A Physical Statistical Sonar Clutter Model for Spatially-Dispersed Scatterers

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***Abstract*—The limiting influence of clutter on active sonar performance has long been recognized, with echoes from complex bathymetry, fish schools, and anthropogenic objects such as wrecks, capable of producing false target detections that can both mask real targets and overload the sonar operator with false alarms. To help reduce the impact of these false target objects, statistical distribution models have been employed to both optimize detection threshold settings and improve echo classification. While many such distribution models exist, very few have a physical basis allowing extrapolation to different environments and sonar systems. This paper describes a new 3-parameter statistical model that provides a physical context for relating the characteristics of matched-filter echo-envelope distributions to scatterer attributes. It extends our 2-parameter Poisson-Rayleigh (P-R) model [1]–[2] by adding a quantitative measure of scatterer spatial uniformity (dispersion) to the P-R model's measures of discrete scatterer density and relative strength. The resulting Conway-Maxwell-Poisson-Rayleigh (CMP-R) model's potential for isolating and characterizing clutter was quantified via shallow-water experimental data containing returns from biologic, geologic and anthropogenic objects with differing spatial separations and scattering characteristics. Analysis results demonstrate the flexibility of the CMP-R model in characterizing differing types of clutter as well as target-like objects in 2 distinct environments. Combined with a demonstrated insensitivity to echo signal-to-noise ratio (SNR), the CMP-R distribution model shows promise with regard to both its general applicability for clutter characterization and the development of robust, physics-based active classification algorithms.**

Keywords—active sonar; clutter model; scattering; spatial distribution; physics-based; echo classification

I. INTRODUCTION

High false alarm rates are a persistent problem for active ASW sonars. Automated detection, classification and localization algorithms need to be robust to overload and being misled by false targets. Additionally, as budgetary and environmental constraints increasingly limit at-sea time for active sonar operations, realistic clutter models are needed for synthetic trainers. Consequently, there is a strong need to develop sonar clutter characterization and control methods that realistically incorporate those environmental and sonar system parameters which impact the clutter statistics.

Previous probabilistic modeling work has included using the K-Distribution (KD) model to analyze the impact of multipath reverberation, signal bandwidth and sonar beamwidth on the KD shape parameter [3]–[5], which represents the effective number of exponentially-sized scattering patches within the sonar footprint. Other efforts have characterized seafloor interface scattering statistics using the Generalized Pareto (GP) distribution, parameterized in terms of the bottom roughness as described by a power law spectrum [6]. Additionally, mixture models based on the Rayleigh and Poisson distributions have been developed to approximate amplitude statistics arising from a collection of identically-distributed and uniformly-spaced discrete scatterers superimposed on a background of diffuse scatterers [1]–[2], [7]. As each model makes different physical assumptions about the nature of the scattering objects, no single model is likely to be the best choice in all cases. In general however, mixture models, such as the exponential-K mixture model [8] and NRL's Poisson-Rayleigh (P-R) model [1]–[2], provide more flexibility in matching distribution shape and thereby can compensate to some degree for non-stationary clutter data, and so improve the accuracy of parameter estimates.

An advantage of multiparameter physical models is that they can provide more information related to scatterer characteristics, which can then be exploited to improve echo classification. This is illustrated in Fig. 1 which compares the P-R, KD and lognormal distributions in terms of the higher-order normalized moments skewness-squared and kurtosis (which provide a measure of echo distribution shape) [9]. The model curves compare with symbols representing echo statistics derived from experimental data sets containing bottom, biologic and anthropogenic objects.

While no distribution model will be optimal for all echo classes, the additional parameter and flexibility of the P-R model in fitting a greater range of distributions provides a valid and useful tool for echo classification by estimating scatterer properties via derived model parameters. By extending the P-R model assumptions to account for a greater variety of scatterer characteristics, its efficacy for false alarm prediction and echo classification can be further improved. To this end, this paper presents the CMP-R distribution which

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models the echo statistics of both uniformly spaced and non-uniformly-spaced discrete scatterers, the latter of which is typically encountered on the ocean bottom and in aggregations of schooling fish.

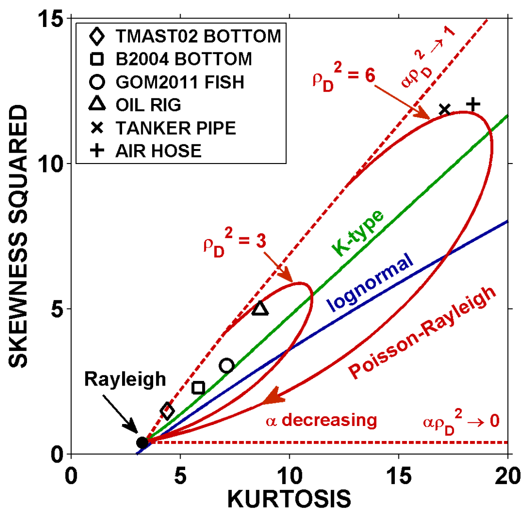

Fig. 1. Average skewness-squared and kurtosis values for experimental echo data (symbols) corresponding to bottom, fish and anthropogenic objects: air-hose reflector, oil rig and its tanker pipe, overlain with PDF model curves. The Rayleigh distribution value (3.245, 0.3982) is shown for comparison. The data points for each clutter object represent 100-m range-bin statistics averaged over multiple pings and beams.

II. CMP-R Distribution Model

In statistics, the variance-to-mean ratio (VMR) provides a normalized measure of the dispersion of a probability distribution. For the Poisson distribution, VMR = 1, which in the context of the P-R model corresponds to uniformly-spaced scatterers. In general, real spatial distributions of anthropogenic, geological and biological scatterers can be spatially spread (under-dispersed; VMR < 1) or spatially clustered (over-dispersed; VMR > 1). To account for this, the Conway-Maxwell-Poisson (CMP) distribution [10] was incorporated into our P-R-based clutter model. The CMP distribution can not only represent uniform data, but over- and under-dispersed data. By applying this extension, the resulting CMP-Rayleigh (CMP-R) model generalizes the P-R model to depend on a third parameter related to the VMR. While the CMP-R distribution has no closed-form expressions definable in terms of higher-order moments, its parameters can be efficiently estimated from data via an iterative maximum-likelihood technique.

The probability density function (PDF) of the CMP-R distribution incorporates the PDF of both the 2-component Rayleigh and the CMP distribution. The PDF of the 2-component Rayleigh distribution is given by:

$$f_R(r,m) = \frac{r}{\sigma_m^2}\exp\left(\frac{-r^2}{2\sigma_m^2}\right), \; \sigma_m^2 = \sigma_C^2 + m\sigma_D^2 . \tag{1}$$

In (1), r denotes amplitude and the Rayleigh scale or power parameter, σ^2_m is defined as the sum of 2 terms consisting of a background component σ^2_C, and a discrete component $m\sigma^2_D$ comprised of m independent identically-distributed discrete returns.

The PDF of the CMP distribution [10] is given by:

$$f_{CMP}(m) = \frac{\lambda^m}{(m!)^\nu}\frac{1}{Z(\lambda,\nu)}, \; Z = \sum_{j=0}^{\infty}\frac{\lambda^j}{(j!)^\nu}, \; E(m) \approx \lambda^{\frac{1}{\nu}} - \frac{\nu-1}{2\nu} . \tag{2}$$

In (2), the Poisson distribution is generalized by the parameter ν which provides a measure of dispersion. As illustrated in Fig. 2, data are over-dispersed when $\nu < 1$ (VMR > 1), under-dispersed when $\nu > 1$ (VMR < 1), and uniformly distributed when $\nu = 1$ (VMR = 1). The effective number of discrete scatterers is given by the first moment of the CMP distribution $E(m)$, where E represents the expected value function. For $\nu < 1$ or $\lambda > 10^\nu$, $E(m)$ is well approximated by the above closed-form expression.

The distributions given by (1)–(2) are combined to form the CMP-R PDF:

$$f_{CMPR}(r) = \sum_{m=0}^{\infty}\frac{\lambda^m}{(m!)^\nu}\frac{1}{Z(\lambda,\nu)}\left(\frac{r}{\rho_m^2}\right)\exp\left(\frac{-r^2}{2\rho_m^2}\right), \; \rho_m^2 = \frac{\sigma_m^2}{E(r^2)/2} . \tag{3}$$

In (3), a transformation of random variables has been applied to obtain a normalized form of the PDF as indicated by the parameter ρ^2_m, where $E(r^2)/2$ is the total Rayleigh power estimated from the data. The model parameters are constrained by:

$$\rho_C^2 + \alpha\rho_D^2 = 1 \quad \text{where} \quad \alpha(\lambda,\nu) = E(m) , \tag{4}$$

generalizes the P-R density parameter α by incorporating the dispersion parameter ν. When $\nu = 1$, the number of discrete component parameters is reduced from three to two, and (3) becomes the P-R distribution.

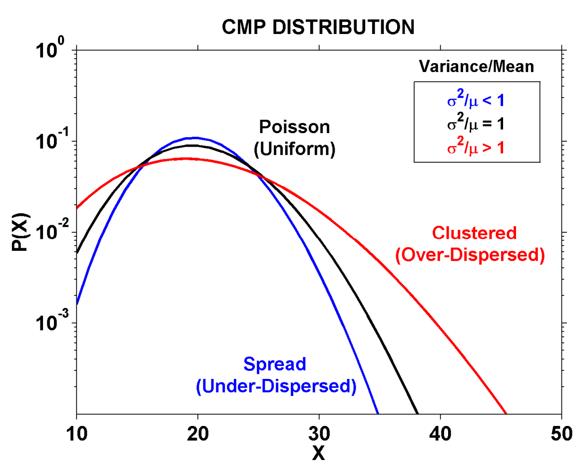

Fig. 2. Representative CMP distribution curves for different dispersion parameter values ($\nu < 1$ red, $\nu > 1$ blue, and $\nu = 1$ black).

III. Data Modeling

The CMP-R model's potential for isolating and characterizing clutter was quantified via shallow-water experimental data containing returns from biologic, geologic and anthropogenic objects with differing spatial separations and scattering characteristics [1], [11]. These objects included ones which were isolated-compact (single isotopic anthropogenic reflectors), clustered-compact (grouped isotropic anthropogenic reflectors and fish schools), and dispersed (bathymetric ridges and fish aggregations). The experimental data included: 1) fish-school data collected by NRL in an ONR-sponsored experiment in the Gulf of Maine, a two-ship, multi-institution sea trial with WHOI and NRL on a UNOLS vessel, and NOAA/NMFS's Northeast Fisheries Science Center on a NOAA vessel that performed extensive net sampling (ground truth); and 2) geologic and anthropogenic scattering data collected by NRL during recent NURC (NATO Undersea Research Centre—now NATO's Centre for Maritime Research and Experimentation) experiments on the geologically-well-characterized Malta Plateau (south of Sicily) [1]. The analyzed data sets consist of multiple pings (10-20) acquired with quasi-monostatic sonar systems consisting of a towed source and horizontal receiver array. The corresponding transmit signals were: 1) 2-s, 3.4-4.1 kHz, and 2) 1.5-s, 0.7-1.7 kHz linear frequency modulated waveforms. Recorded time series from each experiment were appropriately base-banded, beamformed, matched-filtered, split-window normalized, and then georeferenced (Fig. 3).

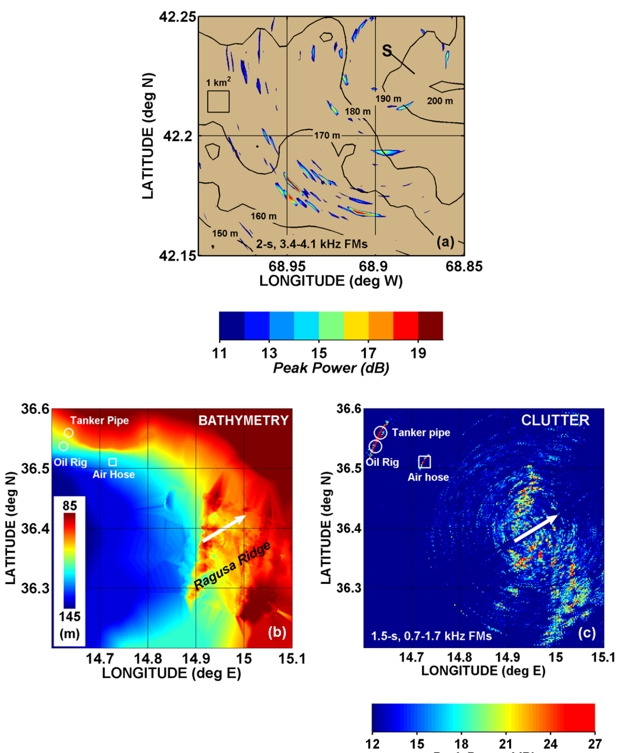

Fig. 3. Bathymetry and georeferenced echo data for (a) Gulf of Maine fish aggregations, and (b)–(c) Malta Plateau bottom features and anthropogenic objects (air hose, oil rig and its associated tanker pipe).

Echo returns from the various scattering objects were identified by correlating threshold exceedances with geographic location and the available ground-truth data. Distributions were formed by selecting data from sample windows of approximately 200 m in range extent corresponding to pings, beams and times associated with the identified returns. Model parameters were then estimated from the sample distributions using an iterative maximum-likelihood technique. Fig. 4 shows results of the model fits in terms of the average parameter values computed over all sample windows.

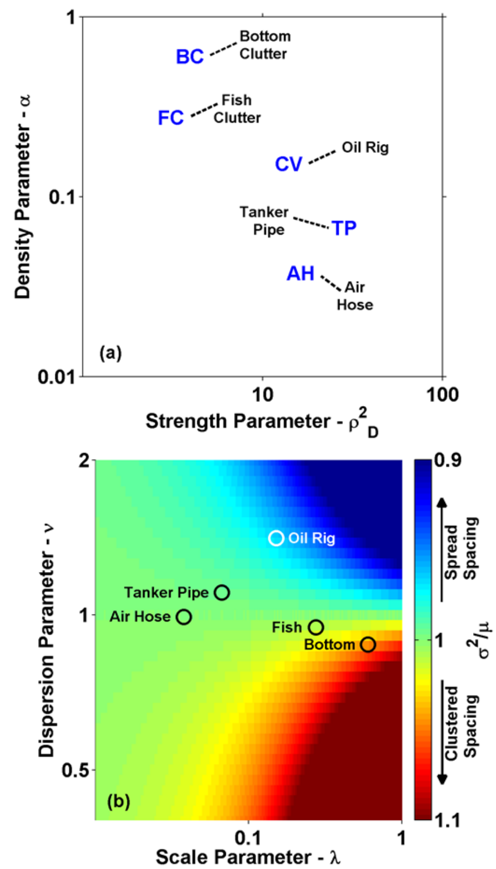

Fig. 4. Average values of CMP-R model parameters: (a) α vs. ρ^2_D, and (b) ν vs. λ overlaid on a color image of the corresponding CMP variance-to-mean ratio. Data values represent 200-m range-bin statistics averaged over multiple pings and beams.

To demonstrate the potential for CMP-R-parameter-based clutter control, classification features defined in terms of kurtosis, the KD shape parameter and the CMP-R discrete component parameters α and ρ^2_D were extracted from sliding sample windows spanning all times, beams and pings of the analyzed Malta Plateau data. The resulting feature sets were used to threshold the data such that each feature excluded the same percentage of all returns above 6 dB SNR. The clutter rejection performance of each feature was then compared by computing the probability of false alarm (PFA) from thresholded data associated with 3 distinct echo classes. These included returns from the target-like tanker pipe, as well as clutter-like bottom and oil rig scattering objects (Fig. 5)[1].

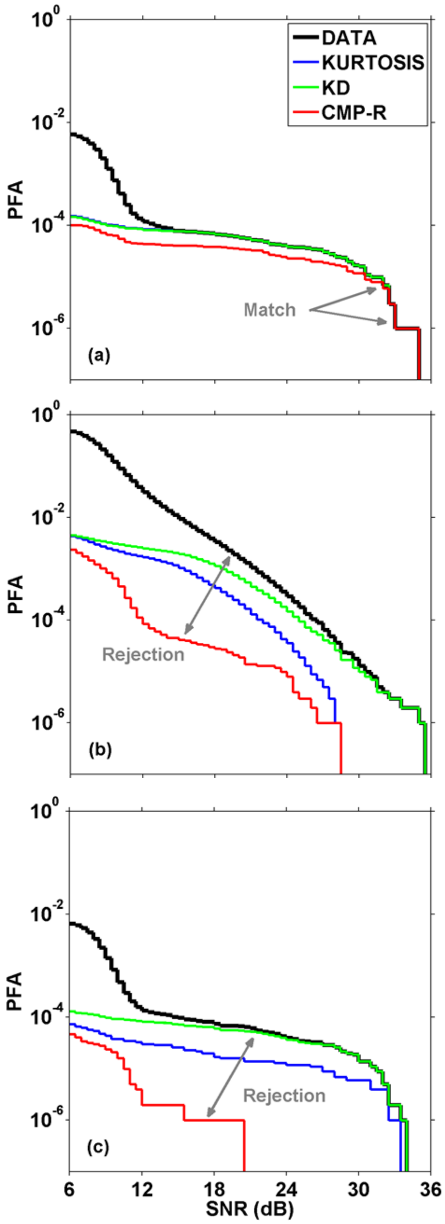

Fig 5. Clutter control performance comparison using Malta Plateau bottom clutter (b) and two anthropogenic objects (tanker pipe (a) and oil rig (c)) for a single threshold criteria based on CMP-R (ν = 1), KD and kurtosis classification features extracted from 100-m range bins. Results show PFA vs. peak normalized power level of the corresponding range bin sample data.

To qualitatively assess goodness of fit, model parameters were estimated from three echo distributions formed by combining samples from range bins associated with returns from fish aggregations, bottom features and the oil rig structure. PFA curves were then generated from the data and overlaid with computed model curves (Fig. 6).

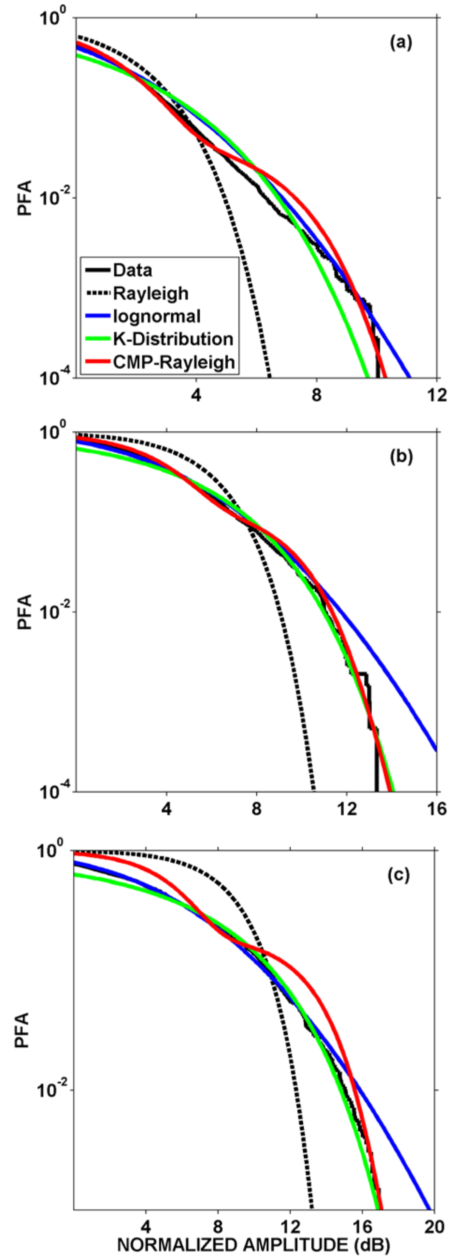

Fig. 6. PFA model fits comparing the CMP-R, KD and lognormal distributions for (a) fish, (b) bottom and (c) oil-rig echo data. Note differing x and y axis limits.

IV. Discussion

The CMP-R clutter model was presented which extends NRL's 2-parameter P-R distribution model by adding a third parameter that provides a measure of the spatial dispersion of acoustically strong discrete scatterers. Model parameters were estimated from data collected in 2 distinct shallow water environments which contained returns from objects with varying size and spatial characteristics. The resulting parameters were shown to be consistent with the scatterer

[1]Fig. 5 results for the CMP-R correspond to the case of $\nu = 1$ and are shown to illustrate general performance characteristics. Comparable or improved results are anticipated when incorporating the dispersion parameter ν into the classification feature.

physical attributes and in general provided good separation between the different classes of analyzed echoes. The extracted CMP-R discrete parameter classification feature demonstrated superior clutter control performance compared to analogous KD and kurtosis features, and was also shown to be less correlated with the peak echo SNR. Lastly, distribution curves fit to echo data illustrated the fact that the CMP-R can be a good choice for representing data distributions arising from scatterers with physical characteristics that are reasonably consistent with the model assumptions. While this requirement will not be satisfied for all classes of clutter, the physical context and multi-parameter form of the CMP-R can still be exploited to good effect for echo classification. These results are encouraging with regard to both the general applicability of the CMP-R model for clutter characterization and its potential for robust, physics-based active classification.

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