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STATISTICAL AND DEMPSTER-SHAFER TECHNIQUES IN TESTING STRUCTURAL INTEGRITY OF AEROSPACE STRUCTURES

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We describe the existing statistics-related methods of testing structural integrity for aerospace structures, describe their drawbacks, how they can be overcome, and compare the resulting techniques.

Keywords: structural integrity, aerospace structures, statistical methods, Dempster-Shafer method.

1. Introduction

Testing structural integrity of aerospace structures is an important practical problem (see, e.g.,[2]). Some of the faults can be detected visually, but other (sometimes potentially dangerous) faults do not show up during the visual inspection. To detect such faults, we must use some indirect (non-destructive) testing techniques.

Several such techniques are known, such as pulse echo, Eddy current, magnetic resonance, etc. Each of these techniques detects some faults but misses others, so it is desirable to combine (fuse) the results of these techniques.

In this paper, we describe different statistical and Dempster-Shafer methods for producing such a combination, describe the optimal variant of these techniques, and test all these methods on a real-life example.

2. Test Study

To compare different fault detection and fault localization techniques, we have taken an $11'' \times 11''$ plate from an actual airplane (B-52) and artificially added several faults to this plate. In total, we added 16 faults: 8 squares and 8 circles. Of these 16 faults, 8 are inside the plate: four squares of sides $1/2''$, $3/8''$, $1/4''$, and $1/8''$; and four circles of diameters $1/2''$, $3/8''$, $1/4''$, and $1/8''$; and 8 are of the exact same size but on the edge of the plate: four squares of sides $1/2''$, $3/8''$, $1/4''$, and $1/8''$; and four circles of diameters $1/2''$, $3/8''$, $1/4''$, and $1/8''$.

For this plate, we have 7 different measurements. None of these methods could detect all the faults by itself without "marking" non-fault points as faults. To be specific, we had the following results:

- Pulse Echo 0 (PE0) well detected edge faults, and not the others.
- Pulse Echo 1 (PE1) detected the boundaries of square edge faults and all circular faults.
- The Eddy Current phase (EC0) detected inside circular faults and nothing else.
- The phase of Magnetic Resonance 0 (RES0) detected all circular faults near the plate's edge.
- The phases of Magnetic Resonance 1 and 2 (RES1, RES2) also detected (but more fuzzily) all circular faults near the plate's edge.
- The phase of Magnetic Resonance 3 (RES3) detected all square faults.

In addition to detecting the faults, all these methods lead to several "false positives", i.e., no-fault points erroneously marked as faults. In particularly, practically all of these methods marked several points on the edge of the plate as faults.

3. Traditional Statistical Approach

The *general idea* of non-destructive fault detection is as follows:

- If one of these techniques leads to the unusual signal value (very different from the normal values), then a fault is probably located at this point.
- The larger the difference, the larger is the fault.

To implement this idea, for each measurement, we compute:

- the (arithmetic) *average* a of all the values, and
- the mean square (standard) deviation σ of the signal x from its average a.

In accordance with the standard statistical techniques (see, e.g.,[9]), we can then consider values x which are outside of the "two sigma" interval $[a - 2\sigma, a + 2\sigma]$ as possible faults. In other words, we compute the "normalized" values $z = (x - a)/\sigma$, and consider points for which $|z| > 2$ to be possible fault locations.

4. The Main Drawback of the Traditional Statistical Approach

The problem with this approach is that the used estimates for average and standard deviation are *biased* because they use not only regular values, but fault values as well.

The computation of the the average a and of the standard deviation σ involve also the fault points, in which the value of the signal is very different from the expected normal value. Hence, the computed σ is much larger than for the normal points. As a result, some true faults – which would have been detected by a correct (smaller) σ – go undetected when we use this larger value.

In our example, for some measurements, the values of x corresponding to most actual fault locations are within a σ or 2σ from the average. Thus, the resulting points are not therefore recognized as fault locations.

5. Iterative Approach: Our Idea

To detect all the faults, we apply the iterative estimation:

- first, we use the traditional procedure and find some faults;
- then, we re-calculate a and σ by omitting known faults;
- we then check for new faults by using these better estimates for a and σ,

and we continue these iterations until no new fault locations are uncovered (it usually takes 7-8 iterations). As a result, we arrive at the following iterative algorithm. At each step $s = 1, 2, \ldots$ of this algorithm:

- new approximations $a^{(s)}$ and $\sigma^{(s)}$ are computed for the desired values of a and σ; and
- some points on the plate are marked as possible fault locations.

In the beginning, we do not know where the faults are, so no points are marked. Each step s consists of the following two operations:

- first, we compute the average $a^{(s)}$ and the standard deviation $\sigma^{(s)}$ based on all un-marked points of the plate;
- then, we check each un-marked point, and mark all the points for which $|x - a^{(s)}| > 2\sigma^{(s)}$.

The process stops when the subsequent values of $a^{(s)}$ and $\sigma^{(s)}$ become close to each other (this usually happens on the 7th or 8th steps). The corresponding final values of $a^{(s)}$ and $\sigma^{(s)}$ are then taken as the desired values of a and σ.

As a result, for each measurement and for each point, we get a normalized value $z = (x - a)/\sigma$.

Our histogram analysis confirmed that the value which are ≤ 2 (i.e., which correspond to probably no-fault locations) are distributed according to Gaussian distribution with the mean 0 and standard deviation 1. Thus, for these points, the use of "three sigma" criterion is indeed justified.

6. How To Combine The Normalized Measurement Values

Since for each measurement i, the distribution for non-fault points is Gaussian with 0 mean and unit standard deviation, the probability that a point for which the normalized measurement result is z_i does not have a fault is proportional to $\exp\left(-z_i^2/2\right)$.

Since different measurement detect different types of faults, it is natural to assume that different measurements are statistically independent. Thus, the probability (density) that a non-fault point can have the measured values $z_1, \ldots, z_n$ is equal to the product of the probabilities corresponding to different measurements, and is, therefore, proportional to

$$\prod_{i=1}^{n} \exp\left(-\frac{z_i^2}{2}\right) = \exp\left(-\frac{\sum\limits_{i=1}^{n} z_i^2}{2}\right).$$

If this probability is too small, this means that we probably have a fault. Thus, the criterion for a fault is that the above probability is $\leq \text{const}_1$ for some constant const_1. By turning to logarithms, we can reformulate this criterion is the equivalent simpler form $\sum z_i^2 \geq \text{const}_2$, or, equivalently,

$$\frac{\sum\limits_{i=1}^{n} z_i^2}{n} \geq \text{const}_3,$$

where n is the total number of measurements. To complete our description, it is therefore sufficient to select an appropriate constant const_3.

In accordance with the traditional statistics, we should choose the threshold value const_3 in such a way that for no-fault points, the probability of exceeding const_3 is $\approx 5\%$ (this corresponds to "two sigma" criterion).

For large n, according to the central limit theorem, the average $\bar{z}$ of the values z_i^2 is distributed approximately according to the normal distribution. The mean $E[\bar{z}]$ of this distribution is equal to the mathematical expectation $E[z_i^2]$ of z_i^2, i.e., to $E[z^2] = \sigma[z] = 1$. The mean square $E[(\bar{z} - E(\bar{z}))^2] = \sigma^2[\bar{z}]$ of the difference between the average $\bar{z}$ and its mean 1 is equal to $(1/n)$-th of the mean square

$$E[(z^2 - 1)^2] = E[z^4] - 2 \cdot E[z^2] + 1 = 3\sigma^4 - 1 = 2$$

(see, e.g., [9]). Thus, the average $\bar{z}$ has the mean 1 and the standard deviation $\sqrt{2/n}$. Thus, if $\bar{z} \geq 1 + 2 \cdot \sqrt{2/n}$, then we can be sure that there is fault at this point.

So, the criterion for declaring a point a fault location is

$$\frac{\sum_{i=1}^{n} z_i^2}{n} \geq 1 + 2 \cdot \sqrt{\frac{2}{n}}.$$

For $n = 8$, we thus get $\text{const}_3 = 2.0$; thus, the criterion is equivalent to

$$\sqrt{\frac{\sum_{i=1}^{n} z_i^2}{n}} \geq \sqrt{2} \approx 1.4.$$

If we want only to consider certain faults, then it may be better to use the "three sigma" rule instead of the "two sigma" rule. In this case, we get $\text{const}_3 = 1 + 3 \cdot \sqrt{2/n} = 2.5$, so the criterion is equivalent to

$$\sqrt{\frac{\sum_{i=1}^{n} z_i^2}{n}} \geq \sqrt{2.5} \approx 1.6.$$

7. How To Improve the Combination Rule

As we have mentioned, one of the measurements may be erroneous, so we would not rather consider a point a fault location if at least two different measurements detect a fault there. On the other hand, we do not want to just dismiss one of the measurements, because if two different measurements point to the same place as a fault location, we thus have more confidence that this is indeed a fault location. Thus, we used the following idea of combining the values of $p_i(A)$ for each point A:

- If at this point,
  - only one of the values $z_i(A)$, $1 \leq i \leq n$, indicates a fault (i.e., is $z_i(A) > 2$), and
  - in a neighborhood of a certain radius d, no other measurement detects any fault (i.e., $z_j(B) \leq 2$ for all $j \neq i$ and for all points b for which $d(A, B) \leq d$),

  then we dismiss this large value of $z_i(A)$, and only combine the remaining values $z_j(A)$, $j \neq i$.
- For all other points A, we combine all the values $z_i(A)$, $1 \leq i \leq n$.

8. Detecting Faults on Edges

The resulting method detects faults inside the plate, but is still has trouble distinguishing between faults near the plate edge and the regular edge points.

The reason for this is that for all the above testing methods, unusual values occur not only at the fault locations, but also at the edges of the plate. This relation between faults and edges is very natural, since, e.g., a typical fault is a hole (or a thinning) in the plate, i.e., an extra edge.

To avoid showing edges as faults, we modified the above algorithm as follows: for points near the edges, we compared the measured characteristic x not with the average value a and standard deviation σ over the entire sample, but only with the average a_e and standard deviation σ_e taken over the edge points. Then, we compute the normalized value as $z = (x - a_e)/\sigma_e$. As a result, we got a much better description of the faults near the edges.

Instead of dividing the plate into two zones: points which are close to the edge, and points which are inside the plate, we used an even finer subdivision into four zones:

- points which are very close to the edge (distance from the edge between 0 and $1/4''$);
- points which are somewhat close to the edge (distance from the edge between $0''$ and $1/2''$);
- points which are a little far from the edge (distance from the edge between $0''$ and $3/4''$);
- points which are inside the plate (distance from the edge is larger than $3/4''$).

For each of these four zones, we computed separate values of a and σ and used these values to normalized the measurement results in the corresponding zone. In this manner, we got an even better description of the faults near the edges. Overall, we have 6,396 false positives and 89 false negatives. The presence of false negatives is not as bad as it may sound: each of 8 faults is actually detected, and the false negatives indicate that we have missed a few pixels on each fault.

9. Dempster-Shafer Approach to Non-Destructive Testing

In this paper, we have described a new idea on how to improve the traditional statistical approach to non-destructive testing. Researchers have also used another idea: using Dempster-Shafer formalism instead of the traditional statistical techniques.

In this approach, for each i-th measurement, we first transform the normalized measurement results $z_i(A)$ in different points A into probabilities $p_i(A)$ by using the follow-up "normalization" into the interval $[0, 1]$ of possible values of probability:

- $p_i(A) = 0$ if $z_i(A) < 0$, and

- $p_i(A) := z_i(A)/Z_i$ if $z_i(A) \geq 0$, where

$$Z_i = \max_A z_i(A).$$

This value $p_i(A)$ is interpreted as the probability that, according to i-th measurement, there is a fault at the point A. We can then, assuming that these measurements are independent, combine these probabilities in a different way:

- We can compute the *plausibility* $Pl(A)$ that there is a fault at the point A as the probability that at least one of the measurements detected a fault. This probability can be computed as follows:
  - the probability that, according to i-th measurement, there is no fault at the point A, is equal to $1 - p_i(A)$;
  - since the measurements are assumed to be statistically independent, the probability that there is no fault according to all the measurements is equal to the product $\prod_i (1 - p_i(A))$;
  - finally, the probability that there is a fault according to at least one measurement is equal to $Pl(A) = 1 - \prod_i (1 - p_i(A))$.
- We can also compute the *belief* $Bel(A)$ that there is a fault at a point A as the probability that all the measurements detected the fault. Since the measurements are independent, this probability is equal to the product $Bel(A) = \prod_i p_i(A)$.

We can then outline the fault location as points in which, e.g., one of the these probabilities exceeds a certain threshold.

In spite of the seemingly *ad hoc* nature of this method, it leads to a pretty reasonable fault localization.

10. Why Do Dempster-Shafer Methods Work: A Problem

The "probabilities" used in this approach differ from the actual frequencies; thus, it is not clear why this method, which relies on these crude approximations for probabilities, leads to such good fault localization results.

11. Why Do Dempster-Shafer Methods Work: An Explanation

We have an explanation for this success, and this explanation is as follows. Let us first present this explanation on the example of the belief function $Bel = \prod p_i$. If we use belief, then the criterion for a point to be a fault is to have $\prod_i p_i \geq \text{const}_1$ for some threshold constant const_1. Substituting the expression for probabilities in terms of measurement values ($p_i = z_i/Z_i$) into this formula, we get an equivalent criterion $\prod_i z_i \geq \text{const}_2$ for some new constant const_2. By turning to logarithms, we conclude that this criterion is equivalent to $\sum_i \ln(z_i) \geq \text{const}_3$.

We know that in non-fault points, the values z_i are distributed according to normal distribution with 0 average and unit standard deviation, and we know that these measurements are independent. Thus, for a large number of measurements, we can say that the sum $\sum_i \ln(z_i)$ is normally distributed, with a certain average a_s and standard deviation σ_s. Hence, we can conclude that if the actual value of the sum is larger than $a_s + 2 \cdot \sigma_s$, then the corresponding point is most probably a fault. This explains why the criterion $\sum_i \ln(z_i) \geq \text{const}_3$ makes sense.

Similarly, for plausibility, the criterion

$$1 - \prod_i (1 - p_i) \geq \text{const}_1$$

is equivalent to

$$\prod_i (1 - p_i) \leq \text{const}_2$$

hence to

$$\sum_i \left(-\log\left(1 - \frac{z_i}{Z_i}\right)\right) \geq \text{const}_3.$$

This sum-using criterion can be statistically justified in the same way as we have justified the similar sum-criterion for the belief function.

12. The New Statistical Method is Better than the Existing Dempster-Shafer Methods

In both approaches, for every point, we produce a numerical "degree" to which this point is a possible fault. In statistical approach, we have a reasonable threshold for separating faults from non-faults. In Dempster-Shafer approach, there is no such threshold, the choice of the threshold is up to us. If we choose a low threshold, then we will most probably capture all the faults, but at the same time, we will have a lot of normal points declared faults. In other words, if we choose a low threshold, we get very few false negatives, but a lot of false positives. Similarly, if we choose a high threshold, then we get few false positives, but a lot of false negatives.

So to compare the quality of the two methods, it is reasonable to choose the threshold in such a way that one of the two characteristics false positives and false negatives coincide, and compare the other characteristic. For fault detection, the most important problem is not to miss any faults. From this viewpoint, false negatives are much more important than false positives. So, to compare the quality of the two methods, we select the threshold for which the number of false negatives for the Dempster-Shafer method equals the number of false negatives for the statistical approach.

There is an additional problem with this comparison, because in both methods, the reconstructed fault locations are slightly shifted with respect to the actual ones. If we ignore this shift, we get a lot of false positives and false negatives that are in reality, not as bad as ignoring the fault. So, to make a fair comparison between the two methods, we shift both pictures to eliminate the reconstruction shifts.

We select the shift for which the total number of false negatives and false positives is the smallest. For statistical method the best shift is $s = 3$. For this shift, we have 11 false negatives.

To find the appropriate shift for Dempster-Shafer approach, we did the following. For each shift, we found the threshold which leads to exactly 11 false negatives, and then selected the shift for which the corresponding number of false positives is the smallest. This turns out to be $s = 2$, and the corresponding threshold is $t = 0.221$. Even for this best shift, Dempster-Shafer method leads to 10,281 false positives, which is much larger than the number of false positives for the statistical method (5,986).

13. Conclusions

In this paper, we:

- Developed a new method which improves the current statistics-based outlier-detecting methodology of locating potential faults by using iterative outlier detection.
- Developed a new method for combining fault probabilities coming from different measurements, method which better takes into consideration that some of the measurements may be not very reliable.
- Developed a new method for separating measurement abnormalities caused by actual faults from abnormalities caused by the closeness to the edge, thus improving the quality of fault detection.
- Combined the above new methods into a new fault-detection methodology and successfully tested it on the example of simulated B-52 faults.

For Dempster-Shafer techniques, we:

- Explained, from the statistical viewpoint, why alternative Dempster-Shafer techniques work so successfully in fault detection.

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