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Inverse parameter identification of cohesive zone model for simulating mixed-mode crack propagation

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ABSTRACT

Inverse analysis is widely applied to the identification of material properties or model parameters. In order to improve the computational efficiency of the inverse method based on the genetic algorithm, an interpolation scheme upon the response surface constructed by the finite element simulation has been adopted in this paper. Meanwhile, a gradual homogenization treatment scheme has also been presented to improve the convergence of the inverse method based on the Kalman filter algorithm. Both methods are proven effective in dealing with the single-objective inverse problem. However, literature studies show that the adoption of multiple types of experimental information is useful to improve the accuracy of inverse analysis. In this case, it turns into a multiple-objective inverse problem. Our practice proved that the above-mentioned two methods might not yield a proper result if the sensitivity issue of different types of information is not considered. Therefore, another multi-objective inverse method, in combination of the above two optimization algorithms and a weight-estimating scheme that can consider such sensitivity, has been further presented. Finally, by using a mixed-mode crack propagation simulation and two types of experimental information (loading-displacement response curve and crack path profile), the parameters of the cohesive zone model were inversely identified and its simulation results are in good agreement with the experiment.

1. Introduction

Cohesive zone models (CZM) are the direct extension of Dugdale (1960) and Barenblatt (1962) models that were originally introduced to consider the effects of plasticity in linear elastic fracture mechanics. They have been widely used to simulate the interfacial delamination and debonding as well as fatigue and fracture of non-interfacial materials. (Xu and Needleman, 1995; Benzarti et al., 2011; Xu and Yuan, 2009a, 2009b, 2011; Zhang and Paulino, 2005; Benabou et al., 2013; Nielsen and Hutchinson, 2012; Scheider et al., 2006). The CZM treats each potential crack as two internal surfaces connected by cohesive tractions, and uses a traction-separation law to describe the separation process. Once the cohesive law is determined, the CZM parameters, mainly consisting of fracture energy and cohesive strength, play an important role in representing the evolution of damage and crack. However, the identification of a cohesive law and its parameters is still an open issue. Direct experimental measurements of the parameters near crack tips are highly non-trivial because the fracture process zone is very small and its stresses cannot be measured directly. Therefore, inverse techniques, depending on experimental information and numerical simulation, have been developed recently in order to obtain an idealized estimation of the CZM parameters (Valoroso and Fedele, 2010; Gustafson and Waas, 2009; Maier et al., 2005; Oh and Kim, 2013; Wang et al., 2010; Bocciarelli and Bolzon, 2007).

There are mainly two types of inverse methods presented in the literature. The first one is to use the global response information, mainly in consideration of single experimental information, e.g., loading-displacement response curve, to perform an inverse identification (Maier et al., 2005; Oh and Kim, 2013; Wang et al., 2010; Bocciarelli and Bolzon, 2007). It is easy to acquire the experimental data and implement its numerical application, but it is difficult to obtain a unique solution close to the exact result since many inverse problems are generally ill-posed (Elices et al., 2002). Accordingly, a well-conditioned inverse scheme is highly desirable, which should not only develop a robust and reliable inverse theory, but also provide sufficient and different types of constraint conditions. Note that the constraint condition in this context means the experimentally obtained information such as loading-displacement response curve and crack path etc. Apparently, different types of experimental information will bring different influences on solution in inverse analysis. However, how to evaluate such influence and combine different experimental information to

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obtain a proper solution of CZM parameters is rarely studied. Recently, Valoroso et al. (2013) used both the loading-displacement curve and the crack extension data to arrive at a useful and practical way to identify the mode-I cohesive parameters for bonded interfaces via inverse method. However, investigation of the differences between the adopted characteristic information and their influences on inverse analysis is not involved.

Another type of inverse method is to employ some advanced experimental techniques, e.g., digital image correlation or electronic speckle pattern interferometry, to perform an inverse analysis (Shen and Paulino, 2011; Hong and Kim, 2003; Fedele et al., 2009; Ferreira et al., 2011; Fedele and Santoro, 2012). They make use of full field information rather than the global response to deduce the model parameters. Despite their rapid development recently, many issues still need to be further addressed, e.g., reliability and convergence etc. Moreover, they need to be equipped with high-performance optical instruments and the test procedures are relatively more complex than the first type of methods. Therefore, this paper does not involve this type of methods at present.

As it is known, optimization algorithms usually play an important role in the inverse methods. They mainly consist of global searching algorithms and gradient-based local optimization algorithms. The global searching algorithms, including the genetic algorithm (GA) (Cropper et al., 2012; Amaya et al., 2003; Jin and Cui, 2010), feature high accuracy but they are often limited by low efficiency in solution, especially when combined with finite element analysis. The gradient-based local optimization algorithms, e.g., the Kalman filter algorithm (KFA) (Gu et al., 2003; Delalleau et al., 2006; Corigliano et al., 2000), can consider the uncertainty in measurement and provide the whole evolution process information for each initial estimate, but they can easily fall into a local optimization solution or cause a convergence problem. Therefore, both types of algorithms have their own drawbacks when applied in the inverse analysis. Besides, the optimization algorithms generally feature a cost function to define the difference between the measured and computed results. The construction of the cost function is generally simple for the single-objective inverse analysis. However, when the multiple-objective inverse analysis is conducted, the influences of different information on solution have to be investigated and the cost function needs to be appropriately constructed.

Aimed at the defects of the above-mentioned optimization algorithms (GA and KFA), this paper proposes certain improvement when they are applied to the inverse analysis. The interpolation calculation on response surface is employed to substitute for a great number of FEM simulations in order to improve the computational efficiency. Besides, a gradual homogenization treatment scheme has also been introduced to improve the convergence of the KFA based inverse method. By taking advantage of both the GA and the KFA based inverse methods, a new method has been developed to perform the inverse analysis considering both the experimental loading-displacement curve and the crack path profile information. Finally, by combining the XFEM with the cohesive zone model, a mixed-mode crack propagation has been simulated and the parameters of the cohesive zone model are inversely identified.

2. Inverse methods

Generally, the inverse analysis is to find the parameters minimizing the difference between the predicted response and the experimental results. Therefore, optimization algorithm is one of the most important parts, determining the accuracy and the efficiency of inverse analysis. In the following, the theoretical basis of the GA and the KFA is briefly reviewed. At the same time, significant improvement against their respective drawbacks is introduced and a new multiple-objective inverse method based on the above two optimization algorithms is proposed.

2.1. Inverse method based on GA

The genetic algorithm was inspired by Darwin's theory of evolution and works in a similar way as the biological evolution (Haupt and Haupt, 2004). As a kind of global optimization technique based on randomized operators (e.g., selection, crossover and mutation), this search method can yield a set of solutions close to the optimum without being trapped into local optimums in a given search domain. The main steps of its application to the present inverse analysis are concluded below. A more thorough description can be found in the book written by Haupt and Haupt (2004).

The structure of the GA applied in the inverse analysis can be seen in Fig. 1. In the first step (Step 1), the area of search is defined based on the number of model parameters N_p that needs to be optimized. The optimum problem is approached in the N_p dimensional space limited by the lower and the upper bounds of each parameter according to a priori knowledge. At the same time, the values of the initial estimates are binary encoded in a form of genes. The combination of genes from different types of parameters will form an individual. The second step (Step 2) is the initialization of population. The population is made of several individuals in the domain. The first generation of population is created by combining different genes picked randomly from the search space.

In the next step (Step 3), the direct problem (e.g., simulating fracture of material) is solved for each individual which corresponds to CZM parameter set in the present study. Note that it is necessary to convert the binary string (genetic chromosome) back to the corresponding real number of CZM parameters before simulation. As we know, such simulation usually incurs a heavy computational expense. Apparently, the calculations based on all individuals are extremely inefficient. To circumvent this problem, an interpolation scheme on response surface is adopted here. Its details will be introduced in the context.

In Step 4, the cost function is constructed to calculate the fitness value in the GA according to the numerical results from Step 3 and the experimental data. It is quite an important step for obtaining an accurate result of inverse analysis. Since multiple kinds of information have been adopted to identify the model parameters in the present study, a weighted sum form has been developed here. The characteristic variables V of different loading steps are chosen to formulate the cost function f

$$f = \sum_{j=1}^{m}\sum_{t=1}^{ns}\overline{w}_j\left(\frac{V_{t,j}^{\mathrm{simu}} - V_{t,j}^{\mathrm{meas}}}{V_{t,j}^{\mathrm{meas}}}\right)^2 \tag{1}$$

where $V_{t,j}^{\mathrm{simu}}$ and $V_{t,j}^{\mathrm{meas}}$, representing reaction forces and crack path information in the upcoming discussed example, are the characteristic sub-variables obtained by simulation and experiment at the load step t, respectively; m is the number of characteristic variable (or information) types; ns is the total number of iterative loading steps; $\overline{w}_j$ is the weight value embodying the influences of different information types on solution, which should satisfy $\sum_{j=1}^{m}\overline{w}_j = 1$. The fitness value *fit* of each individual can be evaluated by

$$fit = \frac{1}{\sqrt{f/ns}} \tag{2}$$

In Step 5 the termination criterion is checked. The inverse analysis is terminated if the prescribed number of generation is reached; otherwise, a new generation is created (Step 6). In this step, based on the previous calculated fitness values of all individuals the population is sorted in an ascending or descending order. To collect the best individual, only a certain ratio of them are