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Target Detection using Marine Radar Data and A Maximum Likelihood Estimator

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***Abstract*— Marine radar data has been applied to the detection algorithm and signal preprocessing. Analyzing the statistical output where the signal to clutter ratio has been reduced by using the Maximum likelihood estimation (MLE) algorithm. Some other estimation methods have been applied to the marine radar row data.**

Keywords—Marine Radar; Likelihood; DSP

I. INTRODUCTION

An X-band radar Marine radar is a reliable and durable kind of radar. It is the over-shelf radar at a low cost. Marine radar is a high-power radar with variable pulse width. These types of radars contain magnetron to generate a sequence of high-power pulses. These pulses are random phases, which constrain the radar to generate a high-resolution image. The whole coherent process is describing in detail in [1].

Phases unwrap method (coarse to fine or C2F) proposed in [2] – [6] which transform the shorter baseline data to longest baseline data. The advantage of C2F methods is to sustain the signal information keeping the longest baseline unwrapped phase, and the other baseline information will be ignored.

The Maximum-likelihood [7] – [10] method computes the phase of the marine radar data, which is a single look complex (SLC) based on the model. By computing the phase, the noise and reliability level will be improved from the radar data. Weighted least squares [11] – [16] and least squares and other methods are helpful to compute the unwrapped phase.

The main purpose of this article is to improve the radar data by reducing the noise level using the Maximum-likelihood method. Real radar data has been processed using MATLAB in a high-performance computer.

II. MEASUREMENT SETUP

The rotating antenna has been replaced by a fixed antenna at the top of the radar. The antenna pointed to the target, which is one steel rod. The target in the turntable rotating 360 degrees. Each rotates the radar sends a transmitter signal and receives it back. The received signal will be down-converting using an RF component. The RF components are connected to a high-performance computer to process the data and record it. The data needs a high-capacity storage system. The radar system parameter is showing in table 1.

TABLE 1. MARINE RADAR SYSTEM PARAMETER

Marine Radar Parameters	
Parameters	***Values***
Opereating Frequency	9.14 GHz
PRF	3000 Hz
Bandwidth	50 KHz
Dutiy Cycle	12%
CPI	9.12 s
Transmitter Power	25 kW

III. SIGNAL PREPROCESSING

After receiving the signal by the monostatic marine radar, the signal down-converted from 9.14 GHz to 100 Hz by RF component (Mixer). Then the 3D data matrix is created by MATLAB for further processes. Transmit signal acquired from signal leakage to perform the cross-correlation process between the transmit and receive signal.

Figure 1 depicts the result of the cross-correlation between the transmit and received signal without any filtering process. Then to reduce the clutter from the antenna we averaged the 3D radar data cube.

A low pass filter is applied to each signal to reduce the high-frequency component from the signal. The characteristic of the low pass filter is the cut-off frequency at 100 Hz. So, it will pass what is below 100 Hz and block what is above 100 Hz.

Before storing the data, the data has been tested using Signatech analog-to-digital converter (ADC) and then the output of the ADC which is a digital signal is the input of a high-performance Keysight digital oscilloscope. the connection between the ADC and the oscilloscope was a long highly sensitive coaxial cable. So, between each coaxial cable, we add an amplifier to reduce or eliminate the signal losses or distortion.

IV. DETECTION USING (MLE) ALGORITHM

The Marine radar data has been tested in two situations:

First: the data acquired for noise and clutter only and the absence of the target.
Second: the data acquired the target, noise, and clutter.

The MLE algorithm is to estimate the content of the noise covariance and mean clutter for both situations as seen in figures 14, 15, and 16. We used the first situation, in which the target is not present, as reference data see figure 4.

V. STATISTICAL ANALYSIS OF THE LOG-MLE DECISION VARIABLE PROPERTIES

The analysis of the real marine radar data demonstrates that the probability density function (pdf) is aligned with the variable of the decision history see figure 2.

While a number of the trial goes to infinite, the histogram looks like Gaussian and the curve is going to be smoother, and maximum likelihood estimate converge to the linear line. The estimate converges in probability-variance is inversely proportional to N. The Max-Likelihood Estimate is consistent as depicted in figures 9, 10, and 11.

It can be seen from figure 13, variance is inversely proportional to N, where N is the sample number, and the Variance of the estimate is decreasing when N is increased. The mean of radar data can be seen in figures 7, 8, and 12.

Figures 3and 5 shows the estimated value for A and B is very close to the real value of A and B. They are unbiased. There is a gap Maximum likelihood estimate and Cramer Rao Bound (CRB). The variance of an unbiased estimate is greater than the maximum likelihood estimate.

The CRB of the estimate of the variance corresponding to the probability density function for a sample of N independent identically distributed normal random variables.

The log-likelihood function associated with the MLE for the variance MLE is corresponding to the probability density function for a sample of N independent identically distributed normal random variables. MLE parameter estimation for the slope can be applied using vector parameter estimation and the Fisher information matrix.

CRB for the variance associated with the maximum-likelihood estimated by using a noise variance of 100. Figure 6 shows the performance for various values of N from 2 to 200 and the results for each as a function of N. MLE of the parameters turn out to be the same as the least square solution (assuming the errors are Gaussian). Under Gaussian distribution assumption for the noise and the clutter could be driven theoretically when N is a small number.

Then after applying the theoretical part for the Gaussian assumption with different thresholds and different false alarm rates to the experimental data, the target detection can be seen in our data as portrayed in Figure 17.

VI. CONCLUSION

The maximum-likelihood algorithm is used to improve the detection of the target. There are two situations of acquiring the radar data in this experiment. The purpose of these situations is to compute the mean clutter and the noise covariance. The probability of detection was computed to check the radar receiver operating characteristics (ROC).

The analysis of the pdf for the radar data describes that there is a huge difference in the histograms. The histograms spikes in the plot assumed to be the signal of the target is present in the examination history.

The result shows the difference between the maximum likelihood estimate and Cramer Rao Bound. There is improving in the results as we can see it in the figures of the real marine radar data.

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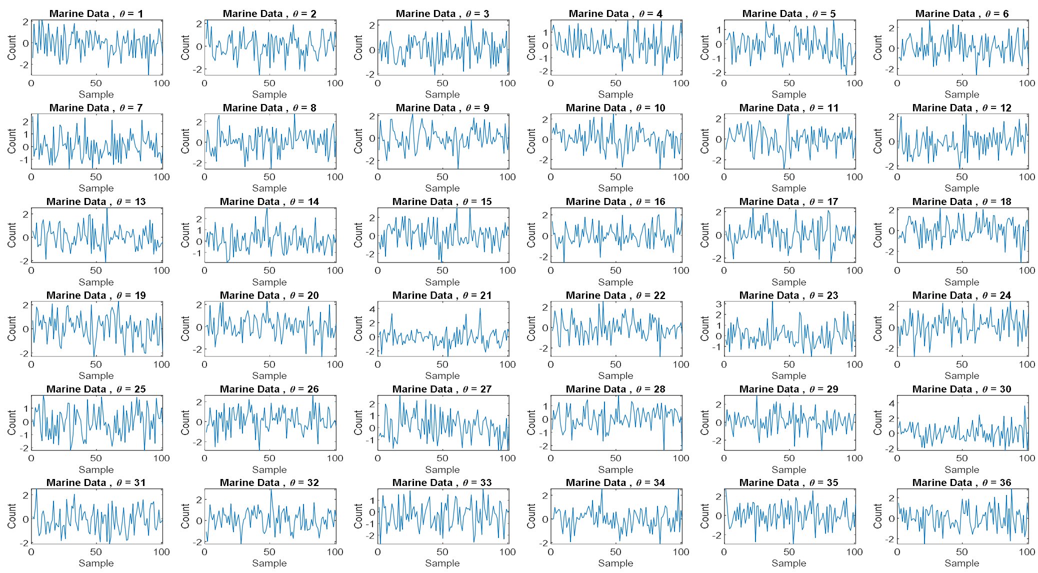

Fig. 1. *Cross-Correlation Result before the filtering*

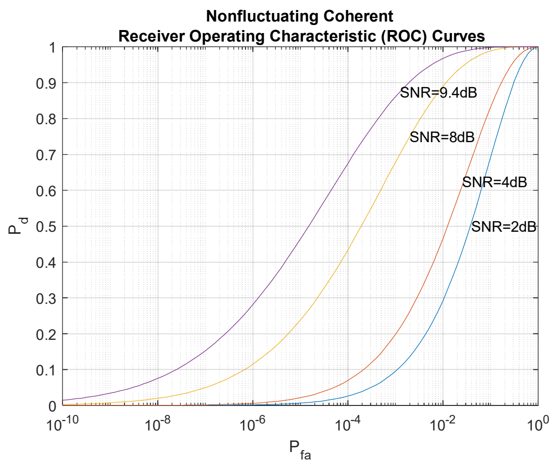

Fig. 2. *PDF of the radra data.*

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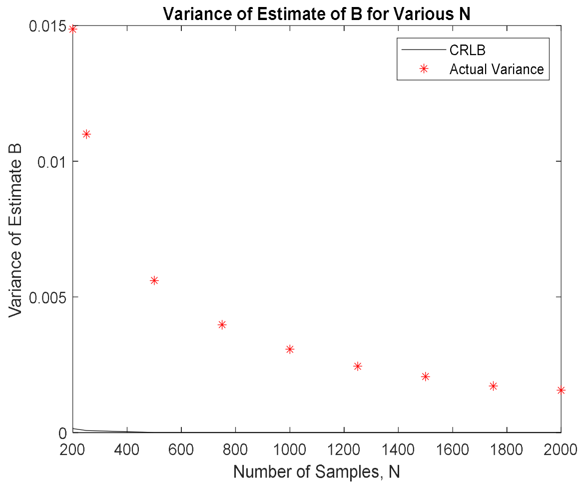

Fig. 3. The *variance of estimate B for various N*

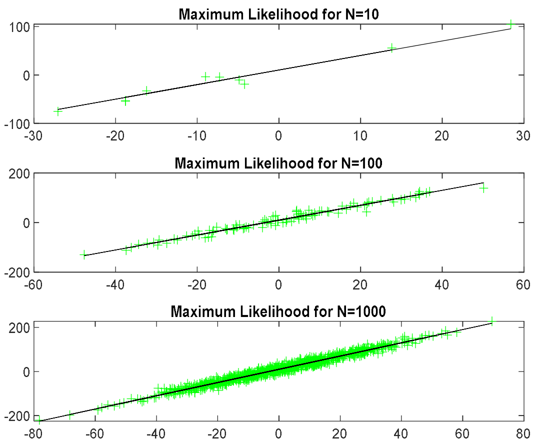

Fig. 4. *Maximum Likelihood of the data*.

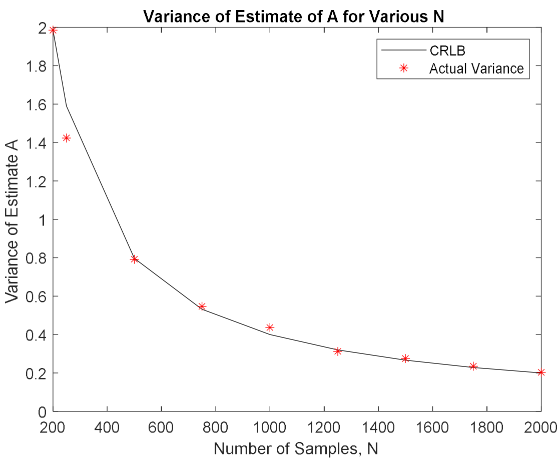

Fig. 5. *The variance of estimate A for various N*

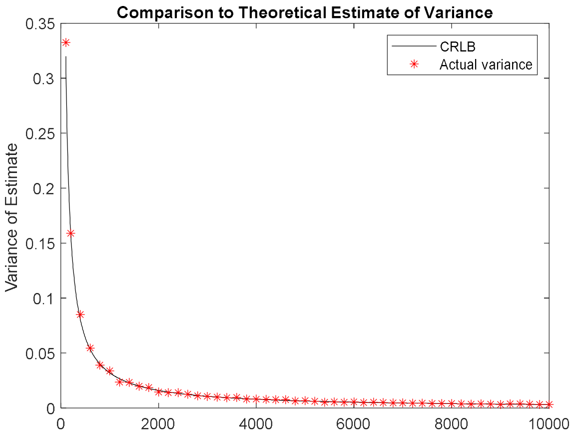

Fig. 6. *Comparison to a theoretical estimate of variance.*

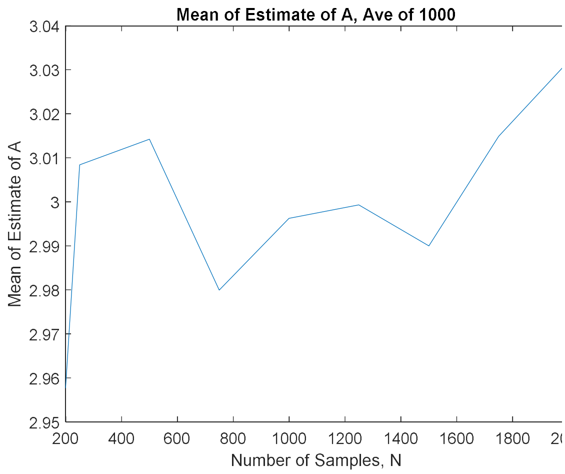

Fig. 7. *Mean of estimate A for various N*

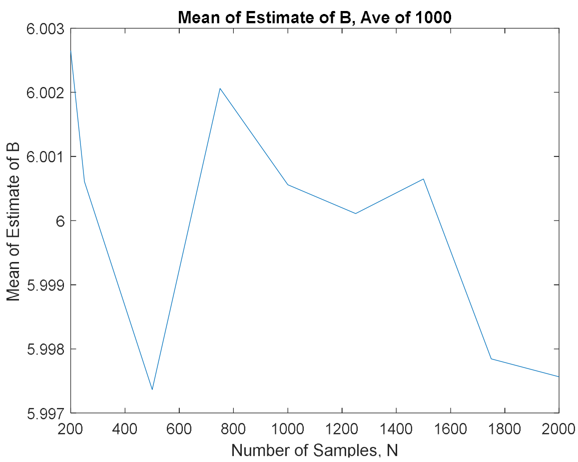

Fig. 8. Mean of estimate B for various N

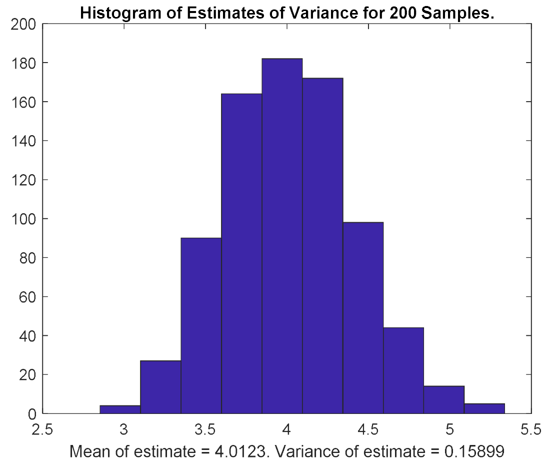

Fig. 9. Histogram of estimates of variance for 200 Samples

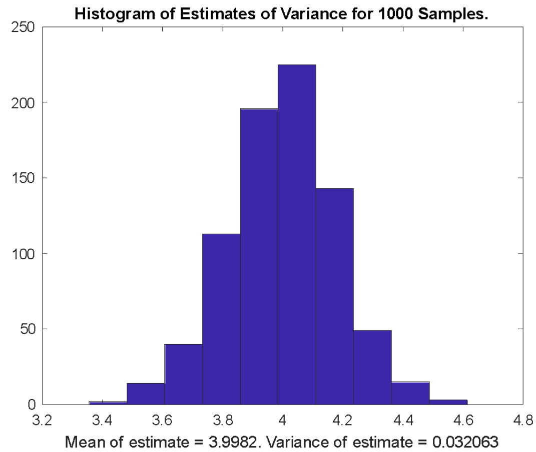

Fig. 10. Histogram of estimates of variance for 1000 Samples

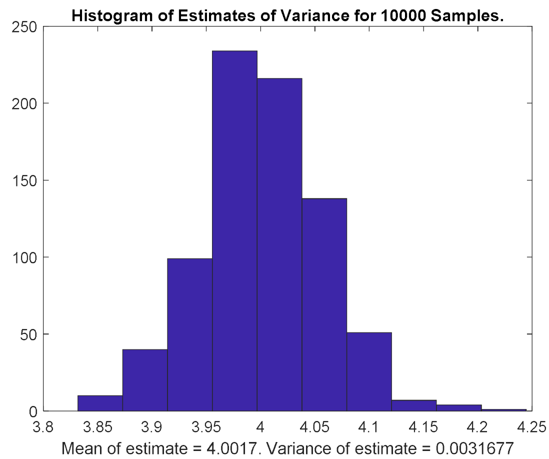

Fig. 11. Histogram of estimates of variance for 10000 Samples.

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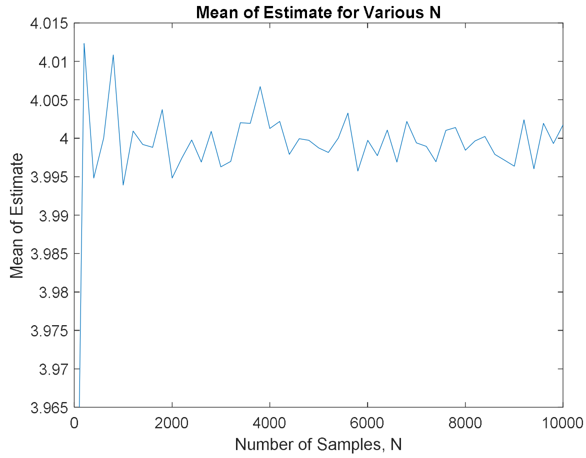

Fig. 12. Mean of estimate various for N

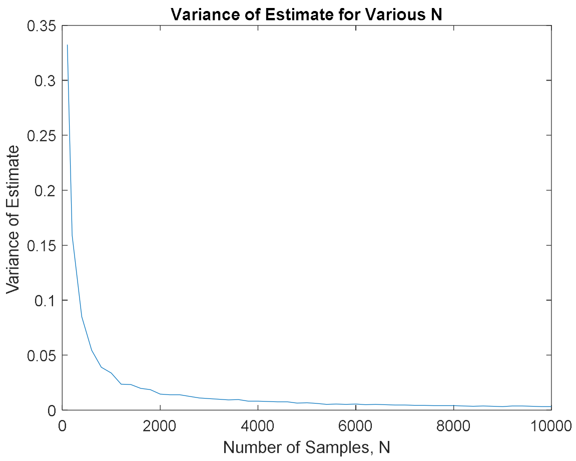

Fig. 13. The variance of estimate for various N

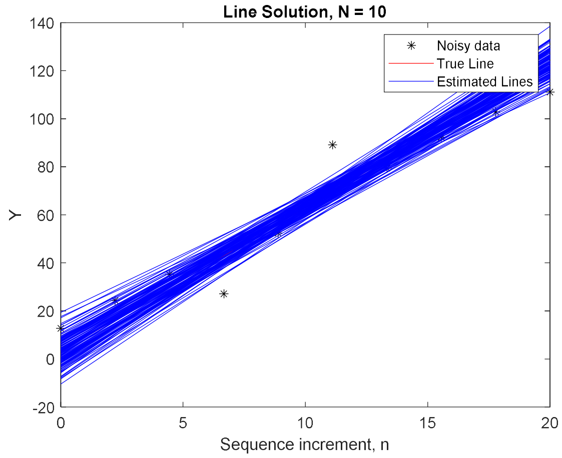

Fig. 14. Line Solution, N=10

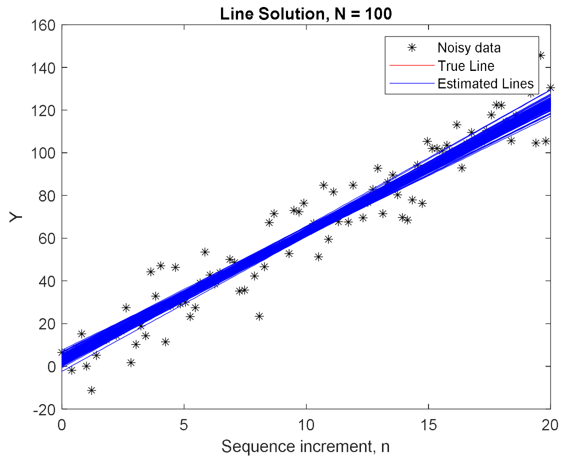

Fig. 15. Line solution for, N=100.

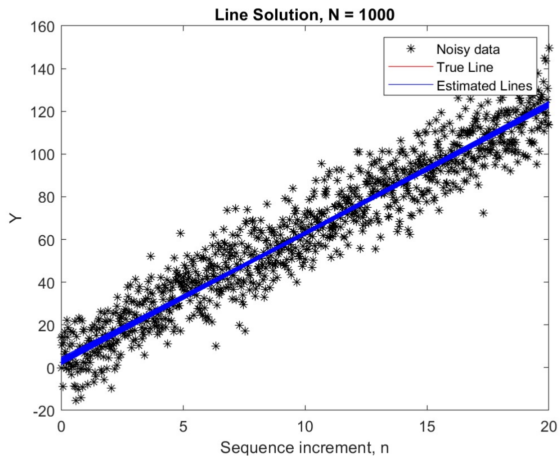

Fig. 16. Line solution for, N=1000.

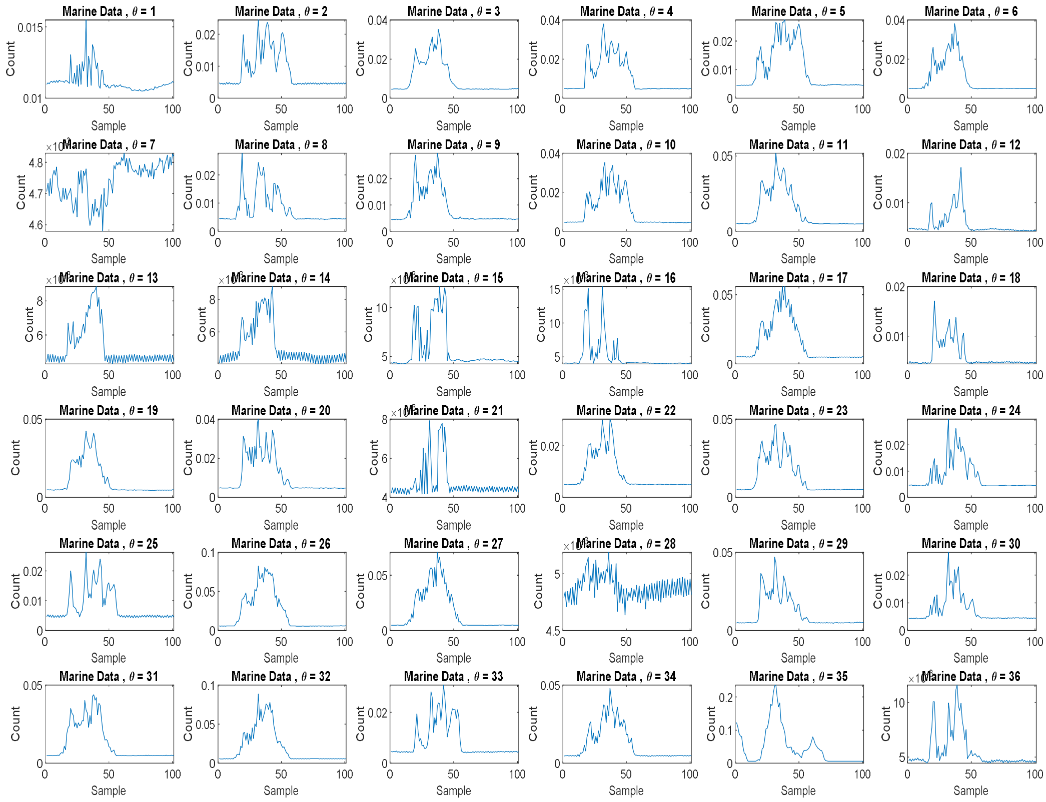

Fig. 17. Cross-correlation after applying the Maximum Likelihood algorithm.