ADVANCED IMAGE PROCESSING METHODS FOR ULTRASONIC NDE RESEARCH

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Abstract: The significant progress in ultrasonic NDE systems has now made it possible to perform many complex inspection tasks. However improved sensors alone cannot meet the increasing demands in NDE. Signal processing has provided powerful techniques to extract from the NDE signals (waveforms) the desired information on material characterization, sizing, and defect detection, etc. The imagery NDE data available can add additional and significant dimension in NDE information and thus for exploiting in applications. To extract such information the use of advanced image processing techniques is much needed. The images are often noisy and blurred by the speckle noise. What is offered by the commercial image processing toolboxes such as in Matlab simply are not adequate. In this paper, advanced image processing techniques such as H-infinity method, high-order statistics method, and independent component analysis method are examined for their superior capability for image restoration, edge enhancement, and speckle reduction. Along with the high speed image acquisition capability offered in some ultrasonic NDE systems, advanced image processing techniques are much needed to extract information from an image sequence, which presumably can provide more NDE information than a single image.

Introduction:

In recent years, there has been much increased use of signal and image processing techniques in ultrasonic NDE. One the one hand, there are many NDE problems which can have much better solution with the use of signal and processing techniques. On the other hand, there are major progress in signal and image processing that can be very useful for NDE problems. In this paper we are concerned only with the use of advanced image processing techniques in ultrasonic NDE. This means that we are mainly dealing with the ultrasonic C-scan images. Both A-scan and B-scan data can use signal processing techniques for signal enhancement. The C-scan data often can provide additional information not available from A and B scans. Major image processing methods (see e.g. [1]) include image restoration and enhancement, morphological methods, 2-D wavelet transforms, image segmentation, motion estimation, object recognition and image compression. These methods can be useful to derive certain desired information from the imagery data, which otherwise may not be available. 3-D image processing can provide even more information if an image sequence is available. Essentially there is no limit on what image processing can help to achieve for ultrasonic NDE problems. One major problem with the imagery data is the additional noise and speckle noise. This paper is concerned mainly with advanced image restoration and enhancement methods, which attempt to remove the noises while preserving the edge information. The edges on an image often correspond to defects or discontinuities. Five methods, all developed by us, are considered, namely the H-infinity method [2,3], the higher order statistics method [4], the subspace method [5], the method using neural networks [6] and method using independent component analysis [7,8]. These are considered blind deconvolution as the knowledge of measurement input and the system (test specimen) impulse response is not required. For NDE problems, we believe the blind deconvolution is a much more important problem as prior knowledge is usually not available or highly unreliable. A good survey of non-blind deconvolution is in Ref. 6. Comparison with the traditional Wiener filter will be made.

Image Degradation Model:

The received image can be considered as a degraded image. In image restoration, a general degraded image formation model can be represented by the block diagram shown in Figure 1

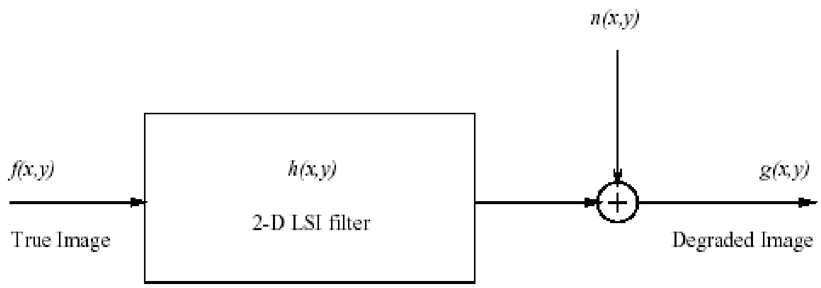

Figure 1 Linear degradation model

where *g* is the degraded image obtained by passing the original image *f* through a low pass filter (blur function) *h* and adding noise *n* to it. In discrete form, we can express this model by the following equation:

$$g(x,y) = f(x,y) \otimes h(x,y) + n(x,y) \qquad (1)$$

where *(x, y)* represents the discrete pixel coordinates, *h(x,y)* is the impulse response of the imaging system (also referred to as the PSF or blur function), *g(x, y)* is the degraded image , *f(x, y)* is the original image , *n(x,y)* is the additive noise, and $\otimes$ represents the two-dimensional discrete linear convolution operator. In NDE, *h(x,y)* may correspond to the impulse response of discontinuity inside the test specimen. The additive noise term *n(x,y)* will further distort the image and is not always negligible. To simplify the computation, Equation (1) can be expressed in frequency domain as:

$$G(u,v) = F(u,v)H(u,v) + N(u,v) \qquad (2)$$

where the capital letters represent the Fourier transforms of their lower-case counterparts. For given *H(u,v),* the Wiener filter takes the form, $H^*(u,v)/\ [H^*(u,v)H(u,v) + K]$, where K is a constant depending on the second order statistics of *f(x, y)* and *n(x,y)*.

Deconvolution Methods and Results:

The main task for image deconvolution is to separate two convolved signals *f* and *h* with or without any prior information of both signals. The basic approach involves using the partial information available as a reference to deconvolve the degraded image. In image processing, the partial information can be in the form of physical properties of the true image such as finite support and nonnegativity. Then such partial information is incorporated in an optimal criterion, which is minimized or maximized to find estimates of the *f* and *h*. If information on *f* and *h* are not available then we have a blind deconvolution problem. Generally speaking, the solution may not be unique and exact deconvolution is impossible as a result of the presence of noise and inherent ill-conditioning nature of the problem. Thus, only an approximate deconvolution can be performed. After the deconvolution process, the resulting image should have much less noise and well preserved edges. We now present the five advanced methods for deconvolution without mathematical details.

1) 2D H-infinity based deconvolution

Step 1 Formulate the Local State Space (LSS) model
Step 2 2D H-infinity identification
Step 3 2D H-infinity filtering, equivalent to solving Riccati equation.
Step 4 At each iteration, edges are calculated using the Canny operator and entropy is calculated. The iterative process stops when the decrease in entropy becomes negative.

2) 2D HOS based deconvolution

Step 1 Image is modeled as 2D autoregressive process. Both 3rd order and 4th order cumulants algorithms are considered.
Step 2 Compute 2D cumulants
Step 3 Obtain the least square estimator of the blur model
Step 4 Perform inverse filtering
Step 5 Follow "Step 4" in H-infinity algorithm given above.

3) Subspace identification method

Step 1 Image is decomposed into the input output matrices that forms MISO system
Step 2 Perform the projection of the row space of future outputs and future inputs
Step 3 Compute the oblique projection, which is then decomposed using singular value decomposition. The procedure is repeated until a measure of convergence is satisfied.
Step 4 Follow "Step 4" in H-infinity algorithm given above.

4) The method of using neural networks [6]

Step 1 Blur identification based on HOS
Step 2 Hopfield neural network is used for image reconstruction.
Step 3 Follow "Step 4" in H-infinity algorithm given above

5) The method using independent component analysis

Step 1 Represent image as a sum of independent components.
Step 2 Classify the coefficient associated with each independent component as texture or edge.
Step 3 Apply nonlinear operation to the coefficients associated with edges
Step 4 Reconstructing the image by setting coefficients with texture as zero.

All five methods require post-processing to extract objects from highly blurred C-scan images. The results of the H-infinity method are shown in Fig. 2. The results for the HOS method and for the subspace method are very similar. The goal for image restoration is to find a good image estimate *f* from the degraded version *g*. This can be considered as a constrained optimization problem and such optimization can be solved by the Hopfield neural network. The result for the fourth method using neural network is shown in Fig. 3. Both pre-processing and post-processing that involve contrast adjustment are required. Results for the fifth method using independent component are reported elsewhere in this proceedings [8].

Concluding Remarks:

All five methods are quite effective as they are theoretically sound. It is difficult to draw definitive conclusion of which one is the best, as this would require much more computer results on different ultrasound C-scan images. All methods perform better than the Wiener filtering as expected with the performance measure of entropy, or mean square error, or ratio of standard deviation to mean. All methods require considerable amount of computation, making it difficult for real-time operation. For three-dimensional image sequence, the computation amount is even more demanding. Further work is needed to improve the implementation of algorithms and to test on additional ultrasonic C-scan images. The potential benefit for ultrasonic NDE research, as well as for medical imaging problems is enormous however.

References:

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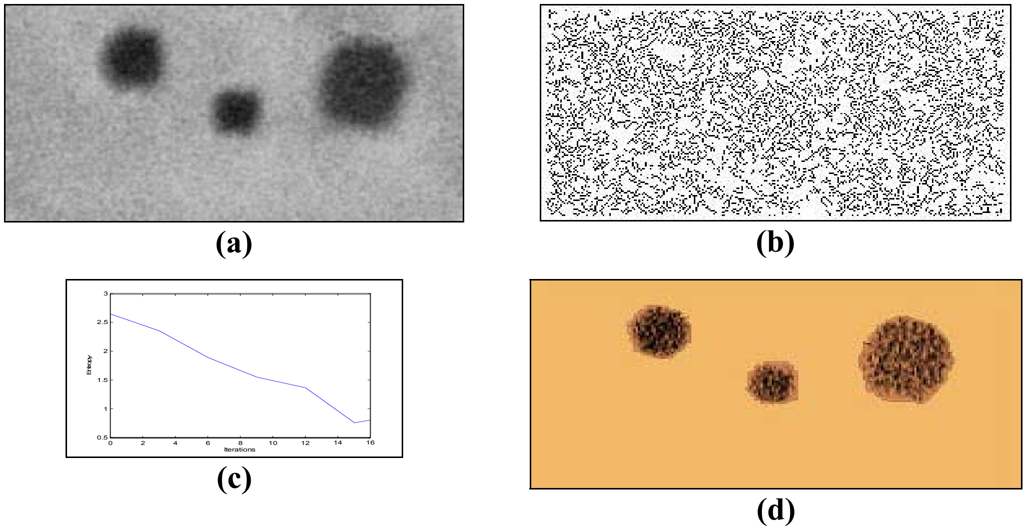

Figure 2 (a) Sample image, (b) corresponding edges, (c) entropy curve, (d) final image after H-infinity deconvolution.

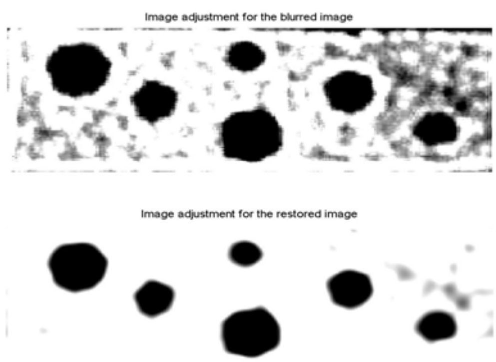

Figure 3 Images after post-processing: original (upper) and neural network (method 4) restoration result (lower), after contrast adjustment.