International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

AN EXPERIMENT ON MSTAR DATA FOR PARAMETRIC CHARACTERIZATION OF SAR CLUTTER

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ABSTRACT

Accurate statistical modelling of SAR clutter is crucial to improve the performance of various SAR image processing applications such as detection, classification, recognition etc. In this paper, various parametric distributions such as Weibull, Lognormal, Rayleigh, Nakagammi, Inverse Gaussian are presented from empirical, scattering and multiplicative modelling perspective. Furthermore, Method of moments (MoM) and Method of Log-Cumulants (MoLC) Estimators for the parameters of the presented parametric distributions are mentioned. MSTAR dataset collected from Sandia National Laboratory are considered for experimental analysis to evaluate the effectiveness of the parametric distributions for modelling SAR clutter using MATLAB tool. Simulation results illustrates the superiority of the MoLC estimators over MoM estimator. Also, Lognormal distribution is found to achieve better goodness-of-fit compared to Rayleigh, Weibull, Nakagammi distributions in modelling SAR ground clutter data.

1. INTRODUCTION

Synthetic aperture radar (SAR) is a form of radar that is used to create images of objects, such as landscapes. It uses the motion of radar antenna and mounted on moving platform. Large aperture antenna can be synthesized by movement of small aperture antenna --synthetic aperture radar. It is an active remote sensing technology that uses microwave energy to illuminate the surface. To achieve much finer resolution of SAR image beam width should be very low.

SAR image consists of both target and non-target pixels. The non-target pixels represent the clutter region in the SAR image data, which also refers to backscattered contributions from the background objects. Example, radars systems are used for detection and tracking of 'targets' such as ships, vehicles etc. For them, backscattered contributions from background objects are soil, rocks, seas, vegetation etc. these are regarded as clutter.

The clutter is further classified into two categories, surface clutter and volume clutter. Interfering returns from ground areas, sea, ocean are usually -surface clutter coming to the volume clutter, it is having large extent like chaff, rain, birds, insects. Clutter is of two types, homogenous and heterogenous. The data of the clutter which contains flat smooth surfaces, sea, ocean etc. can be considered homogenous clutter and the extremely heterogenous clutter that shows the corner reflectors like building, large vehicles etc. are dominant .and in case of moderately heterogenous clutter, it is described as backscattered contributions from vegetation areas and back terrains etc. Amplitude of the backscattered signal varies based on the scene of heterogeneity and accordingly the clutter may either be homogenous or heterogenous.

The clutter data corresponding to the interfering return from non-targeted objects and also the corresponding statistics are very much essential for the improvement of the performances of various SAR image applications. The heterogenous clutter statistics will be depending on the corresponding texture statistics.

2. STATISTICAL DISTRIBUTIONS FOR SAR CLUTTER MODELLING

For the modelling of statistics of SAR clutter data there are three classes such as, non-parametric, parametric, semi-parametric modelling approaches. Non-parametric models may be better representations but do not lend themselves well to analysis .In semiparametric model it allows to have the best of the both worlds: a model that is understandable and can be manipulated and still offering a fair representation of the messiness that is involved in real life[3]. To know briefly parametric models are easy to work and even easy to understand but fails in not giving the fair representation of what is happening in the real world.

We mainly focus on the parametric models for modelling of SAR clutter. As it is Simpler: These methods are easier to understand and interpret results. Speed: Parametric models are very fast to learn from data. Less Data: They do not require as much training data and can work well even if the fit to the data is not perfect.

The Parametric model won't make use of any training pattern, instead it assumes a statistical distribution for modelling SAR clutter. Due to the simplicity and the applicability of parametric model, it got much importance in recent years. It can better be fitted into three ways, namely Empirical model, Scattering model, Multiplicative model.

The main crucial challenge in the context of SAR image processing and applications is to develop accurate models for the SAR clutter statistics. From the last two decades variety of parametric formulation are reported in the literature to model the statistics of SAR clutter data.

The Empirical Model is one of the parametric models, these empirical models are from the straightforward induction of experiment analysis on the actual SAR clutter. Some of the empirical models are namely Lognormal (LGN), Weibull (WBL), Generalized Gamma($G\Gamma$)distributions[4].

The Scattering model is one of parametric models, the complex SAR clutter is the vector sum of backscattered electromagnetic waves from individual scatters contained within the resolution cell. Some of the most used scattering models for the SAR clutter are Rayleigh [17], $\Gamma^{1/2}$, heavy-tailed Rayleigh ,Generalized Gaussian Rayleigh and Generalized Gamma Rayleigh distributions [5,6].

The Multiplicative model is a one of parametric models, the SAR clutter modelled as the product of the two random variables namely, speckle and texture. Various multiplicative models can be implemented by varying the statistics of the texture [7,8]. Mostly used Multiplicative models for SAR Clutter include $K^{1/2}$ distribution, G^0 distribution [9].

Table 1: Application Areas of Parametric Clutter Models

Parametric models	Application Area
Weibull distribution	It is applicable for homogeneous area
Log-Normal distribution	It is suitable for heterogeneous area
$\Gamma^{1/2}$ distribution	It is appropriate for heterogeneous area
Rayleigh distribution	It is suitable for homogeneous area

Weibull (WBL) Distribution: The Weibull distribution is an empirical model of two parameters. It is useful for characterizing non-Rayleigh clutter statistics [10]. The pdf is given by

$$p(x;[K,\eta])=\frac{K}{\eta^{K}}x^{K-1}\exp^{-}\left(\frac{x}{\eta}\right)^{K} \quad (1)$$

This model can capture the statistics of homogeneous clutter with fully developed speckle. The ability of the Weibull distribution to correctly represent multi-look clutter is lacking. Rayleigh and negative exponential distributions are special cases of this density function, with shape parameters K=2 and K=1, respectively.

Log-Normal (LGN) Distribution: The Lognormal distribution is also an empirical model of two parameters. It is appropriate for capturing non-rayleigh behaviour observed in SAR clutter[11]. The pdf is given by

$$p(x;[K,\eta])=\frac{1}{xK\sqrt{2\pi}}\exp\left(-\frac{(\ln x-\eta)^{2}}{2K^{2}}\right) \quad (2)$$

The Log normal distribution is heavily tailed. As a result, the statistics of heterogeneous clutter from urban areas are significantly characterised..

Rayleigh Distribution: The Rayleigh distribution is the fundamental scattering model that results from the central limit theorem (CLT).The pdf can be expressed as

p(x;[η])=x/η^2 e^((-x^2⁄2 η^2)) (3)

Only SAR Clutter amplitude model data from a homogeneous area are included in this distribution.

$\Gamma^{1/2}$ Distribution: The $\Gamma^{1/2}$ distribution is used in homogenous areas for the modelling multilook clutter amplitude data. The pdf is expressed as

$$p(x;[m,\Omega])=\frac{2m^{m}}{\tau(m)\Omega^{m}}x^{2m-1}\exp\left(\frac{-m}{\Omega}x^{2}\right) \quad (4)$$

Where m is the number of looks, $\boldsymbol{\Omega}$ is the spread parameter. The pdf can capture the statistics of moderately heterogenous clutter by adjusting its spread parameter.

3. ESTIMATION STRATEGIES FOR SAR CLUTTER MODELS

To make use of models in clutter modelling we have to estimate the parameters. So that we are going to use the parametric estimation strategies such as [14].

A. Method of Moments (MOM)

B. Method of Log Cumulants (MOLC)

A. Method of Moments: In order to estimate the unknown parameters, we should use moments of distribution. It is a numerical technique used to approximately solve linear operator equations such as differential equations or integral equations [14].

Steps to be followed in Method of Moments are:

Let x be a random variable with probability density function p(x,Θ). μ_r^1 be the rth moment about origin.

$$\mu_r' = E(x^r) \qquad (5)$$

Then $x_1, x_2, \dots . x_n$ be a random sample of size n drawn from the population with density function f(x, Θ). Thus r^{th} sample moment will be

$$m_r' = \frac{1}{n}\sum_{i=1}^{n} x_i^r \qquad (6)$$

From the equation2.10, and solve for Θ

$$m_r' = \mu_r'(\Theta) \qquad (7)$$

1)Gamma distribution:

There are two unknown parameters in Gamma distribution such as shape and scale parameters($\boldsymbol{\kappa}, \eta$). The mean of distribution can be computed using

$$E(x)=\int_{-\infty}^{\infty} x\, p(x)\, dx \qquad (8)$$

The second order moment can be expressed as

$$E(x^2)=\int_{-\infty}^{\infty} x^2 p(x)\, dx \qquad (9)$$

By substituting the gamma pdf in E(x)and $E(x^2)$ we can obtain mean and second order moment.

Variance is obtained by

$$Var(x)= E(x^2)-\big(E(x)\big)^2 \qquad (10)$$

Thus, mean of Gamma distribution is

$$E(x) = \frac{\kappa}{\eta} \qquad (11)$$

variance of Gamma distribution

$$var(x) = \frac{\kappa}{\eta^2} \qquad (12)$$

By dividing (11) and (12)

$$\frac{\frac{\kappa}{\eta}}{\frac{\kappa}{\eta^2}} = \eta = \frac{E(x)}{var(x)} \qquad (13)$$

Parameter estimates for Gamma distribution are

$$\hat{\kappa} = \eta E(x) \qquad (14)$$

$$\hat{\eta} = \frac{E(x)}{var(x)} \qquad (15)$$

Substitute parameter estimates in pdf then we obtain estimated pdf

$$\frac{\eta^{\kappa}}{\Gamma(\kappa)} x^{\kappa-1} e^{-\eta x} = pdf \qquad (16)$$

2)Rayleigh distribution:

There is only one unknown parameter in Rayleigh distribution such as scale parameter (η).[20]The mean of distribution can be computed using

$$E(x)=\int_{-\infty}^{\infty} x\, p(x)\, dx \qquad (17)$$

The second order moment can be expressed as

$$E(x^2)=\int_{-\infty}^{\infty} x^2 p(x)\, dx \qquad (18)$$

By substituting the Rayleigh pdf in E(x)and $E(x^2)$ we can obtain mean and second order moment.

variance is obtained by

$$Var(x)= E(x^2)-\big(E(x)\big)^2 \qquad (19)$$

Thus, mean of Rayleigh distribution is expressed as

$$E(x) = \sqrt{2}\Gamma\left(\frac{3}{2}\right)\eta \qquad (19)$$

Second order moment of Rayleigh distribution

$$E(x^2) = 2\eta^2\Gamma(2) \qquad (20)$$

By rearranging the equation (2.21)

$$E(x) = \sqrt{2}\Gamma\left(\frac{3}{2}\right)\eta \qquad (21)$$

Parameter estimates is

$$\hat{\eta} = \frac{E(x)}{\sqrt{2}\Gamma(1.5)} \qquad (22)$$

Substitute above parameter estimates in pdf then we obtain estimated pdf

$$p(x) = \frac{x}{\eta^2}e^{\left(-x^2/2\eta^2\right)} \qquad (23)$$

3)Inverse Gaussian distribution: There is only one unknown parameter in Inverse Gaussian distribution such as shape parameter (***K***)**.** The mean of distribution can be computed using

$$E(x)=\int_{-\infty}^{\infty} x\, p(x)\, dx \qquad (24)$$

The second order moment can be expressed as

$$E(x^2)=\int_{-\infty}^{\infty} x^2 p(x)\, dx \qquad (25)$$

By substituting the Inverse Gaussian pdf in E(x)and $E(x^2)$ we can obtain mean and second order moment.

Variance is obtained by

$$Var(x)= E(x^2)-\left(E(x)\right)^2 \qquad (26)$$

Thus mean of Inverse Gamma distribution is expressed as

$$E(x) = \mu \qquad (27)$$

Variance of Inverse Gamma distribution is expressed as

$$var(x) = \frac{\mu^3}{k} \qquad (28)$$

By dividing (27) & (28)

$$\frac{\left(E(x)\right)^3}{var(x)} = \frac{\mu^3}{\mu^3/k} = k \qquad (29)$$

Parameter estimates

$$\hat{k} = \frac{E(x^3)}{var(x)} \qquad (30)$$

Substitute above parameter estimates in Inverse Gaussian pdf

$$p(x) = \sqrt{\frac{k}{2\pi x^3}\exp\left(\frac{-k}{2\mu^2 x}(x-\mu^2)\right)} \qquad (31)$$

4)Nakagami distributions ($\Gamma^{1/2}$): There are two unknown parameters in Nakagami distribution such as no of looks and spread parameters. The mean of distribution can be computed using

$$E(x)=\int_{-\infty}^{\infty} x\, p(x)\, dx \qquad (32)$$

The second order moment can be expressed as

$$E(x^2)=\int_{-\infty}^{\infty} x^2 p(x)\, dx \qquad (33)$$

By substituting the Nakagami pdf in E(x)and $E(x^2)$ we can obtain mean and second order moment.

variance is obtained by

$$Var(x)= E(x^2)-\left(E(x)\right)^2 \qquad (34)$$

thus, mean can be expressed as

$$E(x) = \int x\, p(x)\, dx \qquad (35)$$

$$= \int x \frac{x^{2m}}{\Gamma(m)\Omega^m} x^{2m-1} \exp\left(-\frac{m}{\Omega}x^2\right) dx \quad (36)$$

$$= \frac{2}{\Gamma(m)}\left(\frac{m}{\Omega}\right)^m \int x^{2m} \exp\left(-\frac{m}{\Omega}x^2 \quad \right) \qquad (37)$$

$$= \frac{\Gamma(m+1/2)}{\Gamma(m)}\left(\frac{\Omega}{m}\right)^{1/2} \qquad (38)$$

second order moment can be expressed as

$$E(x^2) = \int x^2 p(x)\, dx \quad (39)$$

$$= \frac{2}{\Gamma(m)}\left(\frac{m}{\Omega}\right)^m \int_0^\infty x^{2m-1} \exp\left(\frac{-m}{\Omega}x^2\right) dx \quad (40)$$

$$= \frac{\Gamma\left(m+\frac{2}{2}\right)}{\Gamma(m)}\left(\frac{\Omega}{m}\right)^{2/2} \quad (41)$$

$$= \frac{\Gamma(m+1)}{\Gamma(m)}\left(\frac{\Omega}{m}\right) \quad (42)$$

Variance can be expressed as

$$\mathrm{Var}(x) = \frac{\Gamma(m+1)}{\Gamma(m)}\left(\frac{\Omega}{m}\right) - \left(\frac{\Gamma\left(m+\frac{1}{2}\right)}{\Gamma(m)}\left(\frac{\Omega}{m}\right)^{\frac{1}{2}}\right)^2 \quad (43)$$

$$= \frac{\Omega}{m}\left[1 - \left(\frac{\Gamma\left(m+\frac{1}{2}\right)}{\Gamma(m)}\right)^2\right] \quad (44)$$

Parameter estimates

$$\widehat{m} = \frac{\left(E(x^2)\right)^2}{\mathrm{var}(x^2)} \quad (45)$$

$$\widehat{\Omega} = E(x^2) \quad (46)$$

Substitute above parameter estimates in pdf then we can obtain estimated pdf

$$p(x)= \frac{2m^m}{\tau(m)\Omega^m} x^{2m-1} \exp\left(\frac{-m}{\Omega}x^2\right) \quad (47)$$

5)Log-Normal distributions: There are two unknown parameters in Log-Normal distribution such as shape and scale parameters($\boldsymbol{K}, \eta$).The mean of distribution can be computed using

$$E(x)=\int_{-\infty}^{\infty} x\, p(x)\, dx \quad (48)$$

The second order moment can be expressed as

$$E(x^2)=\int_{-\infty}^{\infty} x^2 p(x)\, dx \quad (49)$$

By substituting the lognormal pdf in E(x)and $E(x^2)$ we can obtain mean and second order moment.

variance is obtained by

$$\mathrm{Var}(x)= E(x^2)-\left(E(x)\right)^2 \quad (50)$$

thus, mean can be expressed as

$$\overline{x^2} = e^{2n+\boldsymbol{K}^2} \quad (51)$$

variance can be expressed as

$$s^2 = \left(\boldsymbol{K}^2 - 1\right)\overline{x^2} \quad (52)$$

From equation (51) & (52)

$$\frac{s^2}{\overline{x^2}} + 1 = e^{\boldsymbol{K}^2} \quad (53)$$

$$\boldsymbol{K}^2 = \ln\left(\frac{s^2}{\overline{x^2}} + 1\right) \quad (54)$$

Parameter estimates of Log-Normal distribution

$$\widehat{\boldsymbol{K}} = \sqrt{\ln\left(\frac{s^2}{\overline{x^2}}\right) + 1} \quad (55)$$

$$\overline{x^2} = e^{2\eta+\boldsymbol{K}^2} \longrightarrow 2\ln\bar{x} = 2\eta + \boldsymbol{K}^2 \quad (56)$$

Parameter estimates of Log-Normal distribution

$$\hat{\eta} = \ln\left(\frac{\bar{x}}{\sqrt{\frac{s^2}{\bar{x}^2}+1}}\right) \quad (57)$$

Substitute above parameter estimates in pdf to obtain estimated pdf

$$P(x) = \frac{1}{x\boldsymbol{K}\sqrt{2\pi}}\exp\left(\frac{-\log x-\eta^2}{2\boldsymbol{K}^2}\right) \quad (58)$$

The estimators for the following distributions are derived using above mentioned MOM steps and final outcomes are presented in this table.

Table 2:MOM for Parameter Estimation

Distribution Models	MOM Parametric Equations
Log Normal	$\hat{\mathbf{K}} = \sqrt{\ln\left(\frac{s^2}{\bar{x}^2}\right)+1}$ $\hat{\eta} = \ln\left(\frac{\bar{x}}{\sqrt{\frac{s^2}{\bar{x}^2}+1}}\right)$
Rayleigh	$\hat{\eta} = \frac{E(x)}{\sqrt{2}\Gamma(1.5)}$
Nakagami	$\hat{m} = \frac{\left(E(x^2)\right)^2}{var(x^2)}$ $\hat{\Omega} = E(x^2)$
Inverse Gaussian	$\hat{k} = \frac{E(x^3)}{var(x)}$

B. Method of Log Cumulants (MoLC): Another method to estimate the unknown parameters is Method of Log Cumulants. By using nth order equation MoLC is calculated[16].

Steps to be followed in Method of Log Cumulants are

Step1: Compute Nth order equation of given distribution

Step2: Replace n with s-1 in Nth order equation then it is represented as 1[st] characteristic function of second kind

$$\phi(s) = E(x^{s-1}) \quad (59)$$

Step3: Apply logarithmic function to 1[st] characteristic equation then it is represented as 2[nd] characteristic function of second kind

$$\psi(s) = \log(\phi(s)) \quad (60)$$

Step4: At first derivate w.r.t 's' to the 2[nd] characteristic function of second kind and then substitute s=1

$$\hat{k}_n = \left.\frac{d^n\Psi(s)}{ds^n}\right|_{s=1} \quad (61)$$

Step5: Compute k1, k2 equations by using above equation. k1 and k2 calculation depends on number of unknown parameters. For example if a distribution consists of 1 unknown then, only k1 is required for finding MOLC.

1)Nakagami distribution($\Gamma^{1/2}$): There are two unknown parameters in Nakagami distribution such as no of looks and spread parameters.

Nth order equation is represented as

$$E(x^n) = \frac{\Gamma\left(L+\frac{n}{2}\right)}{\Gamma(L)}\left(\frac{w}{L}\right)^{n/2} \quad (62)$$

1[st] characteristic function of second kind

$$\phi(s) = E(x^{s-1}) \quad (63)$$

$$= \frac{\Gamma\left(L+\frac{s-1}{2}\right)}{\Gamma(L)}\left(\frac{w}{L}\right)^{\frac{s-1}{2}} \quad (64)$$

2[nd] characteristic function of second kind

$$\psi(s) = \log\frac{\Gamma\left(L+\frac{s-1}{2}\right)}{\Gamma(L)}\left(\frac{\omega}{L}\right)^{\frac{s-1}{.2}} \quad (65)$$

$$=\log\left(\Gamma\left(L+\frac{s-1}{2}\right)\right)+\log\left(\frac{\omega}{L}\right)^{\frac{s-1}{2}}-\log(\Gamma(L)) \quad (66)$$

$$=\log\left(\Gamma\left(L+\frac{s-1}{2}\right)\right)+\frac{s-1}{2}\cdot\log\left(\frac{\omega}{L}\right)-\frac{s-1}{2}\cdot\log(L)- \quad \log\big(\Gamma(L)\big) \quad (67)$$

Compute k1 and k2

$$\hat{k}_1=\frac{d}{ds}\psi(s) \quad (68)$$

$$\hat{k}_1=\frac{\psi(L,0)}{2}+\log\frac{\omega}{2}-\frac{\log L}{2} \quad (69)$$

$$2\hat{k}_1=\psi(0,L)+\log\omega-\log L \quad (70)$$

$$\hat{k}_2=\psi\left(\frac{L+S}{4}\right)\Big|_{s=1} \quad (71)$$

$$4\hat{k}_2=\psi(1,L) \quad (72)$$

2)Log Normal distribution: There are two unknown parameters in Log-Normal distribution such as shape and scale parameters($\boldsymbol{K},\eta$).

Nth order equation can be represented as

$$E(x^n)=e^{\frac{n\eta+n^2K^2}{2}} \quad (73)$$

1st characteristic function of second kind $\phi(s)=E(x^{s-1})=e^{\frac{(s-1)\eta+(s-1)^2K^2}{2}}$ (74)

2nd characteristic function of second kind

$$\psi(s)=(s-1)\eta+(s-1)^2K^2/2 \quad (75)$$

then compute k1 and k2

$$\hat{k}_1=\frac{d}{ds}\Psi(s)|_{s=1} \quad (76)$$

$$\hat{k}_1=\eta \quad (77)$$

$$\hat{k}_2=\eta+2(s-1)\frac{K^2}{2}\Big|_{s=1} \quad (78)$$

$$=\eta+K^2s-K^2 \quad (79)$$

$$\hat{k}_2=K^2 \quad (80)$$

The estimators for the following distributions are derived using above mentioned MOLC steps and final outcomes are presented in this table.

Table 3:MOLC for Parameter Estimation

4. SIMULATION RESULTS

A. Description of Dataset

The Table represents dataset description. These data sets are gathered from Sandia national laboratory which are real data sets. We used two datasets namely dataset3 and dataset5.The data set consists of SAR image data files in .gff file format.

Data Collectors	Sandia National Lab
Radar Platform name	Miniature SAR (Mini-SAR)
Sensor Name	Twin Otter
Range Resolution	0.1016m

Cross range Resolution	0.1016m
Range pixel size	0.0847m
Cross range pixel size	0.0847m
Range Count	1638
Azimuth Count	2510
Operating frequency band	Ku-band
Central frequency	16.8 GHz
Bits per pixel	16
Number of Look	1

B. Qualitative Assessment of goodness-of-fit:

In order to assess the accuracy of the distributions and modelling SAR clutter, we have employed method of moments and method of log cumulants estimation strategies for the parameter estimations. And the obtained parameter estimates are now used for obtaining the estimated pdf. The estimated pdf then compared with data histogram for qualitative assessment. And corresponding plots are illustrated from Figure (1) to Figure (8)

Distribution	Parametric Equations
Log Normal	$\hat{k}_1 = \eta$ $\hat{k}_2 = K^2$
Weibull	$\hat{k}_1 = \log\eta + \psi(1)K^{-1}$ $\hat{k}_2 = \psi(1,1)K^{-2}$
Generalized Gamma	$\hat{k}_1$ $= \log(\eta) + ((\psi(K) - \log(K))\gamma^{-1}$ $\hat{k}_2 = \psi(1,K)/\gamma^2$ $\hat{k}_3 = \psi(2,K)\ /\ \gamma^3$
$\boldsymbol{\Gamma^{1/2}}$**(Nakagami)**	$2\hat{k}_1 = \psi(L) + \log(w) - \log(L)$ $4\hat{k}_2 = \psi(1,L)$

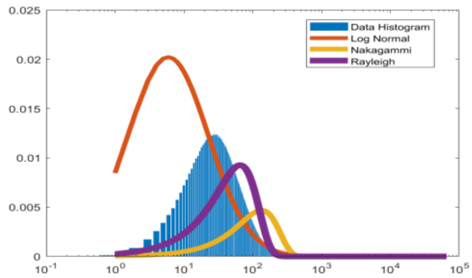

Figure (1): Comparison of Clutter Data Histogram with Estimated Parametric PDFs for Dataset 3 using MoM Estimation.

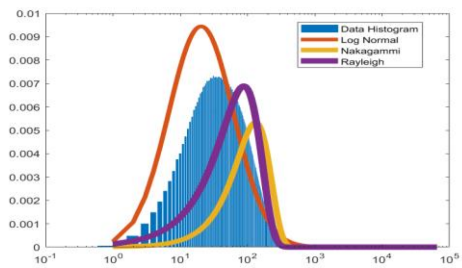

Figure (2): Comparison of Clutter Data Histogram with Estimated Parametric PDFs for Dataset 5 using MoM Estimation.

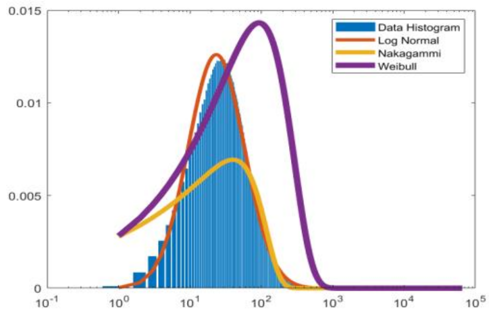

Figure (3): Comparison of Clutter Data Histogram with Estimated Parametric PDFs for Dataset 3 using MoLC Estimation.

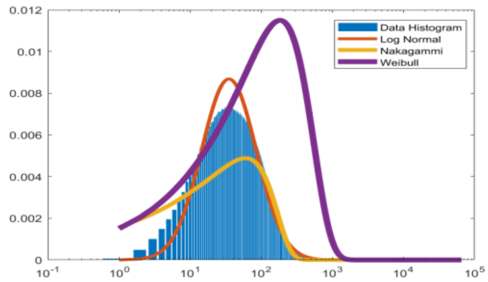

Figure (4): Comparison of Clutter Data Histogram with Estimated Parametric PDFs for Dataset 5 using MoLC Estimation.

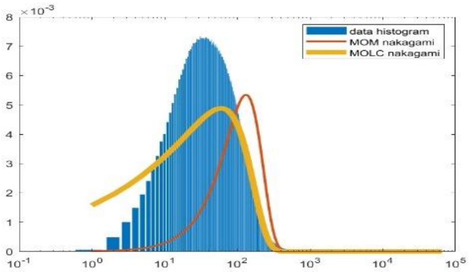

Figure (5): Comparison of Clutter Data Histogram with Estimated Parametric PDFs of Nakagami for Dataset 5 using MoM & MoLC Estimation.

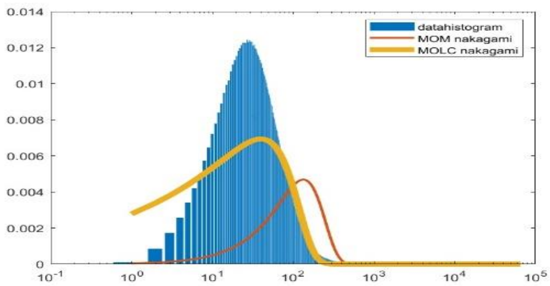

Figure (6): Comparison of Clutter Data Histogram with Estimated Parametric PDFs of Nakagami for Dataset 3 using MoM & MoLC Estimation.

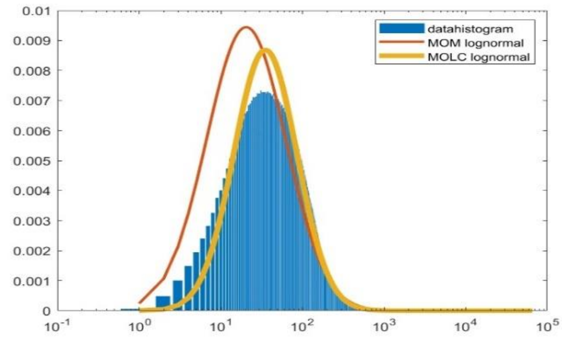

Figure (7): Comparison of Clutter Data Histogram with Estimated Parametric PDFs of Log-Normal for Dataset 5 using MoM & MoLC Estimation.

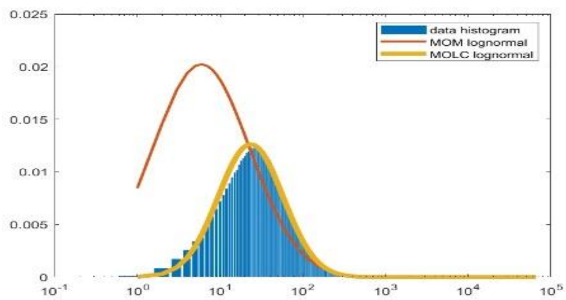

Figure (8): Comparison of Clutter Data Histogram with Estimated Parametric PDFs of Log-Normal for Dataset 3 using MoM & MoLC Estimation.

From the above Figures it is evident that by MoLC strategy Log Normal distribution is giving better goodness-of-fit when compared with MoM strategy. As it exhibits the heterogenous statistics so it is fitting better to given data histogram.

5. CONCLUDING REMARKS

In this paper, various parametric distributions such as Rayleigh, Weibull, Nakagami, Log-Normal, Inverse Gaussian are presented for SAR ground clutter modelling. To make use of the aforementioned parametric distributions in clutter modelling, estimates for the associated parameters are formulated using MOM and MOLC estimation strategies. Finally, qualitative assessment on the above mentioned parametric models is done on real SAR clutter data by comparing clutter data histogram data with the estimated pdf. Experimental results illustrates the effectiveness of MOLC estimation over the MOM estimation for Rayleigh, Nakagami and Lognormal distributions. Furthermore, Lognormal distribution is found to achieve superior "Goodness-of-fit" compared to the other models. (Nakagami, Rayleigh, Inverse Gaussian)

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