APPLICATION OF NOVEL IMAGING TECHNIQUES TO PASSIVE SONAR IMAGE ENHANCEMENT.

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1.INTRODUCTION

The enhancement of sonar images and the subsequent extraction of features is a requirement for automatic classification and localisation. Enhancement can also be used to highlight features of interest to the operator. This paper addresses the requirement for enhancement of a sonar image; improvement of the signal-to-noise ratio (SNR) of desired signals whilst retaining the relative position and magnitude of features on the displayed image.

Existing processing techniques from fields other than underwater acoustics were investigated, particularly aerial/satellite optical imagery and synthetic aperture radar. The problems presented by sonar images are the low SNR and the variations in the statistics of the noise background. These factors distinguish the sonar image from the relatively low-noise, high-contrast satellite image.

The techniques to be described were selected on the basis of their ability not only to enhance the image but also to retain features in a form suitable for presentation to an operator using a conventional display. The first technique, adaptive histogram equalisation, normalises the image and produces a modest improvement in the SNR of the desired features. The second technique is a preliminary version of a Bayesian line tracker. This is a development of an earlier method reported by Maksym et al [1] which produced track-only information, but the current implementation now represents relative amplitude and time varying amplitude.

The test data set consisted of real and synthetic passive frequency-time images (LOFARGRAMS). A lofargram is a 2-dimensional array containing power spectra as a function of time. The synthetic data allowed a quantitative assessment of the relative performance of the algorithms which were developed. This assessment was conducted using a formal decision making technique in order to ensure traceable and objective conclusions.

2. DESCRIPTION OF THE IMPLEMENTED ALGORITHMS

Two algorithms were selected for implementation and testing against real and synthetic passive sonar data.

2.1 Adaptive Histogram Equalisation

Histogram equalisation is a well-known technique for enhancement of satellite and photographic images. When applied globally to a digital image, histogram equalisation redistributes the image pixel values in such a way that the distribution of these values over the image is approximately uniform. In other words the grey levels become equiprobable. In terms of information theory, the equalisation process attempts to maximise the entropy or amount of information per pixel in the resultant image.

In extending histogram equalisation to the local domain by using a local window, the local entropy and information content can be maximised. This algorithm, known as adaptive histogram equalisation, is based on a sliding window approach and computes local histograms and grey-level mappings in order to generate uniform histograms at each pixel location.

The technique has already been applied to the analysis of Landsat images by Tom and Wolfe [2] where the ability to enhance relief patterns was demonstrated. In particular, the method is most effective in enhancing detail in dark regions of an image. Two particularly attractive features are firstly that adaptive histogram equalisation does not embody assumptions about image characteristics which could make the method feature-specific and secondly that the output image is normalised, with a local mean value equal to the display mean.

Enhancement and normalisation are requirements for sonar images which can be provided simultaneously by means of adaptive histogram equalisation. However, the computational overhead for such an algorithm is known to be high although this could be reduced by interpolation or managed by means of a parallel implementation.

2.2 Bayesian Tracker

Bayesian methods have been used extensively to update prior probabilities on the basis of multiple hypotheses. Maksym et al [1] described research into line extraction based on Bayesian probability theory where enhancement of a set of lines in a noise background was demonstrated using a passive sonar image. However, the resultant image did not represent any relative or time-varying amplitude information.

The algorithm described in this paper is a development of the Bayesian tracker which represents amplitude information. An outline of the original tracker is given first.

2.2.1 The original algorithm The original algorithm [1] considered the detection of constant frequency tracks as a decision between two hypotheses: H1 denoting the presence of a track in a given frequency bin; H0 denoting the absence of a track. The posterior probabilities of these hypotheses were updated using evidence provided by each look of data, namely the magnitude $x(f)$ in each frequency bin.

The probabilistic model was described by two probability density functions; $p(x|H1)$ and $p(x|H0)$. These likelihood functions give the probabilities that x (at the new level) satisfies the hypotheses H1, H0. The posterior probability of the signal hypothesis can be expressed as:

$$p(H1)\ \text{posterior} = \frac{L(x)\ P(H1)\ \text{prior}}{1 - P(H1)\ \text{prior} + L(x)\ P(H1)\ \text{prior}} \qquad (1)$$

where L(x) is the likelihood ratio

$$L(x) = \frac{p(x|H1)}{p(x|H0)} \qquad (2)$$

The initial values of P(H1) were assigned arbitrary small values (= 0.1).

The above algorithm was implemented in order to form a baseline for further developments. The data was first normalised in order to provide stable noise background statistics. Normalisation was accomplished using a split-window (boxcar with central gap).

2.2.2 The New Algorithm The algorithm described in the previous section was extended to represent relative and time-varying amplitude variations. This was achieved by the introduction of multi-level signal hypotheses. A number of signal hypotheses were used to track amplitude and subsequently to assign representative grey-levels.

The hypotheses (Hi) and signal amplitude models, $ai = da*i$, were defined for $1 < i < N$, where da was the signal amplitude increment and N was the number of hypotheses. The grey-levels were assigned by summing the normalised posterior probabilities p(Hi) for all hypotheses. The resulting images were substantially noise free and represented faithfully the relative amplitudes of frequency-stable lines and their time-variations.

3. IMPLEMENTATION

The implementation was carried out using an interactive graphics package called PV-WAVE on a VT1300 VAX terminal. As the algorithm developments were only preliminary implementations they were not designed to run in real-time, although consideration was given to future potential for use in real-time systems and the use with parallel architectures.

3.1 Adaptive Histogram Equalization
The algorithm used a sliding window, centred at each pixel in the input image, within which a local histogram was accumulated. This local histogram was used to derive a grey-level mapping which transformed the local histogram into a uniformly distributed one.

The output pixel value was the transformed value of the input pixel at the centre of the local window.

The local window dimensions were selectable. The results shown in this paper used window dimensions based upon preliminary tests which considered the retention of desired broadband features and the elimination of artefacts due to signal drop-out or impulsive noise.

3.2 Bayesian Tracker

The number of signal hypotheses and their increment were selectable but the performance was relatively insensitive to their variation. The test runs were conducted with a number of signal hypotheses at small increments. Increasing the number of hypotheses resulted in slower run times without any significant performance advantages. The selected increment value gave a reasonable signal magnitude range which was compatible with typical sonar data characteristics.

4.RESULTS

4.1 Test Data Sets

An extensive range of real and synthetic images was used during the development, optimisation and subsequent assessment of the two algorithms. The synthetic data consisted of sets of features with varying SNR in a background of Rayleigh distributed noise. The synthetic data set presented in this paper consisted of a set of diffuse frequency stable lines where each line had an independent amplitude variation with time. This type of feature was considered to to be more realistic than amplitude-stable lines.

The real images were generated at different frequency resolutions from the same original data. These images contained several prominent lines and many which were barely discernible. There was also a background of subtle broadband features. The background noise statistics were inspected and found to be Rayleigh distributed on local and global scales.

4.2 Adaptive Histogram Equalisation

A conventionally normalised real image (Figure 1) can be compared with that obtained using the adaptive histogram equalisation technique (Figure 2). The conventional normalisation is optimised to retain features over a relatively small size range such as discrete lines. In contrast, the adaptive histogram equalized image retains detail at larger length scales and more importantly emphasises subtle textural detail which is lost using the conventional normalisation method.

The enhancement capability of the equalizsation algorithm is modest. Figure 3 shows the time averaged spectrum gain (enhanced/original) of a synthetic data set consisting of diffuse lines in a background of noise.The local signal-to-noise gain for the discernible features is typically 0.8 dB.

4.3 Bayesian Tracker

Figure 4 shows a synthetic image containing a set of diffuse lines. The Bayesian tracker output (Figure 5) demonstrates a substantial enhancement of these frequency-stable features, with the ability to extract features that are indiscernable in Figure 4. The main points to note are: the background is largely noise-free; the relative amplitude of the signals is retained; the time-varying amplitude of each line is represented.

The number of false tracks is large during the first (lower) 20 iterations of the algorithm but reduces very rapidly, such that the top half of the image contains few spurious features.

The ability to represent the time-varying amplitude of each line is demonstrated by Figures 6 to 8, which contain amplitude versus time (iterations) for the pure signal (Figure 6), the same signal with noise (Figure 7) and the corresponding output of the Bayesian tracker (Figure 8). The output shows a good representation of instantaneous amplitude despite the relatively low SNR. The ability to discriminate the signal variations in the presence of spurious noise impulses is evident.

5.CONCLUSIONS

The preliminary implementation of the Bayesian line tracker algorithm has shown promising results particularly in its ability to extract signals from low SNR data and to retain the relative amplitudes of these signals.

Further development work is required in order to enable the algorithm to track frequency varying signals.

The adaptive histogram equalization algorithm works well as a normalisation technique but does not give a large improvement in the SNR. It is worthy of consideration for use as a pre-enhancement technique. One area of improvement that has been reported in available literature is to use a hyperbolic function for the equalization.

6. REFERENCES

[1] J.N.MAKSYM et al, 'Machine Analysis of Acoustical Signals', Pattern Recognition,16 p615 (1983)

[2] V.T.TOM & G.J.WOLFE, 'Adaptive Histogram Equalization and its Applications', SPIE 359 p204 (1982)

ACKNOWLEDGEMENT

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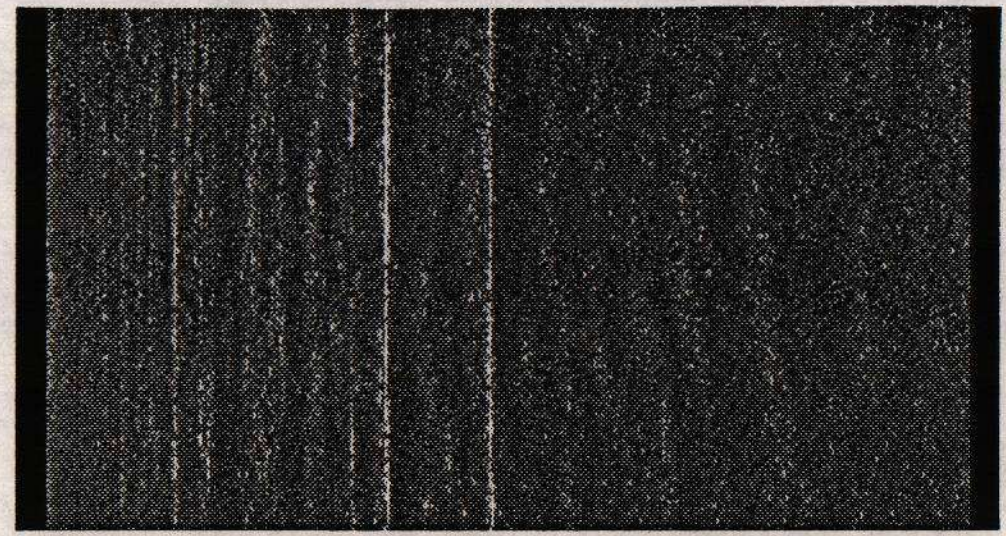

FIGURE 1
NORMALISED IMAGE
REAL DATA

FIGURE 2
HISTOGRAM EQUALIZED IMAGE
REAL DATA

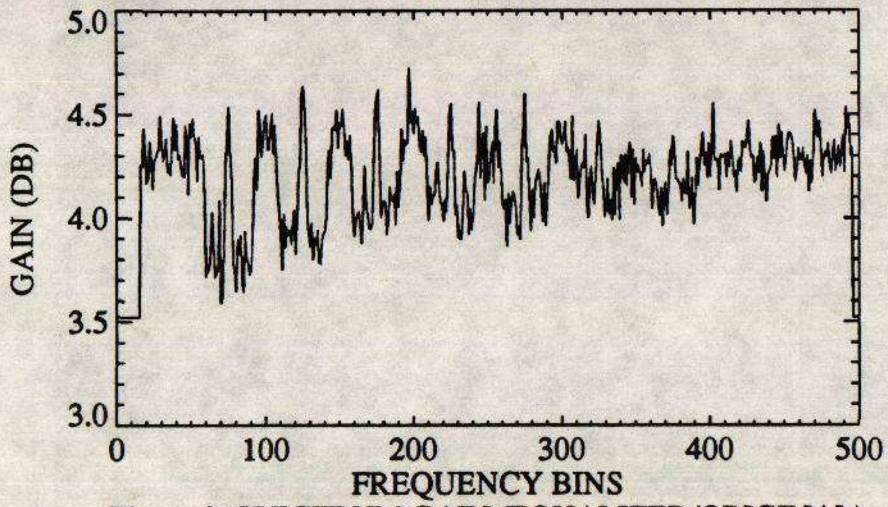

Figure 3 SPECTRUM GAIN (EQUALIZED/ORIGINAL)

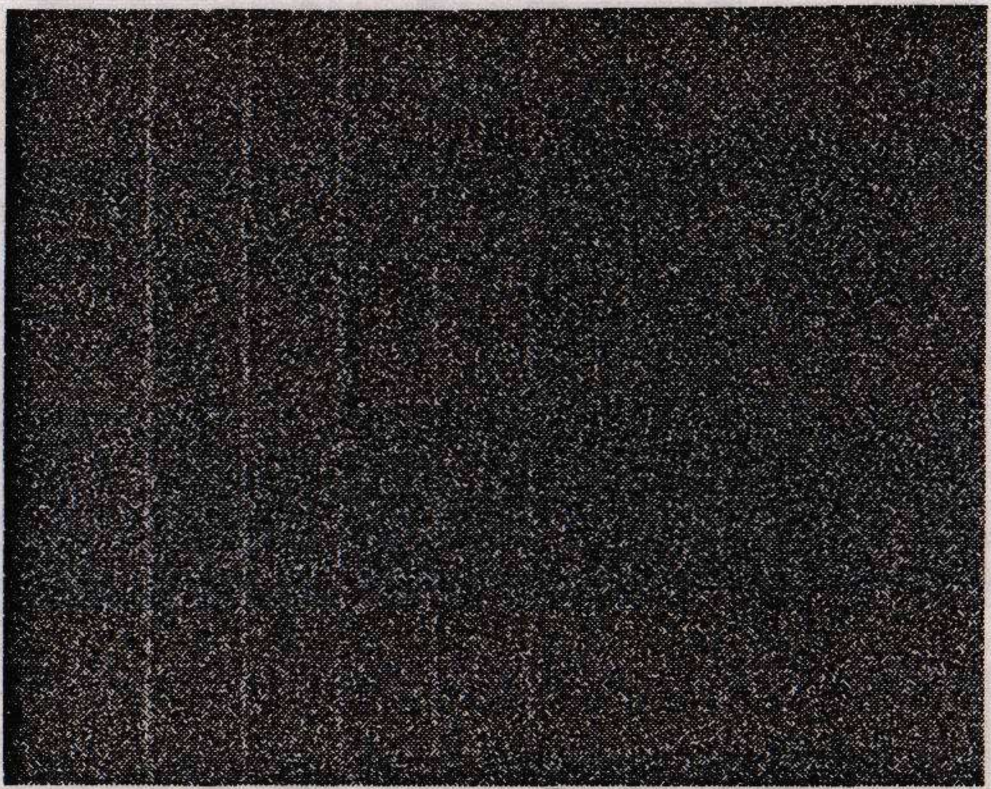

FIGURE 4 SYNTHETIC IMAGE WITH DIFFUSE LINES

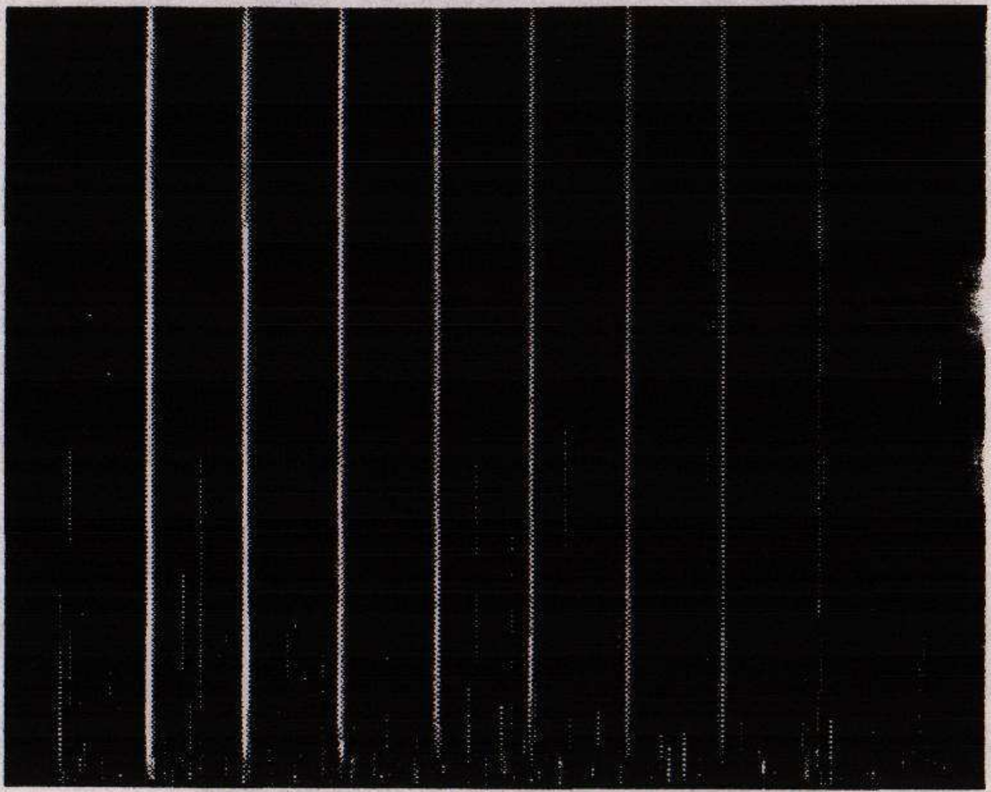

FIGURE 5 BAYESIAN TRACKER OUTPUT

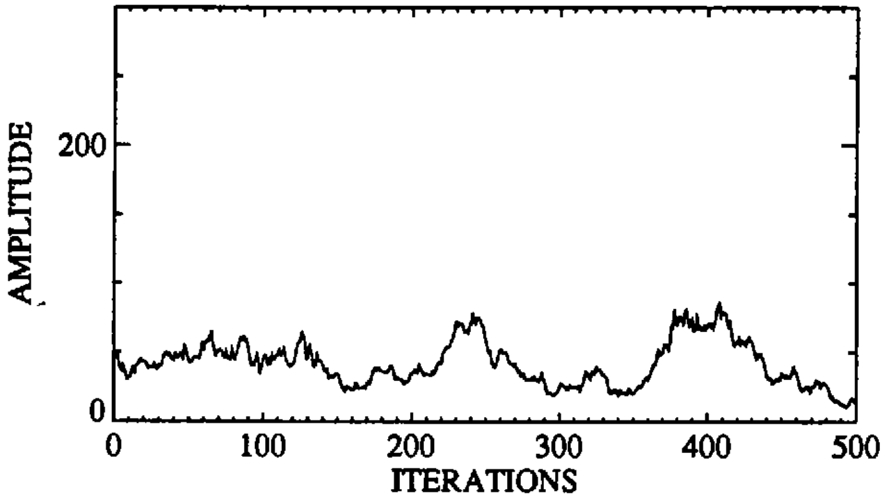

Figure 6 SIGNAL AMPLITUDE VARIATIONS

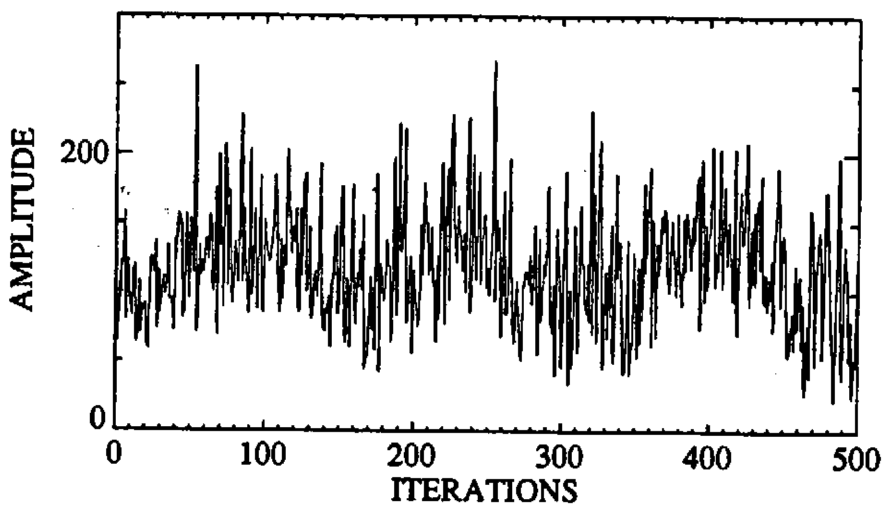

Figure 7 SIGNAL + NOISE AMPLITUDE VARIATIONS

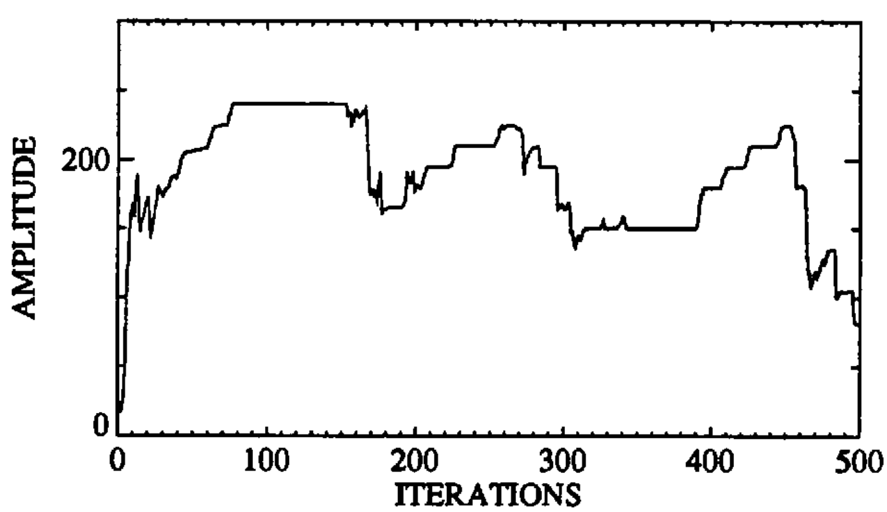

Figure 8 BAYESIAN TRACKER - OUTPUT AMPLITUDE VARIATIONS