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FUNDAMENTAL EFFECTIVENESS OF STRUCTURAL DAMAGE IDENTIFICATION USING GENETIC ALGORITHM

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This paper proposes a structural damage identification method using genetic algorithm. This method estimates the location and severity of damage by minimizing the difference between measured and estimated natural frequencies and by using some a priori information on damage such as test results and theoretical guesses. By giving a priori information which contains some correct information on the damage, the importance of a priori information and the influence of information quality on estimation accuracy are examined. As a result, it was shown that better a priori information produces better estimation accuracy and that the influence of errors in a priori information will be reduced in estimation.

Key Words : *damage detection, genetic algorithm, concrete, non-destructive tests, information quality*

1. INTRODUCTION

Social infrastructures and agricultural facilities such as dams, water channels, head works and so on serve as the foundations of the activities of food production. Many infrastructures are now damaged due to aging, deterioration and lack of repair. Recently, the fall-off and serious deterioration of concrete structures are imminent social problems. To inspect the degree of damage, various non-destructive tests (NDT) are proposed and used to assess the safety of existing structures. Some of them have high accuracy but are expensive, such as the ultrasonic method, acoustic emission method and x-ray method. Others are reasonably priced, but have low accuracy, such as visual inspection method and tapping acoustic method. Since the NDT inspections are used to assess the soundness of the structures as the first examination, it is important to infer the damage with accuracy up to some extent by easy handling. It may be said for such a requirement that structural health monitoring[1)], infrastructure management system[2)] and damage detection techniques using dynamic characteristics[3),4),5)] are the most appropriate.

In general, most NDT methods can either estimate the severity of damage in structures or detect the location of damage. There is no NDT method which can estimate the location and severity of damage at the same time. As a structural damage identification method, the technique which estimates the location and severity of damage from the changes in natural vibration modes due to the damage using finite element method (FEM), or mode-based damage identification technique, are proposed by Ren and De Roeck[6),7)]. However, this technique may need the reduction of the effects of measurement noise on the result in order to apply to actual problems.

In this paper, the method using some a priori information which contains partially correct information on structural damage is proposed and the distribution of the decrease of elastic modulus (hereafter, E.M.) due to the damage is estimated using a priori information. The types of a priori information are divided into two categories. One is related to the severity of damage, e.g., natural frequencies, strengths, changes of E.M. or propagation velocity of elastic wave. The other is information on location of damage, e.g., NDT results, empirical knowledge or theoretical guesses.

For damage identification, these two types of a priori information are combined using genetic algorithm[8] (GA). The distribution of the decreased degree of E.M. is estimated. In the process of GA, GA operations (reproductions by tournament selection among two individuals, uniform crossovers and mutations), are used for searching for a more fitted estimated distribution of the decreased degree of E.M.. In this paper, a hypothetical problem intended for the compressive failure of a rectangular concrete specimen (10×10×40cm) is set up for simulation verification of the proposed damage identification method. This hypothetical problem is supposed for experimental application, which is examined in an accompanying paper[9]. In this technique, a damage index which is based on the decrease of E.M. is used similarly to the method by Ren and De Roeck. Natural frequencies which are calculated from eigen value analysis are used as the a priori information on the severity of damage[10]. Three levels of information on the location of damage (poor, average and detailed) are set and the influence of information quality is examined by comparing with the results from different combinations of a priori information. In addition, the influence of errors in a priori information on the estimation accuracy is examined by using false a priori information. It may be said from the above explanation that the applicable condition of this method is limited to the situation where some information on the damage of the intended structures is gained beforehand.

2. METHODOLOGY

(1) FEM Model and Natural Frequency

FEM mesh used in numerical calculation is shown in **Fig.1**. By distributing heterogeneous E.M. for each element, the situation of damage is represented. Thin elements at the bottom show the capping surface of the concrete specimen. The parameters used in calculation for a reference state are shown in **Table 1**. They are based on the actual concrete specimens.

To calculate natural frequencies from the above mentioned FEM model, eigen value analysis is carried out. The natural frequencies are proportional to the average E.M. of the specimen and they are used as a priori information on the severity of damage in this paper. Natural frequencies and natural vibration modes for the reference state are shown in **Figs.2-5**. In the problem, these four frequencies and vibration modes are focused on because it is possible to identify four natural frequencies from dynamic tests or impact sounds for actual cases[11]. The first vibration mode (**Fig.2**) is regarded as the first deflective resonant vibration. Likewise the second mode (**Fig.3**) is the first torsional resonant vibration. The third mode (**Fig.4**) is the first longitudinal resonant vibration and the fourth mode (**Fig.5**) is the second longitudinal resonant vibration.

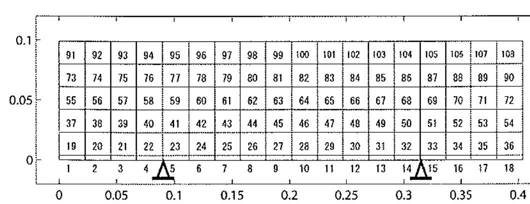


Fig.1 FEM mesh

Table 1 Parameter for FEM model

Elastic modulus (GPa)	30.0
Poisson's ratio	0.17
Mass density (kg/m^3)	2270

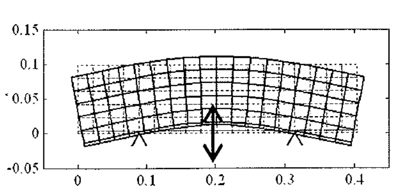


Fig.2 1st natural vibration mode, 1920Hz

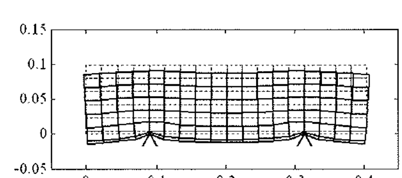


Fig.3 2nd natural vibration mode, 2902Hz

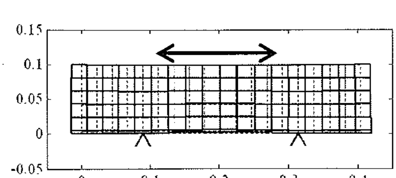


Fig.4 3rd natural vibration mode, 4491Hz

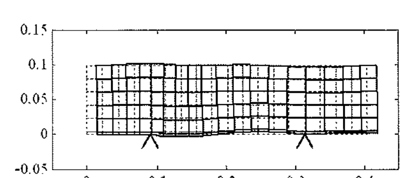


Fig.5 4th natural vibration mode, 8937Hz

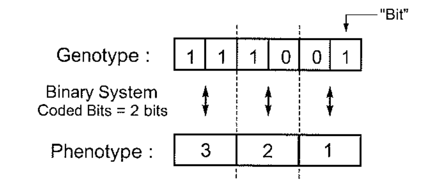


Fig.6 Relationship between genotype and phenotype

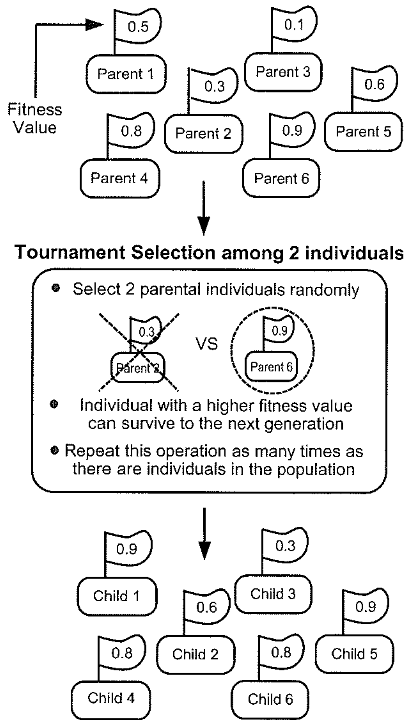


Fig.7 Reproduction by tournament selection

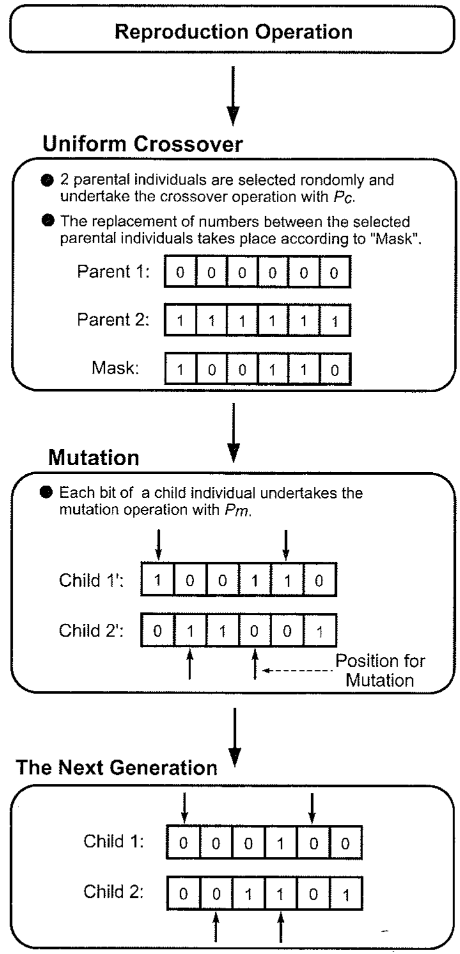


Fig.8 Uniform crossover and mutation

(2) Genetic Algorithm

a) GA operation

GA is a learning algorithm which searches for the solution through a vast number of potential combinations of solutions (hereafter, candidates). An initial generation, which consists of the number of individuals in the population, is produced by using random numbers. The initial generation evolves into the next generations which are more fitted to the answer through GA operations.

GA has three characteristics. The first one is the relationship between genotype and phenotype in the process of evolution (**Fig.6**). Secondly, as an evaluation index for evolution to the next generations, a fitness value is defined. Thirdly, GA operations such as reproduction, crossover and mutation are implemented as evolutionary techniques. In this paper, reproduction by tournament selection among two individuals, uniform crossover and mutation are taken as GA operations.

The operation of reproduction by tournament selection and that of uniform crossover and mutation are illustrated respectively in **Figs.7** and **8**. In the process of reproduction by tournament selection, two parental individuals are selected randomly and the individual having a higher fitness value can survive as a child individual. In the process of uniform crossover, two individuals are selected randomly and undertake the crossover operation with the probability of crossover (P_c). When these two individuals undertake a crossover, the operation is implemented according to a series of random allies of 0 and 1 of the same length, which is called a mask. In the process of mutation, each bit of an individual undertakes the mutation operation with the probability of mutation (P_m). When a certain bit undertakes the operation, the value of the bit changes from 0 to 1 or 1 to 0. Among these operations, the mutation operation is important and the adequate value of P_m prevents the estimation from being led into local solutions and quickens the search for the answer.

b) Objective Function and Fitness Value

In the process of GA, the fitness value is very important because GA continues to search for an individual to make fitness values higher. In this paper, fitness consists of two terms: frequency error which is the error ratio between the calculated and the measured natural frequency, and the correlation coefficient which is the factor of the similarity between the estimated distribution of the decreased degree of E.M. and the a priori information on the inflicted damage. Thus an objective function is defined as follows:

$$Fitness = (Frequency\ Error) + (Correlation\ Coefficient) \quad (1)$$

The frequency error in Eq.(1) represents the reciprocal of the sum of the squared error ratio between the calculated natural frequency $f_{com}^{(i)}$ ($f_{com}^{(i)}$ is calculated from the estimated distribution of E.M. by the GA process) and the measured natural frequency $f_{ans}^{(i)}$. The superscript i indicates the i th vibration mode. The frequency error is given by:

$$(Frequency\ \ Error) = \left\{ \sum_{i=1}^{4} \left(\frac{f_{com}^{(i)} - f_{ans}^{(i)}}{f_{ans}^{(i)}} \right)^2 \right\}^{-1} / Cr \quad (2)$$

where Cr in Eq.(2) is an indicator of squared error ratio. The relationship between Cr and error ratio is shown in **Table 2**. For example, when the squared error ratio is aimed to be under ±0.25%, 40000 should be taken as a value of Cr. If the squared error ratio of the estimated distribution meets the aimed value, the frequency error will be met.

The correlation coefficient in Eq.(1) represents a factor of the similarity between the estimated distribution of the decrease of E.M. due to the damage and the a priori information of the distribution of the damage, and is expressed as follows:

$$(Correlation\ Coefficient) = E\left[\frac{C(X_1, X_2)}{\sqrt{C(X_1, X_1)C(X_2, X_2)}} \right] \quad (3)$$

$$C(X_1, X_2) = E[(X_1 - \mu_1)(X_2 - \mu_2)] \quad (4)$$

where $C(X_1, X_2)$ is a covariance matrix. $E[\bullet]$ denotes an expectation operation. X_1 and X_2 are the estimated distribution and the a priori information of E.M. and μ_1 and μ_2 are the average values of X_1 and X_2 respectively. Frequency error and correlation coefficient have a real number from 0 to 1 and hence the fitness value varies from 0 to 2. In the case that no a priori information on location of damage is available, fitness is examined by only the frequency error.

Table 2 Relationship between Cr and required error ratio

Cr	Error ratio (%)
25000	±0.1
40000	±0.25
10000	±0.5
2500	±1.0

In the searching process, the changes of both the frequency error and the correlation coefficient have to be monitored carefully. This is because the progress of evolution might fall into local solutions if either of them changes radically.

(3) Damage Identification Scheme

The flowchart of damage identification using GA is shown in **Fig.9**. Firstly, unknowns that are searched with GA are transformed from phenotype to genotype. In this paper, the unknown parameter is the decreased degree of E.M. in the damaged body. In GA, since only discrete values can be dealt with, the discrete interval or resolution: dE, has to be decided. If the genotype is represented using n bits, the phenotype is modeled with 2^n levels. Hence, in the case where dE is fixed, the range of the unknown parameter is determined by the number of bits of the genotype. In this paper, dE is fixed and the range of the E.M. is determined by adjusting the number of bits for each element. In addition, the GA parameters, the population number, the number of generations, P_c and P_m, are necessary to be set beforehand.

In the calculation process, the initial genotype population is produced by using random numbers. Transforming the genotype population into phenotype, eigen value analysis is carried out, using transformed phenotype in order to have the calculated natural frequency $f_{com}^{(i)}$ for each individual. Then the fitness value is calculated from Eqs.(1), (2) and (3). Unless the calculated fitness value meets the criterion, each genotype individual undertakes three GA operations and evolves into the next generations. This will be repeated until either the fitness value agrees with the criterion or the number of generations reaches the limit number. It is clear that GA does not give a correct real situation, but the approximate situation.

3. SIMULATION VERIFICATION

(1) Model Description

a) A Priori Information

The model for simulation verification is set up

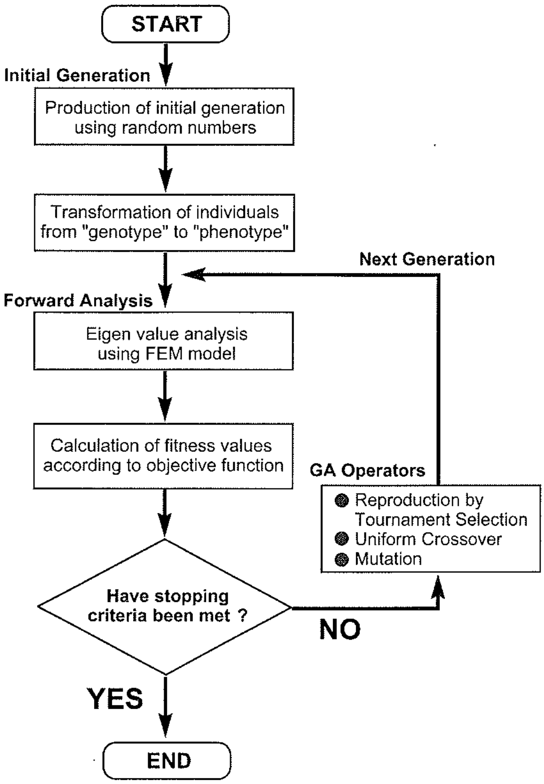


Fig.9 Damage identification scheme

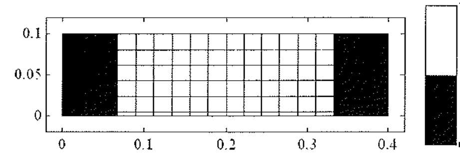


Fig.10 A priori information: poor (Case 2)

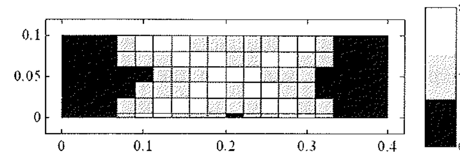


Fig.11 A priori information: average (Case 3)

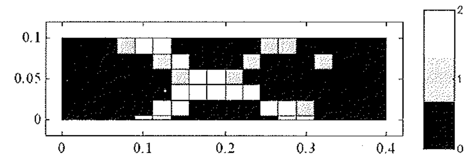


Fig.12 A priori information: detailed (Case 4)

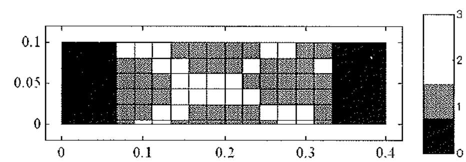


Fig.13 A priori information: poor & detailed (Case 5)

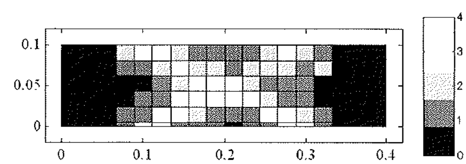


Fig.14 A priori information: average & detailed (Case 6)

based on laboratory experimental results. Three levels of a priori information (poor, average and detailed) which contain partial information about true damage distribution of the decreased degree of E.M., are shown in **Figs.10-12**. In addition, the combination of poor and detailed a priori information and that of average and detailed are shown in **Figs.13** and **14**. The color bar represents the relative severity of inflicted damage in the specimen. In the problem, the true damage distribution is set with the combination of average and detailed a priori information shown in **Fig.14**. Thus every case contains some of the true damage distribution.

Case 2 is defined as the case when information on the damage area is roughly available. However, it does not contain the detailed location of the damage and the relative severity. In **Fig.10**, the damaged elements are represented as 1 and the undamaged ones are represented as 0. These values represent the existence of damage. In real situations, the poor information corresponds to results from rough inspections such as visual inspection and tapping acoustic method.

Case 3 is defined as the most popular situation when the location of damage and its relative severity can be inferred. In **Fig.11**, the maximum damage is represented as 2, intermediate damage is represented as 1, and undamaged elements are represented as 0. These values represent the relative severity of the inflicted damage in each element. In real situations, the average information will be obtained from general experiences and theoretical guesses on failure modes.

Case 4 is defined as the case when further information on the detailed location of damage is available. In real situations, the detailed information corresponds to results from advanced inspections on deterioration and damage such as ultrasound method and acoustic emission method.

b) Simulation Cases

The GA parameters are shown in **Table 3**. The simulation cases are shown in **Table 4**. The number of candidates in the table is represented on an approximation of $2^{10} \approx 10^3$. The true damage distribution of the decreased degree of E.M. in this problem is shown in **Fig.15**.

Because information on the detailed location and relative severity is not obtained in Cases 1 and 2, the fitness value is calculated only from the term of the frequency error in Eq.(1) in these cases. In both cases, 3 coding bits of genotype are used for representing a decreased degree of E.M. for each element. This means that all the damage situations are modeled by 8 ($=2^3$) levels of E.M..

In Cases 3-6, the number of coded bits of the genotype is determined according to the kind of a priori information. The low damaged elements are expressed with fewer coded bits of the genotype than high damaged ones. The number of the coded bits varies from 0 to 3. In this way, it is possible to reduce the number of candidates and make a search of the solution quickly.

(2) Influence of Information Quality

By comparing the results in Cases 1-6, the influence of a priori information quality on estimation accuracy is examined. The results of the simulation cases are shown in **Figs.16-21**. For each case, the following is depicted: the estimated E.M. distribution in the best fitness situation (hereafter, the best fitness distribution), the maximum, average and minimum fitness values as a function of generation, the estimated E.M. distribution in the least absolute error situation (hereafter, the least error distribution) and the least absolute error as a function of generation. The absolute error is a substantial evaluation standard for estimation accuracy, while it is not possible to obtain in actual problems. The best fitness distribution in each case should be compared with the true damage distribution.

As shown in the best fitness distribution in Cases 1 and 2, those are quite different from the true E.M. distribution. There are two possible reasons for this. One is that the search for the solution has not been fully completed with a population of 30 and 100 generations because of the enormous number of candidates. The other is that only the frequency error has been taken as an objective function. In both cases, the criterion value is set at 10^8, and this corresponds to the error ratio of $\pm 0.005\%$. This is a strict criterion and, for the longitudinal natural frequency, since the measured value is approximately 4500Hz, this criterion satisfies an error of ± 0.2Hz. As shown in **Fig.16(a)**, the highest value of fitness is 0.23. Therefore, longitudinal natural frequency satisfies with the error of about ± 1.0Hz for 4500Hz. Hence, it is found that it is still difficult to obtain a well-estimated damage distribution just from a priori information on only the frequency error, even if the criterion value is strictly set.

In Cases 3-6, some a priori information which gives a distribution of damage is used. As a result of those cases, estimated damage distributions approach closer to their a priori information. This is, for example, shown in the results of Case 4 (**Figs.19(a)** and **(c)**). This inconsistency might be derived from the fact that the candidates do not include the true damage distribution in Case 4.

Table 3 GA parameters used in the examination

Population	30
The number of generation	100
P_c	0.9
P_m	0.01
dE (Pa)	1.0E9

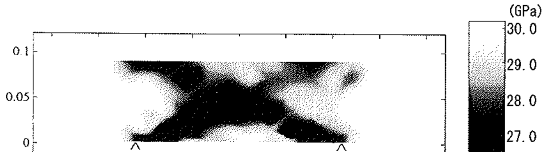
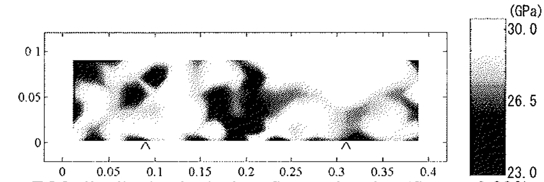


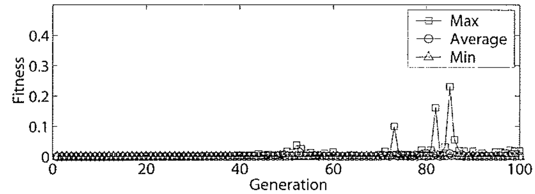
Fig.15 True damage distribution

Table 4 Simulation cases

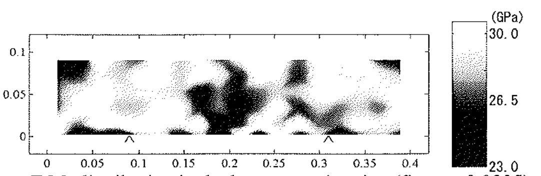
	Cr	Candidates	A priori information			
			Frequency	Poor	Average	Detailed
Case 1	10E8	10E98	○	×	×	×
Case 2	10E8	10E66	○	○	×	×
Case 3	10E5	10E48	○	×	○	×
Case 4	10E5	10E22	○	×	×	○
Case 5	10E5	10E36	○	○	×	○
Case 6	10E5	10E37	○	×	○	○



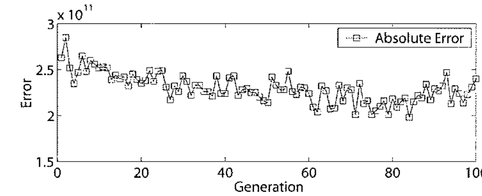
(a) E.M. distribution in the best fitness situation (fitness=0.230)



(b) Fitness (max., average, min.) as a function of generation

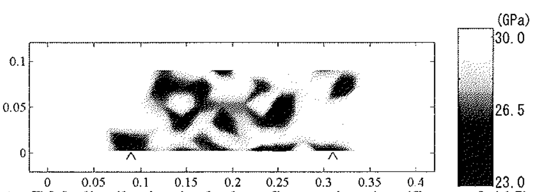


(c) E.M. distribution in the least error situation (fitness=0.0325)

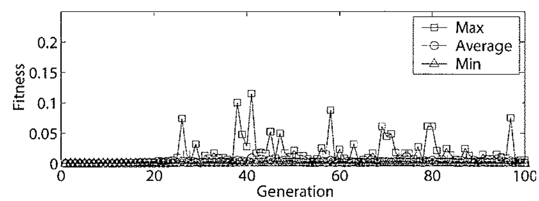


(d) Absolute error as a function of generation

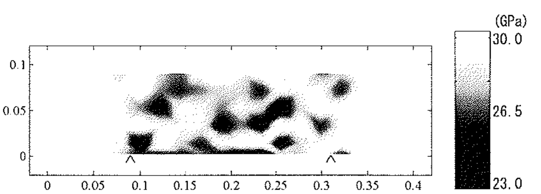
Fig.16 Result of Case 1



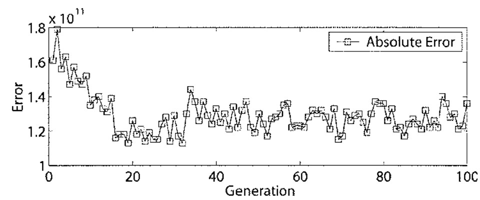
(a) E.M. distribution in the best fitness situation (fitness=0.115)



(b) Fitness (max., average, min.) as a function of generation

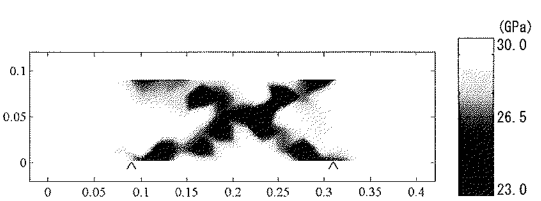


(c) E.M. distribution in the least error situation (fitness=0.00287)

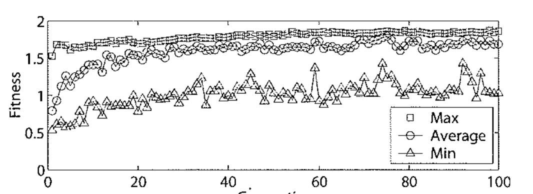


(d) Absolute error as a function of generation

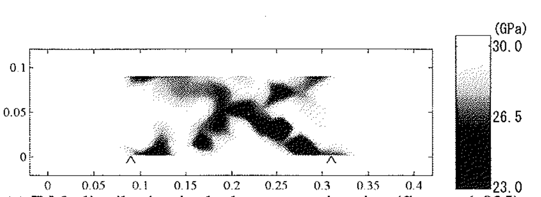
Fig.17 Result of Case 2



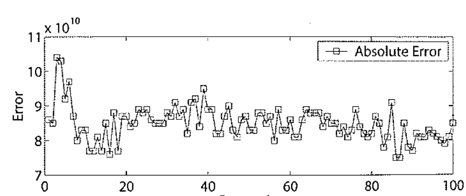
(a) E.M. distribution in the best fitness situation (fitness=1.873)



(b) Fitness (max., average, min.) as a function of generation

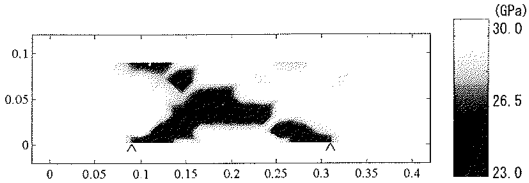


(c) E.M. distribution in the least error situation (fitness=1.835)

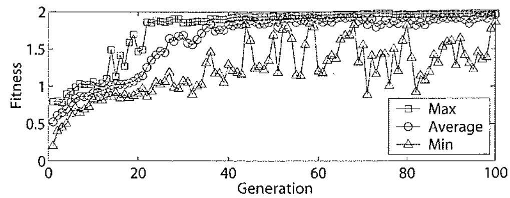


(d) Absolute error as a function of generation

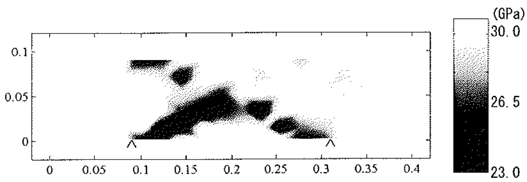
Fig.18 Result of Case 3



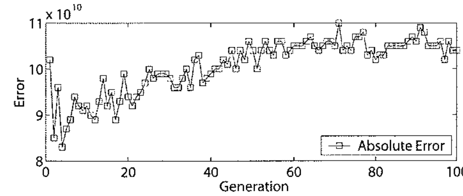
(a) E.M. distribution in the best fitness situation (fitness=1.984)



(b) Fitness (max., average, min.) as a function of generation

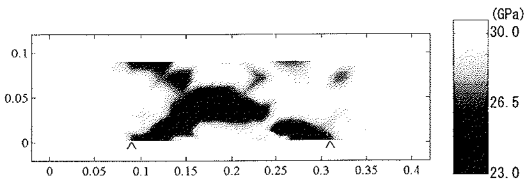


(c) E.M. distribution in the least error situation (fitness=0.895)

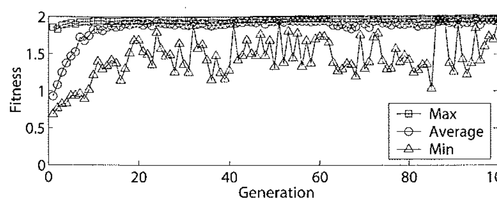


(d) Absolute error as a function of generation

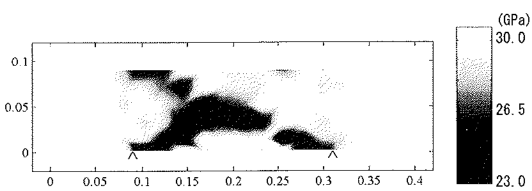
Fig.19 Result of Case4



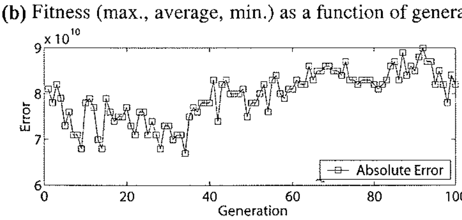
(a) E.M. distribution in the best fitness situation (fitness=1.987)



(b) Fitness (max., average, min.) as a function of generation

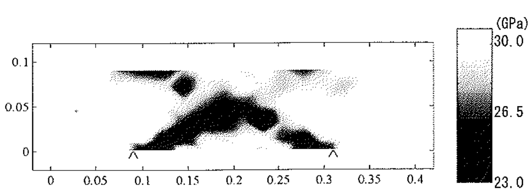


(c) E.M. distribution in the least error situation (fitness=1.954)

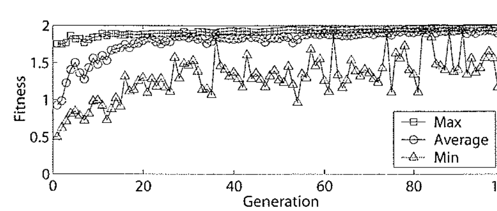


(d) Absolute error as a function of generation

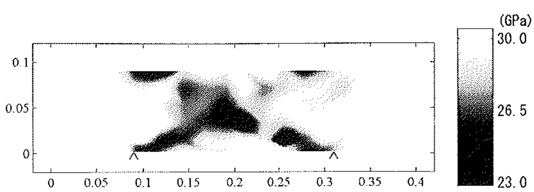
Fig.20 Result of Case5



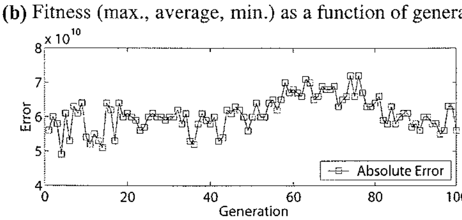
(a) E.M. distribution in the best fitness situation (fitness=1.972)



(b) Fitness (max., average, min.) as a function of generation



(c) E.M. distribution in the least error situation (fitness=1.862)



(d) Absolute error as a function of generation

Fig.21 Result of Case6

Table 5 Influence of a priori information quality

Case	Information quality	Correlation coefficient in the best fitness situation	Error in the least error situation
Case 1	0.0	0.0491	198E9
Case 2	0.6507	0.4324	113E9
Case 3	0.8987	0.7370	75E9
Case 4	0.8929	0.8765	83E9
Case 5	0.9490	0.8939	67E9
Case 6	1.0	0.9328	49E9

Table 6 Cases for examination for errors of a priori information

Case	Summation of absolute error	Initial correlation coefficient with true damage distribution
Case *a*	20E9	0.9031
Case *b*	50E9	0.8143
Case *c*	80E9	0.7004

Table 7 Influence of errors on correlation coefficients

Case	Correlation coefficient with false a priori information	Correlation coefficient with true damage distribution
Case *a*	0.9265	0.9244
Case *b*	0.9098	0.8854
Case *c*	0.8690	0.8838

However, for the other cases including the true distribution in a priori information, the pattern having the lowest absolute error gives a relatively high fitness value.

The influence of a priori information quality on both the correlation coefficient in the best fitness situation and the error in the least error situation is shown in **Table 5**. Information quality is defined as a correlation coefficient between the a priori information and the true damage distribution. It is found from the table that the correlation coefficient increases with the decrease of the absolute error and the increase of the information quality. Thus it is concluded that better estimated damage distribution is obtained as the information quality is improved.

As further implications, it can be said that the information on the location of damage is more important than that on the severity of damage by comparing the achieved correlation coefficient in the best fitness situation for Cases 3 and 4 (**Table 5**). For Cases 3 and 4, given information qualities are similar however the better estimation accuracy is achieved in Case 4.

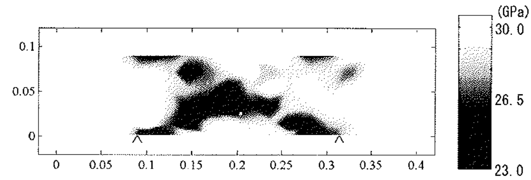


Fig.22 Case *a*: E.M. distribution in the best fitness situation (fitness=1.9265)

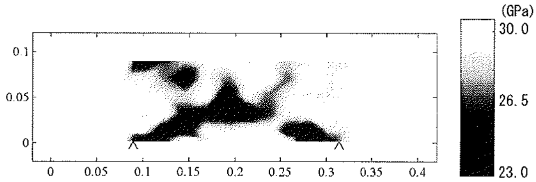


Fig.23 Case *b*: E.M. distribution in the best fitness situation (fitness=1.9098)

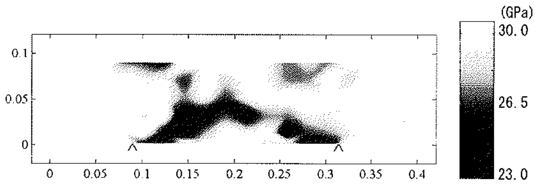


Fig.24 Case *c*: E.M. distribution in the best fitness situation (fitness=1.8690)

(3) Influence of Errors in A Priori Information

In this section, the influence of errors in a priori information is examined. By adding three different errors to the true damage distribution, three false a priori information are produced using random numbers. By manipulating the summation of absolute error, these three pieces of false information are set to have different values of correlation coefficients with the true damage distribution, as shown in **Table 6**. Using the false a priori information, the distribution giving the best fitness is searched for in each case.

The distributions giving the best fitness distributions for Cases *a*-*c* are shown in **Figs.22-24**. Looking at the changes in their appearance, it seems that the damaged area decreases as the summation of absolute error increases.

In **Table 7**, the correlation coefficient with the false a priori information in the best fitness situation, and the one with the true damage distribution in the same situation are shown. From **Tables 6** and **7**, it is found that the correlation coefficient with true damage distribution is improved from the initial value shown in **Table 6**. The one with false a priori information also becomes a higher value. In an actual problem, although the correlation coefficient with true damage distribution cannot be obtained, it is found that the correlation coefficient with a priori information is very corresponding to the one with true damage distribution. Moreover, for example, even though the initial correlation coefficient between the false information and the answer distribution decreases by 0.2 from Case a to c, the resultant correlation coefficient between the best fitness distribution and the false information decreases by only 0.057 and the one between the best fitness distribution and the answer distribution decreases by only 0.04. From these results, it is concluded that the influence of errors in a priori information on the estimation accuracy will be improved through the damage identification scheme using GA. Combining these results with the ones in the previous section, it is also concluded that the information on the location of damage has more influence on the estimation accuracy than on the severity of damage.

4. CONCLUSIONS AND DISCUSSIONS

This paper proposes a structural damage identification method using GA. The simulation verification of this method is tried by setting up a hypothetical problem. The proposed method is able to estimate the location and severity of inflicted damage at the same time. In this paper, the natural frequency and the information on the distribution of damage are considered as a priori information. The influence of the quality and the errors of the a priori information is examined. From the results of simulation verification, the following observations and conclusions can be made:

1. By using two different objective functions, i.e. the natural frequency and a priori information of damage distribution, it is possible to estimate the damage distribution in the structure. In this process, it is necessary to pay attention to the changes in each standard and keep an adequate balance among their changes to avoid falling into local solutions.
2. It is difficult to obtain a well-estimated damage distribution from only the natural frequency.
3. To search for a more fitted estimated distribution efficiently, the reduction of the number of candidates is necessary.
4. If the a priori information contains correct information about the inflicted damage, the estimation accuracy will be improved as the a priori information quality is improved. Hence, the quality of the a priori information has a great influence on the estimation accuracy.
5. In case the a priori information contains errors, this has a negative influence on the estimation accuracy, however the influence of the errors is reduced.
6. Information on the location of the damage is more important for the estimation accuracy than that on the severity of the damage.

Through the simulation verification, the efficiency of this method is verified. In the next step, 10
this method undertakes an experimental verification in the accompanying paper. The strongest point of this method is that it is more suitable for experimental application than other damage identification methods and it can cope with larger noises and errors. For the improvement of estimation accuracy, a better definition of objective function is necessary.

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