

FREQUENCY DIVERSITY ULTRASONIC FLAW DETECTION USING ORDER STATISTIC FILTERS

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ABSTRACT

Split-spectrum processing of broadband ultrasonic echoes for NDE has resulted in significant improvements in clutter suppression and flaw detection over narrowband echo techniques and broadband echo reception without split-spectrum processing. An important aspect of this research involves developing signal processing algorithms for the received echo once its spectrum has been partitioned. This paper presents a class of nonlinear signal processing techniques, referred to as Order Statistic (OS) filters, an alternative approach to the popular averaging techniques. Experimental and simulation results for the OS filter are presented for flaws embedded in steel specimens. The application of the OS filters and the averaging algorithms for flaw detection are compared. It is shown that the OS filter can improve the flaw to clutter echo ratio better than averaging algorithms for a broader class of clutter and flaw echo statistics.

I. INTRODUCTION

The ultrasonic pulse-echo imaging of materials for the purpose of flaw detection is hampered by the presence of interfering and attenuating random scatterers (i.e. grains) associated with the targets environment. The energy loss caused by grain scattering and absorption is frequency dependent. In the Rayleigh scattering region, it has been shown [1] that grain scattering results in an upward shift in the expected frequency of the broadband ultrasonic signal. However, this is not the case for flaw echoes since flaws are generally larger in size than the grain and behave like geometrical reflectors. In fact flaw echoes often display a downward shift in their expected frequency caused by the overall effect of attenuation. This downward frequency shift of the flaw is a productive attribute since the grain noise and flaw echoes are coherently received and bandpass filtering can improve the signal-to-clutter ratio [2,3]. It must be noted that the information-bearing frequency bands are dependent on the specific characteristics of materials which must be known a priori. Therefore, other alternative flaw detection techniques which show less sensitivity to the environment are desirable.

Effective techniques for detecting targets in coherent noise are frequency agility and frequency diversity which have been investigated in radar detection for several

decades [4,5] and more recently in ultrasound [6,7]. In an ultrasonic imaging system, a practical adaptation of these techniques has been examined [7] and referred to as split spectrum processing (SSP). This entails transmitting a broadband signal into the media which, when received, is partitioned in several narrowband channels as shown in Figure 1. The output of these channels is then sent to a processor for detection.

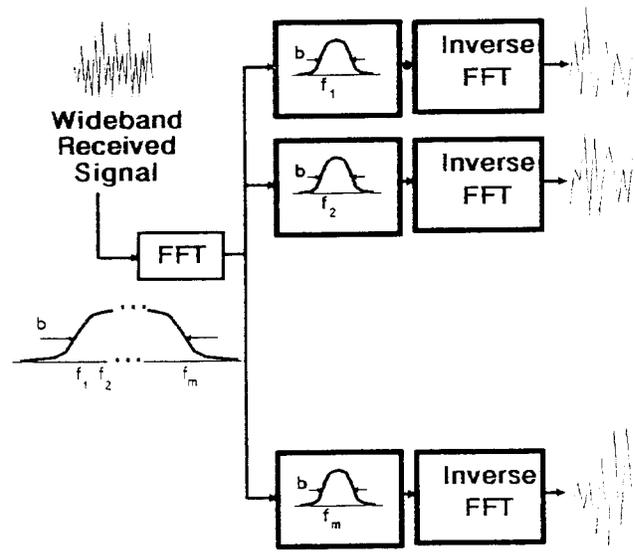


Figure 1. Block diagram of split spectrum processing.

An important step in detection is to extract target information via improving the signal-to-clutter ratio. Several types of processors such as minimization and averaging [8] have been examined in the past. The more effective procedure was shown to be minimization for the case in which the flaw was stationary and present in all of the channels, although, this is not always the case in practice. The flaw may not be present in some frequency bands due to the sensitivity of flaw to frequency shifts and/or significant attenuation caused by the grain signal. Under these circumstances, a more robust operator is needed to be insensitive to the behavior of the underlying media. Examples of such processors are the maximum or median detector which has been used in other fields such as radar or image processing.

Minimization, median, and maximization processors all fall under the category of Order Statistic (OS) filters which have been readily developed in the statistics field [9]. OS filters have the ability to emphasize statistical differences between two classes or hypothesis within a defined region where large statistical differences exists [10].

In this paper, the performance of order statistic filters in conjunction with split spectrum processing technique are analyzed in the context of flaw detection. The split spectrum techniques provides a set of observations features corresponding to different frequency bands which will decorrelate the microstructure noise. The order statistic filter is implemented with experimental and simulated results to show how information contained in these bands can be extracted.

II. THEORY OF ORDER STATISTIC FILTERS

In this section, the Order Statistic filter will be analyzed in an effort to optimize the detector in a robust manner. The OS filter is shown to be a quantile estimator of the input density function which describes a specific point on the probability distribution function. The performance of the detector can be improved by choosing the position of the estimate where there are large statistical differences between the two hypothesis (flaw present or not present).

The order statistic filter is a discrete processor that operates on a set of n input values corresponding to simultaneously sampled values of the n channels of the SSP output, $(z_1, z_2, z_3, \dots, z_n)$ which are ordered according to amplitude to produce the sequence below:

$$z_{1:n} \leq z_{2:n} \leq z_{3:n} \leq \dots \leq z_{n:n} \quad (1)$$

where a given order or rank, r is chosen and $z_{r:n}$ is passed to the output. The OS filter can be expressed by:

$$z_{r:n} = OS_{r:n}\{z_1, z_2, z_3, \dots, z_n\} \text{ for } 1 \leq r \leq n \quad (2)$$

This filter is the median detector when $r = (n + 1)/2$ (for odd n), the maximum detector when $r = n$ and the minimum detector when $r = 1$.

A fundamental question for optimizing this OS filter involves finding the relationship between the input and output statistical behavior of the data. Assuming that the input signals, z_i , are independent and identically distributed with probability distribution function $F_Z(\cdot)$, and probability density function $f_Z(\cdot)$. The distribution function for the output of the OS filter can be found by applying the binomial distribution which gives:

$$F_{Z_{r:n}}(z) = \sum_{i=r}^n \binom{n}{i} F_Z^i(z) (1 - F_Z(z))^{n-i} \text{ for } 1 \leq r \leq n \quad (3)$$

where z represents the real value of the observations of the input sequence and $z_{r:n}$ is the real value of the ordered input sequence, while Z is the random variable for the input of the OS filter and $Z_{r:n}$ is the random variable for

the ordered sequence of the OS filter. The density function is found by taking the derivative of Equation 3 to obtain

$$f_{Z_{r:n}}(z) = r \binom{n}{r} F_Z^{r-1}(z) (1 - F_Z(z))^{n-r} f_Z(z) \text{ for } 1 \leq r \leq n \quad (4)$$

This equation is a well known result in order statistics. Equation 4 completely describes the output statistics of a general OS filter given the density function of the independent and identically distributed inputs.

Equation 4 demonstrates that the input density function, $f_Z(z)$, is weighted by another function given by

$$w_{r:n}(u) = r \binom{n}{r} u^{r-1} (1 - u)^{n-r} \text{ for } 0 \leq u \leq 1 \quad (5)$$

where

$$u = F_Z(z) \quad (6)$$

and $w_{r:n}(u)$ is referred to as the *sort function* [11,12]. The sort function is the beta probability density function and an example of the possible sort functions are shown in Figure 2 where $n=5$. The expected value for the output of the OS filter is

$$E[Z_{r:n}] = \int_0^1 F_Z^{-1}(u) w_{r:n}(u) du \quad (7)$$

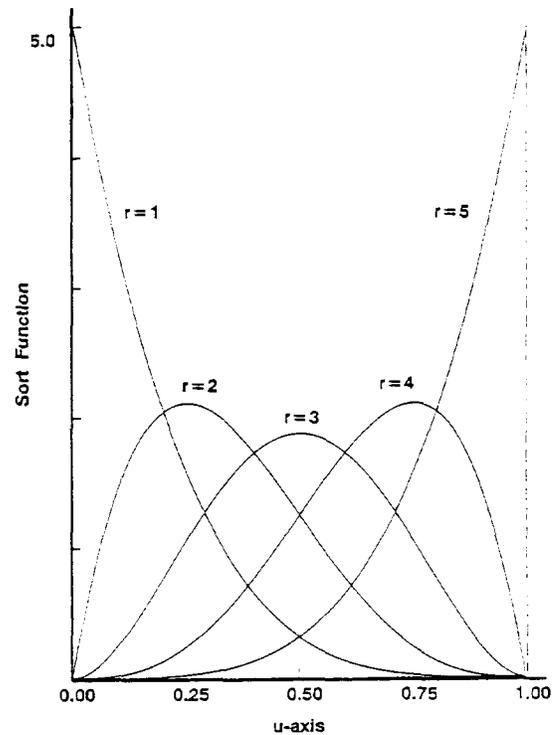


Figure 2. All possible sort functions with $n=5$.

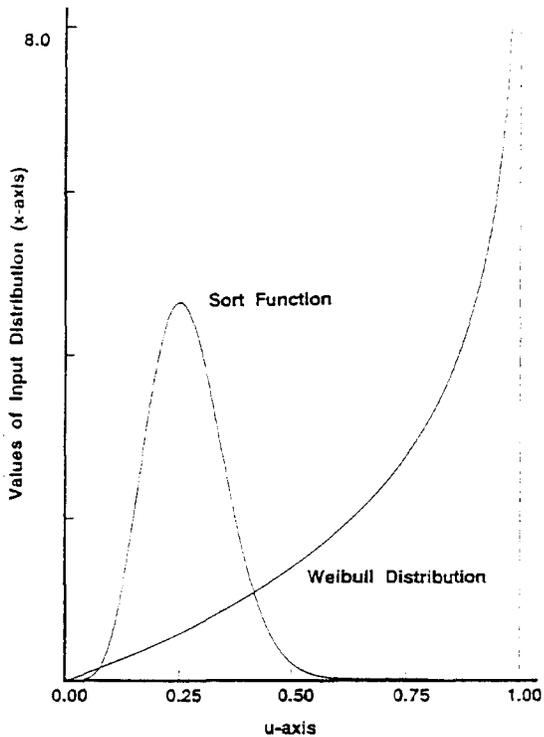


Figure 3. An example of a sort function imposed on a Weibull distribution where region around $u=0.25$ (2nd quantile) is highly weighted.

Figure 3 shows an example of the sort function with $r=7$ and $n=25$ superimposed on a Weibull inverse distribution function with a shape parameter equal to 1.5. The sort function acts as a weighting function to emphasize a particular region of the inverse distribution function over the integration as stated in Equation 7. It has been shown through earlier work that the OS filter with increasing n approaches a consistent estimator of a specific quantile value of the distribution function [11]. Quantile values are a set of points that divide the distribution function domain into equal probability regions. The OS filter as a consistent quantile estimator can be written in the form

$$\lim_{n \rightarrow \infty} E[Z_{t:\infty}] = F_Z^{-1}(t) \quad (8)$$

where

$$t = \left[\frac{r-1}{n-1} \right] \quad \text{for } 1 \leq r \leq n \quad (9)$$

In the limit both r and n approach infinity but t remains a finite ratio of n and r . For infinite n the OS filter is an unbiased estimator. With finite observations, n , the sort function will have some dispersion about the quantile value, t , that allows the values of neighboring quantiles to influence the output. It should be noted that the performance of the OS filter will improve with increasing observations n .

The performance of the OS filter can be observed by assuming some common input distributions and comparing with the performance of a simple averaging technique. Let us assume a Chi distributed target immersed in Weibull distributed clutter. The plot of the inverse distribution functions are shown in Figure 4, where the target plus clutter represents an random mixing of the two distributions [12]. The resulting distribution functions show great separability in lower quantile regions which suggest that low rank OS filters are preferable. The plot of

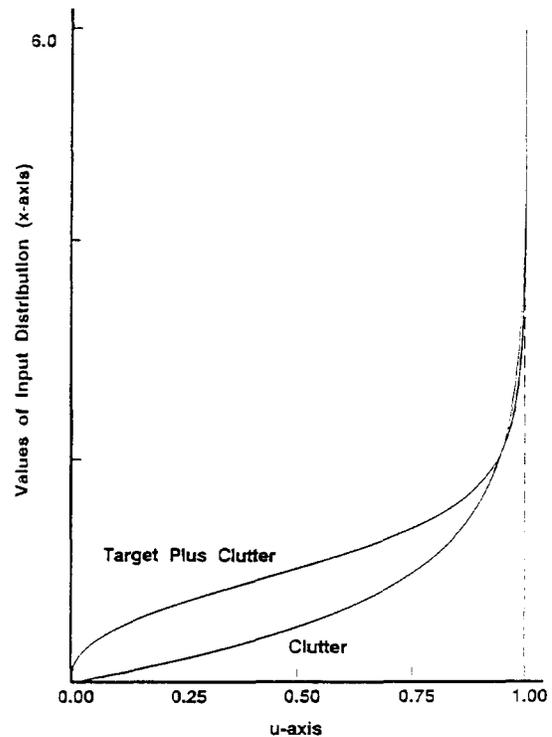


Figure 4. Inverse distribution functions for the target (flaw) plus clutter (grain) and the clutter alone.

the required SCR against the number of processed samples with the probability of false flaw alarm fixed at 10^{-3} is shown in Figure 5. The probability of detection is held at 0.5 which would be improved with the addition of more observations. As shown in Figure 5, the performance of the OS filter with $n=5$ and output ranks of one and two both outperformed the n pulse integrator (averaging) since at all SCR levels they require less samples to achieve the same probability of detection. In fact the OS filters were able to meet the performance criteria for the cases of very small input SCR with the addition of more processed samples.

So far the discussion has been confined to the assumptions of iid for input observations. The above example showed better performance with the lower ranks when all the observations were of the same underlying distributions. When this assumption is violated

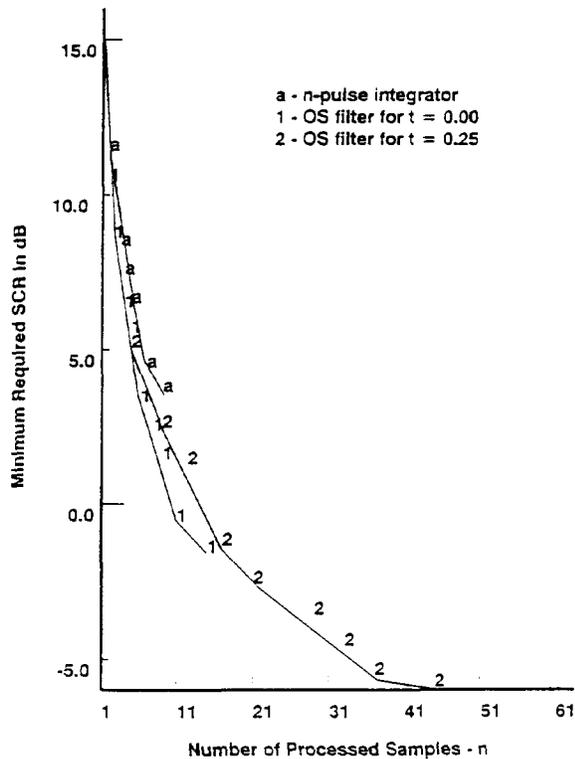


Figure 5. Performance of OS filter for rank one ($t=0.0$) and two ($t=0.25$) and the n -pulse integrator (averaging) is shown in terms of the minimum SCR and the number of processed samples.

minimization and other low ranked outputs will be more sensitive to a deteriorated signal in one of the channels and will exclude all information in other channels. These variations in the underlying density function of the observations can be dealt with by concentrating on higher order ranks which exhibit the property of inclusion whereas all the strong amplitude information is passed to the output. It is important to mention that with this operation only limited improvement can be made depending on the statistical nature of the noise.

III. SIMULATION AND EXPERIMENTAL RESULTS

Both simulated and experimental grain signals were used to illustrate the performance of the OS filter in improving the flaw to clutter ratio. The computer simulations used a signal composed of randomly positioned echoes with random amplitudes and phases with the flaw being inserted with a given amplitude corresponding to a given flaw to clutter ratio. The bandwidth of the flaw signal is equivalent to that of the noise bandwidth resulting in no flaw echo rejection in any of the channels, unlike the experimental studies in which the frequency shift of the grains must be taken into account. The computer simulation illustrates the ability of the OS filter to extract flaw information from all channels.

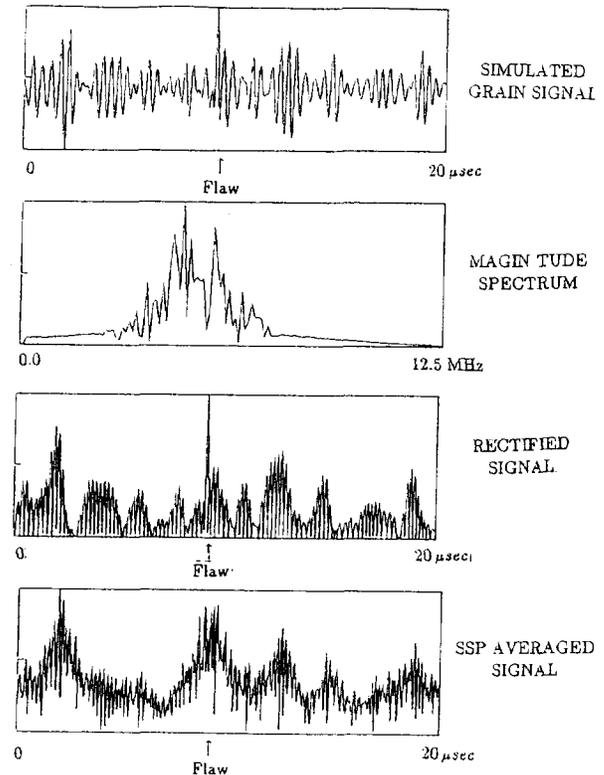


Figure 6. Simulated input grain signal with its corresponding magnitude spectrum, rectified version, and the SSP averaged output.

Figure 6 shows the simulated grain signal with a flaw present roughly in the center of the signal. The simulated grain signal is composed of 512 randomly positioned echoes with random amplitude. The echoes have a center frequency of 5 MHz and a 3-dB bandwidth of 2.5 MHz. The input signal to flaw ratio is approximately 1dB. The split spectrum processor is implemented with eight channels, where each bandpass filter has a Gaussian shape spectrum and a bandwidth of 0.75 MHz and the step between any two adjacent filters is 0.5 MHz. The output of the various ranks of the OS filter are shown in Figure 7. The comparison of outputs of the OS filters indicate that higher order ranks (e.g. maximum detector) performs superior to averaging and minimum detector. This result clearly shows the failure of the minimum detector to resolve the flaw which implies that the statistics of the flaw and clutter are very similar for small values of observations.

The experimental results were obtained using a steel specimen and a Panametric transducer with 6.22 MHz center frequency and a 3-dB bandwidth of 2.75 MHz. The flaw is formed by drilling a flat-bottom hole with a 1.5 mm diameter and 2.5 cm depth into the sample. The measurements were made using the contact technique and

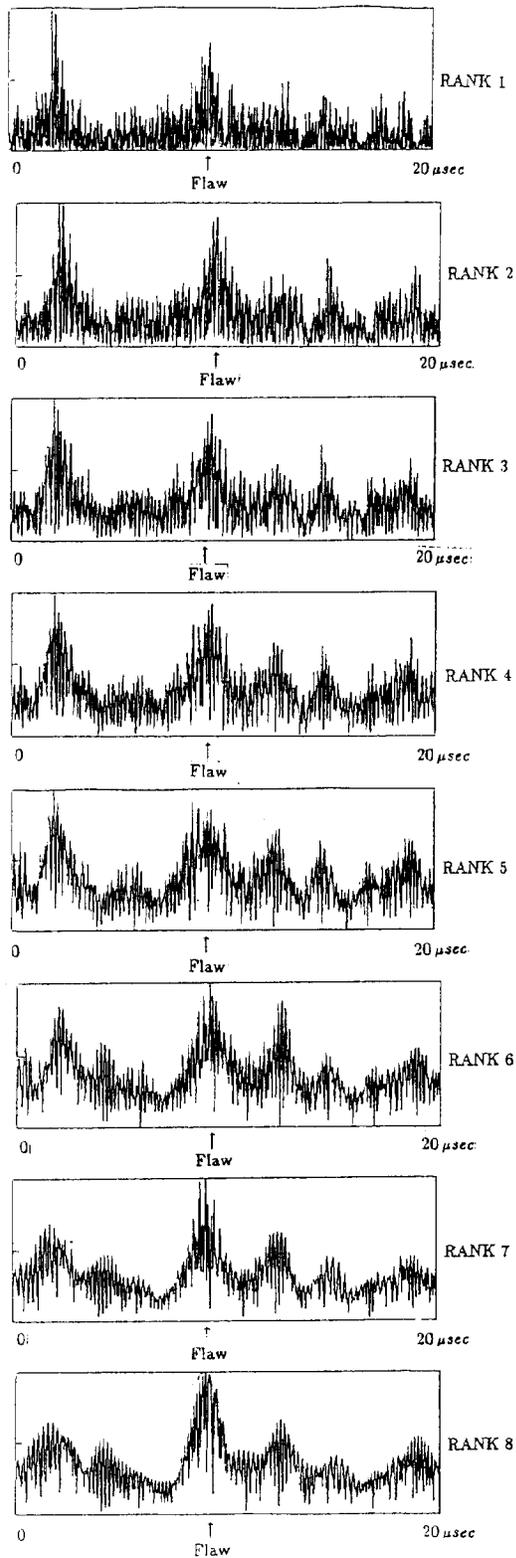


Figure 7. Outputs of the OS filter for simulated data with $n=8$.

data was acquired using 100MHz sampling rate. The SSP is constructed using 8 bandpass filters with bandwidth of 0.75 MHz and 0.5 MHz steps between adjacent filters starting at 3MHz. Figure 8 shows the experimental signal and the results of averaging where the input flaw-to-clutter ratio is about 0dB. In this particular example, the performance of averaging shows significant improvement which intuitively indicates that the median will also perform well. This can be seen from the OS processor outputs of Figure 9, where all the ranks greater than or equal to the median show similar performance. The maximum detector is not optimal but does provide significant improvement in flaw visibility. The poor performance of the lower ranks can be attributed to the frequency effects of the grains.

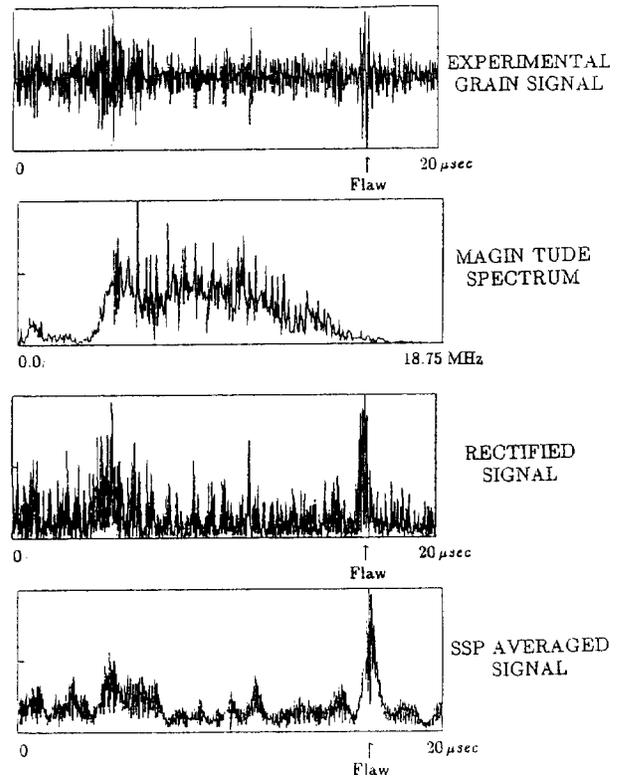


Figure 8. Experimental input grain signal including its magnitude spectrum, rectified version, and SSP averaged output.

IV. CONCLUSION

In this report, we have presented a theory and application of OS filter in ultrasonic flaw detection problems. The theory suggests that the optimal rank can be founded upon the knowledge of the distribution of flaw and the grains. We have shown through simulated and experimental results that the maximum and median detectors perform well in various scenarios where the a priori knowledge of the distributions is incomplete or inadequate to adapt to varying environments. In practice,

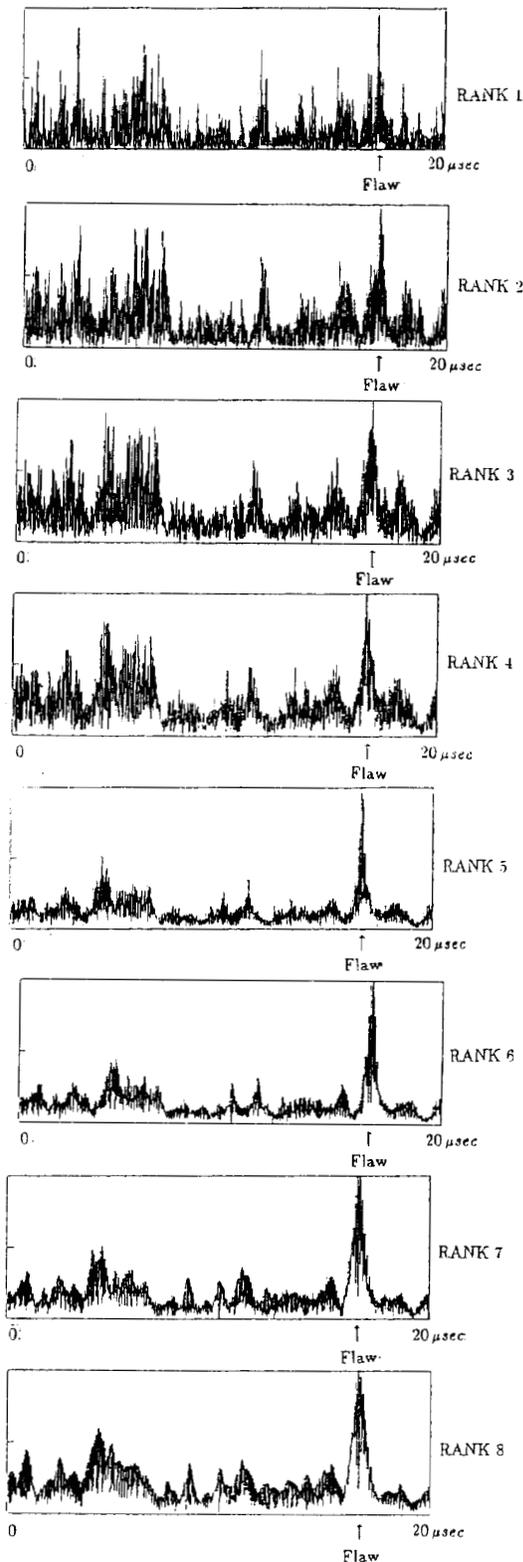


Figure 9. Outputs of the OS filter for experimental data with $n=8$.

a careful evaluation of the statistical properties of the flaw and grains are needed prior to application of OS filters with an optimal rank.

ACKNOWLEDGEMENTS

This work was supported by SDIO/IST funds managed under contract no. S4000RB01 by the Office of Naval Research, and Electric Power Research Institute, RP 2405-22.

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