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APPLICATIONS OF COMPUTATIONAL INVERSE TECHNIQUES TO AUTOMOTIVE ENGINEERING

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Abstract – Several applications to automotive engineering of the advanced computational inverse techniques have been reported in this paper. The computational inverse techniques, such as gradient based methods with genetic algorithms, intergeneration projection genetic algorithms, progressive neural networks, reduced-base methods, etc. are firstly introduced. After that the applications to automotive engineering for material characterization of the cold-working metal, identification of geometric parameters of drawbead, and identification of spring-force factors of suspension system of tracked vehicles, have been presented to demonstrate the applications to automotive industry.

1. INTRODUCTION

Inverse problems have attracted a lot of attentions in a variety of fields, and many useful theories and techniques [17] have been developed in past decades. Some robust and practical computational inverse techniques [12] have been developed by the authors and their research teams in the past years through the combination of different types of optimization methods, such as gradient-based methods with genetic algorithms and intergeneration projection genetic algorithms as well as the neural networks. Applications of computational inverse techniques in practical complex automotive engineering problems have been reported as well. In this paper, several advanced applications of the computational inverse techniques [3,5,8,18] will be presented to demonstrate the broadness of the applications of these techniques. These applications include: material characterization of the cold-working metal, identification of geometric parameters of drawbead, and identification of spring-force factors of suspension systems.

2. COMPUTATIONAL INVERSE TECHNIQUES

Computational techniques are presented for inverse problems in the areas of structural parameter identification, source identification, material characterization and crack detection using dynamic behavior of the structures. In these techniques, the inverse problems are formulated into parameter identification problems in which a set of parameters corresponding to the characteristics of the structure, source, material property, and crack can be found by minimizing error functions formulated using the measured dynamic behavior (such as displacement responses, etc) and that computed using forward solvers based on projected candidates of parameters. In what follows several improved optimization methods as well as improved neural network are briefly introduced.

2.1 Genetic algorithms

Genetic algorithms (GAs) [4,7] are methods to search a set of parameters in parameter space that optimizes the objective function based on the Darwinian principle of natural selection. An initial population sampled randomly from the search space is first created. The fitness is evaluated for each of the individuals based on the evaluation criterion that is the error function. Successive new generation is created through selection, crossover and mutation operations process until the best-fit individual is obtained. Genetic algorithms are stochastic global search methods and differ in the fundamental concepts from those traditional gradient-based search techniques. One important feature of GAs is that they work on groups (generations) of points in the whole search space, this feature gives the GAs an edge in dealing with complicated, non-linear and multimodal optimization problems. Furthermore, GAs require only objective function information, while many other search techniques usually require auxiliary information in order to work properly. However, conventional GAs are usually very poor in terms of convergence performance, especially when the searching has reached a local region near the global optimum. Moreover, the solution appears to be relatively imprecise when compared with the so-called gradient-based optimization techniques. Since its invention, different versions of GAs have been developed. Combinations of GAs with traditional optimization methods or hybrid GAs have also been proposed by many and proved to be very effective for a large number of problems [1,2,6,10,11,12,13]. The more novel hybrid genetic algorithm uses one more additional operator called *intergeneration projection* (IP), and hence the algorithm is termed as intergeneration projection GA or (IP-GA) [12,19,20,22]. In the conventional GAs, the child generation is produced using the parent generation based on the fitness of the parent individuals. In the IP-GA, however, the child generation is produced using both the parent and grandparent generations. Construction of the move direction of best individual is a key of implementing projection operator. In the IP-GA, the best individual of *j*th generation p_j^b and the best individual of the *(j-1)*th generation p_{j-1}^b are used only if they are not identical, otherwise, p_j^b and p_j^s (the second best individual of *j*th generation) should be used instead. This means that the better individual *c* is obtained by:

$$f(c) = \max\{f(c_1), f(c_2)\} \qquad c \in \{c_1, c_2\}$$

$$c_1 = p_j^b + \alpha(p_j^b - p)$$

$$c_2 = p_{j-1}^b + \beta(p_j^b - p) \tag{1}$$

$$p = \begin{cases} p_{j-1}^b & p_j^b \neq p_{j-1}^b \\ p_j^s & p_j^b = p_{j-1}^b \end{cases}$$

where α and β are recommended to be within 0.1 ~ 05 and 0.3 ~ 0.7, respectively. It is clear that α and β decide how far the newly generated individual *c* is from the present best individual p_j^b.

2.2 Combined GA and nonlinear least squares methods

The least squares methods (LSMs) have a high probability to converge to local optima from the initial guesses. The advantage of LSM is that it converges very fast to the optimum, especially when the initial guess is close to the optimum. However, the search for suitable initial points for locally converged optimization method, such as the LSM, often proves to be difficult. On the other hand, GAs hold complementary promises in searching for the global optimum in comparison with the LSMs. The other advantages of GAs are the capability to escape local optima and no need for initial guesses. GAs are, however, computationally expensive. Their converging performance slows down significantly at the later stage of searching. It is hence expected to combine a GA and an LSM so as to provide an ideal performance for the optimization procedure, which is often vital in non-linear optimization problems. As such, we can not only ensure the global optima but also obtain the results at a reasonably fast speed. The method combining GA and nonlinear LSM searches the global optimum in three steps [12,13]. First, GA is used to determine the initial points. The main purpose is to select a set of better solutions close to the optima. The selection criterion is imposed to limit the function value below a required value. Secondly, each set of these solutions is used as the initial point in searching for the individual local optimum using the nonlinear LSM. Thirdly, all solutions from nonlinear LSM searching are considered as the local optima of the function. The global optimum is found from these solutions simply by comparing their corresponding error function values.

2.3 Progressive neural network

A neural network (NN) model is referred to as a type of computational models that consists of hidden layers of neurons connected between the input and output neurons. The connections between the neurons are described by weights which are to be determined through a process of the NN training. Neural network is a novel and robust tool for information processing. The robustness of NN enables it to solve many problems that cannot be handled by analytical approaches. In addition, the NN techniques are well known for their ability to model the nonlinear and complex relationship between the structure parameters and the dynamic characteristics. However, the relationship between the specified inputs and the outputs for practical engineering problems could be extremely complex. It is very difficult and impossible, to train an NN model for such a relationship valid in a wide range of parameters. Thus a progressive NN model for practical engineering problems has been proposed [14,21].

2.4 Reduced-basis methods for inverse problems

Some of the forward solvers are very computational expensive due to the complexity of real life systems. A single run can take days or even weeks, which is one of the bottleneck problems in the inverse analysis of complex systems. The reduced-basis approach [15,16] can significantly reduce the computational complexity in each forward analysis. Reduced-basis method is a rapid, reliable, and accurate evaluation of functional outputs of parametrized elliptic partial differential equations. In this method, a posteriori error estimator is firstly given for noncoercive problems. The critical ingredients are the residual, an appropriate bound conditioner, and a piecewise-constant lower bound for the INF-SUP stability factor. In addition, globally nonaffine and nonlinear problems are also considered: in particular, through appropriate sampling and interpolation procedures, these more difficult problems can be reduced to the more tractable affine case. Finally, a real-time - procedure is proposed for inverse problems associated with parametrized partial differential equations based on the reduced-basis approximations and error bounds. In general practice, many inverse problems are formulated as an error minimization statement relating the calculated and measured outputs. This optimization procedure requires many evaluations of the output: the reduced-basis method --- with extremely low marginal cost --- is thus very efficient for this class of problems.

3. APPLICATIONS

Three problems arising from the automotive engineering will be reported as the applications of the advanced computational inverse techniques.

3.1 Material characterization of the cold-working metal

Cold working metal process is always companied with serious plastic deformation. When the deformation occurs in the same direction, material property will be changed a lot. Experiments prove that the volume deformation of the metal is elastic under hydrostatic pressure and it can spring back after discharging. Furthermore the whole volume variation (density change) is very small after plastic deformation. For a common metal, neglecting its volume variation is reasonable [9]. As a result, the material density is treated as a constant. In general, cold working can decrease the metal's Young's modulus, but the change extent is slim (reduce 5% at most after large plastic deformation). Nevertheless it can increase remarkably under intense orientative deformation, because the crystals' preferential orientation forms orientative texture [23]. The latter case is considered in our study [5]. One simplified material model has been proposed to describe the elastic property of the plate after deformation. As long as the material hasn't been damaged, Young's modulus will vary continuously. A quadratic polynomial is employed to approximate its distribution in the thickness direction, in which the values E_1, E_2, E_3 of the upper, middle and lower surface of the plate, respectively, are selected to characteristic the quadratic polynomial variation of the Young's modulus of the plate. A uniform μGA is used as the inverse solver. The displacement transient responses on the upper surface subjected to an impact load are used to identify these three parameters. The sample point is at the position provided on the upper surface of the plate. In the GA run, generation number, possibility of uniform crossover, individual number of every generation are 500, 0.5 and 5, respectively. The search space of the GA and the computation results are listed in Table 1. As shown in Table 1, the deviation of the variables is below 4%. The results can satisfy the engineering requirements. It demonstrates that the present inverse procedure of material property characterization is accurate and efficient.

Table 1. The search space of the GA and the identified results.

variable	Original data	Search range	Results(deviation)
E_1	1.5	1.2~1.8	1.54(3%)
E_2	2.0	1.6~2.4	2.02(1%)
E_3	1.6	1.3~1.9	1.66(4%)

3.2 Identification of geometric parameters of drawbead

Sheet forming is the main manufacture process for the car body. In a sheet forming process, the drawbeads play an important role for the control of the material flow. Figure 1 shows a typical drawing die of the corner backstop of the front floor of a truck. A good drawbead design can avoid the necking, wrinkling and other imperfections. The effect of drawbead depends on its placed position, structure and geometric parameters, material properties and process parameters. Traditional drawbead design mainly depends on designer's experience. In our study [5] the computational inverse techniques were used for the design of the drawbead. The geometric parameters of drawbead in the drawing procedure of the corner backstop of the front floor of a truck were identified using the combination of a neural network and a genetic algorithm. The maximal effective stress (x_1 (MPa)), maximal effective strain (x_2) and maximal thinning ratio of sheet thickness (x_3) were used as the inputs for the NN model. The outputs of the NN model were radius of the male bead (y_1 (mm)) and radius of the female bead (y_2 (mm)). The initial neuron number of 1st and 2nd hidden layers corresponding to the initial training samples was 12 and 12 respectively, which would be optimized dynamically using GA. Table 2 shows geometry parameters of the drawbead identified by this approach and the corresponding errors with respect to their actual values. It has been found from the numerical results that the proposed method could be used to identify the geometric parameters of the drawbead. The present technique is efficient and accurate in numerical computation. Nevertheless, the experimental techniques should be developed to put the present method into the practice.

Figure 1. A drawing die of the corner backstop of the front floor of a truck.

Table 2. Comparison of partial desired outputs and corresponding outputs of trained NN model.

Inputs of NN			Desired outputs		Outputs of trained NN model (Relative calculated error δ)	
x_1 (MPa)	x_2	x_3	y_1^t (mm)	y_2^t (mm)	y_1 (mm)	y_2 (mm)
660.587	0.532	0.4102	5	6	4.978 (0.4%)	5.991(0.2%)

3.3 Identification of spring-force factors of suspension systems

High-mobility and high-speed tracked vehicles (Figure 2 [18]) are generally fitted with the suspension systems to attenuate shocks and vibrations from dynamic vehicle-terrain interactions. As such, the design and optimization of suspension system are very important topics in modern military industries. However, the actual field-testing of prototypes is expensive and time-consuming. As an alternative to field testing, the development of simulation systems for subpart or overall vehicle is in great demand. The spring forces of the different road-wheel suspensions are followed the same characteristic but with different multiplication factors. The configuration of the spring-force factors in the suspension system may greatly affect the stiffness property of the entire suspension system and the riding dynamic performance of the tracked vehicle. In engineering practice, the suspension factors may not be accurately known although the basic properties of road-wheel suspension are available to engineers. Identification of the suspension factors based on experimental data is of great interest. Identified suspension factors can be used to improve the accuracy of computer simulation models and further improve the design of the suspension system. The displacement between the road-wheel and the hull will be used for the identification of suspension factors. It is because that the displacement can be easily measured in experiments by using a rope-length sensor. Furthermore, in computation, simulation results of displacements are usually more accurate than the results of accelerations. In the numerical testing, it has been found that the simulation results of the displacement can match with the field-testing data very well. In this study, we try to inversely determine these multiplication factors from the measured displacement of the road-wheels based on a validated ATV model. An NN model is suggested for the identification of the suspension properties of the tracked vehicle. The outputs of the NN model are the multiplication factors representing a configuration of the spring forces of the suspension system. The inputs of the NN model are the selected values of displacements of the road-wheels which can be easily measured using conventional experimental techniques. The identified result is given in Table 3. It can be found from Table 3 that the identified result becomes very accurate after 5 progressions.

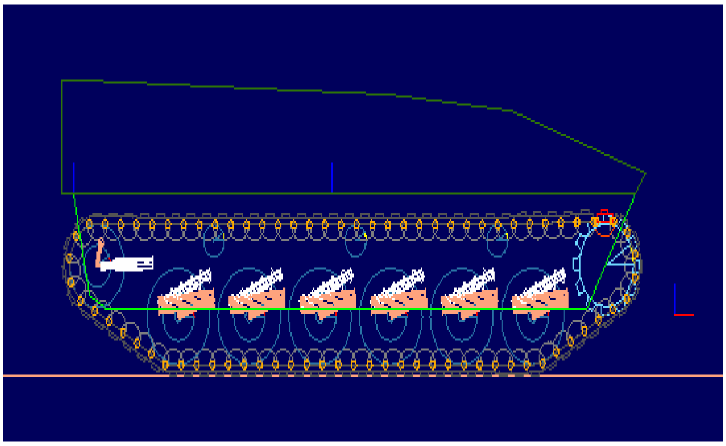

Figure 2. A typical tracked vehicle [18].

Table 3. Identified result of the spring multiplication factors of the suspension system.

Roadwheel	Spring multi-plication factors	original data	Result (deviation) at the 5^{th} progression
1	c_1	1.47	1.37(7.2%)
2	c_2	1.43	1.46(1.7%)
3	c_3	1.27	1.31(2.9%)
4	c_4	1.12	1.20(7.5%)
5	c_5	1.31	1.24(-5.1%)
6	c_6	1.35	1.27(5.8%)

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