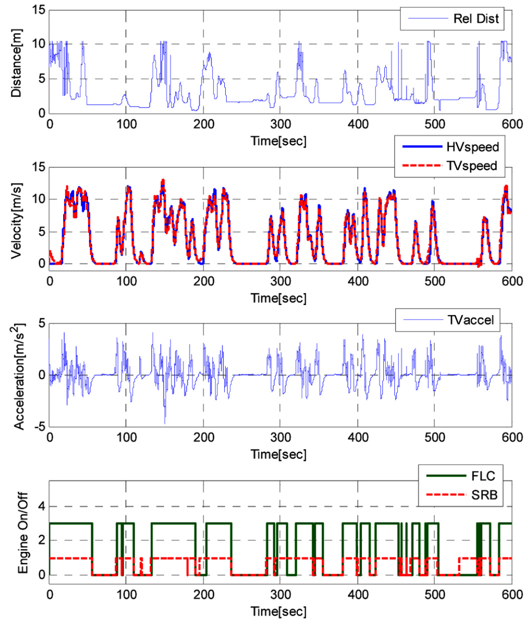


Figure 11. ISG engine on/off control results : Case 2 (10 minutes).

fuzzy system is applied to the collected driving test data. In the last graphs of Figure 10 through Figure 13, the engine on/off control results are compared against the intuitive judgment of the driver assessing the situation. Figure 10 and Figure 11 confirm that, compared to a simple rule based (SRB) control system using only host vehicle information, the fuzzy logic expert knowledge-based ISG controller (FLC) is very effective in cutting fuel consumption while dramatically reducing unnecessary and annoying frequent engine on/off at the same time. Figure 10 shows that unnecessary engine on/off events are reduced significantly. Figure 11 shows the results of applying the controller to 10 minutes of continuous data. FLC seems to work reasonably well in most cases. However, both SRB, which applies only host vehicle data to idle stops, and FLC, which is a fuzzy controller based on expert knowledge, suffer from some limitations. Therefore, a more optimized approach, such as a neural network-based fuzzy control (FNC), is proposed in this paper. One pertinent example is shown in Figure 12, where the host vehicle is stopped 2 m or more from the preceding target vehicle, but the target vehicle acceleration is very low. In this case, SRB and FLC call for engine on because the engine is set to turn on whenever the relative distance exceeds 2 m. However, with FNC, which is restricted using clustering and a neural network, the engine is turned on/off according to vehicle data specific to the situation, as shown in Figure 12 and Figure 13. Based on these results, it is verified that FNC is more adaptive to driving conditions and that it successfully minimizes repetitive engine on/off to produce results that closely approximate the intuitive judgment of the driver.

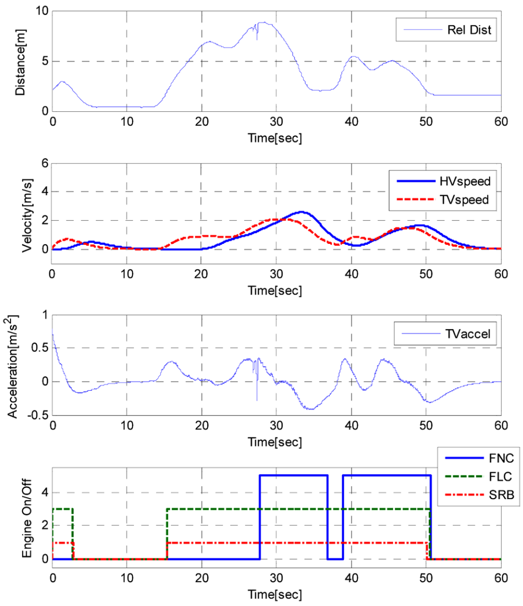


Figure 12. ISG engine on/off control results : Case 3 (60 seconds).

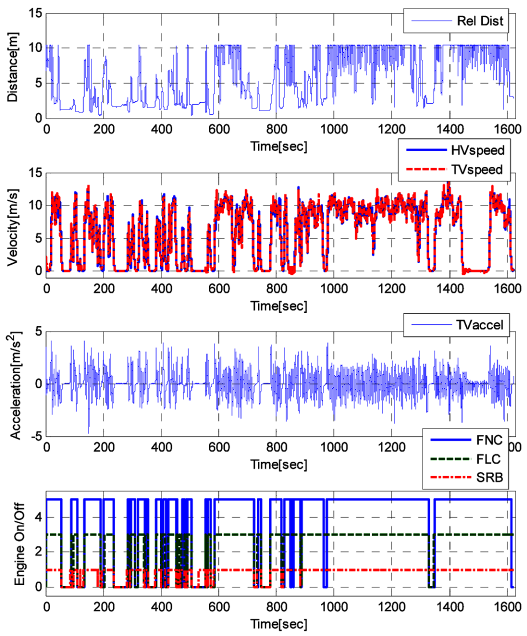


Figure 13. ISG engine on/off control results : Case 4 (27 minutes).

In Figure 13, the FNC optimized using one set of data is applied to another data set collected in a wholly different place at a different time. The results show that the performance of the FNC is fairly robust to general driving conditions and is not depending upon any specific data set. Therefore, the FNC algorithm trained off-line with pre-collected traffic data can be applied on-line in real vehicles.

5. CONCLUSION

This study proposes a new ISG system whose performance is enhanced by additionally monitoring the behavior of a target vehicle. The most significant difference between the system developed and those based on conventional control rules or expert knowledge is seen in the following instance. Rather than keeping the engine on when the relative distance or host vehicle speed exceeds a certain pre-defined threshold, the system developed uses the target vehicle acceleration as additional data to achieve superior engine on/off control. The off-line test results thus confirm that the system makes judgments that closely approximate human judgments. Compared to SRB, the controller developed enables an additional 15% reduction of fuel consumption while noticeably reducing the events of unnecessary and malfunctioning engine on/off. The results of this study have profound significance in that this controller can be implemented on production vehicles easily using data that are already available, i.e., speed and distance. In future studies, the performance and efficacy of the proposed ISG fuzzy controller will be verified through additional testing on actual roads, and the performance of the controller will be further optimized adaptively to coincide more closely with the intentions of the driver depending on traffic conditions.

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