DETECTING PARABOLAS IN ULTRASOUND B-SCAN IMAGES WITH GENETIC-BASED INVERSE VOTING HOUGH TRANSFORM

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ABTRACT

In this paper we propose a Genetic-Based Inverse Voting Hough Transform (GBIVHT) method for detecting parabolic shapes in B-scan images obtained by the ultrasonic Time Of Flight Diffraction inspection technique. These parabolic shapes are characteristics of the presence of crack defects in the engineering structure under inspection. In our method, the local peak detection problem in the parameters space of conventional Hough Transform is converted into a parameter optimization problem that operates directly on the ultrasound B-scan image. The optimization is done using the well-known Genetic Algorithms. Our main goals are an accurate detection of the parabolas while circumventing the computational complexity and huge storage problem tied to conventional Hough Transform.

Keywords: *Ultrasound B-scan image, Crack defect, Hough Transform, Genetic Algorithm (GA).*

1. INTRODUCTION

Ultrasonic non-destructive inspection is today the most suitable and the most employed technique for the detection, localization and sizing of surface and buried defects in engineering structures. It consists in scanning the structure under inspection using an ultrasonic transmitter/receiver pair. For each position of the transducer pair, an ultrasonic signal is fired and the resulting echo recorded. The whole set of data corresponding to an ultrasonic non-destructive inspection are next displayed in the form of mainly three types of images known as B-scan, C-scan and D-scan images on which image processing tools and algorithms can be applied in order to detect and characterize defects [1].

The ultrasonic data acquisition technique used for the detection of cracks is the ultrasonic Time Of Flight Diffraction (T.O.F.D) [2] one. It is based on the measurement of the time of flight of the diffraction echo produced by the extremities of the crack using a symmetrical and separate transmitter/receiver pair (Figure-1).

For a particular position of the transducers pair the energies arriving on the receiver can be represented by a one-dimensional signal called as an A-scan. When the transducer pair is scanned over the inspection surface according to any one of the two directions (the *x* direction for example), while keeping the other one (the *y* direction) constant, and the successive A-scan stacked together, we obtain what is called as a B-scan image (Figure-2) in which the intensity of the pixels represents the amplitude of the signal in the A-scan. Consequently, each position of the transducer pair in the y direction of the scan will produce a B-scan, and the ultrasonic data obtained during a non-destructive inspection of an engineering structure can be represented by a set of successive B-scan images.

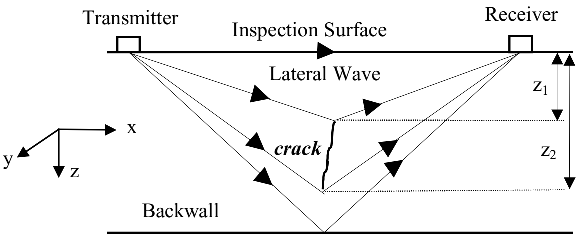


Figure 1. Ultrasonic Time Of Flight Diffraction technique

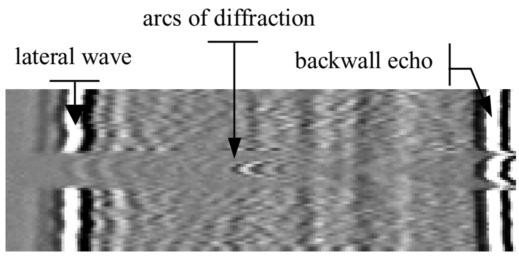


Figure 2. Example of B-scan image

When a crack defect is present in the material under inspection, it gives rise to multiple diffraction echoes in the

B-scan image (Figure-2). Modeling these diffraction echoes, due to the extremities of the crack, by arcs of parabolas, it becomes possible to detect them by the Hough Transform (HT) [1][3][4]. Moreover, the depth of the crack in the material can be determined knowing the position of the summit point of the first black to white transition parabolas, with respect to either the lateral waves or the back-wall echo.

The main disadvantages of using HT for detecting the diffraction echoes in B-scan images are its large data storage requirements and expensive computation time. Both the storage and computation time grow exponentially with the number of parameters. Moreover, the ranges of the parameters are heuristically determined. To detect a curve with a higher accuracy, the parameters space must be partitioned into smaller cells. The two factors together may lead to a large accumulator array even for a small number of parameters.

To circumvent these disadvantages, we propose a genetic-based inverse voting HT, where the local peak detection problem in the parameter space is converted to a parameter optimization problem. GAs are used to perform the optimization problem.

As a result, there is no longer need to allocate a large memory space for the partitioned parameters space. Moreover, the storage requirements and the computational time are much lower than the conventional HT method.

2. PARABOLIC SHAPE DETECTION USING INVERSE VOTING HT

In the T.O.F.D. technique, crack defects in engineering structures are characterized by multiple diffraction echoes that have a parabolic shape in the B-scan images. It has been shown by Bolland et al. [1] that these diffraction echoes, due to the extremities of the cracks, can be modeled by the following equation of a parabola:

$$t(x) = \alpha(x - X)^2 + T \tag{1}$$

where *(T, X)* are the coordinates of the summit point of the parabola and α the curvature. α is a function of the time of flight T and it is expressed as:

$$\alpha(T) = \frac{2(c^2T^2 - 4d^2)}{c^4T^3} \quad , \quad \mathrm{T} = \frac{2\sqrt{\mathrm{z}^2 + d^2}}{c} \tag{2}$$

where

z = depth of the crack (z ≥ 0)

c = speed of the ultrasonic waves in the matter

2d = distance separating the symmetrical transducers

Substituting (Eq. 2) for α in (Eq. 1) allows the model to be expressed in terms of only the two parameters, *(T, X),* instead of three. For more details see Bolland et al. [1].

$$t(x) = \frac{2\left(c^2\, T^2 - 4\, d^2\right)}{c^4\, T^3}\left(x - X\right)^2 + T$$

In conventional HT, the parameters space is represented by the parameters *(T, X)* and it is divided into $(\, m \times p\,)$ cells. The voting process is done in a two-dimensional space that satisfies the following equation for each edge point (t_i, x_i):

$$f(X, T, x_i, t_i) = t_i - \alpha(x_i - X)^2 + T = 0 \tag{3}$$

Then, the local peak values are detected in the accumulator array after voting was done for all the edge points in the image space.

Contrary to the conventional method, the Genetic-Based Inverse Hough Transform method, that we propose, will perform the voting process in the image space. Let $P_i = (T_i, X_i)$ be an arbitrary point in the parameters space, as shown in Figure 3-b, which corresponds to a parabola in the image space (Figure 3-a), satisfying the equation:

$$f(X, T, x_i, t_i) = 0 \tag{4}$$

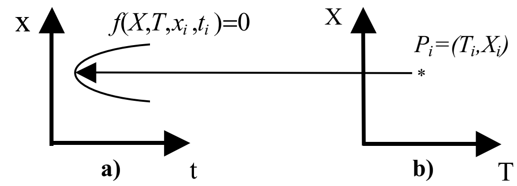


Figure 3. a- Image space, b- Parameters space

In this case, the local peak detection problem in the parameters space is converted into a parameter optimization problem. Thus, GAs can be used to optimize the parameters in order to detect the parabolas.

3. A QUICK INTRODUCTION TO GENETIC ALGORITHMS

Genetic Algorithms (GAs) [5][6] are pseudo-stochastic search methods that derive their fundamental ideas and terminology from the Darwinian *Natural Selection* theory, according to which individuals that are better fit to a given environment are more likely to survive.

Unlike conventional techniques, GAs can be successfully applied to problems characterized by a large and irregular search space. In those cases, they have been shown to compare favorably, in terms of applicability and efficiency, with other methods, such as simulated annealing. Furthermore, GAs do not require that the search space be continuous, but can act effectively in discrete and mixed discrete/continuous spaces.

While solving an optimization problem using GAs, each solution is usually coded as an alphabet string of finite length called chromosome. Each string or chromosome is considered as an individual. A collection of M individuals is called population. GAs start with a randomly generated population of size M, and at each iteration, a new population of the same size is generated from the current population by applying genetic operators, termed selection, crossover and mutation, that mimic the corresponding processes of natural selection.

In simple GA, the old population is completely replaced by the offspring population after reproduction, crossover, and mutation. In this way, it is possible that the best chromosome (solution of the problem) in the old population disappears in the current generation. A reasonable improvement is reached by preserving the best string obtained so far in a separate location outside the population so that the algorithm may report the best value found, among all the solutions inspected during the whole process. In this work, we have used the elitist model of De Jong [7] where the best string in the previous iteration is copied into the current population.

4. GENETIC IMPLEMENTATION

In this section we describe in details the proposed genetic algorithm for detecting the characteristic parabolas of crack defects in B-scan images. First, the choice of the initial population and the definition of the fitting function for the problem under consideration are discussed. Then, the genetic operators and the way they are used are described. Finally, the stopping criteria of the GA are presented.

4.1. Initial population

To solve the parabola detection problem in B-scan images using GA, one must encode the parameters of the parabolas in such a way that genetic operators can manipulate them. In our case, binary strings of length N are used to represent the chromosomes.

The phenotype of individual k is defined by:

T_k	X_k

The genotype (chromosome representation) of individual k is defined by

$\alpha_1, \alpha_2, \ldots\ldots\ldots\ldots\alpha_N$

where α_i is a binary value, $i=1, \ldots, N$.

The initial population of parameter vectors is generated randomly. There are no guidelines for choosing the appropriate value of the size M of the initial population; this is fixed throughout the training stage. There is the intuitive dilemma that is discussed in [7] and which shows that a large number of individuals in the population can speed up the convergence of the GA toward the optimal string.

4.2. Fitting function

Each individual in the population is evaluated by its fitness value. In the proposed method, the fitness value is considered as the voting value $U(T_i, X_i)$ at the point P_i which is given by the curvilinear integral along the previous curve in the edge image $B(t, x)$:

$$U(T_i, X_i) = \oint_f B(t,x)\, ds \qquad (5)$$

where

$$B(t,x) = \begin{cases} 1 & \textit{if (t,x) is an edge point} \\ 0 & \textit{otherwise} \end{cases}$$

4.3. Selection

The ‘selection’ operator identifies the fittest individuals of the current population that will serve as the parents of the next generation. The fitness value of each individual is given by a problem-dependent function. The selection mechanism can take many forms, but it always ensures that the best individuals have a higher probability to be selected in order to produce and form a new population. Here, strings are selected from a population to create a mating pool. The size of the mating pool is taken to be the same as that of the initial population (M).

The selection probability of a particular individual is directly or inversely proportional to the fitness value, depending on whether the problem is a maximization or minimization one.

4.4. Crossover

The ‘Crossover’ is the key operator for GA. This operator randomly chooses a pair of individuals, among those previously selected, and exchanges tracks of their DNA (corresponding sub-string) in order to generate offspring. For example, let $parent_1$ and $parent_2$ be two randomly selected chromosomes from the mating pool:

$Parent_1$	α_1	α_2	….	α_N
$Parent_2$	β_1	β_2	….	β_N

α_i and β_i are binary values, $i=1,\ldots N$.

If pos denotes an integer position generated from the interval [1, N-1], then, the two chromosomes produced after the mating operation will be:

$Offspring_1$	α_1	…	α_{POS}	β_{POS}	…	β_N
$Offspring_2$	β_1	…	β_{POS}	α_{POS}	…	α_N

The crossover operation is performed at a rate controlled by the probability p_c, which usually has a high value close to 1. The operation stated above, is referred to as single-point crossover [5].

4.5. Mutation

The ‘mutation’ operation has an important role in the generation process. Its main function is to restore diversity that might have been lost due to the repeated application of the selection and the crossover operations. This operation randomly introduces a new gene by flipping one or more allele value (1 to 0 or 0 to 1). Following nature’s example, the probability p_m of applying the mutation operator is very low compared to the probability p_c of applying the crossover. Thus, the value of p_m is chosen in the interval [0, 0.5].

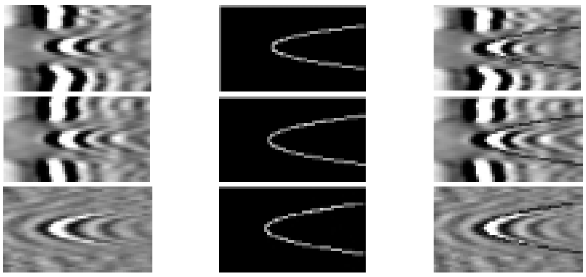
4.6. Stopping criteria

There exists no criterion in the literature, which ensures that the GAs will converge to an optimal solution. Usually, two stopping criteria are used in GAs. In the first one, the process is executed for a fixed number of iterations and the best individual obtained is taken to be the optimal solution. In the second one, the algorithm is terminated when no significant improvement in the fitness value of the best individual is noted after a fixed number of iterations. This best individual is considered as the optimal solution for the problem. In this work, we have used the first stopping criteria in our experiments.

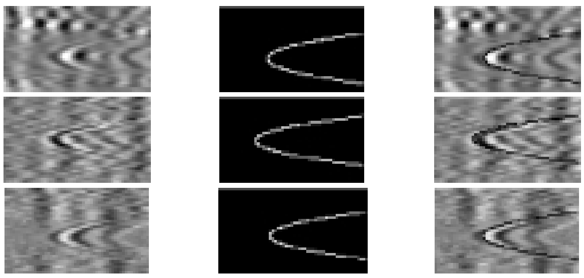
5. EXPERIMENTAL RESULTS

To evaluate the performances of the proposed method, we have applied the GBIVHT algorithm to a test set composed of 25 B-scan sub-images. The algorithm must be able to detect the outermost parabola and locate the corresponding summit point with an error of less than 1 pixel along the x-axis (vertical axis) and 2 pixels along the t-axis (horizontal axis), or returns no parabola if there is no arcs of diffraction in the B-scan sub-images.

Figure-4 shows some examples of parabolas detected in two kinds of B-scan sub-images: the first (Figure 4-a) concerns sub-images where the arcs of diffraction appear clearly; the second (Figure 4-b) concerns sub-images where the arcs of diffraction are blurred. The parabolas detected in Figure-4, correspond exactly to the ones we are looking for.



a) Parabolas detected in sharp B-scan sub-images



b) Parabolas detected in blur B-scan sub-images

Figure 4.Parabolas detected in B-Scan sub-images.

For the remaining B-scan sub-images of the test set, only two tests have failed. The failures are not only due to the performance of our method, but also to the quality of the arcs of diffraction in the B-scan images. The two sub-images for which our method has failed are shown in Figure-5. One can note here that the parabolic shape of the arcs is questionable.

Figure 5. B-scan sub-images where tests have failed

6. CONCLUSION

In this paper, we have presented a new approach, based on Genetic Algorithms and the Hough Transform, for detecting parabolic shapes in B-scan images. In the proposed method, the voting process is performed on the B-scan images rather than in the parameters space. Indeed, the local peak detection problem in the conventional HT is converted to a parameter optimization problem solved using GAs. This method allows us to avoid the computational complexity of, and huge storage required in conventional HT. The results obtained are very interesting. Among the 25 B-scan sub-images belonging to the test set, only two tests have failed.

ACKNOWLEDGEMENT

The authors would like to thank company FRAMATOME, for providing the ultrasound images and for granting the permission to publish them. This research work is supported by a post-doctoral research grant given by the "Conseil Régional de Bourgogne".

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