Estimate modelling for assessing the safety performance of occupant restraint systems

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Abstract

In this research, some estimate models of occupant's injury criteria at a frontal crash were constructed by using two machine learning methods, Gaussian Process and Kriging from sampling data sets computed by multi-body dynamics simulation. Then we evaluated the performance and their properties of the learning and the sampling methods. Although substituting virtual evaluation by computational simulation for physical crash tests has brought significant reduction of the time and the cost for design and evaluation of the occupant restraint system, the virtual evaluation of the crash has a problem to be solved. That involves huge computation time caused by the combinatorial explosion of various factors such as the crash condition, the design variables of the restraint system and the posture of the occupant. Since complex interaction among the various factors affect response of the injury criteria, repetitious computation and evaluation are required. Therefore, a quantitative and qualitative virtual evaluation method reducing the number of times for computation is demanded. This research investigated the applicability of machine learning methods as a means of estimating the highly nonlinear and multimodal response. Machine learning is an artificial intelligence technology which acquires rules behind observed data set automatically. Generally, efficiency is opposed to precision and complexity, that is, improving the precision of the estimate requires high density sampling in a design variable space. Furthermore, estimating complex input-output response requires various combinations of the design variables. So, in order to find an efficient sampling policy, we investigated the trade-off relationship among "the sampling method and the number of samplings" and "the precision of the estimate response and the complexity of the response".
Keywords: occupant safety, injury criteria, CAE, machine learning, estimate modelling.

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1 Introduction

Since physical prototyping and testing at design and development of a vehicle consume huge time and cost, virtual prototyping and testing by using numerical simulation are employed at early stage of the design. At the virtual prototyping and testing, many draft designs' evaluation indexes, such as safety, stress and weight, are calculated and then designers examine the draft designs while referring trade-off and restraint of those indexes.

At an occupant restraint system design, analytical model of the occupant's behaviour is constructed by using CAE such as finite element analysis and multi-body dynamics, then impact responses at various crash conditions and various evaluation indexes based on safety regulations are calculated. Substituting such virtual evaluation by using CAE for physical crash testing has brought significant reduction of the time and the cost for design and evaluation of the occupant restraint system nowadays [1]. However the virtual evaluation of the crash has a problem to be solved. That is huge computation time which caused by combinatorial explosion of various factors such as crash condition, design variables of a restraint system and a posture of an occupant. Since complex interaction among the various factors affect response of injury criteria, repetitious computation and evaluation are required. Therefore quantitative and qualitative virtual evaluation method with reducing the number of times for computation is demanded.

One natural idea is to estimate by extrapolation and interpolation using polynomial approximation as a means of reducing repetitious computation. However, the idea is not appropriate, since it is difficult to represent responses of a crash by using polynomial functions, because the responses are highly nonlinear and multi-modal. So, this research investigates the applicability of machine learning methods as a means of estimating the highly nonlinear and multi-modal responses. Machine learning is an artificial intelligence technology which acquires hidden rules behind observed data set automatically. Machine learning is widely used in various areas such as pattern recognition and bioinformatics nowadays.

In this research, we construct an analytical model of occupant behaviour at a frontal crash by using multi-body dynamics simulation. Then estimate models are constructed by means of two machine learning methods, Gaussian Process and Anisotropic Kriging from input-output data set of the analytical model. The input parameters are control parameters of the restraint system and the output parameters are the injury criteria, head injury criterion, chest resultant acceleration and femur load.

Generally, efficiency of estimate modelling is opposed to precision and complexity. That means improving the precision of the estimate modelling requires high density sampling of data set in design variable space. Furthermore estimating complex input-output response requires various combinations of the design variables. So, in order to find efficient sampling policy, we investigate trade-off relationship among "the sampling method and the number of samplings" and "the precision of the estimate response and the complexity of the response".

2 Estimate modelling of frontal crash

In this research, injury criteria of an occupant at a frontal crash are estimated by using a two machine learning method, Gaussian Process and Anisotropic Kriging. Input-output data set for estimate modelling is called training data set. The training data set is obtained by an occupant behaviour model of multi-body dynamics. The training data set is composed of control parameters of the restraint system as the input and injury criteria as the output.

2.1 Machine learning

Machine Learning is an artificial intelligence technology which acquires hidden rules behind observed data set automatically. This research employs two machine learning methods, Gaussian Process and Anisotropic Kriging which are suitable for estimating nonlinear or multi-modal responses.

Gaussian Process (GP) is a Bayesian approach, based upon the expression of knowledge in terms of probability distribution [2]. This method is a powerful regression model specified by parameterized mean and covariance functions, and suitable for estimating non polynomial responses.

Kriging is also a Bayesian approach widely used in geostatistics, suitable for estimating nonlinear responses [3, 4]. The Kriging behaviour is controlled by a covariance function, called a variogram, which ruled how varies the correlation between the values of the function at different points. This research employs Anisotropic Kriging (AKR) which is a refined version of the Kriging method [5]. This method controls the relative importance among input variables.

2.2 CAE modelling via multi-body dynamics

An occupant's behaviour model of a full-frontal crash testing shown in Figure 1 is constructed by using the multi-body dynamics tool, MADYMO. The model is composed of a Hybrid-III dummy, surrounding equipments such as a seat and a steering wheel, and restraint equipments such as an airbag and a seatbelt. The model simulates the occupant's behaviour at the crash for 0.12 sec.

The behaviour of the model is controlled by 6 design variables regarding an airbag, a seatbelt and a knee bolster which strongly affect safety indexes. The design variables are shown in Table 1. A gas generant of the airbag inflator is ignited at x_1 [sec.] which is the time after collision detection (AB_TTF), and then the gas inflates the airbag. The inflation speed is controlled by x_2 which is a mass flow rate of the generated gas (AB_MFR). Normally, it takes 0.04 to 0.05 sec. for finishing the inflation. A part of the kinetic energy of an occupant is consumed by discharging the gas of the airbag from a vent hall after the collision of the head and the airbag. Discharging of the gas is controlled by x_3 which is a design variable of the size of the vent hall (AB_VHF).

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The model of the seatbelt contains a pretensioner system and a load limit system. The pretensioner system which restrains an occupant to a seat by drawing a seatbelt in improves an effect of a seatbelt at a crash. The pretensioner system works at x_4 [sec.] which is the time after collision detection (SB_TTF). The load limit system cushions an impact of a chest by keeping a certain prescribed load while letting out a seatbelt. The variable x_5 [N] is the prescribed load (SB_LL).

The knee bolster receives a load from an occupant's knee at a crash. The variable x_6 is the knee bolster stiffness factor which controls the stiffness of the knee bolster (KB_SF).

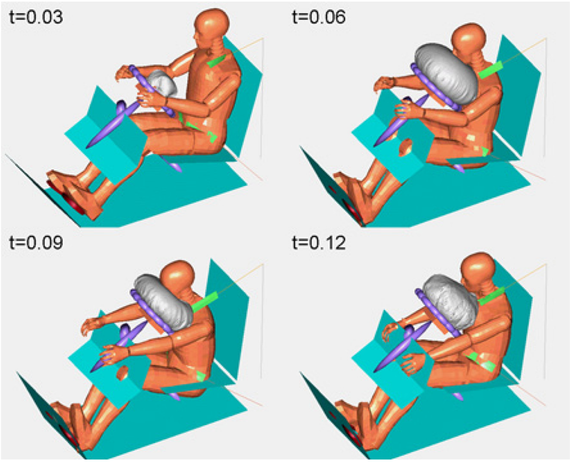

Figure 1: Frontal crash model via multi-body dynamics simulation.

Table 1: List of input design variables.

Variable		Name	Lower Limit	Upper Limit
Airbag:	Time to Fire [sec.] / AB_TTF	x_1	0.015	0.035
	Mass Flow Rate / AB_MFR	x_2	0.5	2.0
	Vent Hole Factor / AB_VHF	x_3	0.5	2.0
Seatbelt:	Time to Fire [sec.] / SB_TTF	x_4	0.01	0.03
	Load Limit [N] / SB_LL	x_5	2000	6000
Knee Bolster:	Stiffness Factor / KB_SF	x_6	0.5	2.0

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2.3 Criteria of occupant behaviour

The output parameters are head injury criterion, chest resultant acceleration and femur load which are safety indexes based on the Japan NCAP. The head injury criterion (HIC), f_1 which is an index of head injury risk is calculated by using the following eqn (1).

$$f_1 = \left[\left(\frac{1}{t_1 - t_2} \int_{t_1}^{t_2} a(t)dt \right)^{2.5} (t_2 - t_1) \right]_{\max} \tag{1}$$

where $a(t)$ is a temporal waveform of a head acceleration which is measured by an accelerometer mounted on centre of mass of a dummy's head.

The chest resultant acceleration (ChestG) is measured by an accelerometer mounted on centre of mass of a dummy's chest. The femur load (FL) is measured by load cells mounted on the dummy's right and left femurs.

In this research, we try to estimate the HIC, the ChestG and the right and left FLs (FL_R and FL_L) as criteria of an occupant's behaviour.

3 Numerical experiment

This section describes construction of estimate model, and then describes the result of evaluation of its accuracy. Input-output data set for estimate modelling is called training data set and input-output data set for evaluation of the model is called testing data set.

3.1 Estimate modelling via machine learning

Estimate models were constructed by using Gaussian Process (GP) and Anisotropic Kriging (AKR). Number of sampling of the training data set was set for 100, 200, 300 and 400 points respectively. In order to avoid extrapolation, firstly the sampling was obtained from the corner of the design variable space – in other words, combination of upper and lower limit of each variable, that is 2^6 points in case of 6 variables. And then the rest of the sampling was obtained from the inside of the design variable space randomly.

3.2 Evaluation method

The testing data set was obtained from the inside of the design variable space at random besides the training data set. Number of the sampling was 100 points. Accuracy of the estimate model was evaluated by using mean magnitude of relative error, MMRE between actual value and estimated value of the training data and the testing data. E [%] of the MMRE was calculated by the following eqn (2).

$$E = \frac{1}{n} \sum_{i=1}^{n} \frac{\left| f(\boldsymbol{x}_i) - \hat{f}(\boldsymbol{x}_i) \right|}{f(\boldsymbol{x}_i)} \times 100 \tag{2}$$

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where $\mathbf{x}_i$ is a vector of an input parameters of each sample. $f(\mathbf{x}_i)$ is an actual value and $f^{\wedge}(\mathbf{x}_i)$ is an estimated value of the output. n is number of the sampling.

3.3 Results and discussion

The MMRE between the actual value and the estimate value of the training data set is shown in Table 2. Both GP and AKR estimated the output value precisely. The MMRE of estimate by GP was $7.06\times10^{-12}\%$ to $1.99\times10^{-5}\%$, and that by AKR was $1.97\times10^{-5}\%$ to 1.68% respectively. These results were sufficient precision.

The MMRE of the testing data set is shown in Table 3 and Figure 2. At the testing data set, the accuracy has improved when the number of training data increases as a general trend. The trend was remarkable at HIC of GP. The MMRE of HIC of GP was 6.21% to 18.09%, and that of AKR was 4.08% to 6.35%. On the other hand, the accuracy of the estimate of the other criteria was sufficient precision. The reason is assumed that the nonlinearity of HIC is higher and its estimate is more difficult than the other criteria since HIC was calculated from a response of a collision between a head and an airbag. Therefore the improvement of the accuracy of HIC is important problem to precise approximate model.

The above results can be confirmed by visualizing the response of the input and the output; Figures 3 and 4 are shown as the example. Contour of the response of HIC and ChestG of AKR when the number of training data set was set for 400 is shown in Figures 3 and 4 respectively.

In Figure 3, each nine figures shows the response of HIC when two of six design variables, AB_TTF and SB_TTF were varied. Another two variables, AB_MFR and AB_VHF were fixed to 3 values, 0.5, 1.0 and 2.0 respectively. The rest two variables, SB_LL and KB_SF were fixed to 4000 and 1.0 respectively since these variables affected to HIC little. For example, the upper right figure shows the response when the variables were fixed to AB_MFR: 2.0, AB_VHF: 2.0, SB_LL: 4000 and KB_SF: 1.0 respectively. As for Figure 4, it is similar that each figure shows the response of ChestG when AB_TTF and SB_TTF were varied. AB_MFR were fixed to 0.5, 1.0 and 2.0, and SB_LL were fixed to 2000, 4000 and 6000 respectively. AB_VHF and KB_SF were fixed to 1.0 respectively since these variables affected to ChestG little.

These results show that the landscape of each response changes variously by combination of the design variables. The changing of the response of ChestG was relatively simple, while that of HIC was complex. This result means that the estimate of the response of HIC is more difficult than that of the other criteria. However, because the response in the area of AB_MFR from 1.0 to 2.0 is simple, we assume that the accuracy can be improved by the following method. Firstly, the design variable space is divided into several spaces and the estimate models of these divided spaces are constructed respectively. And then the whole estimate model is constructed by combining these models. That is our future subject.

Table 2: MMRE of GP and AKR of training data set.

Num. of training data		100	200	300	400
GP:	f_1 / HIC	4.85×10^{-11}	3.55×10^{-11}	2.15×10^{-11}	1.06×10^{-11}
	f_2 / ChestG	1.22×10^{-11}	7.06×10^{-12}	7.35×10^{-12}	4.41×10^{-11}
	f_3 / FL_L	1.70×10^{-5}	2.92×10^{-11}	8.46×10^{-8}	3.35×10^{-6}
	f_4 / FL_R	1.99×10^{-5}	3.31×10^{-11}	1.30×10^{-11}	3.21×10^{-6}
AKR:	f_1 / HIC	4.95×10^{-1}	1.12×10^{0}	1.97×10^{-5}	1.68×10^{0}
	f_2 / ChestG	1.00×10^{0}	1.12×10^{0}	1.12×10^{0}	1.09×10^{0}
	f_3 / FL_L	5.01×10^{-1}	3.94×10^{-1}	5.61×10^{-1}	8.00×10^{-1}
	f_4 / FL_R	5.07×10^{-1}	4.80×10^{-1}	6.25×10^{-1}	7.92×10^{-1}

Table 3: MMRE of GP and AKR of testing data set

Num. of training data		100	200	300	400
GP:	f_1 / HIC	18.1	8.56	6.21	6.77
	f_2 / ChestG	2.30	1.87	1.35	2.56
	f_3 / FL_L	3.33	2.89	3.07	3.13
	f_4 / FL_R	3.07	2.55	2.78	2.35
AKR:	f_1 / HIC	6.35	4.12	5.24	4.08
	f_2 / ChestG	1.66	1.34	1.30	1.27
	f_3 / FL_L	3.32	3.64	3.64	3.24
	f_4 / FL_R	2.55	2.85	2.71	2.25

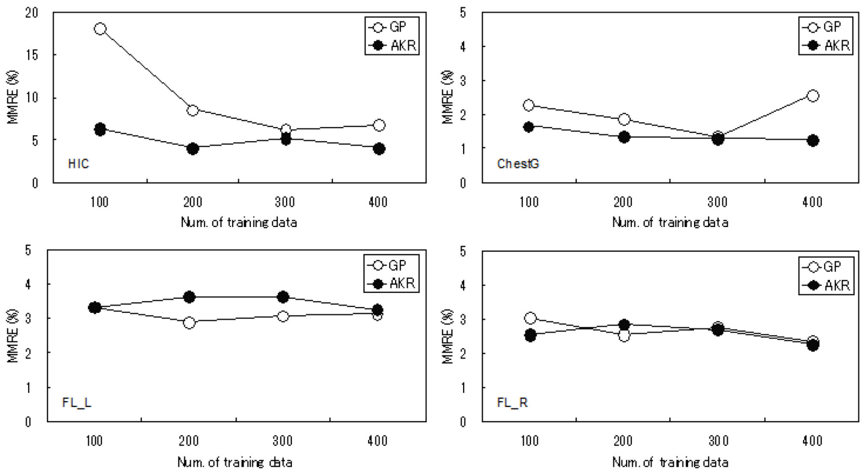

Figure 2: MMRE of GP and AKR of testing data set.

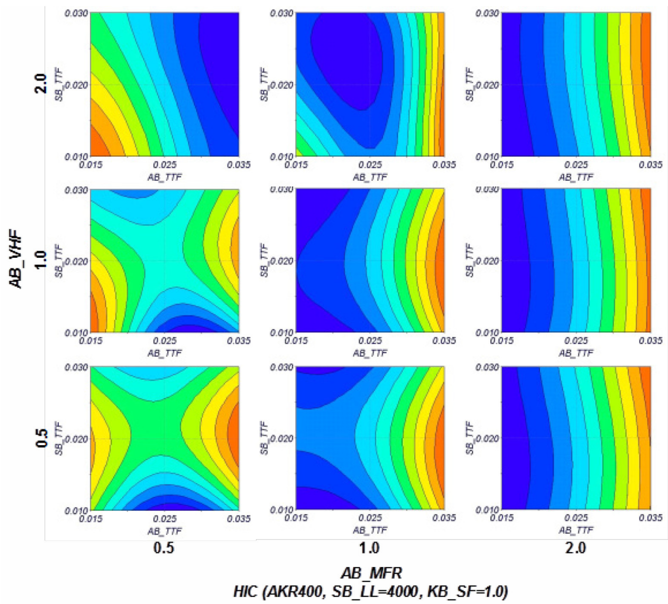

Figure 3: Response of HIC by using AKR.

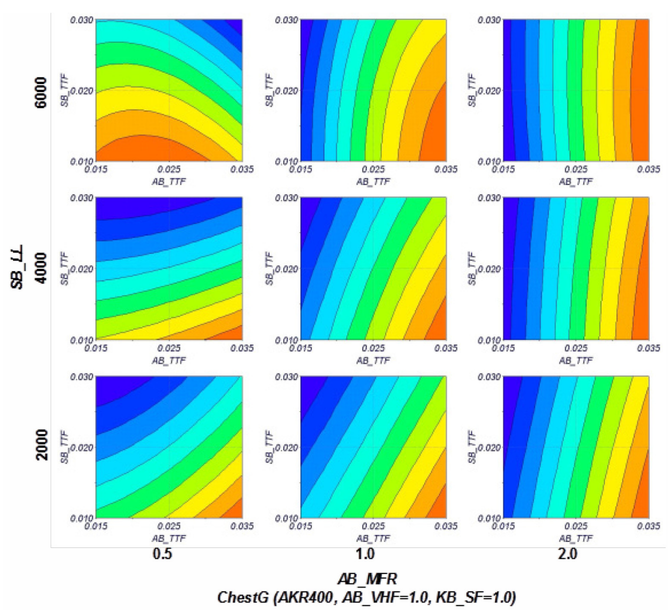

Figure 4: Response of ChestG by using AKR.

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4 Conclusion

In this paper, two machine learning methods, Gaussian Process and Anisotropic Kriging were employed to construct an estimate model of injury criteria at a frontal crash. The accuracy of the estimate model was evaluated and the results were shown below. The chest resultant acceleration and the femur load were estimated precisely even if the number of sampling of the training data was the smallest 100. On the other hand, the head injury criteria required more sampling to precise estimation since the nonlinearity of the response was higher than the other criteria. The improvement of the accuracy of the head injury criteria is important problem to precise approximate model. Visualization of the landscape of the response has shown the above results clearly and also that has indicated an idea for improvement.

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