Sonar Object Discrimination via Spectral Density Analysis

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***Abstract* - Current underwater sonar exploration often neglects the information that exists in the spectral density of object returns. The attempt to perform spectral density exploration of objects is complicated by the difficulty to present informative spectral content of each location pixel on a 2D image. Spectral content is best represented by the spectral density; however, it does not make sense to explore the detailed spectral density for each pixel in the image. In this work, we outline a general approach for spectral density analysis which is intended for enhancing object discrimination and delivers an easy to interpret, image enhancement of sonar returns. This method actually enhances the sonar image with acoustic color which emphasizes an optimal combination of frequency bands of the returned spectrum for the purpose of object discrimination. This is achieved by analyzing the discriminating power of different frequency bands and creating an optimal association with different bands to a corresponding color map.**

I. INTRODUCTION

Current underwater sonar exploration often neglects the information that exists in the spectral density of object returns. Detailed exploration of the spectral content of object returns is often done using wide band light (which may also include invisible light as well). In sonar systems, such exploration is not very common and has only recently been considered [1]. The attempt to perform spectral density exploration of objects is complicated by the difficulty to present informative spectral content of each location pixel on a 2D image. Spectral content is best represented by the spectral density; however, it does not make sense to explore the detailed spectral density for each pixel in the image. In this work, we outline a general approach for spectral density analysis which is intended for enhancing object discrimination and delivers an easy to interpret, image enhancement of sonar returns.

A typical return from an object undergoes pulse compression via convolution with the pinging signal (more precisely, with a signal template that is recorded by the sensing device). The recorded data then undergoes some aperture focusing, or, in the case of multiple sensors, beam forming. Narrower sonar beam can be created using synthetic aperture sonar systems which utilize multiple recordings of the object field from different locations (usually along a straight line) which leads to better cross range accuracy [2]. Following beam forming, the signal undergoes some image enhancement to remove noise and emphasize the important details in the sonar image. This amounts to thresholding in the simplest case and, in more advances systems, denoising via some object modeling or via a general system like Winner filtering, or wavelet denoising [3]

The pulse compression stage attempts to sharpen the return for improving the delay estimation of the pulse and, therefore, the estimation of object location. However, for the purpose of analyzing the frequency content that is absorbed by the object, it is better to consider the returned signal before the pulse compression. This provides a better estimation of the discrepancy between the frequency content that has been sent to the object and the frequency content that has been reflected back from the object. Due to dissipation and interference along the path to the object, as well as, transmitter/receiver transfer function, it is difficult to know the exact frequency content of the pulse that hits the object. However, we provide a method that overcomes this problem and concentrate on those frequency bands which emphasize discrimination between objects. If an object absorbs the frequency content in the pinging pulse uniformly, then the returned echo should have a frequency content that is similar to that of the transmitted pulse (ignoring the above transfer function issues). The amplitude of the returned signal is smaller, due to energy dissipation along the path and absorption by the object. In fact, as the dissipation along the path is frequency dependent, the amplitude of the returned signal should reflect that. When the absorption is not uniform, the spectral content of the returned echo is much more different than the spectral content of the pinging signal. This phenomenon resembles color and is thus termed acoustic color. Our task is to find a way to emphasize those frequency bands where discrimination between objects is better seen and to find a way to compress the spectral content difference into a single color pixel.

II. METHODOLOGY

The key point of our method for emphasizing object discrimination via acoustic color is related to the object discrimination power of each frequency. Before describing that point, we need to better define the spectral content that we are analyzing. We consider the difference between the spectral content of the transmitted signal *s(t)* and the spectral content of a segment (with same temporal length) in the returned signal *r(t)*. The returned signal has to be normalized in amplitude so that the average absorption is removed, and it is only the relative absorption of each frequency that is considered. This is done by finding the amplitude normalization μ_0 such that

$$\mu_0 = \arg\min_\mu \left\| s - \mu \cdot r \right\|. \quad (1.1)$$

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We subtract the frequency representation of the pinging signal so that a resulting frequency representation of the difference between the pinging signal and the returning signal is analyzed. A normalization of the returned echo is performed before the subtraction to compensate for the lower energy of the returning echo. Using a collection of objects from different classes (without loss of generality, we shall assume two classes), we create a normalized collection of spectral density differences (NSDD) for each class, and for each frequency, study their mean mf and standard deviation σf per class. The discriminatory power of each frequency is given by

$$\theta_f = | m_f^1 - m_f^2 | / \sigma_f^1 + \sigma_f^2 \qquad (1.2)$$

This Fisher discrimination coefficient [4] provides a fundamental way to determine the discrimination power under the assumption that the return of each object class is normally distributed around each mean (for every frequency). This assumption can be validated easily on the collection of returns. By analyzing the discrimination power, we provide a solution which overcomes the problem of lack of knowledge of the transfer function that includes the media, transmitter and receiver. This follows from the simple fact that the signals that are returned from all object classes undergo the same transformation, thus, the discrimination power as is calculated above is not affected, and the relevant frequency bands can be found independently of that transformation.

The general framework is depicted in Fig. 1. The method is applicable to single sensor, and multiple sensor sonar. This method is useful for wide-band radar, hyper-spectral analysis and sonar systems. It is applicable when there is a single receiving sensor, or an array of sensor

When considering multiple sensors, the returned signals have to be aligned, as they are otherwise forming a hyperbola due to the different distance between each sensor and the object (Fig. 2.) The signals are aligned using the peak of the matched filter response. Then, the Fourier transform of the signal that is recorded by each sensor is performed (as seen around the peak in Fig. 3).

Each spectral representation is then normalized and the difference from the spectral content of the transmitted signal is taken. The normalized spectral differences are then averaged. Using the discrimination factor that was calculated on set of training objects containing two classes, the integrated energy in each frequency band (Fig. 4) is then calculated and the resulting energy is used as the intensity in an RGB representation (using a color scheme that has been determined useful for the desired discrimination).

The final part in creation of the spectral difference representation includes a compression of the energy in each of the three frequency bands which are determined to be useful for object discrimination into intensity levels of the Red Green and Blue channels for a color display.

Fig. 3 demonstrates the spectral density as is recorded by multiple sensors from the returns due to the front and back highlights of an object. In the case of multiple sensors, this data is collapsed by the beam-forming processing into a single point at every range. This enables the observation of the spectral density difference at a region around an object as well as inside the object

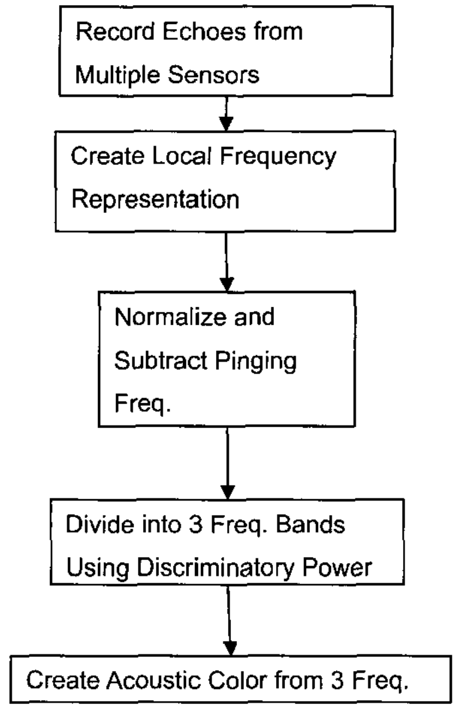

Fig. 1. Schematic diagram of the proposed Synthetic Aperture Sonar image-enhancement using acoustic color.

We have collected such frequency difference returns from the objects we have at hand and then determined the band-widths which most emphasize the difference between objects. These bands are then assigned to the different RGB channels (Fig. 4).

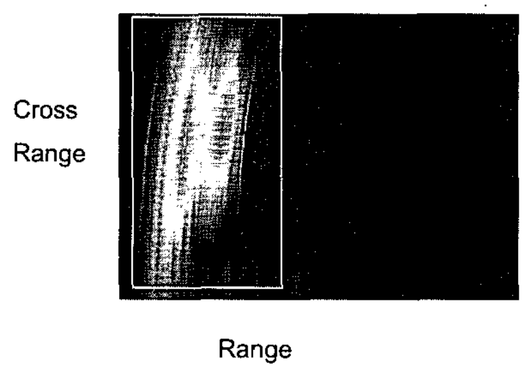

Fig. 2. A highlight of the front and back edge of an object from the collection of sensors.

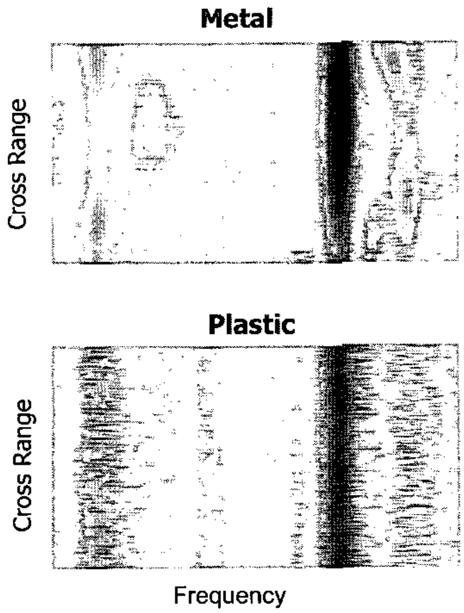

Fig. 3. A detailed frequency representation of the highlights of two objects. The Y axis represents the steering angle, the X axis represents the Frequency and the color represents the energy in that frequency.

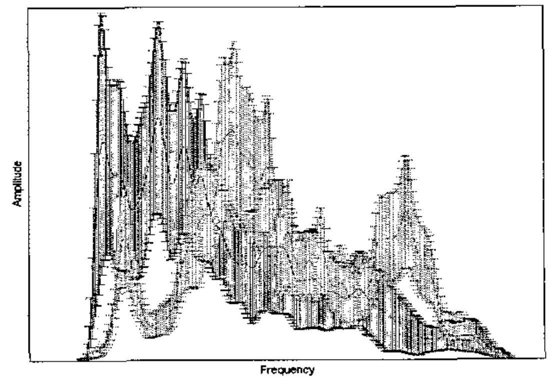

Fig. 4. Difference between the spectral contents of a plastic and metallic object. The error bars demonstrate clear separation for some frequencies.

III. CONCLUSIONS

In conclusion, it is clear from Fig. 4 that it is possible to find frequency bands which demonstrate clear separation between different object classes. The assignment of different RGB values to the integrated energy in these bands is simple and would result in a clear color difference between images.

REFERENCES

[1] Buckingham, M. J., Potter, J. R., Epifanio C. L. Seeing Underwater with Background Noise. Scientific Am. 1996.

[2] Harger, R. O. Synthetic aperture radar systems: Theory and design. Academic Press, 1970.

[3] Donoho, D. L. De-Noising by soft thresholding. IEEE Trans. Info. Theory 41 pp. 613—627, 1995.

[4] Fisher, R. A. The use of multiple measurements in taxonomic problems. Annals of Eugenics, 7(II) pp. 179-188, 1936.