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Mathematical Model for Modulation Detection in Adaptive Modulation System

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ABSTRACT

Modulation detection is the one the main process in Adaptive Modulation Systems. In this paper, propose the seven parameters to identify the best modulation. Modulation selection based on Amplitude, Phase, Frequency and Environment. The Seven Parameters are absEnv (Abstract environment), absPhase, rEnv (Environment), absEnv2 (Environment 2), absFreq, absFreq2, absPhase2. These modulation selections improve the Quality of Services and avoid the Multipath fading, Delay in Transmission/Receiving, Bandwidth limitation.
Keywords: Adaptive Modulation, QOS, Multipath Fading, Delay

I. INTRODUCTION

The mathematic distribution is related to the logistic distribution in an identical fashion to how the log-normal and normal distributions are related with each other. It is related to work towards Environment, Phase and frequency. A logarithmic transformation on the logistic distribution generates the log-logistic distribution. The probability density function (pdf) of the log-logistic distribution is f (x | α, β). where α > 0 is the scale parameter, and is the median of this distribution; β > 0 is the shape parameter, which controls the shape of the distribution observe that this distribution has radically different shapes, as the distribution can be strictly decreasing, right-skewed, or unimodal. As β increases this distribution becomes more symmetric. Because of its flexible shapes, the log-logistic distribution has been illustrated to provide useful fits to data from many different fields, including engineering, economics, hydrology, and survival analysis. For instance, adopted this distribution in modeling economic data. Superior performance on fitting precipitation data from various Canadian regions. [3] applied this distribution to maximum annual stream flow data. For further topics related to the log-logistic distribution.

The estimating the unknown parameters of the log-logistic distribution. It is well-known the maximum likelihood method is a common choice to estimate the unknown parameters. This is due to its various attractive properties, such as being asymptotically consistent, unbiased, and normal as the sample tends to infinity. However, these attractive properties may not be valid when the sample size of the data is small or moderate, as is encountered in many practical applications. For instance, the maximum likelihood estimators (MLEs) may be severely biased to a certain order for a small sample size among others. It deserves mentioning that [1] recently considered Bayesian estimation of the log-logistic distribution using objective priors. They showed the performances of the Bayesian estimators and the

MLEs are quite similar with the various sample sizes, indicating the bias of the Bayesian estimators for small and moderate sample sizes. This motivates a study for obtaining unbiased or nearly unbiased estimators of the unknown parameters for the log-logistic distribution. First consider a certain 'corrective' approach developed in part by [7], which can correct the bias to the second order of magnitude. The main idea of this 'corrective' approach is to adjust the bias by subtracting it from the original MLEs, and so the obtained estimators are often referred to as bias-corrected MLEs. It is bias-corrected MLEs of the log-logistic distribution not only have explicit expressions in terms of a convenient matrix notation, but also simultaneously reduce the biases and the root mean square errors (RMSEs) of the parameters. Then consider Efron's bootstrap resampling method [8] which can also reduce the bias to the second order. However, this estimator may accomplish this with an expense of increased variance. As a comparison, we also consider the generalized moments (GM) method, a method commonly used in Hydrology. Monte Carlo simulation studies and real-data applications are provided to compare the performances of the various estimators under consideration. Numerical evidence shows that the proposed bias-corrected MLEs should be recommended for use in practical applications, especially when the sample size is small or moderate.

II. ESTIMATION METHODS

Automatic modulation detection extracts seven parameters (Features based on amplitude, frequency and phase) for identification of different modulation techniques, namely: ASK, FSK, PSK, QAM16 and QAM64. The thresholds of different parameters have been calculated from the classification during training in real time situation. The parameters are carefully chosen based on signal statistics. The parameters selected area The methods are based on the environment, Phase and frequency equations. This equation gives the best modulation identification in real time environments. Maximum Likelihood Estimation Suppose that we have n observations from the log-logistic distribution, denoted by X1 , · · · , Xn . The log-likelihood function of α and β can be written as

$$\log L = n\log(\beta) - n\beta\log(\alpha) + (\beta-1)\sum_{i=1}^{n}\log(X_i) - 2\sum_{i=1}^{n}\log\left[1+\left(\frac{X_i}{\alpha}\right)^{\beta}\right].$$

Differentiating the above function with respect to α and β, we have

$$\frac{\partial \log L}{\partial \alpha} = -\frac{n\beta}{\alpha} + \frac{2\beta}{\alpha}\sum_{i=1}^{n}\left(\frac{X_i}{\alpha}\right)^{\beta}\left[1+\left(\frac{X_i}{\alpha}\right)^{\beta}\right]^{-1},$$

Table 1

Parameter Name	Mathematical Model
AbsEnv	$absEnv = \frac{1}{N}\sum_{i=1}^{N}\lvert A_{cn}[i]\rvert$
AbsPhase	$absPhase = \frac{1}{C}\sum_{A_n[i]>a_t}\lvert\phi_c[i]\rvert$ $\phi_c[i] = \phi[i] - \frac{1}{N}\sum_{j=1}^{N}\phi[j]$
rEnv	$rEnv = \frac{1}{N}\sum_{i=1}^{N}\lvert A[i]-m_a\rvert \Big/ m_a$

absEnv2	$rEnv2 = \frac{1}{N}\sum_{i=1}^{N}\lvert B_{cn}[i] - m_b \rvert$ $B_{cn}[i] = \lvert A_{cn}[i] \rvert$ $m_b = \frac{1}{N}\sum_{i=1}^{N} B_{cn}[i]$
absFreq	$absFreq = \frac{1}{C}\sum_{A_n[i]>a_t}\left\lvert \frac{f[i] - f_a}{Fsym} \right\rvert$ $f_a = \frac{1}{C}\sum_{A_n[i]>a_t} f[i]$
absFreq2	$absFreq2 = \frac{1}{C}\sum_{A_n[i]>a_t}\left\lvert f_2[i] - \frac{1}{C}\sum_{A_n[j]>a_t} f_2[j] \right\rvert$ $f_2[i] = \left\lvert \frac{f[i] - f_a}{Fsym} \right\rvert$
absPhase2	$absPhase2 = \frac{1}{C}\sum_{A_n[i]>a_t}\left\lvert \phi_2[i] - \frac{1}{C}\sum_{A_n[j]>a_t} \phi_2[j] \right\rvert$ $\phi_2[i] = \lvert \phi_c[i] \rvert$

The MLEs can be obtained by setting the above two equations to zero. Due to the lack of explicit solutions to the above Equations, numerically estimate the MLEs using the logic MLE function from the R STAR package, created. It is well- known that the MLEs are biased with small sample sizes and the bias of an estimator may lead to misleading interpretations of phenomena in practical applications. This motivates a study for obtaining unbiased or nearly unbiased estimators to reduce the bias of the MLEs of the log-logistic distribution.

$$\frac{\partial \log L}{\partial \beta} = \frac{n}{\beta} - n\log(\alpha) + \sum_{i=1}^{n}\log(X_i) - 2\sum_{i=1}^{n}\left(\frac{X_i}{\alpha}\right)^{\beta}\log\left(\frac{X_i}{\alpha}\right)\left[1+\left(\frac{X_i}{\alpha}\right)^{\beta}\right]^{-1}$$

The corrective approach Suppose that based on ‘n’ randomly selected observations, we are interested in estimating the ‘p’ unknown parameters, expressed as θ = (θ1, · · · , θp) The joint cumulates of the derivatives of the log-likelihood function L(θ) are given by

$$k_{ij} = \mathbb{E}\left[\frac{\partial^2 L}{\partial\theta_i\partial\theta_j}\right],\quad k_{ijl} = \mathbb{E}\left[\frac{\partial^3 L}{\partial\theta_i\partial\theta_j\partial\theta_l}\right],\quad k_{ij,l} = \mathbb{E}\left[\left(\frac{\partial^2 L}{\partial\theta_i\partial\theta_j}\right)\left(\frac{\partial l}{\partial\theta_l}\right)\right],$$

where i, j, l = 1, 2, · · · , p. The derivatives of the joint cumulates

Here, assume that L(θ) is regular with respect to all derivatives up to the third order, inclusively. Also assume that all expressions in are of order O(n). Then bias can be writer as,

$$\text{Bias}(\hat{\theta}_s) = \sum_{i=1}^{p}\sum_{j=1}^{p}\sum_{l=1}^{p} k^{si}k^{jl}\left[\frac{1}{2}k_{ijl} + k_{ij,l}\right] + O(n^{-2}),\quad s = 1, 2, \cdots, p,$$

Correcting Bias Using the Bootstrap will consider Efron’s bootstrap resampling method, which was introduced by [8]. The main idea of this method is to generate pseudo-samples from the original sample to estimate the bias of the MLEs. Then subtract the estimated bias from the original MLEs to obtain bias-corrected MLEs. Let x = (x1, · · ·, xn)0 be a sample of n randomly selected observations from the random variable X with its cumulative distribution function (cdf) given by F . Let the parameter υ be some function of F , denoted by υ = t(F). Let υˆ be some estimator of υ. We obtain pseudo-samples x∗ = (x∗, · · ·, x∗)0 from the original sample x by resampling observations with replacement. We compute the bootstrap replicates of υˆ from these pseudo samples, denoted by υˆ∗ = s(x∗). Use the empirical cdf (ecdf) of υˆ∗ to estimate the cdf of υˆ, Fυˆ . We obtain a parametric estimate for F by using a consistent estimator for Fυˆ , provided F belongs to a parametric family which is known and has a finite dimension, Fυ . The bias of the estimator υˆ = s(x) can be estimated by using BF (υˆ, υ) = EF [υˆ] − υ(F). Generalized Moments As a comparison, consider another commonly used method, the generalized moments (GM) method, which utilizes moments of the form E[X k] = Mk , where k can take on a diverse range of values, being positive or negative. In general, the values of k can be chosen to suit the user's needs, and the GM method can thus provide differing weights to the data values [4] have implemented the GM method for the log-logistic distribution based on similar techniques as are used for the generalized probability weighted moments (GPWM) method, introduced by [12]. For our problem, we consider probability weighted moments (PWMs) of the form

$$M_{k,h} = \mathbb{E}[X^k F^h] = \int_{-\infty}^{\infty} x^k F^h(x) f(x) dx$$

$$= \alpha^k B\left(h + 1 + \frac{k}{\beta}, 1 - \frac{k}{\beta}\right),$$

III. RESULTS AND DISCUSSION

The conduct Monte Carlo simulations to evaluate the performances of the various considered estimators of the log-logistic distribution. The data were simulated using the rllogis function in the STAR package created.

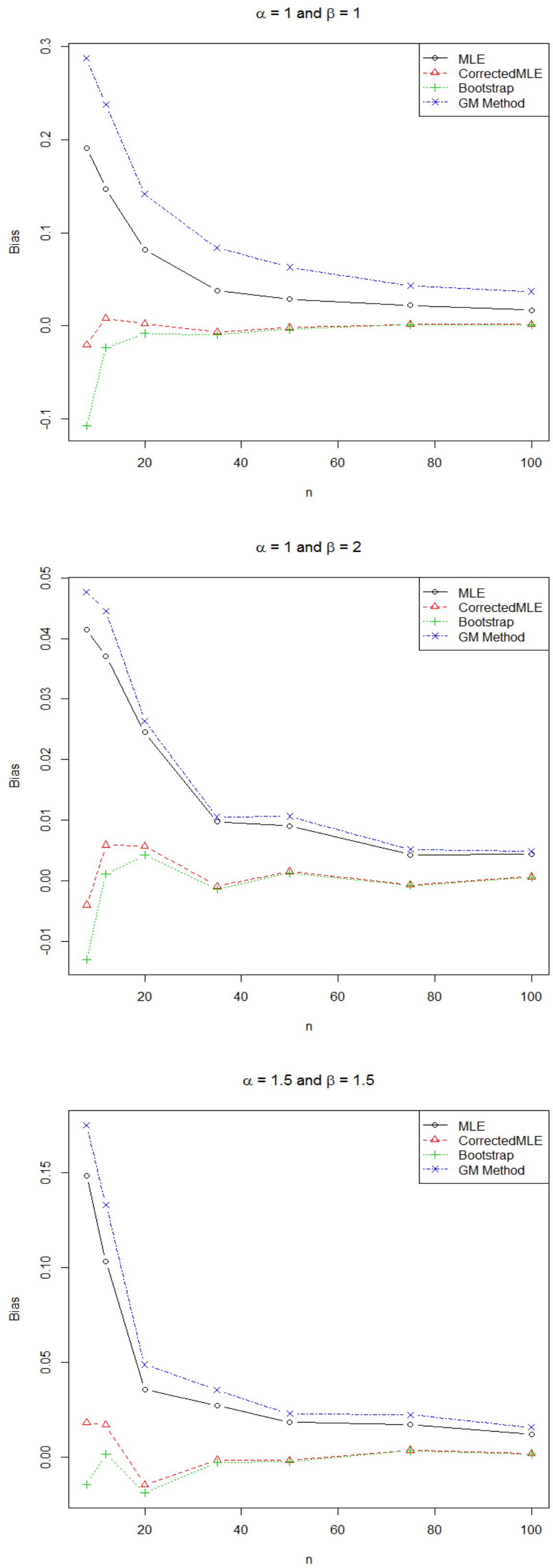

Figure 1. Comparison of the average biases of the four different estimation methods for

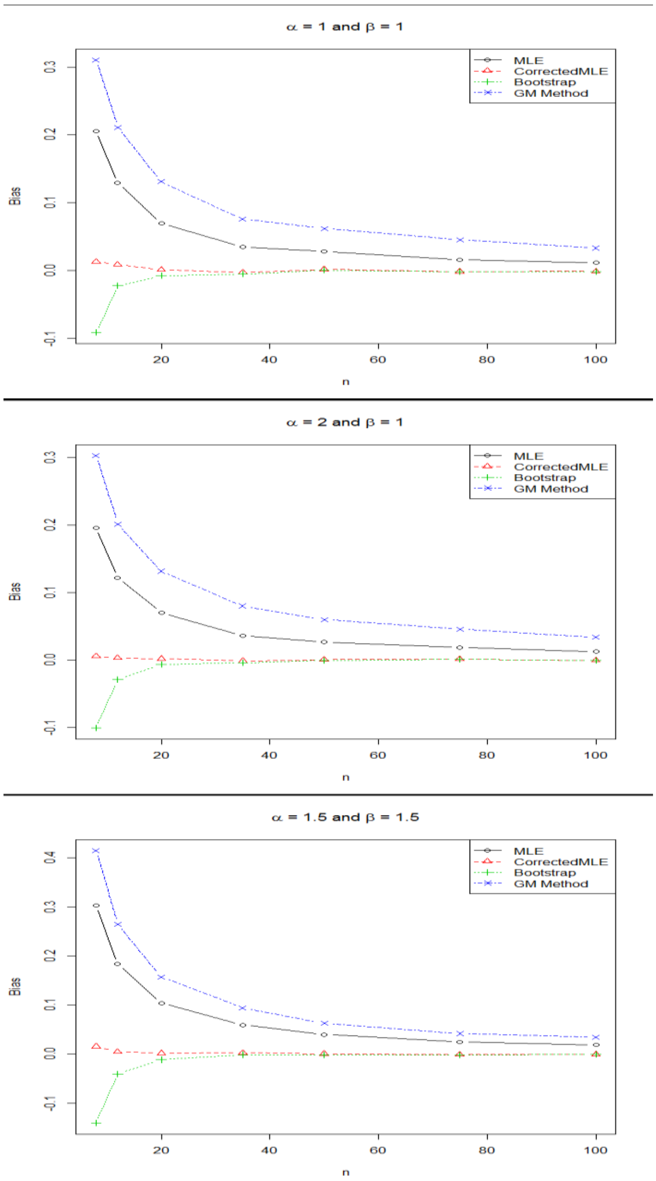

Figure 2. Comparison of the average biases of the four different estimation methods for β.

IV. CONCLUSION

The mathematical analysis can have performed with several parameters. Those parameters are analyzed with several conditions. Result show the best modulation identification based on the value of the α and β. Calculation are based the values represent in the graph MLE, Corrected MLE, Bootstrap and GM method. In future the work focused on the simply the calculations and increase the complexity also improve the security the modulation schemes.

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