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Predictability of Impact Force Localization by Using the Optimization Technique

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Abstract

This work focuses on the analysis of some parameters that govern convergence of an adapted version of Particle Swarm Optimization and genetic algorithm which are used for identifying location of an impact occurring on an elastic beam structure. The problem takes the form of population number, the acceleration coefficients and a constrained nonlinear mathematical program for which the fitness function is obtained through Maxwell-Betti theorem. Sensors are assumed to be implemented in judiciously chosen locations and emphasis is done on the geometrical constraints that are introduce to limit the possible domain of impact location as well as on the stability coefficients that are specified in PSO and GA algorithms. It was found both that the chosen constraints, population number and stability coefficients control to large extent performance of these algorithms.

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1. Introduction

Identification of impact force location for impact events occurring on elastic structures can be performed by various methods that were proposed in the literature [1-3]. To review briefly some of the important contributions in this filed, Martin and Doyle [4] have described how to find the location of an impact force using dynamic response measurements. They proposed a solution procedure using the spectral element method with a stochastic iterative

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search. Experimentally measured acceleration responses from two frame structures were used to achieve force localization by minimizing a fitness function. A genetic algorithm was used to guess iteratively the minimum through monitoring the actual error associated to a given sampling generation. The process enabled to discriminate between good and bad guesses and gave at convergence the correct impact location. An alternative technique which employs the arrival time of each frequency component of a pulse detected by means of wavelet transform was proposed by Inoue et al. [5]. But, this approach suffers from lack of accuracy in measurement of small arrival times of signals. Yen and Wu [6, 7] have used multiple strain responses along with a mutuality relationship based on Green's functions and measured strains to achieve identification of force location on two-dimensional plate-like structures. Choi and Chang [8] minimized the error between measured strain responses in PZT sensors and numerically evaluated impact force locations. Shin [9] proposed a technique for identifying the force location using modal displacements and transient signal measured by accelerometers.

Identifying the characteristics of the force generated by impact can be used to better assess in real time the health of a structure that was impacted by a projectile. This enables to reduce favorably the required experimental effort and thus the derived cost of diagnosis. In case of simple linear elastic structures with homogeneous geometric and material properties such as beams or plates, identification of impact characteristics can be implemented through using a structural model.

When the impact location is known, the impulse response functions between the impact zone and the sensors placed at known positions, allows by using a regularized deconvolution to reconstruct the force signal. When the impact location is unknown, the inverse formulation uses a minimization technique between the measured and calculated responses to iteratively reconstruct the impact characteristics: point location and force time evolution.

In this work, separation of the localization and reconstruction phases of the impact force inverse problem is adopted. Elastic structures subjected to non-punctual impacts for which the resulting force field can be assumed to be uniformly distributed over a finite domain of the structure are considered. The localization problem is solved by using minimization procedures that are of evolutionary type. Two methods are examined in the following: Genetic Algorithm (GA) based strategy [10] and the Particle Swarm Optimization (PSO) approach [11, 12].

Here, a variant of Yen and Wu approach is implemented. Localization is expressed as a nonlinear mathematical problem with some geometrical constraints that fixes the domain where impact is expected to happen. Solution of this mathematical program is searched by means of a modified PSO algorithm and GA. The purpose is to analyze the effect on convergence that are resulting from the considered constraints as well as the effect due to some choice of the stability coefficients in the PSO algorithm and GA. The study is performed by fixing the population size at 100 and by assuming on the other hand that the sensors implementation configuration is given.

Nomenclature

L	Length of beam
s_0	Centre of the impact domain
u	Extent of the impact zone
P	Pressure
Y	Measured signal
N	Size of the sample
ΔT	Time discretisation
T_c	Calculation time
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
R_1^t, R_2^t	Random numbers
p_i^t	Best position
p_g^t	Position of swarm
ω	Inertia of the particle
c_1, c_2	Two trust parameters
G_0	Initial population of GA

2. Direct problem

An elastic beam is considered. The beam having the length L is assumed to be pinned - pinned. It is assumed to be impacted by a non-punctual object such that a uniform pressure develops over an interval having the form $\left[s_0 - u/2; s_0 + u/2\right]$ where s_0 is the center of the impact domain and u is the extent of the impact zone. The temporal approach to inverse problem is considered. It is based on the analytical expression of the transfer function between the impact zone and the sensors placed at known points. Solving the equation of motion of the beam yields a linear system of the form.

$$Y_k = G_k P \quad k = 1, 2, \ldots, N. \tag{1}$$

$$\begin{aligned} Y &= \left[y(1) \quad y(2) \quad \cdots \quad y(N) \right]^t \\ P &= \left[p(1) \quad p(2) \quad \cdots \quad p(N) \right]^t \end{aligned} \tag{2}$$

$$G = \begin{bmatrix} g(1) & 0 & \cdots & 0 \\ g(2) & g(1) & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ g(N) & g(N-1) & \cdots & g(1) \end{bmatrix} \tag{3}$$

where G is a Toeplitz like matrix between the pressure and the measured signal, and the size of the sample determined by the choice of the increment of time discretization and the calculation time.

3. Inverse problem localization

If $k = i$ and $k = j$ are substituted in equation (1), the following equations are obtained:

$$Y_i = G_i(s_0, u_0)P \qquad Y_j = G_j(s_0, u_0)P. \tag{4}$$

The commutative property and the writes the Maxwell-Betti theorem yield

$$G_i(s_0, u_0)Y_j = G_j(s_0, u_0)Y_i \tag{5}$$

This equation does not involve the force history vector P , enabling thus to decouple localization and pressure signal reconstruction. Knowing the measured responses $\tilde{Y}_i$ and $\tilde{Y}_j$, the tow parameters that define the impact location: s_0 and u_0 , can be found by minimizing the following fitness function

$$(s_0, u_0) = \underset{(s,u)}{A\mathrm{rg}\min} \left\{ \phi(s,u) = \sum_{i=1}^{N_s} \sum_{\substack{j=1 \\ j \neq i}}^{N_s} \alpha_{ij} \left\| G_j(s,u)\tilde{Y}_i - G_i(s,u)\tilde{Y}_j \right\|^2 \right\} \tag{6}$$

4. Optimization technique

4.1. PSO

A PSO based method was proposed initially by Kennedy et al. [12]. This approach has gained since then considerable interest as being one of the most promising optimization methods that is able to provide high speed and high accuracy. PSO mimics the social behavior that a population of individuals adapts to its environment by returning to promising regions that were previously discovered. This adaptation to the environment is a stochastic process that depends on both the memory of each individual, called particle, and the knowledge gained by the population, called swarm.

In the simplest numerical implementation of this method, each particle is characterized by four attributes: the position vector in the search space, the velocity vector, the best position achieved in its track and the best position achieved by the swarm. The process steps can be outlined as follows:

Step 1. Generate the initial swarm involving N given particles placed at random.

Step 2. Calculate the new velocity vector of each particle, based on its actual attributes.

Step 3. Calculate the new position of each particle from the current position and its new velocity vector.

Step 4. If the termination condition is satisfied, stop. Otherwise, go to Step 2.

To be more specific, the new velocity vector of the ith particle at time $t+1$, denoted v_i^{t+1}, is calculated according to the following Shi and Eberhart (1998) formula

$$v_i^{t+1} = \omega^t v_i^t + c_1 R_1^t (p_i^t - x_i^t) + c_2 R_2^t (p_g^t - x_i^t) \tag{7}$$

In equation (7), R_1^t and R_2^t are random numbers between 0 and 1, p_i^t is the best position of the ith particle in its track, and p_g^t is the best position of the swarm. There are three problem dependent parameters that fix performance of this algorithm, namely: the inertia of the particle ω^t and the two trust parameters c_1 and c_2.

The new position of the ith particle at time t, denoted x_i^{t+1}, is then calculated as follows

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{8}$$

where x_i^t is the current position of the ith particle at time t. The ith particle actual position enables to determine the best position in its track p_i^t. When considering all the particles, the global best position of the swarm p_g^t is then obtained.

PSO algorithm works such that particles concentrate on the best search position of the swarm. They cannot easily escape from the local optimal solution since the search direction vector v_i^{t+1} calculated by (7) always includes the direction vector to the best search position of the swarm. This shows the major feature of PSO algorithm as being a robust process of continuous enhancement for optimum search.

In the presence of constraints a particle move should be restricted in order to remain in the feasible solution space by examining the given constraints. A modified PSO version was introduced for constrained problems in order to manage this situation [13].

4.2. GA

Genetic Algorithm (GA) was firstly introduced by Holland [10]. It is a probabilistic optimization method that is able of achieving global search by mimicking natural biological evolution. GA operates on a population of individuals called the set of potential solutions. Each individual is represented by an encoded string (chromosome) that contains the decision variables (genes). Traditionally, GA uses binary strings as chromosome representation.

The GA has an iterative procedure structure that comprises generally the following five main steps:

Step 1. Creating an initial population (G_0).

Step 2. Evaluation of the performance of each individual or chromosome (c_k) of the population, by means of a fitness function to be maximized.

Step 3. Selection of individuals for reproduction of a new population.

Step 4. Application of genetic operators: Crossover and Mutation.

Step 5. Iteration of steps 2 to 4 until a termination criterion is fulfilled.

In the localization problem considered in this work, the candidate solution is the centre position s_0 and the extent of the impact zone u. These variables are then coded in a chromosome using a binary coding scheme.

To start the algorithm, an initial population of individuals (chromosomes) is defined. The GA is configured, so that it creates a fixed number of initial individuals at random from the whole feasible solution space. An important parameter in initialization is the population size. In general, the population size affects both the ultimate performance and the efficiency of GA and should be determined in a case by case study.

5. Results and discussion

Let's consider a beam having length $L = 0.5m$ and the following sets of domains containing respectively s_0 and u_0 : Three constraints were considered in order to give the configurations of both PSO algorithm.

They correspond to: constraints 1: $[0, L]$, $[0, L]$, constraints 2: $[L/40, L - L/40]$, $[L/40, L/2]$ and constraints 3: $[-\infty, +\infty]$, $[-\infty, +\infty]$. In parallel, let's consider the following two sets of stability coefficients:

case 1: $w_0 = 0.4$; $c_1 = 1.25$; $c_2 = 0.5$ and case 2: $w_0 = 0.8$; $c_1 = 2.5$; $c_2 = 1$.

Table 1. Positions of the gauge sensors considered for measurement of axial strain at the upper beam fiber

Sensor	Position
#1	5L / 24
#2	L / 3
#3	L / 2
#4	2L / 3

Four gauge strain sensors were used in this study. Their labelling and positions are indicated in table 1.

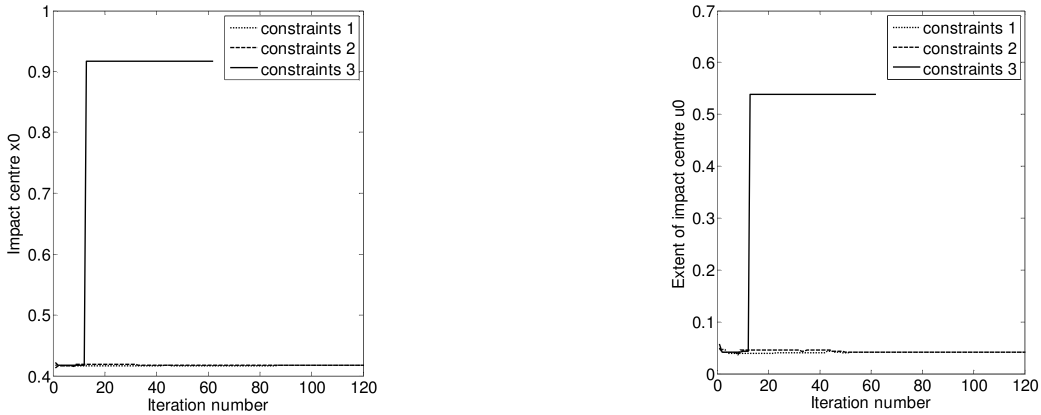

Fig. 1. Variation of impact characteristics as function of constraints, case 1.

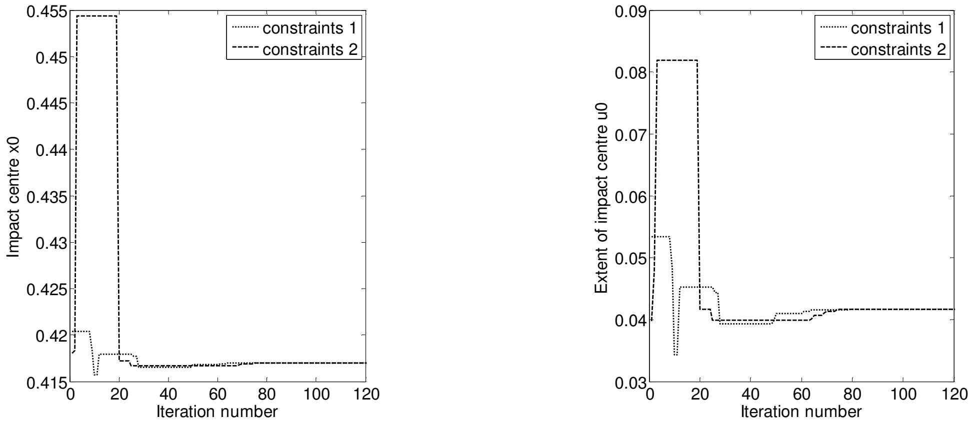

Fig. 2. Variation of impact characteristics as function of constraints type; case 2.

From figure1, one can see that if no constraints are imposed on the impact characteristics convergence is not reached. Figures 1 and 2 show that convergence is obtained for both constraints 1 and 2. Convergence is however better for constraints 2. The two sets of stability coefficients yield almost the same result but convergence is quicker with case 1.

In the rest of this work, we can give the best configurations of PSO and GA based algorithm with constraints 2.

The parameters used for GA were as follows:

- Stopping test: 10^{-6}
- Population size: 100;
- Probability of intersection: 1;
- Probability of mutation: 0.05;
- Maximum number of generation: 200.

For GA algorithm the first values of the unknown parameters impact centre and extent were initialized with $x_0 = u = 1.25\times10^{-2}$.

For PSO algorithm, the following stability parameters were used: $w_0 = 0.4$; $c_1 = 1.25$; $c_2 = 0.5$ and size population: 100.

a b

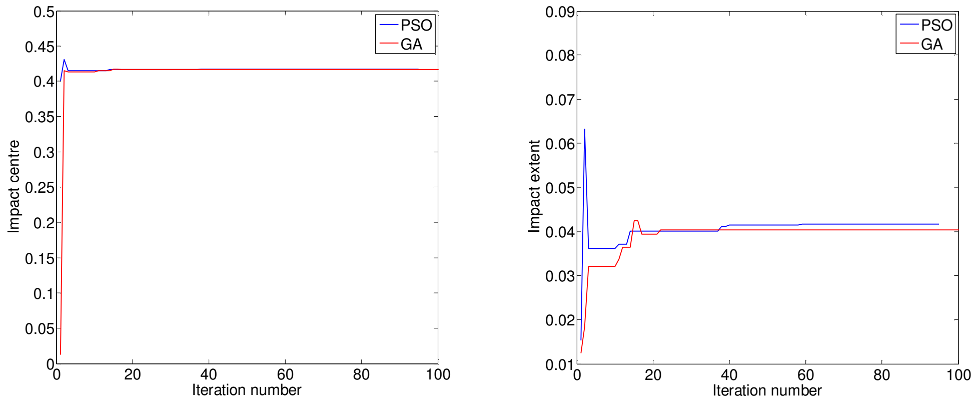

Fig. 3. Evolution of impact zone characteristics (a) Impact center; (b) Impact zone extent

Figure 3 gives evolution of impact location characteristics as function of iterations in case 1. One can see the difference existing between these two algorithms; PSO algorithm gives the exact solution of the impact location. On the opposite, GA has not converged to the right solution.

6. Conclusions

Based on the separation approach that decouples force location from force signal reconstruction in an inverse impact problem occurring on an elastic beam, robustness of a particular localization procedure was analysed. This uses a modified fitness function derived from Maxwell-Betti theorem by applying some filtering coefficients that enable to remove parasitic solutions. Solution of the obtained constrained nonlinear mathematical program that provides the impact zone location was performed by GA and PSO based algorithms. Predictability of force location was studied as function of constraint and stability coefficients control.

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