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DIFFERENTIAL EVOLUTION APPLIED TO PLANAR LOCALIZATION OF CRACKS THROUGH ACOUSTIC EMISSION SIGNALS

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Abstract. *In the present work, an alternative method for cracks localization in steel plates using acoustic emissions signals is presented. The method relies in the use of differential evolution optimization to find the position of a source of acoustic signals generated by a crack propagation. The proposed technique main's advantage is to avoid iterative differentiation of non-linear functions and the iterative calculus of trigonometric functions. In addition, it has outperformed the traditional application of Newton-Raphson method in 39.4% when evaluating the mean error between the estimated solution and the actual signal source. Considering the reduction of complex calculus in the crack localization procedure, thereby this method allows embedded applications, which can provide a useful solution to continuous monitoring of risk structures.*

Keywords: *Non-destructive testing, Acoustic Emission, Crack Localization, Optimization, Differential Evolution*

1. Introduction

Acoustic Emission (AE) is a non-destructive and non-invasive test based on detection of waves emitted by alterations on the structure of materials, and can be related with several damage mechanisms. AE is useful in detecting the propagation of cracks, corrosion and leaks on tanks, pressure vessels and pipes, and it is widely used in continuous monitoring of risk structures, especially in gas industry.

The process of finding the AE source is done by comparing the different times and amplitudes of waves received by sensors installed on the materials surface. The source localization can occur along one dimension, two dimensions and three dimensions, depending on the device being tested. As the solution to AE localization is given by a system of multivariate nonlinear equations, involving trigonometric functions, the usual path to solve this equation system is by applying the Newton-Raphson method (NRM).

There are several researches trying to define the best distribution pattern to AE sensor, such as Liu *et al.* (2018) and Axinte *et al.* (2005), some in new AE applications or combination with other non-destructive testing (NDT) methods (Jafari *et al.*, 2018; Zhao and He, 2013; Cowart *et al.*, 2019), and some exploiting the potential of computational intelligence methods in AE signals (Ahn *et al.*, 2019; Behnia *et al.*, 2019). However, works attempting to find alternatives to AE source localization still scarce.

Metaheuristics are a set of methods employed in finding an optimal value to functions which deterministic methods are unable to provide an efficient or feasible solution (Boussaid *et al.*, 2013; Mahdavi *et al.*, 2015). Concerning to these methods, the most widespread ones are: Genetic Algorithm (Goldberg, 1989), Differential Evolution (Storn and Price, 1995, 1997) and Particle Swarm Optimization (Kennedy and Eberhart, 1995).

This work aims to provide an alternative method to determine the planar localization of a crack in a steel plate, through the application of a Differential Evolution (DE) optimization metaheuristics in a set of data obtained through AE sensors. The proposed method has the advantage of avoiding the differentiation of non-linear equations and the iterative calculus of trigonometric functions. Which reduces the AE source position estimation calculation complexity and enables the development of low cost embedded systems to continuous monitoring, that can be applied to critical structures or devices.

2. ACOUSTIC EMISSION SOURCE LOCALIZATION

AE is useful in detecting the propagation of cracks, active corrosion, and leaks in pressure vessels, storage tanks, and pipes, respectively, and it is widely used for continuous monitoring of high risk structures, especially in the oil and gas industry. The location algorithms used to determine the position of the acoustic sources are applicable in one, two or three dimensions, depending on the equipment being tested. There are several studies in trying to define the best distribution pattern for the AE sensors, such as Liu *et al.* (2018); Axinte *et al.* (2005). However, works attempting to find alternatives to AE source localization are still scarce.

2.1 PLANAR LOCALIZATION CONVENTIONAL ALGORITHM

The process of locating AE sources is based on the comparison of the different times of arrival of the acoustic waves at different sensors. In addition to this time based information, it is also necessary to know the speed of propagation of the acoustic waves in the specific material, as well as the spacial coordinates of the sensors being used in the process. Through the combination of these parameters, it is possible to estimate, with a reasonable degree of accuracy, the location of the acoustic source, and thus, where the defect is most likely to be found. The calculated position of the source is commonly given in Cartesian coordinates. For a bi-dimensional calculation, a minimum of three sensors must be used, one for triggering and time reference, and the others to obtain two distinct time differences. Using basic algebraic, geometric, and trigonometric approaches, a set of multi-variate nonlinear equations is obtained. Due to the complexity of finding an analytic solution to theses equations, numerical methods, such as the Newton-Raphson method (NRM), are applied to obtain solutions to these equations.

In order to further explain this procedure, figure 1 (a) depicts the distance traveled by the AE signal from the source to the sensors, represented by concentric circles of radii R_i, where the index i is the sensor/channel number. Alternatively, this distance can be thought of as being the time (t_i) elapsed from the instant of emission until the wave reaches the sensors, therefore, each circle represents the same wave arriving at different times at each sensor. Considering this concept, it is possible to understand the following relations about the two distance differences from the first arrival (trigger):

$$\Delta R_{1,2} = R_2 - R_1 \quad \text{and} \quad \Delta R_{1,3} = R_3 - R_1, \tag{1}$$

where $\Delta R_{1,2}$ is the additional distance travel by the wave until the second arrival, that is, when the second sensor detects the arrival of the acoustic wave, and $\Delta R_{1,2}$ the additional distance travel by the wave until the third arrival. Similarly, it is possible to obtain the following time differences:

$$\Delta t_{1,2} = t_2 - t_1 \quad \text{and} \quad \Delta t_{1,3} = t_3 - t_1. \tag{2}$$

The distances from the source to the sensors can be obtained using the velocity of propagation of the wave in the material, given by v. The value of v for different materials can be found in tables or can be calculated using two sensors mounted in the structure. By introducing an excitation in the material and dividing the distance between the sensors by the difference of arrival times of the acoustic wave at each sensor, the value of v can be experimentally calculated. Using the propagation velocity and sensor distances, the following relations are obtained:

$$R_1 = v \cdot t_1, \quad R_2 = v \cdot t_2 \quad \text{and} \quad R_3 = v \cdot t_3 \tag{3}$$

If each of the concentric circles are rearranged in such a way that the corresponding sensor lies at the center of the circle, every combination of two of the circles will cross in two different places, but there will only be one single point

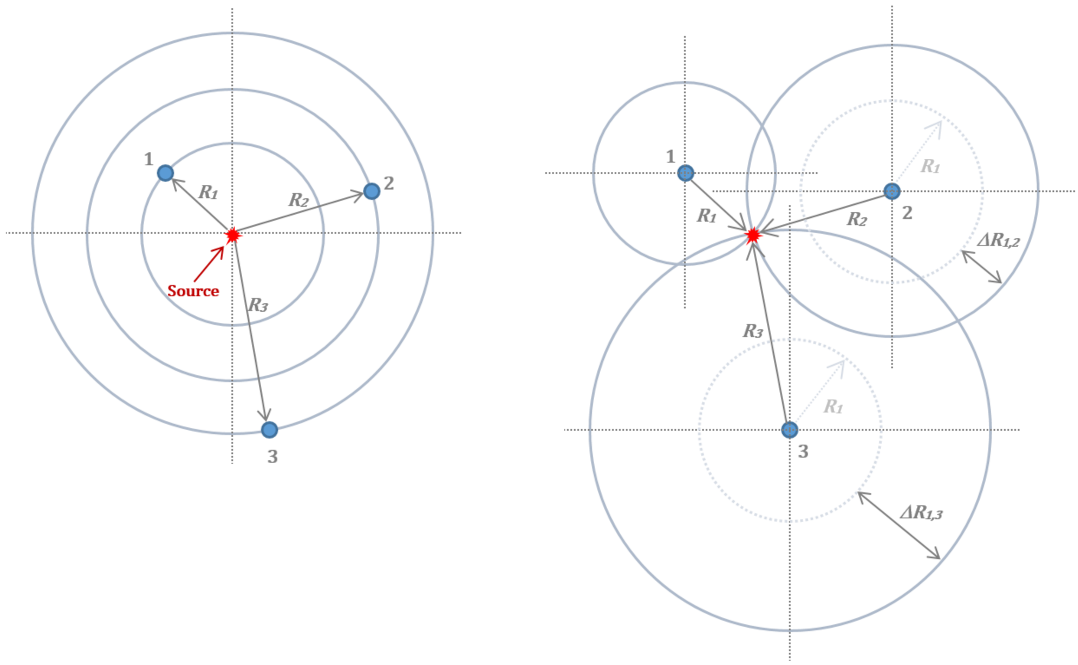

Figure 1. (a) Two dimensions AE detection sketch. (b) Two dimensional location reasoning.

where the three circles meet, thus indicating the position of the acoustic source. This concept can be visualized in figure 1 (b).

The geometrical way to express this reasoning is to select two of the circles, one corresponding to the trigger sensor and the other to the later arrival sensor, and draw a hyperbola which passes through the intersection points of these two circles, having the trigger sensor as its focus. When this process is repeated using the other combination of trigger and latter arrival sensor, the common point where the two hyperbolae intersect will give the location of the source of the AE signals. Figure 2 illustrates the hyperbola approach used. Any point that lies on the hyperbola delineated by the combination of the trigger sensor 1 and the latter arrival sensor (i.e. 2 or 3), satisfies the relation $R_i - r_i = C$, where R_i is the distance of the point i that lies on the hyperbola to the trigger sensor 1, r_i the distance of the same point to the later arrival sensor, and C is a constant, independent of the point chosen on the hyperbolae.

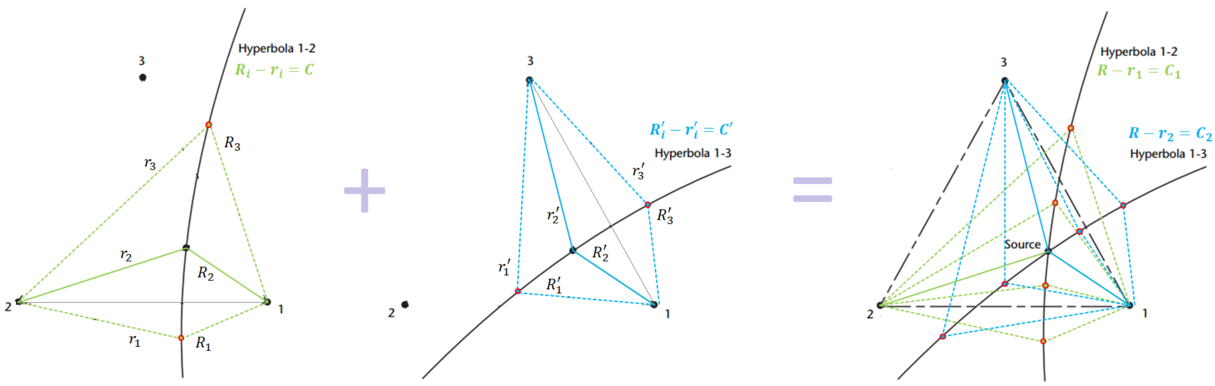

Figure 2. Hyperbola approach for two dimension localization.

Based on this geometrical / analytic approach to determine the position of the AE source and using the trigger sensor and one of the other sensors that detect the later arrival of the acoustic wave, and equation for the distance separating the source and the trigger sensor is obtained, and is given by

$$d_1 = \frac{L - v^2 \Delta t^2}{2(v\Delta t + L\cos\theta)} \tag{4}$$

where d_1 is the distance between the AE source and the trigger sensor (i.e. sensor 1), L the distance separating the trigger sensor from a second sensor, θ the angle that the line connecting the source to the trigger sensor makes with the line connecting the trigger sensor to the second sensor, v the speed of the wave as it propagates through the material, and

Δt the time difference between the arrival of the acoustic wave at the trigger sensor and later at the second sensor. The limitation with this single equation is that there are two unknown variables, namely d_1 and θ, but only one equation. The solution to this problem is to introduce a third sensor, and consequently finding another equation. Figure 3 depicts the arrangement of the three sensor array used for obtaining a second equation for d_1, given by

$$d_1 = \frac{L_{1,2} - v^2 \Delta t_{1,2}^2}{2[v\Delta t_{1,2} + L_{1,2}\cos(\theta_s - \theta_{1,2})]} \qquad d_1 = \frac{L_{1,3} - v^2 \Delta t_{1,3}^2}{2[v\Delta t_{1,3} + L_{1,3}\cos(\theta_{1,3} - \theta_s)]} \tag{5}$$

where the angle θ_s, $\theta_{1,2}$, and $\theta_{1,3}$ are the angles from the reference axis to the lines connecting the trigger sensor to the AE source, to the second sensor, and to the third sensor, respectively, as shown in figure 3. Subtracting d_1 from both sides of equations 5 and setting them equal to zero, two functions $f(d_1, \theta_s)$ dependent on the source distance and angle are obtained. By making the appropriate substitutions for the time differences, given by equation 2, and the associated substitutions for the distances between sensors and angles to the reference line,as shown below,

$$L_{1,i} = \sqrt{(x_i - x_1)^2 + (y_i - y_1)^2} \qquad \theta_{1,i} = \tan^{-1}\left(\frac{y_i - y_1}{x_i - x_1}\right) \qquad i = 1,2 \tag{6}$$

it is possible to apply the NRM. In the equations given in 6, the x_i and y_i parameters stand for the Cartesian coordinates of the i-th sensor. Once the functions $f_1(d_1, \theta_s)$ and $f_2(d_1, \theta_s)$ are defined and the appropriate substitutions made, the

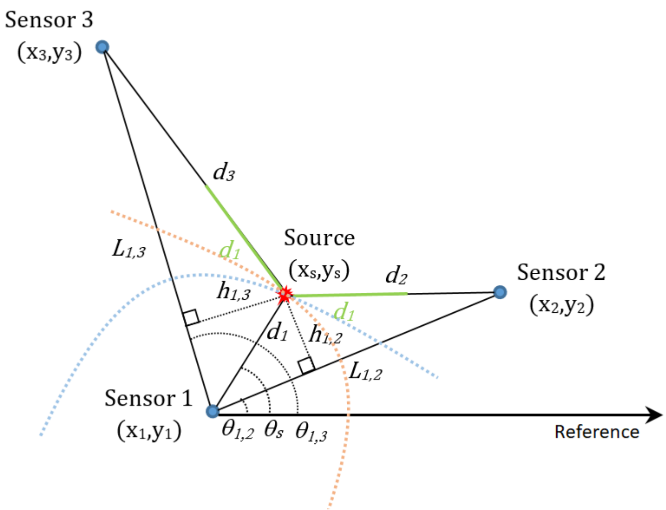

Figure 3. An array of three sensor yields three points of measurement, two time differences, and consequently, two hyperbolae that cross at the location of the AE source.

NRM is applied. The N-th iteration o the method is given by

$$\begin{pmatrix} d_{1_N} \\ \theta_N \end{pmatrix} = \begin{pmatrix} d_{1_{N-1}} \\ \theta_{N-1} \end{pmatrix} - J_f^{-1}\left(d_{1_{N-1}}, \theta_{N-1}\right) \begin{pmatrix} f_1\left(d_{1_{N-1}}, \theta_{N-1}\right) \\ f_2\left(d_{1_{N-1}}, \theta_{N-1}\right) \end{pmatrix},$$

where J is the jacobian matrix.

Finally, the conversion from polar coordinates to Cartesian coordinates of the source location is obtainable by the following procedure:

$$\begin{pmatrix} x_s \\ y_s \end{pmatrix} = d_{1_N} \begin{pmatrix} \cos\theta_N \\ \sin\theta_N \end{pmatrix}$$

2.2 Loss function for optimization

In order to avoid the use of NRM, which requires the calculus of the Jacobian matrix of non-linear equations, an objective function to be used with an optimization method is proposed. The objective is to minimize the error between the measured wave propagation time and the calculated time for a candidate solution given by DE, once the sound speed in the material is known. In addition, the signal magnitude is used to weight the errors to each sensor in the objective function, once the closer the sensor is to the signal source the higher is the measure accuracy and the magnitude. Thus, the objective function is formulated as:

$$minJ = \sum_{n=2}^{N} mag_n * (\Delta t_n - \hat{\Delta t}_n)^2 \tag{7}$$

where mag_n is the magnitude in dB in the n_{th} sensor S_n, Δt_n is the time between the magnitude threshold trespassing in the first sensor S_1 and the sensor S_n, and $\hat{\Delta t}_n$ is the estimated time given a candidate solution coordinate $\boldsymbol{P} = (x, y)$.

Thus, knowing the sound speed in the used material, in the studied plate is $v = 5263.157 m/s$, and that $\hat{\Delta t}_n$ is defined as follows:

$$\hat{\Delta t}_n = \frac{\sqrt{(x - x_1)^2 + (y - y_1)^2}}{v} \tag{8}$$

where (x_1, y_1) is the pair of coordinates of S_1 location in the steel plate. It is possible to find an accurate planar position to the AE signal source using a minimum of three piezoelectric sensors.

3. DIFFERENTIAL EVOLUTION FUNDAMENTALS

Differential Evolution is population-based method, stochastic function optimizer which was firstly introduced by Storn and Price (1995). This metaheuristic draw attention due to its performance on the *First International Contest on Evolutionary Computation* managing to finish at the third place. After that, a detailed description of the algorithm was presented in (Storn and Price, 1997). Following the success of this algorithm many variants derived from the original method (Das and Suganthan, 2011), and it was applied in a variety engineering problems (Wong and Dong, 2005; Qing, 2009).

DE algorithm consists of several steps which are basically the initialization of the population, mutation of the population, crossover of the generated offspring, and selection of the individual with better fitness. An individual, also known as chromosome, is D-dimensional vector $\vec{x} = (x_i, \ldots, x_D)$, where D is the dimension of the objective function. A population consists of NP D-dimensional chromosomes $\vec{x}_{i,G}, i = 1, 2, \ldots, NP$ and G denotes one generation. The main idea behind DE is to form trial chromosomes with mutation and crossover operators and determine which of the chromosomes will survive to the next generation with selection operator (Brest *et al.*, 2006).

3.1 Initialization

In order to create s starting point for the optimization method in initial population must be created. All NP individuals in the population are initialized randomly distributed in the search space of the decision variables of the problem, where $\vec{x}_{min} = \{x_{1,min}, x_{2,min}, \ldots, x_{D,min}\}$ and $\vec{x}_{max} = \{x_{1,max}, x_{2,max}, \ldots, x_{D,max}\}$ are the minimum and maximum values that the decision variables can assume respectively. Finally, each chromosome in the population is initialized in the following way

$$x_{j,0} = x_{j,min} + r_j(x_{j,max} - x_{j,min}) \tag{9}$$

where, $j = i, \ldots, D$ and r_j is a random number uniformly distributed in the interval [0, 1], generating a new value for each decision parameter.

3.2 Mutation

During a specific generation G, all elements in the population are applied to the mutation operation. The specific chromosome being used in the operation is called target vector $\vec{x}_{i,G}$, and for each target vector, a mutant vector $\vec{v}_{i,G+1}$ is generated in accordance with:

$$\vec{v}_{i,G+1} = \vec{x}_{r_1,G} + F * (\vec{x}_{r_2,G} - \vec{x}_{r_3,G}) \tag{10}$$

with randomly chosen indices $r_1, r_2, r_3 \in \{1, 2, \ldots, NP\}$ and $r_1 \neq r_2 \neq r_3 \neq i$. F is a parameter control of DE and is called scale factor Storn and Price (1997).

3.2.1 Crossover

The crossover operation has the purpose of generating new chromosomes using the target and mutant vector. The generated vector is called trial vector $\vec{u}_{i,G+1}$, and its creation follows the equation:

$$u_{ij,G+1} = \begin{cases} v_{ij,G+1}, & rand(j) \leq \textit{ CR or } j = j_{rand} \\ x_{ij,G+1}, & rand(j) > \textit{ CR or } j \neq j_{rand} \end{cases} \tag{11}$$

where $j = 1, 2, \dots, D$ and $rand(j) \in [0, 1]$ is the j^{th} evaluation of a uniform number generator. CR is another parameter control called recombination rate. The parameter j_{rand} is a value uniformly chosen from the interval [0, 1], which guarantees that at least one new element is introduced in the generated trial vector.

3.3 Selection

The last step in DE algorithm is to decide which chromosome survives, that means having the best fitness in the objective function, to the next generation. If the trial vector has better fitness than its generator vector, it replaces the generator in the population. For a minimization problem, this selection is evaluated as follows:

$$\vec{x}_{i,G+1} = \begin{cases} \vec{u}_{i,G+1}, & f(\vec{u}_{i,G+1}) < f(\vec{x}_{i,G}) \\ \vec{x}_{i,G}, & f(\vec{u}_{i,G+1}) \geq f(\vec{x}_{i,G}) \end{cases} \tag{12}$$

4. RESULTS AND DISCUSSION

The dataset used to generate the results and validate the proposed method is composed by the measures of a laboratory experiment designed to emulated the wave caused by a crack in a steel plate. These crack simulations are performed by carefully breaking small pieces of a graphite bar at specific points on the steel plate surface. The dataset has a total of 116 samples, in 33 distinct positions spread over the steel plate. Thus, there are three to six crack simulations measures at each position.

4.1 Detailed results

A graphical visualization of the results can be seen in Fig. 4, where the black crosses presents the actual AE signal source locations in the steel plate, the red diamond shape and the blue circle display the ED and NRM estimated positions, respectively. Through the presented image is possible to notice that the ED was more accurate when the sources were closer to the steel plate borders, and the NRM has found better solutions to sources located from 50 to 75 cm of the plate origin along x-axis. Despite the better accuracy of NRM in this specific location, ED has presented an overall better accuracy.

Fig. 5 depicts the boxplot of both methods localization errors, it can be seen that ED has a smaller interquartile, lower median, and less dispersion than NRM. Also, as seen in Tab 4.1 the metrics of ED are $39,4\%$ and 41.2% smaller to mean value and the standard deviation, respectively, when analyzing the euclidean distance between the estimated solution and the real signal source. Therefore, the presented solution not only has a smaller error, but a guarantee that ED's crack localization is going to be more accurate than the NRM's.

	Mean		Maximum		Minimum		Standart Deviation	
Abs. error	DE	NRM	DE	NRM	DE	NRM	DE	NRM
x axes	**18.01 mm**	32.36 mm	**100.67 mm**	139.00 mm	**0.51 mm**	0.70 mm	**12.67 mm**	24.73 mm
y axes	**17.86mm**	24.10mm	**48.38mm**	88.60mm	0.39 mm	**0.00 mm**	**13.47 mm**	21.91 mm
2D	**27.73 mm**	45.77 mm	**108.70 mm**	142.48 mm	**2.29 mm**	3.49 mm	**14.66 mm**	24.92 mm

5. CONCLUSION

This work has explored the potential application of a metaheuristics optimization method in the localization of damaged area in a material through acoustic emission signals. As a result, it has provided an alternative method to find the position of a crack in a steel plate through the acoustic signals emitted by the crack propagation. The analysis of a laboratory experiment pointed to a better performance to the proposed method, which uses differential evolution, against the traditional method applied in commercial software.

Once the application of ED to AE source localization was tested using an specific laboratory experiment, other tests still needed. In further work, the application of the proposed method in data collected from devices operating in real world conditions, such as pipes and pressure vessels, is suggested.

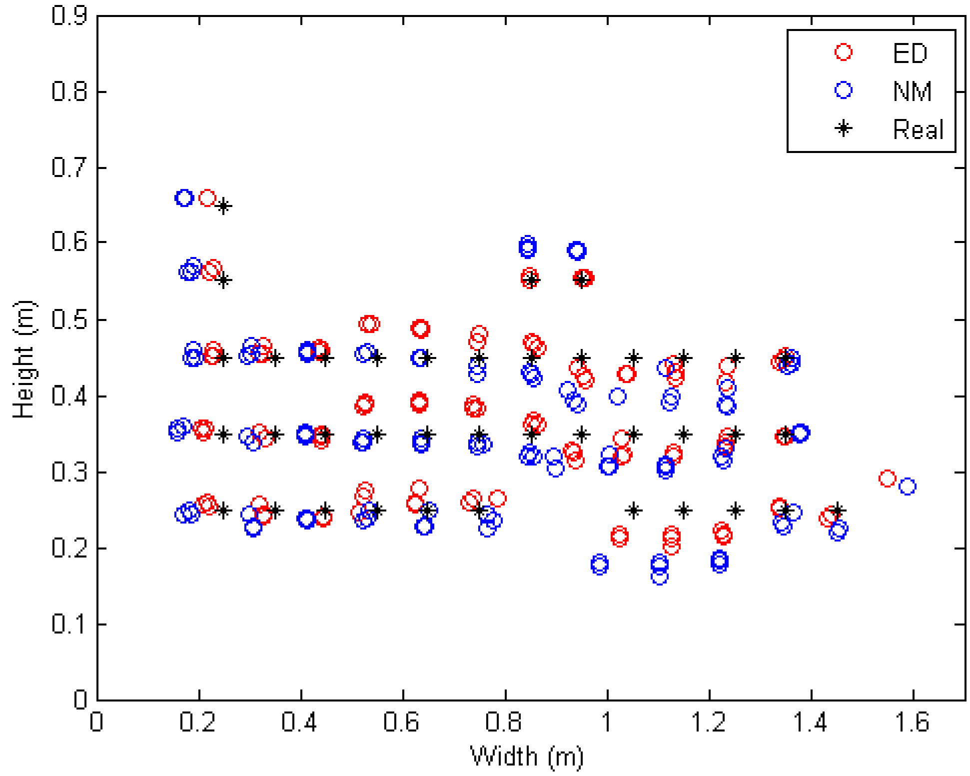

Figure 4. Localization results

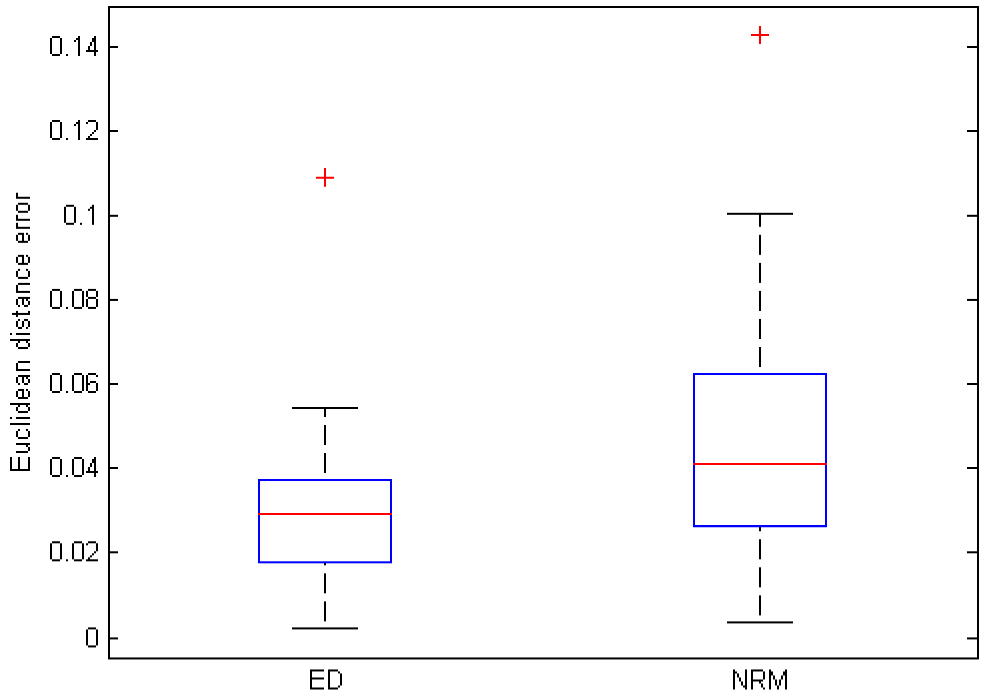

Figure 5. Boxplot of euclidean distance error to ED and NRM

Furthermore, as DE optimizes values performing simple calculations iteratively, the proposed methodology reduces the amount of complex calculus in the localization procedure, avoiding differentiation of non-linear equations and the iterative calculus of trigonometric functions as in NRM. Thereby enabling this application to run in low cost processors used in embedded applications, then allowing it to be applied in continuous monitoring of structure and devices.

6. ACKNOWLEDGEMENTS

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