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Intelligent Vehicle Airbag Controller Design

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***Abstract*--An intelligent vehicle airbag controller design methodology is proposed in this paper. Firstly, the vehicle impact severity is analyzed to get four characteristic factors utilized as fuzzy inputs. From these four characteristics factors, the 'two stages fuzzy algorithm' is developed and used as the airbag deployment algorithm to identify the vehicle impact severity. Finally, the Fuzzy-Gaussian Neural Network (FGNN) is used to train the suitable fuzzy membership functions and fuzzy rules based on this proposed 'two stages fuzzy algorithm'. Simulation results for different vehicle crash data demonstrate the validity and effectiveness of the proposed design methodology.**

Keywords- fuzzy, vehicle airbag, algorithm design, FGNN

I. INTRODUCTION

The airbags have been standard accessories of cars for quite some time. There are four essential components of an airbag system: the sensor, the inflator, the bag and the vehicle interior. The airbag should trigger or not depends upon the front-impact severity of the car. In a low-speed collision situation, such as 8 Km per-hour (Kmph) which is about 5 miles per-hour (mph) vehicle-to-barrier crashes, the sensing systems should not trigger the airbags. In modest collisions, such as 24-32 Kmph (15-20 mph) vehicle-to-barrier or vehicle-to-pole crashes, the sensing systems are usually designed to trigger the bags, especially when the passengers are not belted. From the onset of the collision, the sensing system typically triggers within 40-60 milliseconds in these medium-speed crashes. In severe collisions, such as 48-56 Kmph (30-35 mph) crashes, the sensing system will trigger within 10-20 milliseconds [1].

There are several researches for determining when an airbag should trigger, such as acceleration or power rate analysis method [2], sliding windows algorithms [3], and predictive algorithms [4]. There also exists a method for triggering an airbag when the acceleration signal detected by an occupant detector exceeds a certain threshold value [5]. In Ref. [4], the conception of jerk is introduced to distinguish between the impact severity at 30 mph and on rough roads, as the rate of change of velocity cannot do this. But it provides no algorithmic methods for distinguishing impact severity. In Ref. [5], it provides a method that uses noise reduction methods and occupant position sensors for detecting the displacement of occupants to distinguish the severe and light impact with similar wave shapes. But it does not consider suitable trigger time. For any of these aforementioned methods have both advantages and disadvantages, and none of them can consistently identify when an airbag should be triggered. It would be very beneficial, then, if there existed an algorithm that could more precisely identify the severity of a vehicle impact and provide that identification information to an airbag-triggering electronic control unit (ECU).

Fuzzy logic control (FLC) using fuzzy if-then rules can model the qualitative aspects of human knowledge without employing precise quantitative analyses. The FLC using linguistic information possesses advantages such as robustness, model-free, universal approximation and rule-based algorithm [6]. In recent years, FLC has been shown to be a powerful technique for control system designs. In traditional FLC designs, the membership functions have to be tuned by trial-and-error in order to achieve the desired performance; however, this tuning procedure is time-consuming. Fuzzy-Gaussian Neural Network (FGNN) [7] are appropriate learning procedures to cope with this shortage. The membership functions of FGNN are constructed as a Gaussian-type function with a neural network based of fuzzy inference system. The back-propagation training algorithm is used to adjust the weightings of each neuron connection. Because the network of FGNN demonstrates the rules of fuzzy inference system, the weightings of FGNN can be thought as the fuzzy membership functions. And the membership function is on-line tuned at the moment of every weighting is on-line tuned.

II. VEHICLE AIRBAG CONTROLLER ARCHITECTURE

The physical diagram of vehicle airbag controller is shown as in Fig. 1. For frontal airbag system, the acceleration pulse generated by accelerometer is the signal used for vehicle airbag controller for crash detection and identification. The vehicle airbag controller comprises an accelerometer and an impact severity identification circuit (ISIC). The accelerometer is installed in the vehicle for detecting the acceleration of vehicle and generating an acceleration signal G value. An A/D (analog to digital) converter electrically connected to the accelerometer for converting the acceleration signal G value to a digital acceleration signal G value. The ISIC is installed in the vehicle and electrically connected to the accelerometer for identifying the impact severity of vehicle according to the digital acceleration signal G. In addition, the vehicle comprises an airbag module and an electronic control unit (ECU)

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electrically connected to the airbag module and the vehicle ISIC. The ECU is used to control the triggering of the airbag module according to the identification signal generated by the vehicle airbag controller.

III. VEHICLE AIRBAG DEPLOYMENT ALGORITHM DESIGN

In this paper, the design method is developed from a "Two stages fuzzy algorithm" design methodology [8]. The conceptual diagram is illustrated as in Fig. 2. The differential of the digital acceleration signal G with respect to time is called "jerk". There are four signals used in this design methodology. The meanings of these four signals are depicted as:

- displ: the displacement during a predetermined period;
- disp2: the total displacement;
- njerk: The number of times that the "jerk" exceeds a threshold value after the digital acceleration signal G exceeds the start value;
- tw: the time interval between the first G signal exceeds the start value and the first jerk exceeds the threshold value;

During a frontal impact, in the first stage (0ms~10ms), when the acceleration value of the digital acceleration signal G exceeds a predetermined start value during an impact, the ISIC will determine if the impact is a 'severe impact' based upon 'displ'. If the impact cannot be identified as a 'severe impact', then a second stage (10ms~40ms) of computing begins. In the second stage, the ISIC will successively identify the impact severity of the vehicle based upon the 'displ', 'disp2', 'njerk' and 'tw' until the identification signal is generated and outputted. The impact severity of the second stage has three classifications of impact: "severe impact", "moderate impact", and "light impact".

A. *Test model establishment*

The purpose of the establishment of the test model is to simulate the impact identification from experimental data which physical acceleration characteristics are got from the accelerometer during a real vehicle collision. The design of the ISIC in this paper adopts four impact pulse data sets: the two data sets are at 30 mph and rough roads [4], and the other two data sets are at 17 mph and 8 mph [5]. These data are used to determine four physical characteristics, i.e. the 'displ', 'disp2', 'tw'. and the 'njerk'. By analyzing these physical characteristics, their relationships to impact severity can be found, and they serve as a foundation of the design of the fuzzy rules of the airbag deployment algorithm.

B. *Two stages fuzzy algorithm design*

The fuzzy rules are the kernel of the ISIC. The fuzzy variables of the ISIC comprise the fuzzy input variables 'displ', 'disp2', 'njerk' and the 'tw'. The fuzzy output variable is impact severity 'svty'. The Table 1 is a table of the fuzzy rules of the ISIC. Each fuzzy rule has the form of "if.... then..." The part "if" describes the input state of the ISIC, and the part "then" describes the reaction state of the ISIC. Each fuzzy rule can induce a fuzzy value by a fuzzy inference process, and the fuzzy values will be translated to the digital values by a defuzzification process. To make the fuzzy rules more precise to deal with various types of impacts, the ISIC adopts the "two stages fuzzy algorithm", which is described below:

When the acceleration value of the digital acceleration signal G exceeds the predetermined start value during the impact, the fuzzy unit of the ISIC will begin calculating the displacement during the predetermined period, generating the first fuzzy input variable 'displ'. The design of the first stage fuzzy rules utilizes the fuzzy input variable 'displ' to determine if the impact is a severe impact. If it is not a severe one according to the fuzzy input variable 'displ', the ISIC will stay in a "waiting" state. If the first displacement fuzzy input variable 'displ' exceeds a predetermined value, then the ISIC will identify the impact as a severe impact; if the first displacement fuzzy input variable 'displ' is lower than the predetermined value, then the ISIC will decide later, rather than at that moment. That means the ISIC will decide if the impact is severe in the second stage.

The design of the second stage fuzzy rules utilizes the fuzzy input variable 'displ', the fuzzy input variable 'disp2', the fuzzy input variable 'tw', and the fuzzy input variable 'njerk' to determine if the impact is a "severe impact", a "moderate impact", or a "light impact". These four factors are used as the foundation for identifying the impact severity in the second stage. The fuzzy rules are constructed by human knowledge and the signal power rate [2]. From the energy and power equations, the following equations can be got

$$E = \frac{1}{2} m V^2 \tag{1}$$

$$P = \frac{dE}{dt} = m \cdot V \cdot A \tag{2}$$

where E is the signal energy, P is the signal power, m is the mass of vehicle, V is the vehicle velocity and A is the vehicle acceleration. The power rate is defined as the derivative of P with respective to time. From Eq. (2), we can get

$$\frac{dP}{dt} = mA^2 + m \cdot V \cdot J\ ; \tag{3}$$

where J is the signal jerk which is the double derivative of vehicle velocity with respective to time. From Eq. (3), when the vehicle velocity variation is small at the moment of vehicle crash, we can infer the displacement is small and the jerk is the dominant factor. The more 'njerk' exceeds threshold implies that the power rate has large variation, that is the accumulated energy is large. Based on this phenomenon of energy variation at the moment of vehicle crash, the second stage fuzzy rules can be got as Table 1. The meanings are explained as follows:

- When 'disp1' exceeds 0.3, 'disp2' exceeds 1, 'tw' lower than 5ms and 'njerk' exceeds 10, it implies that the crash energy makes the large variation of jerk. And after 20ms, the big displacement arises. In general, this kind of crash is 'severe impact'.
- When 'disp1' is about 0.3, 'disp2' is about 0.5, 'tw' lower than 5ms and 'njerk' exceeds 10, it implies that the crash energy makes the large variation of jerk. And after 20ms, the mediate displacement arises. In general, this kind of crash is 'moderate impact'.
- When 'disp2' exceeds 1, 'tw' higher than 12ms and 'njerk' exceeds 4, it implies that the crash energy makes the small variation of jerk. In general, this kind of crash is 'moderate impact'.
- If 'disp1' is about 0.3, 'disp2' exceeds 1, 'tw' higher than 20ms and 'njerk' less than 4. In general, this kind of crash is 'moderate impact'. It implies that the crash energy first makes the displacement then release the energy. In general, this kind of crash is also 'moderate impact'.
- If 'disp1' is about 0.2, 'disp2'less than 1, 'tw' higher than 12ms and 'njerk' less than 4. In general, this kind of crash is 'light impact'.

C. The FGNN training rules

For a fuzzy system which has r rules, its ith rule can be expressed as

$$R_i : If \;\; x_1 = A_{i1} \;\; and ... x_n = A_{in}$$

$$Then \;\; u_1 = B_{i1} \;\; and ... u_p = B_{ip} \tag{4}$$

where R_i denotes the ith fuzzy rule, A_{in} is the fuzzy set in the antecedent associated with the nth input variable at the ith fuzzy rule, and B_{ip} denotes a constant associated with the pth output variable in the consequence at the ith fuzzy rule.

The inferred output is

$$u_j^* = \frac{\sum_{i=1}^{r} h_i B_{ij}}{\sum_{i=1}^{r} h_i} \;, j = 1, ..., p \;; \tag{5}$$

where

$$h_i = u_{A_{i1}}(x_1) \cdot u_{A_{i2}}(x_2) .... u_{A_{in}}(x_n) \;; \tag{6}$$

is inferred grade of every fuzzy rule, $u_{A_{iq}}(x_q)$ is the value of the membership function of fuzzy variable x_q associated with the nth input variable at the ith fuzzy rule.

The Gaussian-type membership function is used as [6]

$$f(x) = e^{\ln(0.5) \cdot x^2} \;; \tag{7}$$

and the neural network is constructed as in Fig. 3. From (7) and Fig. 3, the following modified equation is used

$$f(x_i) = e^{\ln(0.5)(\gamma x_i - \alpha)^2 \beta^2} \Big|_{\substack{\alpha = w_c \\ \beta = w_d \\ \gamma = w_s}} \;. \tag{8}$$

When w_s, w_c and w_d are adjusted, the equivalent membership function is got and demonstrated as in Fig. 4. Figure 5 illustrates the structure of FGNN with two-input one-output and three membership functions. At layer F, the symbols of g and $\sum$ stand for the following equations

$$g(x) = \frac{1}{x} \;; \tag{9a}$$

$$u_j^* = \sum_{i=1}^{r} h_i B_{ij} \;\;, \;\; j = 1, ..., p \,. \tag{9b}$$

The layers from (A) to (E) stand for the antecedent parts of fuzzy rules, and the layers from (G) to (H) stand for the conclusion parts of fuzzy rules. At layer (F), every rule grade h_i is calculated to get the result of (6). The meaning of w_s, w_c and w_d is the same as (8), and Fig. 3, and the w_b stands for the fuzzy consequent part which equivalent to B_{ij} of (5). There are two types for FGNN network connections of Fig. 5:

Case A: for that connections including nodes $\sum$.

Case B: for that connections including nodes $\prod$.

The delta calculations are based on the back-propagation algorithm. The calculation equations are got as follows:

output layer:

$$\delta_j^M = f'(i_j^M) \sum_{i=1}^{m} (y_{di} - y_i) \frac{\partial y_i}{\partial u_j} \;; \tag{10}$$

hidden layer:

for case A

$$\delta_j^k = f'(i_j^k) \sum_l \delta_l^{k+1} w_{jl}^{k,k+1} \;;$$

for case B (11)

$$\delta_j^k = f'(i_j^k)\sum_l \delta_l^{k+1} w_{jl}^{k,k+1} \cdot (\prod_{i \neq j} w_{il}^{k,k+1} o_i^k).$$

From (7) and (8), the derivative functions can be got as

$$f'(i_j^k) = 2\ln(0.5) i_j^k o_j^k \quad , for\ layer\ D$$
$$f'(i_j^k) = -(o_j^k)^2 \quad , for\ first\ unit\ of\ layer\ F \qquad (12)$$
$$f'(i_j^k) = 1 \quad , \qquad for\ other\ linear\ units.$$

Hence, the weighting calculation equations are got as follows:

$$w_{ij}^{k-1,k}(t+1) = w_{ij}^{k-1,k}(t) + \eta\delta_j^k o_i^{k-1} + \alpha\Delta w_{ij}^{k-1,k}(t) \qquad (13)$$

$$w_{ij}^{k-1,k}(t+1) = w_{ij}^{k-1,k}(t) + \eta\delta_j^k o_i^{k-1}(\prod_{l \neq i} w_{li}^{k-1,k} o_l^{k-1}) + \alpha\Delta w_{ij}^{k-1,k}(t) \qquad (14)$$

where η is the learning rate, and α is a stabilizing factor.

In order to improve the accuracy of the weightings calculation, equation (11) is used to adjust w_c, w_d and w_b. And the w_s which has larger variation range is used to cope with the input signals, the weighting calculation of w_s should be modified as:

$$w_{ij}^{k-1,k}(t+1) = w_{ij}^{k-1,k}(t) + \eta\delta_j^k w_{ij}^{k-1,k}(t)^2 o_i^{k-1} + \alpha\Delta w_{ij}^{k-1,k}(t) \qquad (15)$$

IV. SIMULATION RESULTS

The goal of simulating and testing is to verify if the impact severity can be identified in a timely manner by the ISIC under various types of impacts. Herein after, the presented test model, fuzzy rules, membership functions, and the use of "Two Stage Fuzzy Algorithm" are tested using the previously mentioned impact data to verify the practicability and precision of the ISIC according to the proposed airbag deployment algorithm design method. From Fig. 6(a) to Fig. 6(d) are testing results of the airbag deployment algorithm based on the impact data sets at 30mph, rough road, 17 mph, and 8 mph. Each of the testing results is successful. During the impact test at 30 mph, a severe impact is identified at 18 ms as shown in Fig. 6(a) which satisfies the requirement of that the sensing system must trigger within 10-20 ms. During the rough road impact testing, a light impact was consistently identified, as shown in Fig. 6(b). These two results show that a severe impact and rough road can be distinguished from crash data mentioned in [4]. During the impact test at 17 mph, a moderate impact is identified at 30 ms, as shown in Fig. 6(c) which better than the requirement of that the sensing system must trigger within 40-60 ms. For impact testing at 8 mph, as shown in Fig. 6(d), a light impact is consistently identified. These two results show that a moderate impact can be distinguished from two similar impact waves mentioned in [5]. According to the above simulating and testing results, the airbag deployment algorithm using a "Two Stages Fuzzy Algorithm" can correctly distinguish various types of impact waves.

In order to verify the reliability of the proposed airbag deployment algorithm design method, we develop a graphic user interface (GUI) such as in Fig. 7 to test different crash data. From this developed GUI, the crash data can be opened by keying in the file name of the crash data. By clicking the "Run" pushbutton, the simulation begins and the results are shown in four different axes. In this GUI of the proposed airbag deployment algorithm, the performance of algorithm can be justified by opening different type of crash data then run test to identify if it can successfully trigger airbag within a desired time interval.

V. CONCLUSIONS

An improved vehicle airbag deployment decision algorithm has been developed in this paper. This designed algorithm adopts a "Two stages fuzzy algorithm" possessing the functions of "prediction" and "distinction" so that it can distinguish between various types of impact waves and trigger the airbag in a desired time interval. According to the impact data sets at 30 mph, rough roads, 17 mph, and 8 mph, the proposed algorithm can tune an optimal fuzzy membership functions and fuzzy rules to identify the impact severity within a suitable trigger time interval. From the test results, it reveals that the proposed vehicle airbag deployment decision algorithm can possess good identification and control ability for different type of vehicle impact conditions.

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REFERENCES

[1] C.Y. Chan, *Fundamental of Crash Sensing in Automotive Air Bag Systems*, Society of Automotive Engineers, Warrendale PA, 2000.

[2] J.L. Allen, "Power-rate crash sensing method for safety device actuation," *SAE paper* (920478), pp. 55-60.

[3] S. M. Mahmud, A.I. Alrabady, "A new decision making algorithm for airbag control," *IEEE Trans. on Vehi. Tech.* Vol. 44, no. 3, pp. 690-697, 1995.

[4] T. Gioutsos, "A predictive based algorithm for actuation of an airbag," *SAE paper* (920479), pp. 61-66.

[5] E.J. Gillis, T. Gioutsos, "The use of signal processing techniques in an occupant detection system," *SAE paper* (940906), pp. 65-70.

[6] C. T. Lin, C.S.G. Lee, *Neural Fuzzy Systems: A Neural-Fuzzy Synergism to Intelligent Systems*, Prentice-Hall, Englewood Cliffs NJ, 1996.

[7] K. Watanabe, J. Tang, M. Nakamura, S. Koga, and T.

Fukuda, "A fuzzy-Gaussian neural network and its application to mobile robot control," *IEEE Trans. on Control Syst. Tech*, vol. 4, no. 2 pp. 193-199, 1996.

[8] Y.J. Mon, K.T. Luo, Y.M. Lin, "Vehicle impact severity identification device," *U. S. Patent*, US 6,275,755 B1, 2001.

TABLE I. THE "SECOND STAGES FUZZY RULES"

	disp1	disp2	njerk	tw		severity
If	>0.5	any	any	any	Then	severe
	>0.3	>1	>10	<5		severe
	0.3	0.5	>10	<5		moderate
	0.3	>1	>4	>12		moderate
	0.3	>1	<4	>20		moderate
	0.2	<1	<4	>12		light

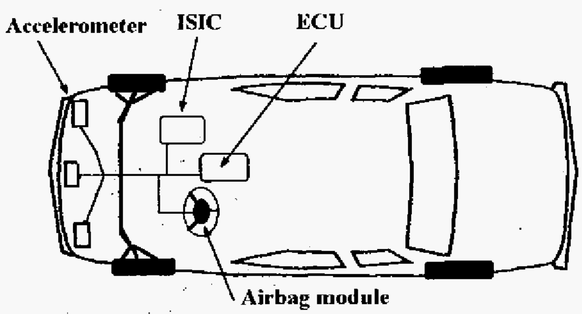

Fig. 1. The physical diagram of vehicle airbag controller

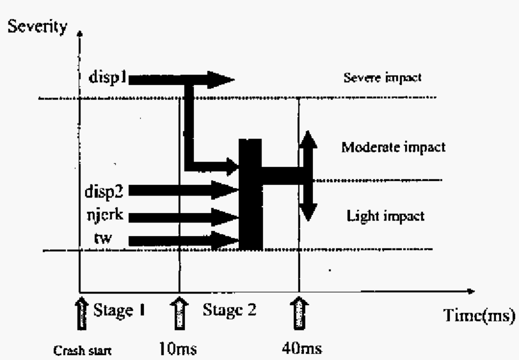

Fig. 2. The conceptual diagram of "Two stages fuzzy algorithm"

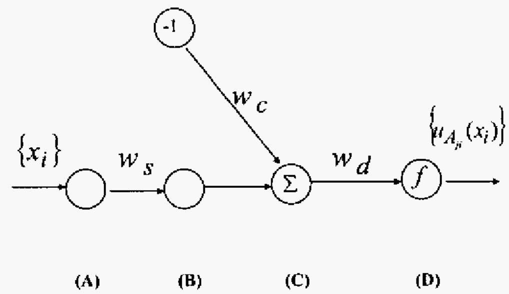

Fig. 3. The neural network of Gaussian function

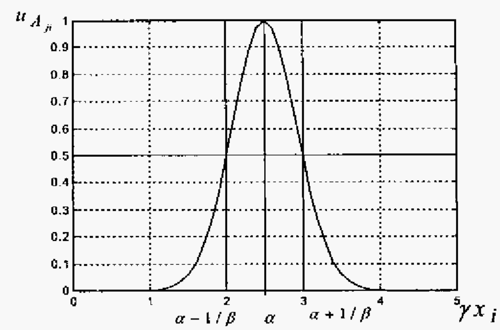

Fig. 4. The Gaussian-type membership function

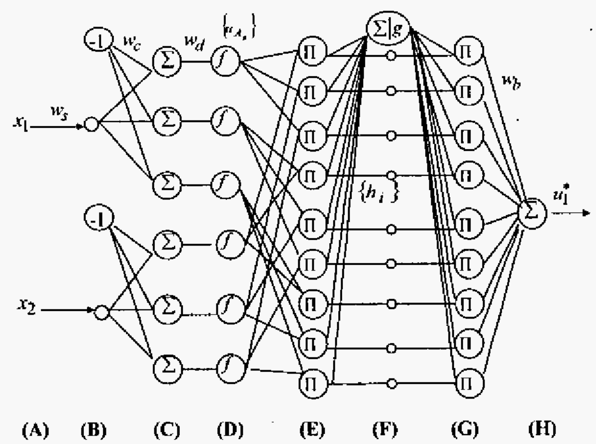

Fig. 5. The architecture of FGNN

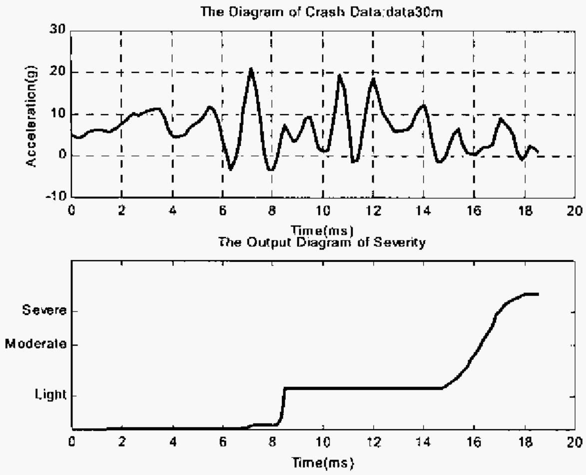

Fig. 6(a). The simulation result of 30 mph crash data

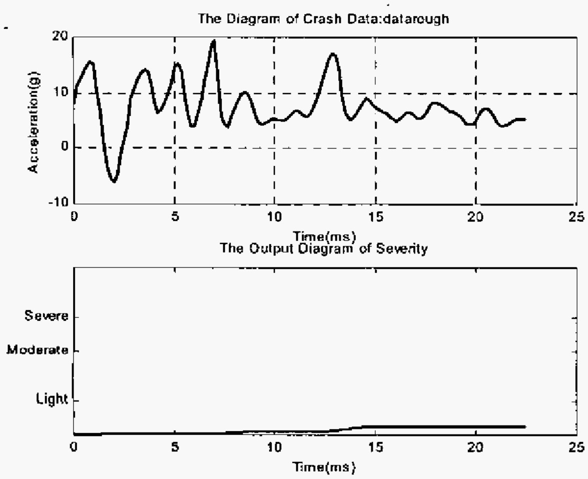

Fig. 6(b). The simulation result of rough road data

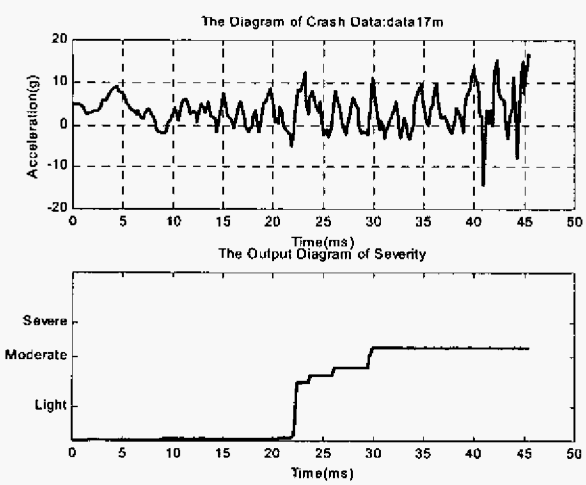

Fig. 6(c). The simulation result of 17 mph crash data

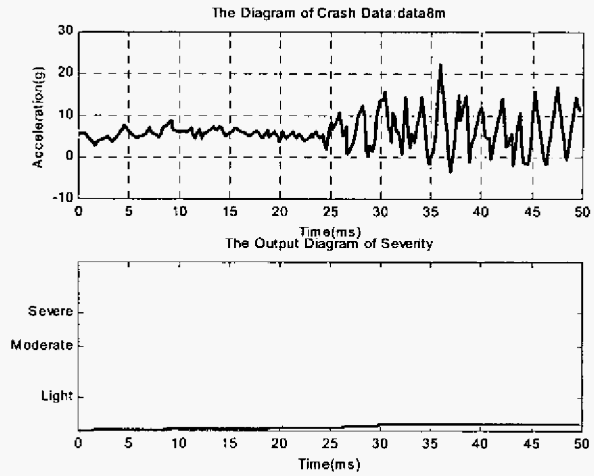

Fig. 6(d). The simulation result of 8 mph crash data

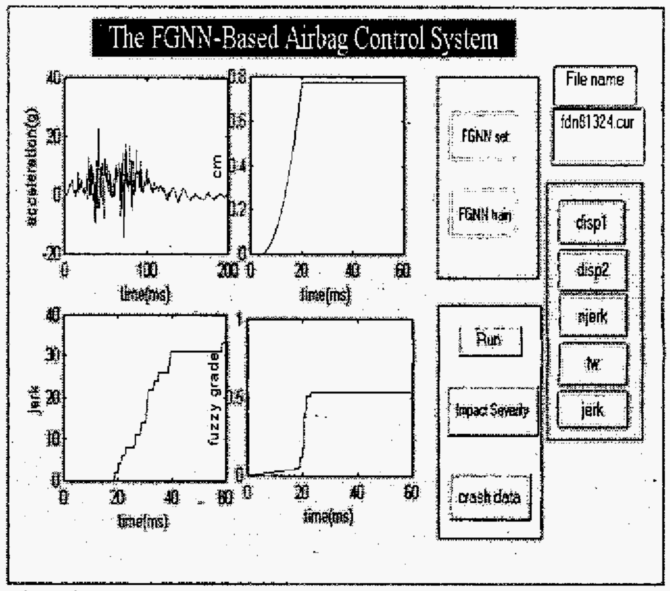

Fig. 7. The GUI of airbag control system