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WAVELET TRANSFORM AND SOFT COMPUTING IN DAMAGE IDENTIFICATON

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Abstract. *The paper demonstrates the potential of combination of inverse analysis and wavelet transform in a discrete form for structural damage identification. The efficiency of the method is tested through series of numerical examples, where the real structure is simulated by a parametrized finite element model. The eigenvibrations of cantilever steel beam are taken into consideration, structural response signal is computed in discrete points uniformly distributed along the beam span. Analyzes are performed for eigenmodes expressed in amplitudes of vertical displacements. By changing control parameters embedded in numerical model the minimization of the discrepancy between the wavelet representation of both 'real' and numerically computed data is presented. To minimize the objective function a global minimization technique, namely genetic algorithm, is employed in the study. Computer tests proved that the identification of more than one defect in the structure with the unequal number of measurement points in both 'real' and numerical experiments is possible.*

1 INTRODUCTION

The damage generally can be defined as a change in the material (e.g. crack, void, inclusion or delamination), which impairs the functioning of the structural element currently or in the future and may lead to destruction of this element or, in the worst case, it can initiate progressive failure of a whole structure. Early detection, localization and estimation of structural damage is one of the most important engineering issues and belongs to a wide class of identification problems, where unknown parameters of a structure are determined from experimental tests.

Non-destructive testing is relatively young and still developing field of science. There are different approaches and many advanced methods, most of them based on the analysis of the structural response signals. Radiography [1], used in almost all manufacturing processes of industrial equipment, is considered as a very reliable method of non-destructive damage detection method. Ultrasonic methods (see e.g. [2]) use transmission of high-frequency sound waves in a material and make possible to detect cracks, delamination, porosity and other discontinuities within the elements. Acoustic emission method [3] has the capability of detection of the elastic waves generated by crack initiation or growth and generally allows continuous monitoring of damage progress. Another method of non-destructive testing uses a magnetic field effect. This technique was applied for damage detection in e.g. [4]. Eddy current method is based on inductive properties of alternating current and is suitable for inspection of the surface and just beneath the surface of conductive materials e.g. for crack detection or defect classification [5]. Infrared and thermal testing have proved to be an effective, convenient, and economical method. Involving the measurement of surface temperatures as heat flows to, from and/or through an object makes possible to detect and characterize the damage in homogenous [6] or heterogenous material [7]. A great potential is assigned to soft methods, mainly evolutionary algorithms [8] and artificial neural networks [9] which give an extensive possibilities of applications for structural health monitoring.

An important role in the damage detection play methods based on modal analysis and the use of dynamic characteristics of the structure. It was observed that even small and local damage leads to stiffness reduction, decrease of natural frequency and increase of damping of examined structure. Already about 70 years ago the relationship between the eigenfrequency and the introduction of crack in the steel beam was described in [10]. This approach, based on analysis of structural dynamic response, is further developed through the years and can be easily applied to identify the presence of damage (see e.g. [11]).

Different types of response, namely eigenfrequencies/eigenmodes, displacements, velocities and accelerations can be usefull for structural health monitoring. Nevertheless, it happens that the experiments limited to measurement of eigenfrequences are insufficient, since the global dynamic response is rather insensitive to damage localized on a small area, so the localization and severity of defect is not easy to identify. Therefore, attempts have been taken to increase the sensitivity of vibration methods. In [12] an additional parameter as an elastic or rigid support and a mass was introduced into the structure. The change in a natural frequencies for varying parameter values with respect to damage location is analyzed. To assess the location and severity of defect the damage indices were applied and the identification problem was solved by the minimization of the parameter dependent distance functional. Optimization of unspecified distribution and orientation of loading in order to minimize the distance norm between model prediction and experimental data was discussed in [13]. The sensitivity derivatives with respect to load parameters and respective optimality conditions were derived using the adjoint variable approach. The closed form solutions for optimal load in structural problems were derived for statically determinate beam-column structures. Structural identification using a min-max approach applying FEM solutions was discussed for a propped cantilever beam.

The method which enables to extract the desired detailed information from a numerous data representing the global response of a defective structure called Wavelet Transformation (WT) is proposed in the paper. An indicator of the damage presence and location in this type of analysis are the strong disturbances of the transformed signal. There are many wavelet functions e.g. Haar wavelet, Symlet, Coiflet, Meyer, Gaussian, Mexican hat or Morlet and new ones are constantly developed. Previous studies of the authors (see [14], [15]) proved that, in the class of considered problems, the most effective appeared to be Daubechies wavelet of 4th order [16]. Severity of the damage can be estimated using e.g. Lipschitz exponent [17] but the structural response signal processing using CWT or DWT has turned out to be ineffective in identification damage details such as the type or shape. Therefore, some alternative method which provides a more precise damage identification is needed. In the literature a few attempts can be found, e.g. a combination of WT and artificial neural networks. In [18] the authors proposed the method which combines the continuous wavelet transform (CWT) and artificial neural networks (ANNs) with their possibility of learning, remembering or recognition and called it neuro-wavelet technique. To collect the ANN training data the experiment and numerical simulation was conduct on CWT moduli of a simple cantilever beam static deflection line. The method was validated on experimentally determined mode shapes of a beam and more complex structures, like plate or shell.

For characterization of damage details such as type, intensity and size, in the locally defective elements of the structure, an important tool proved to be inverse analysis. This method, besides data obtained as a result of the experiment, uses also numerical counterpart of the signal obtained from the computer simulations. In the current study the structural response signal is represented by the wavelet coefficients. At the present stage, the experiments are limited only to computer test simulations in order to check the robustness of the proposed approach. For the discrepancy minimization a variety of different minimization techniques can be employed in inverse analysis. The objective function, meaning the discrepancy between experimental and numerical measurable quantities, is usually minimized in the frame of least square approach [19]. Inverse problems are often solved by making use of iterative minimization gradient based algorithms (e.g. [20]), based on soft computing methods (e.g. [21]), etc. Structural or constitutive parameters, which are usually unknown or uncertain, are not easily accessible from the experiment. Indirect measurements, used in inverse analysis with any minimization algorithm, makes determination of them possible. Many researchers have found this approach useful and successfully applied it in various fields e.g. [22, 23], [24], [25], [26]. The contribution of this work is the application of WT in its discrete form together with inverse analysis for structural diagnosis, which is a novel approach to Structural Health Monitoring. However, it is still an open and unsolved problem.

2 GENERAL INFORMATION ON WAVELET TRANSFORMATION

Any signal can be portrayed as a sum of sinusoidal signals. It becomes a basis for widely used Fourier analysis, which is a perfect tool for analyzing the stationary signals representing them in frequency domain. In wavelet transform (WT) for the representation of the signal f(t) a linear combination of wavelet functions is used. Wavelets are localized in time and frequency domain and have advantages over Fourier transform in situations when the signal contains discontinuities, spikes or sharp edges. The data are cut into different frequency components and then each component is analyzed with resolution matched to its scale reducing the effects of the Heisenberg uncertainty principle [27]. In this case it means the inability of precise signal analysis in time domain and frequency domain at the same time.

It is considered that $\psi\ (t) \in \mathbf{L}^2(\mathbb{R})$ is a wavelet (mother) function if it satisfies admissibility condition:

$$\int_0^\infty \frac{|\Psi(\omega)|^2}{\omega} d\omega < \infty, \tag{1}$$

where $\Psi(\omega)$ is Fourier transform of function $\psi(t)$. Average value of wavelet function is equal to zero, it means that the wavelet integral over real axis disappears:

$$\int_{-\infty}^{\infty} \psi(t)\, dt = 0. \tag{2}$$

In wavelet transform there is only one wavelet (mother) function. For signal decomposition copies of wavelet, which are called wavelet family, are used. They are obtained by scaling and translating ψ according to formula:

$$\psi_{a,b} = \frac{1}{\sqrt{|a|}} \psi \left(\frac{t-b}{a} \right), \tag{3}$$

where the variable t denotes time or space coordinate, a is the scale parameter and b indicates the wavelet translation in time/space domain; $a,\ b \in (\mathbb{R})$; $a \neq 0$. The scale factor $|a|^{-1/2}$ is a normalization coefficient which ensures constant wavelet energy regardless of the scale. This means that $\|\psi_{a,b}\| = \|\psi\| = 1$ [28].

Continuous wavelet transform of given function $f(t)$ is obtained by integrating the product of the signal function and the wavelet functions [29]:

$$W\ f\ (a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f\ (t) \cdot \bar{\psi} \left(\frac{t-b}{a} \right) dt = \langle\ f\ (t),\ \psi_{a,b} \rangle\ , \qquad f \in \mathbf{L}^2(\mathbb{R}). \tag{4}$$

An important role in applications, due to numerical efficiency, plays wavelet transformation in its discrete form . Substituting $a = 1/2^j$ and $b = k/2^j$, $k,\ j \in \mathcal{C}$ in the (3) a wavelet family is obtained:

$$\psi_{j,k}(t) = 2^{j/2} \psi \left(2^j t - k \right), \tag{5}$$

where $j = 0, ..., J-1$ is scale parameter, $k = 0, ..., 2^j - 1$ translation parameter and J is the maximum level of transformation. Meaning of these parameters for the simplest Haar wavelet is shown in Fig.1.
Discrete wavelet transform is defined as:

$$W\ \psi_{j,k} = 2^{j/2} \int_{-\infty}^{\infty} f\ (t) \cdot \bar{\psi} \left(2^j t - k \right) dt = \langle\ f\ (t),\ \psi_{j,k} \rangle \tag{6}$$

and wavelet coefficients are given by:

$$d_{j,k} = \langle\ f\ (t),\ \psi_{j,k} \rangle\ . \tag{7}$$

A linear combination of wavelet functions $\psi_{j,k}$ and wavelet coefficients $d_{j,k}$ allows to represent a discrete signal (the number of data is equal to 2^J) in the form:

$$f(t) = \sum_{j=0}^{J-1} d_{j,k}\, \psi_{j,k}(t) \tag{8}$$

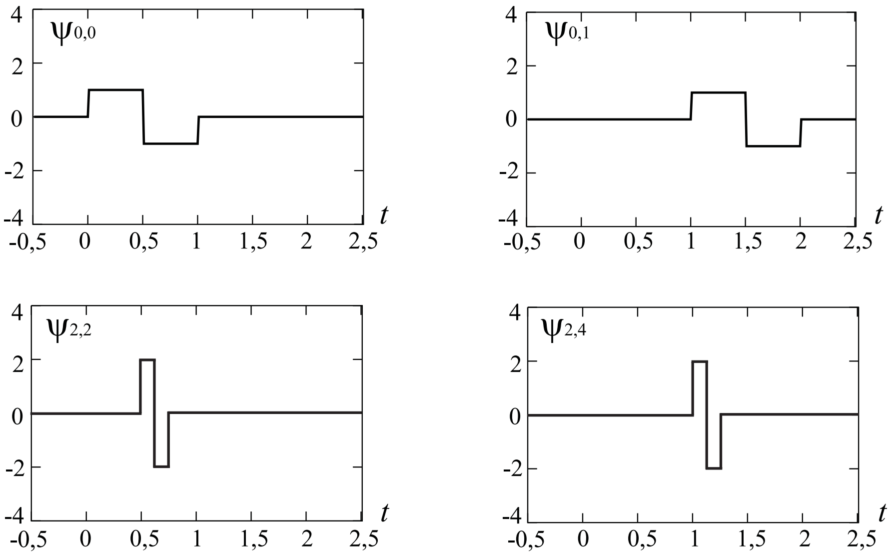

Figure 1: Haar wavelet with different j and k parameters.

Multi-level signal representation is possible thanks to multi-resolution analysis (MRA) (see [30]), closely connected with wavelet transform. For multi-resolution signal analysis a scaling wavelet $\varphi(t)$ (father) is required:

$$\varphi_{j,k}(t) = 2^{j/2}\varphi\left(2^j t - k\right). \tag{9}$$

Discrete signal $f(t)$ can be approximate using wavelet $\psi(t)$ and scaling $\varphi(t)$ functions according to:

$$f(t) = \sum_{k=-\infty}^{\infty} a_{j,k} \cdot \varphi_{j,k}(t) + \sum_{k=-\infty}^{\infty} \sum_{j=0}^{\infty} d_{j,k} \cdot \psi_{j,k}(t), \tag{10}$$

where $a_{j,k}$ are scaling function coefficients derived from the formula:

$$a_{j,k} = \langle\, f\,(t),\ \varphi_{j,k} \rangle\,. \tag{11}$$

A wavelet function has a band-like spectrum, so the coefficients $d_{j,k}$ have high frequencies information (details). Coefficients $a_{j,k}$ have low-pass information with a constant component which is called signal approximation.

Multi-resolution analysis of discrete signal can be expressed in Mallat's algorithm:

$$f_J = S_J + D_J + ... + D_n + ... + D_1, \qquad n = J - j \tag{12}$$

where S_J is a smooth signal representation, D_n and are S_n are details and rough parts of a signal, j is the level of decomposition and J level of MRA.

In this work Daubechies wavelet of fourth order was implemented. Daubechies 4 wavelet (mother) function and scaling (father) function are shown in Fig.2. Daubechies wavelet was invented by Belgian mathematician Ingrid Daubechies (see [16]). This is the first discovered family of orthogonal continuous wavelets with compact support. These wavelets are asymmetrical, compactly supported, with sharp edges. They require a small number of coefficients therefore are widely used in solving a broad range of problems, e.g. image analysis. Their order is between 2 and 20 (always even numbers). Each wavelet has a number of zero moments or vanishing moments equal to half of the order. Second order Daubechies wavelet corresponds to the simplest Haar wavelet.

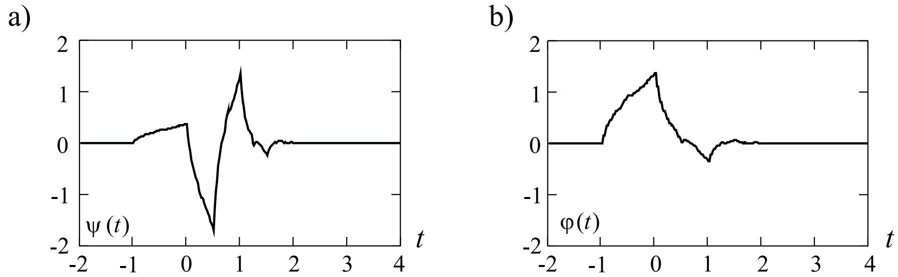

Figure 2: Daubechies 4: a) mother wavelet, b) father wavelet

3 GENETIC ALGORITHMS IN INVERSE PROCEDURE

Search for the solution in inverse problems usually consists of two parts, i.e. the numerical discretization methods for direct computations of assumed structure and the iterative procedures that are used to seek for the actual structural and geometrical configuration. The discretization schemes for the structure in the literature include e.g. finite difference methods, the finite element (FE) method or the boundary integral equation (BIE) technique, to list just a few. The most crucial part in the formulation and numerical solution methods for realistic inverse problems, however, lies in finding a robust iterative procedures for a large variety of complex problems that will proceed towards the final configuration. Numerous of the iterative procedures in the literature are based upon various gradient-based optimization and/or sensitivity analytical schemes in which the Jacobian and/or the Hessian matrices (or their approximations) of the system must be calculated in the iterative procedures. One of the advantages of gradient-based solution schemes is that good starting points usually lead to fast convergence for structures with relatively simple configurations. On the other hand gradient methods may not produce a good solution if local optima exists, they may then oscillate between several local minima, need cumbersome regularization procedures, need penalty constraint formulations, or other augmentation schemes when a reasonable starting point is difficult to find. These techniques may also destabilize as the number of parameters increases.

Here, a methodology based on Genetic Algorithms (GA) for the solution of inverse problems pertaining to the identification of the damage severity and localization in simple structural elements is selected and described. Genetic algorithms are probabilistic parallel search algorithms based on natural selection. GAs were designed to efficiently search large, non-linear, poorly understood search spaces where expert knowledge is scarce or difficult to encode and where traditional optimization techniques fail. They work with a population of individuals (usually encoded as bit strings) that represent candidate solutions to a problem. The population is modified by the application of genetic operator from one iteration (generation) to the next until a stopping criterion is met. The algorithm evaluates, selects, and recombines members of the population to form succeeding populations. Evaluation of each string which encodes a candidate solution is based on a fitness function that is problem dependent. For our problem, the mean square root of the differences between the measured quantities at each sensor location and the corresponding computed quantities from the assumed structural configuration provides a measure of 'fitness'. This fitness measure is used by the selection operator to select relatively fitter individuals in the population for recombination, crossover and mutation. Mutation insures against the permanent loss of genetic material. Crossover is the main recombination operator. It is a structured yet stochastic operator that allows information exchange between candidate solutions. Two point crossover is implemented by choosing two random points in the selected pair of strings and exchanging the substrings defined by the chosen points.

The GA offers several advantages over the traditional methods. First, unlike various traditional gradient based formulations, the present method does not require the calculation of the Jacobian and/or the Hessian matrices or the various sensitivity parameters of the system. The corresponding numerical procedures are therefore much simpler and more stable than traditional methods. This is important because the Jacobian, Hessian matrices, and the various sensitivity parameters are usually sensitive to the ill-posed nature of the structure system. Second, unlike the traditional methods in which various penalty functions or Lagrangian multiplier procedures are used to impose the required constraints such as the internal structure sizes, location ranges etc., treatments for these constraints are much simpler in the GA. Finally, because the GA performs the solution search globally, the problem of local minima in traditional gradient based analytical search methods is mitigated.

4 FORMULATION OF THE PROBLEM

Using this approach, the inverse problem is expressed as a minimization problem with the objective function being the mean square root of the differences between the wavelet representation of the vertical displacement measurements at each sensor location and the corresponding computed quantities from the assumed structural configuration, i.e.

$$\omega = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[U_i^{\mathrm{EXP}} - U_i^{\mathrm{NUM}}]^2} \tag{13}$$

where N is the number of DWT coefficients, $\mathbf{U}^{\mathrm{EXP}}$ and $\mathbf{U}^{\mathrm{NUM}}$ are, respectively, the wavelet representations of measured and calculated values of the signal composed of vertical displacements amplitudes at the j-th sample point. This objective function is used by the GA to measure the fitness of individuals in a population of candidate solutions. Possible approximate solutions are found by the GA gradually leading to an increase in the average fitness of the population.

For a given structure and boundary conditions, the values of the variables describing the damage locations and dimensions are obtained from a FE method. The outline of an algorithm is presented below:

1. randomly generate an initial population of solutions, each of which is an assumed damage configuration;

2. use the FE method to compute the eigenvalues and corresponding eigenvectors of the structure;

3. compute the wavelet coefficients of the deformation modes of structure;

4. compare the values of wavelet representation of deformation mode computed from the FE with measured values and compute the mean square root error using the error expression defined in 13;

5. if the mean square root error is smaller than a predetermined value, stop;

6. produce a new generation using cross-over and mutation, and go to the second step.

5 EXAMPLES AND RESULTS

The efficiency of damage detection and identification using a combination of DWT and inverse analysis is studied here. It is assumed that the information specifying the response of the undamaged structure are unknown. Hence, the wavelet transformation is applied only to response signals of defective structures. The authors analyze a cantilever beam made of steel, with a span $l = 1.0$ m and a rectangular cross section with dimensions of 4×8 cm. Young's modulus E is equal to 200 GPa, mass density $\rho = 7850\text{kg/m}^3$. In the study the Euler-Bernoulli beam theory is applied, which means that any transverse shear deformation is ignored. Ten percent severe failure in one beam element is introduced into the structure as a hight reduction of cross section from $h = 8$ cm to $h_1 = 7.2$ cm (see Fig.3a) or as a change of Young's modulus value from $E = 200$ GPa to $E_1 = 180$ GPa (Fig.3b), d denotes the length of defective part of the structure and corresponds to the dimension of one finite beam element. The number of damaged elements may vary from one to several at various locations along the beam span. The real structure, subjected to a dynamic excitation, is simulated by parameterized Finite Element (FE) model. At the present stage of the study the real experiment is mimic by its numerical simulation, called pseudo-experiment, in which all parameters $\mathbf{x}_{\text{ref}}$ are known. All control parameters gathered in the vector $\mathbf{x}$ are embedded in the numerical model (different then pseudo-experimental one). For initial guess of sought parameters i.e. damage position (x_1), number of defective elements (x_2) and amount of damage (x_3) numerical experiment is performed. For minimization of the discrepancy between the results obtained from numerical model and pseudo-experiment model the genetic algorithm is employed.

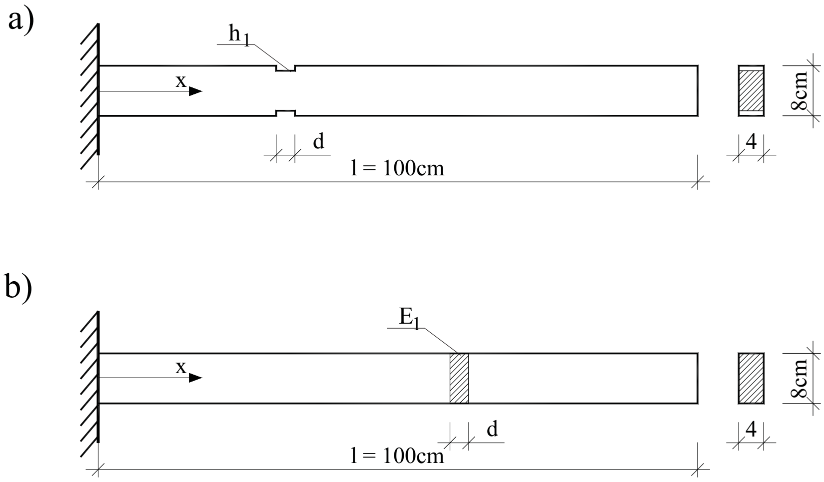

Figure 3: Steel cantilever beam: a) damage modeled as hight of cross section reduction, b) damage modeled as Young's modulus reduction.

Here the population in GA is chosen to consist of 20 individuals randomly initialized, from which 2 best fitted are selected as elite at each iteration, remaining members are subjected to crossover (80%) and mutation (20%). Both operations create new individuals within feasible domain through subjected constrains, here location of damage is bounded within $[0, L]$ and amount of damage is limited to $[0, 50\%]$. Since crossover combines two individuals to form a new child for a next generation, an important issue is to properly mix genes of both parents. Here a scatter algorithm is implemented, which uses random selection of genes to be used from first and second parent to form a child's gene. Mutation is realize in a very similar way, first, the algorithm select a fraction of a vector entries of an individual for mutation and later each selected entry which chosen probability is replaced by a random number from a range for that entry.

The response signal is computed in discrete points uniformly distributed at the longitudinal axis of the beam, which however are not at the same position as nodal coordinates in FE model. This is due to fact that both numerical model and psudo-experimantal one use different meshes in order to not bias the results. As an input signal to wavelet decomposition a first eigenmode expressed in amplitudes of displacements is taken into consideration. Inverse analyzes are performed on DWT represented by the wavelet coefficients of original signal. By different initialization of the vector $\mathbf{x}$ in the numerical model (which is different from the pseudo-experimental one $\mathbf{x}_{\text{ref}}$), and by comparing the converged values of the sought parameters to those parameters used for pseudo-experimental data generation, one can check the robustness of the proposed method. The novelty, compared to earlier studies of the authors (see [31]), is the identification of more than one defect in the structure with the unequal number of measurement points in both pseudo-experimental and numerical experiments.

Here below, some selected examples of damage identification in deteriorated cantilever beam are presented. First example concerns a beam with a stiffness reduction of 10% in two locations: 0.33 m and 0.66 m. Both damaged zones have width of 0.01 m. In second example two variants are considered: in both a beam has one damaged section located in 0.33 m. In the first one the stiffness is reduced by 10 % on the length of approximately 0.01 m, in the other the beam hight is reduced by 10 % on the length of approximately 0.02 m.

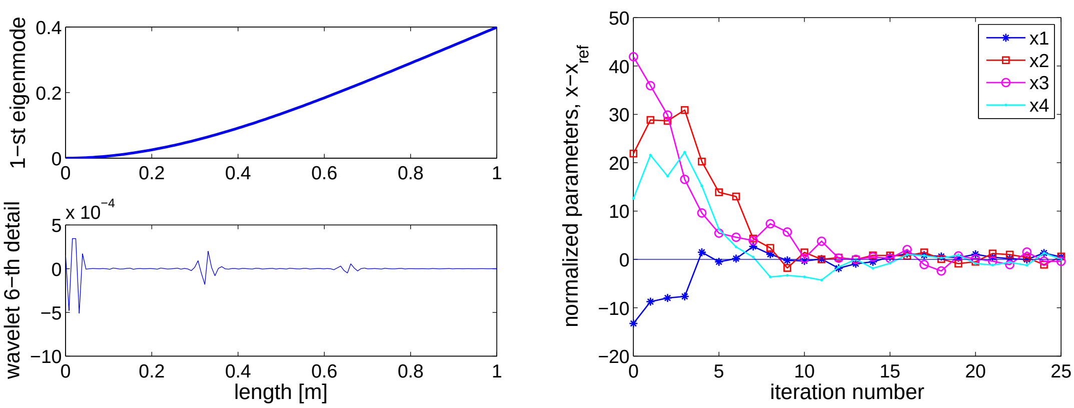

Figure 4: 1-st eigenmode and its wavelet representation (left); convergence of the four parameters, x1 - damage location ‘a’, x2 - damage location ‘b’, x3 - deterioration ‘a’, x4 - deterioration ‘b’ (right)

Figure 4 shows the result of first example. A beam has two damaged zones located in 0.33 m and 0.66 m what is evidenced in the Fig.4 by the wavelet decomposition of an eigenvector. Here, four parameters are unknown, namely: (x1) 1-st damaged zone location, (x2) 2-nd damaged zone location, (x3) an amount of 1-st damage and (x4) and amount of 2-nd damage. All four parameters converged to their reference values within approximately 10-12 iterations (Fig.4).

Figure 5 shows the histogram of each sought parameter within population in each iteration. It is evidenced in the Fig.5 that mean values of each parameter converge to their reference values.

Figure 6 shows the result of second example - variant (1). A beam has one damaged zones located in 0.33 m what is evidenced in the Fig.6 by the wavelet decomposition of first eigenvector. Here again four parameters are unknown, namely: (x1) 1-st damaged zone location, (x2) 2-nd damaged zone location, (x3) an amount of 1-st damage and (x4) and amount of 2-nd damage.

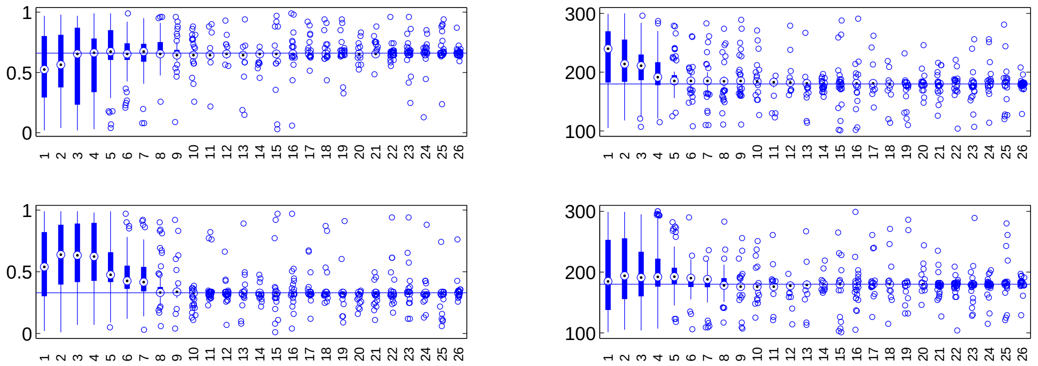

Figure 5: Histogram of population's components: x1 - damage location 'a' (left-up); x2 - damage location 'b' (left-down); x3 - deterioration 'a' (right-up); x4 - deterioration 'b' (right-down): black line points out the reference value

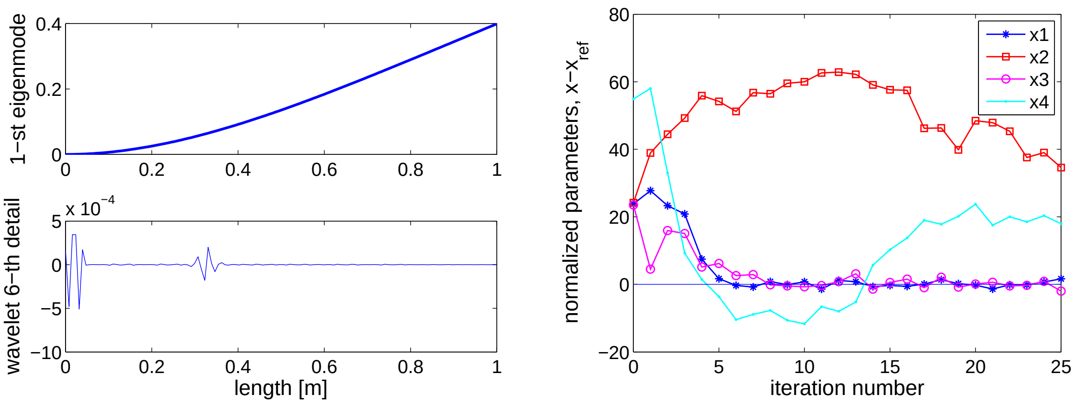

Figure 6: 1-st eigenmode and its wavelet representation (left); convergence of the four parameters, x1 - damage location 'a', x2 - damage location 'b', x3 - deterioration 'a', x4 - deterioration 'b' (right)

Only two parameters (x1 and x3) converged to their reference values within approximately 8-10 iterations (Fig. 6). The remaining two parameters (x2 and x4) have oscillated during analysis and finally start to diverge once the damage was located by a first pair of parameters (x1 and x3). This phenomenon is due to a very narrow width (0.01 mm) of the zone where the stiffness was reduced in the model. Therefore only one searching pair was sufficient to localize and estimate a damage zone.

Figure 7 shows the histogram of each sought parameter within population in each iteration of the second example. It can be observed in the Fig.7 that mean values of two parameter x1 and x3 converge to their reference values but mean values of x2 and x4 oscillate during the inverse analysis and finally deviate from their reference values.

Figure 8 shows the result of second example - variant (2). A beam has one damaged zones located in 0.33 m what is evidenced in the Fig.8 by the wavelet decomposition of first eigenvector. Same parameter as in previous analyses are unknown here, namely, x1, x2, x3 and x4. This time all four parameters converged to their reference values (Fig.8) though the convergence was observed only in the last iteration. Successful identification in this example can be explained by the fact of relatively wide zone when the hight of the beam was reduced. Therefore two small virtual damaged zones concentrate around its real location.

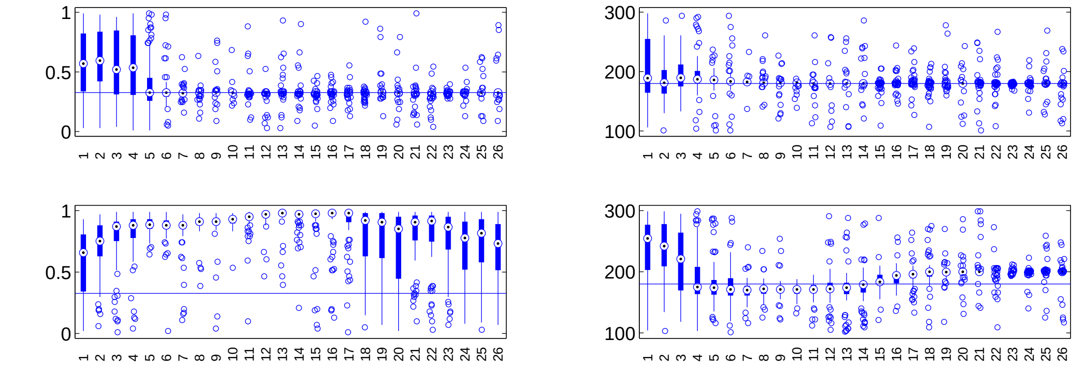

Figure 7: Histogram of population's components: x1 - damage location 'a' (left-up); x2 - damage location 'b' (left-down); x3 - deterioration 'a' (right-up); x4 - deterioration 'b' (right-down); black line points out the reference value

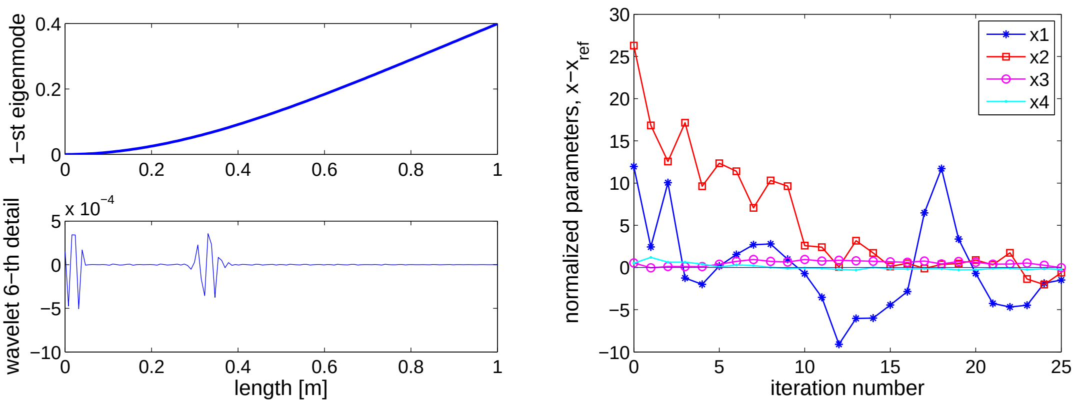

Figure 8: 1-st eigenmode and its wavelet representation (left); convergence of the four parameters, x1 - damage location 'a', x2 - damage location 'b', x3 - deterioration 'a', x4 - deterioration 'b' (right)

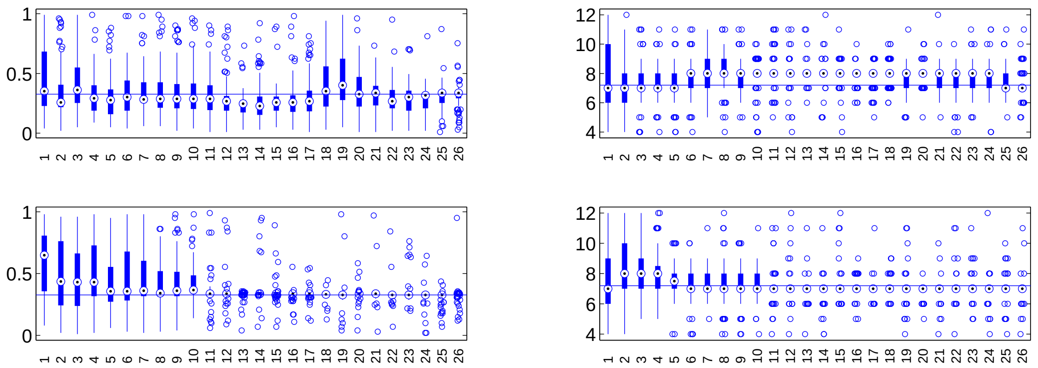

Figure 9: Histogram of population's components: x1 - damage location 'a' (left-up); x2 - damage location 'b' (left-down); x3 - deterioration 'a' (right-up); x4 - deterioration 'b' (right-down); black line points out the reference value

Figure 9 shows the the histograms of the last example. It is visible that mean values of each parameter converged to their reference values, though the convergence of second pair (parameters x2 and x4) was much slower the the convergence of first pair of parameters, namely x2 and x4.

6 CONCLUSIONS

In this communication authors present an approach to damage detection in structural model through wavelet transformation of a discrete signal measured on a structure and the inverse analysis based on soft computing. Here, as a signal the eigenmodes expressed in amplitudes of displacements computed in discrete measurement points are taken into consideration. The efficiency of the method is studied through series of numerical examples, where the real structure is simulated by a parametrized finite element model. By changing control parameters embedded in a numerical model the minimization of the discrepancy between the wavelet representation of both pseudo-experimental and numerically computed data was presented. The analyzes proved that application of genetic algorithms is very effective in determining the details of damage such as location, severity, its shape or the number of defective zones. It is possible to obtain the desired information regardless of the type of defect or the number of damaged areas. The novelty of presented approach is the identification of more than just one defect in the structure. It was evidenced that assumed model with a priori chosen two damaged zones can successfully identify two or one damage in the real structure. This is an important observation. By extending the numerical model used to detect defective zones in the structure to have more then one (possibly three or more) damaged areas it seems to be possible to correctly identify more then just one or two locations and severity of damage.

REFERENCES

[1] T. Kersting, et al. High end inspection by filmless radiography on LSAW large diameter pipes. *NDT & E International*, **43(3)**, 206–209, 2010.

[2] P. Kolakowski, J. Szelazek and K. Sekula, Structural health monitoring of a railway truss bridge using vibration-based and ultrasonic methods. *Smart Materials and Structures*, **20(3)**, 035016 (10pp), doi: 10.1088/0964-1726/20/3/035016, 2011.

[3] R. Sklodowski, et al. Identifying subsurface detachment defects by acoustic tracing. *NDT & E International*, **56**, 56–64, 2013.

[4] X. Wang, J. Tang, Structural damage detection using a magnetic impedance approach with circuitry integration. *Smart Materials and Structures*, **20(3)**, 035022 doi:10.1088/0964-1726/20/3/035022, 2008.

[5] T. Chen, et al. Feature extraction and selection for defect classification of pulsed eddy current NDT. *NDT & E International*, **41(6)**, 467–476, 2008.

[6] K. Ziopaja, Z. Pozorski and A. Garstecki, Damage detection using thermal experiments and wavelet transformation. *Inverse Problems in Science and Engineering*, **19(1)**, 127–153, 2011.

[7] H.T. Banks, A. K. Criner, Thermal based methods for damage detection andcharacterization in porous materials. *Inverse Problems*, **28(6)**, 065021 (18pp) doi:10.1088/0266-5611/28/6/065021, 2012.

[8] T. Burczynski, et al. Optimization and defect identification using distributed evolutionary algorithms. *Engineering Applications of Artificial Intelligence*, **17**, 337–344, 2004.

[9] Z. Waszczyszyn, L. Ziemiaski, Neural networks in mechanics of structures and materials - new results and prospects of applications. *Computers and Structures*, **79, 22-25**, 2261–2276, 2001.

[10] P. G. Kirmser, The effect of discontinuities on the natural frequency of beams. *Proc. of American Society of Testing and Materials* **44**, 897–904, 1944.

[11] P. Cawley, R. D. Adams, The location of defects in structure from measurements of natural frequencies. *Journal of Strain Analysis*, **14**, 49–57, 1979.

[12] K. Dems, Z. Mroz, Identification of damage in beam and plate structures using parameter dependent frequency changes. *Engineering Computations*, **18, 1/2**, 96–120, 2001.

[13] Z. Mroz, A. Garstecki, Optimal loading conditions in design and identification of structures. Part I: Discrete formulation. *Structural and Multidisciplinary Optimization*, **29(1)**, 1–18, 2005.

[14] A. Knitter-Piatkowska, Z. Pozorski and A. Garstecki, Application of discrete wavelet transformation in damage detection. Part I: Static and dynamic experiments. *Computers Assisted Mechanics and Engineering Sciences*, **13**, 21–38, 2006.

[15] A. Knitter-Piatkowska, M. Guminiak and M. Przychodzki, Damage detection in truss structure being the part of historic railway viaduct using wavelet transformation. Eds. T. Lodygowski, J. Rakowski, P. Litewka eds. *Recent Advances in Computational Mechanics*, Taylor & Francis Group, London, 157–163, 2014.

[16] I. Daubechies, *Ten lectures on wavelets*. Philadelphia: Society for Industrial and Applied Mathematics, 1992.

[17] J.C. Hong, et al. Damage detection using the Lipschitz exponent estimated by the wavelet transform: applications to vibration modes of a beam. *International Journal of Solids and Structures*, **39**, 1803–1816, 2002.

[18] M. Rucka, K. Wilde, Neuro-wavelet damage detection technique in beam, plate and shell structures with experimental validation. *Journal Of Theoretical and Applied Mechanics*, **48(3)**, 579–604 2010.

[19] T. Kariya, H. Kurata, *Generalized Least Squares*, Chichester: John Wiley and Sons), 2004.

[20] T. Garbowski, G. Maier and G. Novati, Diagnosis of concrete dams by flat-jack tests and inverse analyses based on proper orthogonal decomposition. *Journal of Mechanics of Materials and Structures*, **6, 1-4**, 181–202, 2011.

[21] T. Garbowski, G. Maier and G. Novati, On calibration of orthotropic elastic-plastic constitutive models for paper foils by biaxial tests and inverse analyses. *Structural and Multidisciplinary Optimization*, **46, 1**, 111–128, 2012.

[22] T. Gajewski, T. Garbowski, Calibration of concrete parameters based on digital image correlation and inverse analysis. *Archives of Civil and Mechanical Engineering*, **14, 1**, 170–180, 2014.

[23] T. Gajewski, T. Garbowski Mixed experimental/numerical methods applied for concrete parameters estimation, *Recent Advances in Computational Mechanics - Proceedings of XX International Conference on Computer Methods in Mechanics, CMM2013*, CRC Press, 293–302, 2014.

[24] G. Maier, V. Buljak, T. Garbowski, G. Cocchetti and G. Novati, Mechanical characterization of materials and diagnosis of structures by inverse analyses: some innovative procedures and applications *International Journal of Computational Methods*, doi:10.1142/S0219876213430020, 2014.

[25] G. Maier, G. Bolzon, V. Buljak, T. Garbowski and B. Miller, Chapter 24. Synergistic combinations of computational methods and experiments for structural diagnosis. *Advanced Structured Materials - Proceedings of the 18th International Conference on Computer Methods in Mechanics, CMM 2009*, Springer-Varlag Berlin Heidelberg, 453–476, 2010.

[26] A. Zirpoli, G. Novati, G. Maier and T. Garbowski, Chapter 35. Dilatometric tests combined with computer simulations and parameter identification for in-depth diagnostic analysis of concrete dams. *Proc. of the International Symposium on Life-Cycle Civil Engineering IALCCE '08*, CRC Press, 259–264, 2008.

[27] O. Masanao, Universally valid reformulation of the Heisenberg uncertainty principle on noise and disturbance in measurement. *Physical Review* A, **67(4)** id. 042105, 2003.

[28] G. Strang, T. Nguyen, *Wavelets and filter banks*. Wellesley: Wellesley-Cambridge Press, 1996.

[29] C.K. Chui, *An introduction to wavelets*. San Diego: Academic Press, 1992.

[30] S.G. Mallat, A theory for multiresolution signal decomposition: The wavelet representation. *IEE Trans. on Pattern Anal. and Machine Int.*, **11(7)** 674–693, 1989.

[31] A. Knitter-Piatkowska, T. Garbowski, Damage detection through wavelet transform and inverse analysis. J.P. Moitinho de Almeida, P. Díez, C. Tiago and N. Parés eds. *Proc. VI International Conference on Adaptive Modeling and Simulation ADMOS 2013*, CIMNE Barcelona, peer-review article in proceeding, 389–400, 2013.