

## ‘Statistical methods for automatic crack detection based on vibrothermography sequence-of-images data’ by M. Li, S. D. Holland and W. Q. Meeker: Discussion 1

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### SUMMARY

In the following notes I comment the paper of Li *et al.*, mainly from the point of view of its original contribution to the methods of analysis of special image data. In particular, I concentrate on several questions connected with the proposed procedure and its results. Copyright © 2010 John Wiley & Sons, Ltd.

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### 1. SUMMARY OF THE PAPER

Since the vibrothermography is a relatively new method, analysis of its results (images given by the heat intensity) leads to development of new and improved techniques. Li *et al.* contribute both to the method of image processing and to its analysis. First, the authors propose a filter matched to expected 3D signal caused by a material crack. They show a significant increase of the signal-to-noise ratio (SNR) in filtered image. Second, a criterion of crack detection is proposed and its performance is evaluated on a set of material samples, though of the same kind and under the same test configuration. Further, the results are compared with a method based on a physical model of temperature increase (the method derived recently by the same authors, [1]). It is shown that the method based on the matched filter has better detection power.

In the follow-up, I shall concentrate on two particular problems. They both are mentioned briefly in the concluding part of the discussed paper. Namely, they concern to

- Dependence of the recognition power on a proper selection of matched filter.
- Possible use of other characteristics of textural image.

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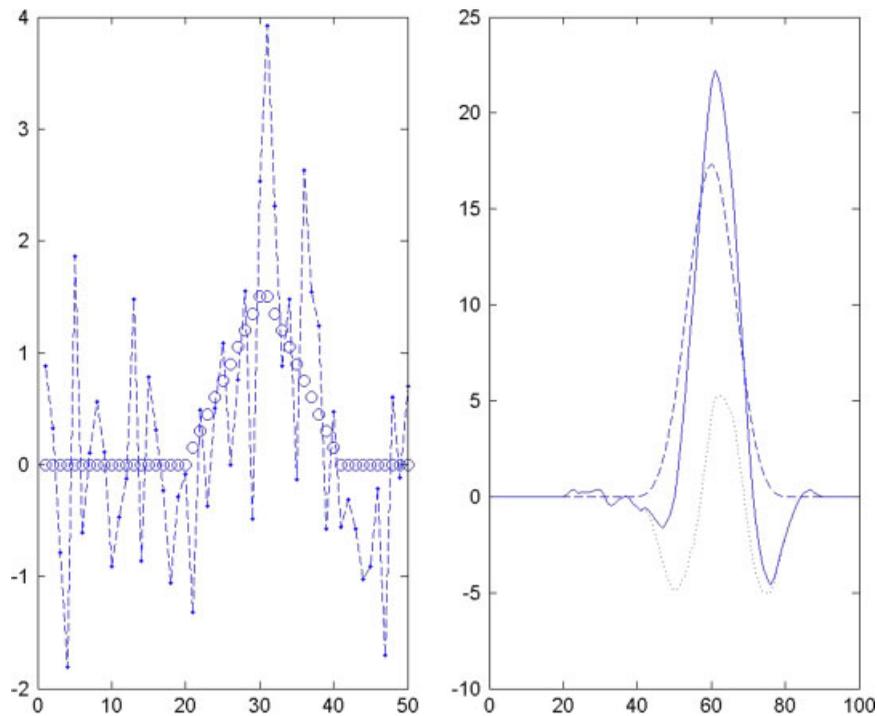


Figure 1. Left: signal (circles) and signal with noise (dots). Right: filtered signal (dashed), noise (dotted), and signal with noise (full).

## 2. 'ROBUSTNESS' OF MATCHED FILTER METHOD

The method of signal filtration based on the idea of matched filter assumes the knowledge of signal character. Consequences of selection of an inaccurate mask have been studied by some authors, too, c.f. [2]. The paper by Li *et al.*, in Figure 2, presents an example of matched filter performance. I shall repeat it here, with another example showing that the lack of knowledge of a true signal character does not need to be crucial.

Thus, Figure 1 left shows a signal (circles) and the same signal with a noise (points connected by dashed lines). The noise is a standard Gaussian white noise. The signal was then used as a mask of matched filter. The right plot shows filtered pure signal (dashed), pure noise (dotted) and filtered signal with noise (full curve). Figure 2 shows the same in the case that the signal is just a vertical line (shown by circles). We again used the triangular signal from Figure 1 as a mask. In the right plot of Figure 2 it is seen that now the SNR is smaller than in an ideal case, nevertheless it is still remarkable.

One can expect that in a multidimensional case (considered in the paper of Li *et al.*) the consequences will be similar, i.e. that even the use of non-optimal mask will preserve certain recognition power. Nevertheless, it could have a sense to explore such cases, either on real data or by a simulation study.

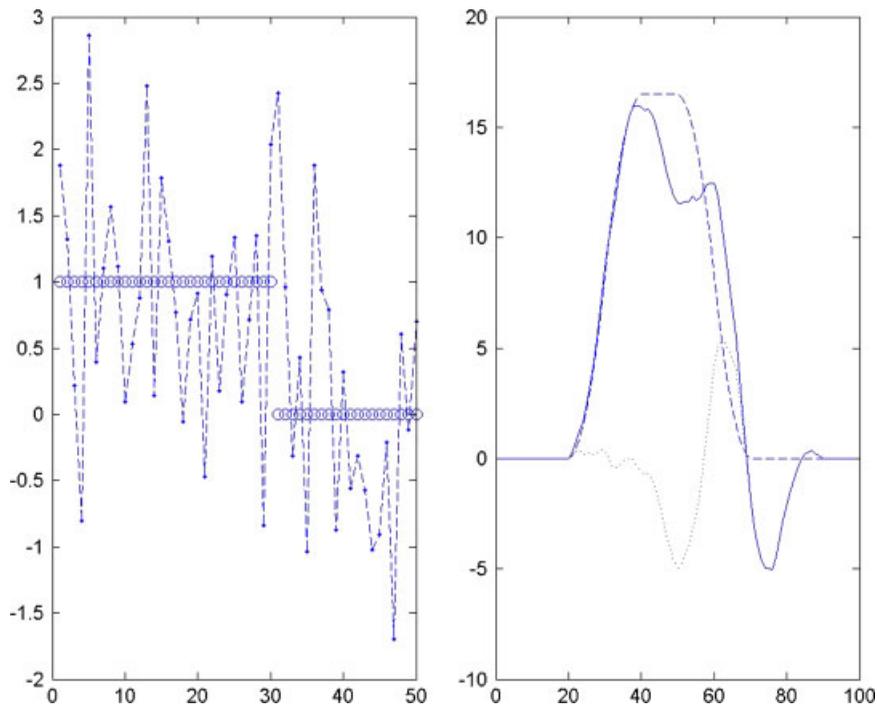


Figure 2. Left: signal (circles) and signal with noise (dots). Right: filtered signal (dashed), noise (dotted), and signal with noise (full).

### 3. ON TEXTURAL CHARACTERISTICS

In Li *et al.*, it is shown how the use of matched filter increases the SNR. Then, the detection is based on the comparison of values of intensity in images after filtration. There arises a question whether other (statistical) textural characteristics can be used for the same purpose. The problem is similar (but not the same) to the problem of detection of defects in textile materials. For instance, in [3] the authors considered a set of statistical characteristics of the first and second order and selected several ‘most powerful’ among them on the basis of classification techniques. They used a classification tree for learning whose characteristics performed best for a given type of material and defect.

I present here just a small example, using the same images as Li *et al.* used in their Figure 5, namely the upper right image with a crack and bottom right image without crack. I copied them with resolution about  $330 \times 330$  pixels and with the same color scale from 0 to 64. The images were inspected by a square window of size  $40 \times 40$  pixels. The window was moved from the left to the right side and then from the upper part down, in such a way that in each row and column I fixed 10 windows, with a regular shift. Hence, 100 (mutually overlapping) windows were obtained. Figures 3 and 4 show values of selected statistical characteristics (namely, from above down: the means, standard deviations, maxima in window, kurtoses, correlations with lag

5 both horizontally and vertically, and contrasts) computed in each window. Contrast is here defined simply as the correlation multiplied by standard deviation). Sequences of characteristics are displayed in the form of 'control charts', i.e. with the central line and  $\pm 3$  sigma control lines computed from the characteristics of sample without defect (Figure 3). In Figure 4, characteristics are computed from the image with defect, control lines are the same as in Figure 3. The region with maximal temperature was covered repeatedly by several windows. We can see that except the maximal values in the third chart (as expected), also the means (the first chart), std-s (second chart) and the contrast (sixth chart) can have certain power to detect regions with changes. Further, it is seen that the charts of characteristics have still certain periodic (and noisy) component, so that its removal could improve the recognition. Further improvement of recognition could be achieved by optimizing the window and by the use of different lags for correlation (lag equal to one means the correlation of neighbors).

From the charts (and from the images of Figure 5 in Lin *et al.*) it is also seen that the intensity is not stable even in regions without defect, and it changes (from left to right in the upper image, from

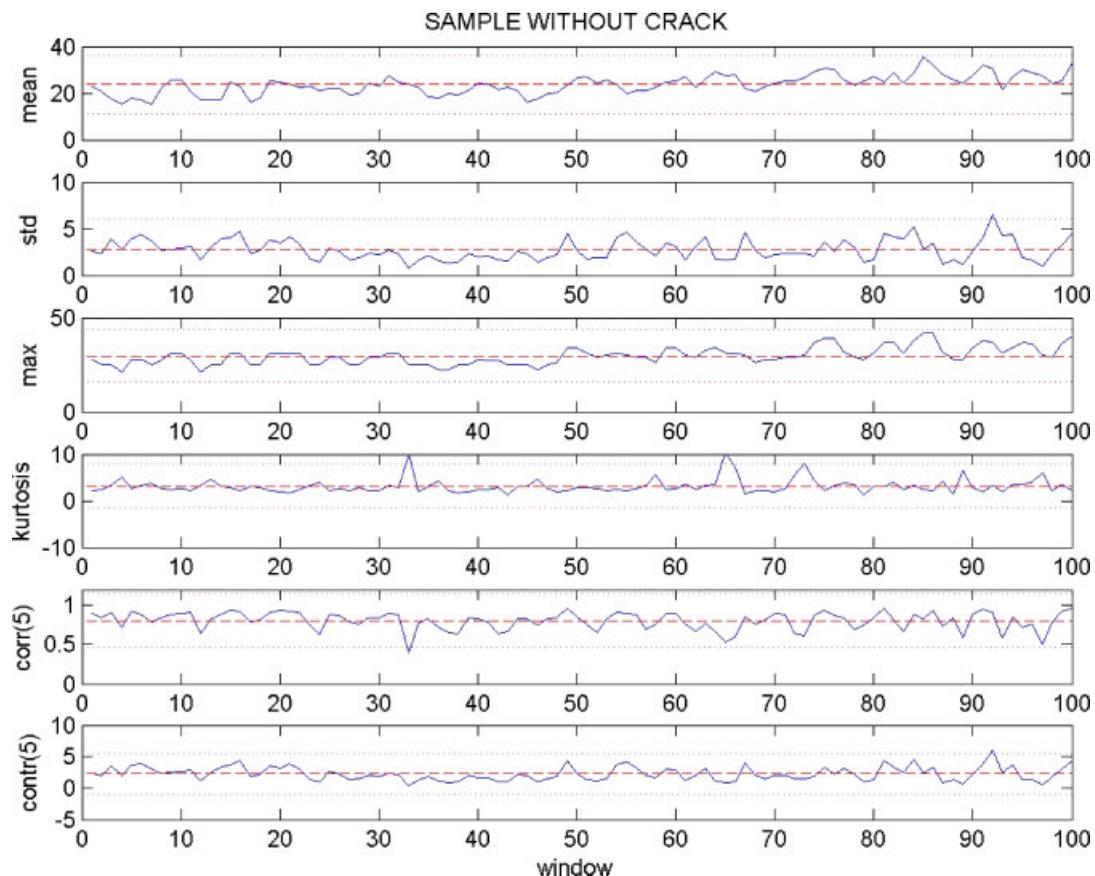


Figure 3. Values of selected textural characteristics in 100 windows computed from the image of region without defect (in Li *et al.* Figure 5 bottom right).

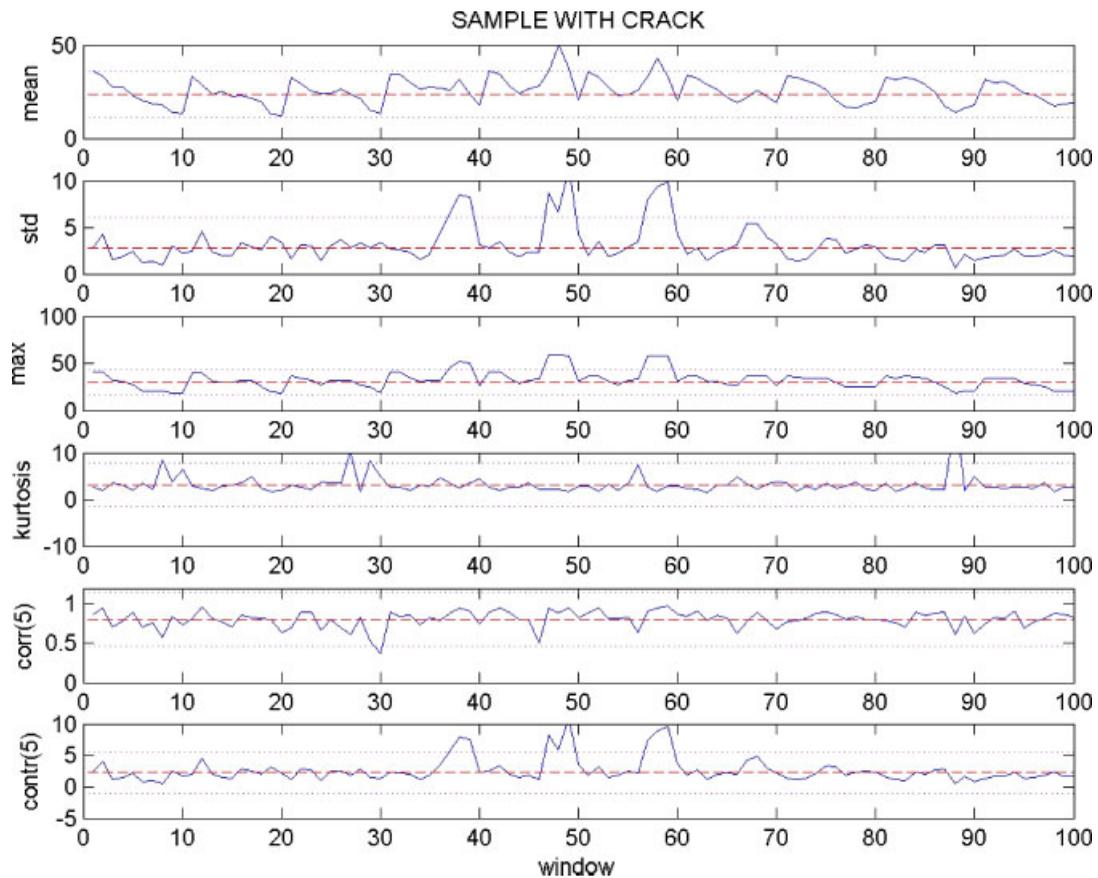


Figure 4. Values of textural characteristics in 100 windows computed from the image of region with a defect (In Li *et al.* Figure 5 above right).

below to the upper part in the bottom image). There arises a question whether it is a significant phenomenon and what can be a cause of it.

It could be also reasonable to compare the results with some other methods of vibrothermography tests analysis (if there are any, except the already mentioned method based on the 'temperature increase' model, derived in [1]).

#### 4. CONCLUSION

The paper of Li *et al.* is well-organized and logically structured. It contains a clear and detailed description of a new methodology and its performance, it also presents basic information on the test organization and technical background. Hence, the paper provides an original contribution to several aspects of the methodology and evaluation of material tests.

## REFERENCES

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