

# Noise Pattern Recognition in Oceanic Environment Using Statistical Characterization of Oceanic Noise in Deep Sea

## A Computational Design Approach

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**Abstract** – Seemingly ocean is silent but this is not so true. Ocean is always filled with a circumstantially interfering noise known as ambient noise produced by turbulence, heat, wind and some natural phenomenon and other activities. This ambient noise put considerable intrusions in underwater acoustic communication which is so crucial for Oceanographic Monitoring. There exist numerous undersea applications under the umbrella of Oceanographic Monitoring like climate change detection, offshore explorations, oceanographic data acquisition, pollution monitoring, disaster prevention, seismic monitoring etc. In recent years, on different widespread geographical sea regions, this ambient noise has been observed for showing the varying shapes of Gaussian distribution. In order to design and deploy any undersea application, it is of prime importance to explore the variations in the shape of statistical distribution of background underwater ambient noise. This paper has been intended to put forward a computational design approach to compare and find the proximity of experimental/empirical noise pattern with that of hypothesized Gaussian noise pattern using Kolmogorov-Smirnov (KS) test statistic. This computation for the noise pattern recognition is so much conducive to simulate the oceanic environment using the hypothesized / controlling parameters of Gaussian noise pattern in order to design and deploy any undersea application.

### I. INTRODUCTION

In last few years, an escalating interest has been observed in marine environment monitoring. The instruments utilized for the oceanographic monitoring have extended from small-scale underwater wireless sensor networks (UWSN) to highly multifaceted and complex surveillance systems [10][11]. There exist numerous undersea applications under the umbrella of Oceanographic Monitoring like climate change detection, offshore explorations, oceanographic data acquisition, pollution monitoring, disaster prevention, seismic monitoring etc.

For the remote examination of the marine environment, acoustic communication is the leading tool to characterize the only mechanism for a rapid transmission of energy over the large distances [9]. But, the undersea background ambient noise offers considerable limitations to acoustic communication channels in the region of the deployment of communication system. The behavior of ambient noise is so different in shallow water as compared with deep water. Based on ambient noise evidences found globally on different geographical regions of the sea, shallow water can be modelled by a lognormal distribution [3][8] and the deep water noise can be modelled by a Gaussian distribution [2][4].

This paper has been envisioned to put forward a computational design approach to compare and find the proximity of experimental / empirical noise pattern with that of hypothesized Gaussian noise pattern using Kolmogorov-Smirnov (KS) test statistic. Noise pattern recognition is so much conducive to simulate the oceanic environment using the hypothesized / controlling parameters of Gaussian noise pattern for the purposes of design and deployment of any undersea application.

### II. STATISTICAL CHARACTERIZATION OF OCEANIC NOISE IN DEEP SEA

Estimating from a vast set of data, the statistical distribution defines the underlying energy probability density function (pdf) in a discrete-time window of some appropriate size. From all specified shallow regions, the pdf pattern follows the lognormal distribution [3][8]. Whereas in case of deep sea regions, the pdf pattern follows the Gaussian distribution [1][2][4].

# A Computational Design for Noise-Pattern Recognition based on Statistical Characterization of Oceanic Noise in Deep Sea

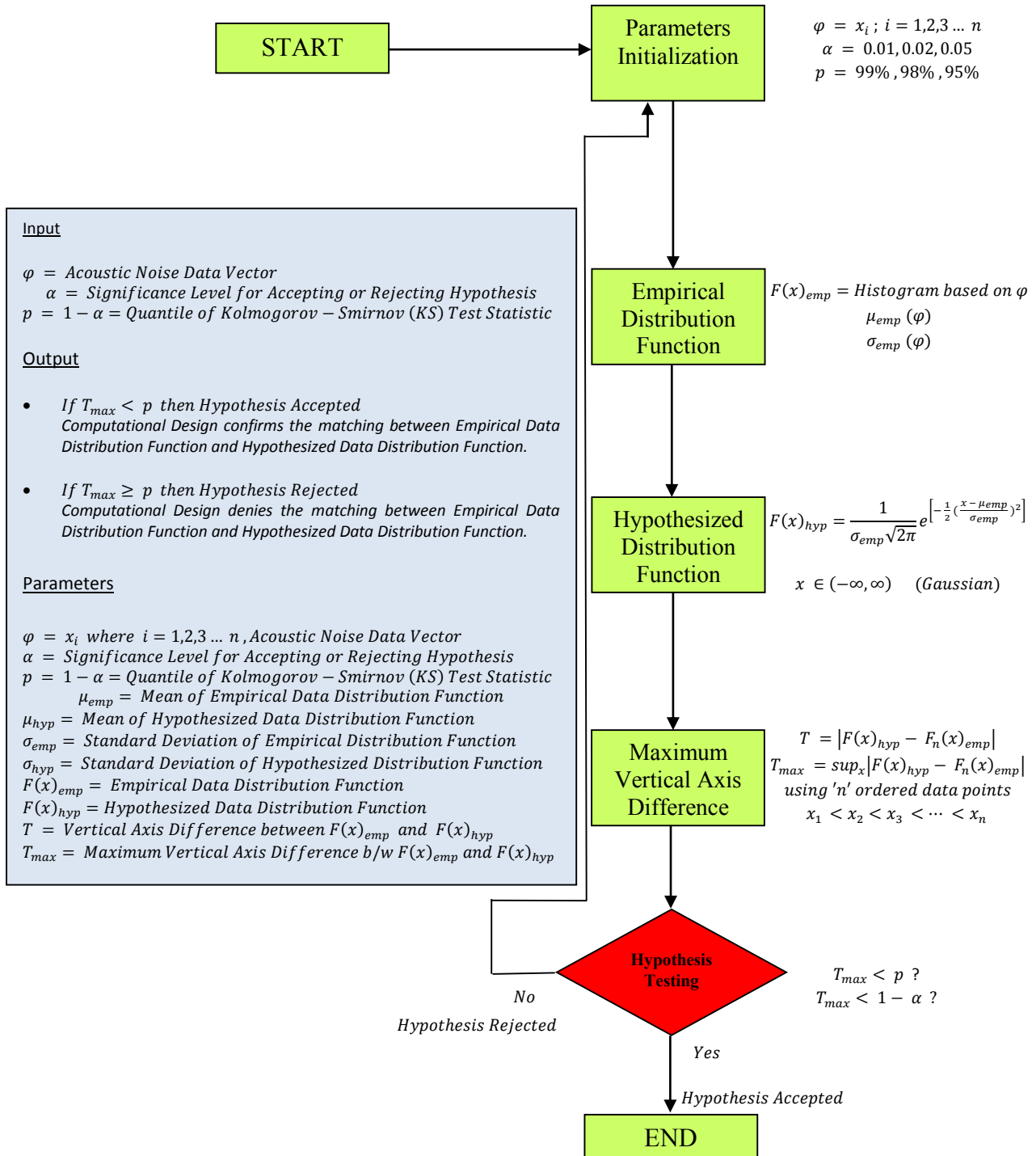


Figure 1: A Computational Design for Noise-Pattern Recognition based on Statistical Characterization of Oceanic Noise in Deep Sea

From a variety of data sources, long-term time series data measurements of underwater ambient noise have been analyzed to get temporal fluctuation statistics. In this way, several sets of long-term time series data measurements of underwater ambient noise (omnidirectional and beam noise data) from towed sensor arrays and fixed sensors were analyzed in order to identify the core and meaningful statistical characterization parameters [1].

One of the most important and noticeable observation from the time series data yields the typical histograms of noise level (measured in dB) which are closely matched with Gaussian Distribution with a specific mean  $\mu$  and standard deviation  $\sigma$ . In such cases, the core properties of noise is truly reflected by selecting only two statistical characterization parameters as mean and standard deviation [1].

### III. KOLMOGOROV-SMIRNOV (KS) TEST STATISTIC

Referencing the Conover (1999), Kolmogorov-Smirnov test statistic (also known as KS test statistic) comes under a supremum class of Empirical Distribution Function (EDF) statistics and this statistics has its root or foundation on the maximum vertical-axis difference between empirical and hypothesized distribution function.

The Kolmogorov-Smirnov one-sample test is a non-parametric alternative to the chi-square goodness-of-fit test. The test compares a cumulative distribution function based on sample observations with some specified population distribution from which the random sample has been drawn. The hypothesis to be tested is that the random sample comes from a completely specified distribution. The Kolmogorov-Smirnov one-sample test is also used for testing hypothesis about discrete distributions. The test is more powerful than the chi-square test.

Given  $n$  ordered data points,  $x_1 < x_2 < x_3 < \dots < x_n$ , the test statistic is proposed by Kolmogorov (1933) and defined by Conover (1999) as [6][7]:

$$T_{max} = \sup_x |F^*(x) - F_n(x)| \quad \dots (1)$$

Here 'sup' refers to supremum which signifies the greatest.  $F^*(x)$  denotes Hypothesized Distribution Function and  $F_n(x)$  is the Empirical Distribution Function whose estimation is based upon the acquired random sample. In KS test statistic of normality,  $F^*(x)$  is modeled as normal distribution with a known mean  $\mu$ , and standard deviation  $\sigma$ .

KS test statistics is intended for testing,

$$H_0 : F(x) = F^*(x) \text{ for all } x (-\infty \text{ to } \infty)$$

(A specified distribution is followed by data).

$$H_a : F(x) \neq F^*(x) \text{ for atleast one value of } x$$

(A specified distribution is not followed by data).

While referring the table of quantiles for the KS test statistics, if  $T$  is exceeded from the  $1 - \alpha$  quantile then we reject the Hypothesis  $H_0$  at the level of significance  $\alpha$ .

### IV. A COMPUTATIONAL DESIGN FOR THE NOISE-PATTERN RECOGNITION USING KOLMOGOROV-SMIRNOV (KS) TEST STATISTIC

In this section, a computational design has been proposed for the noise-pattern recognition based on the statistical characterization of oceanic noise in the deep sea. This design acquires the acoustical noise data or data samples for a specified time  $t$  and allocates it in a variable  $\varphi$  and assumes a hypothesis with a specified level of significance  $\alpha$ . It then extracts the  $F(x)_{emp}$  EDF (Empirical Distribution Function) along with its mean  $\mu_{emp}(\varphi)$  and standard deviation  $\sigma_{emp}(\varphi)$  from the data allocated in variable  $\varphi$  as shown in fig: 1. Computational design utilizes the  $\mu_{emp}(\varphi)$  and  $\sigma_{emp}(\varphi)$  to create a hypothesized PDF (Probability Density Function)  $F(x)_{hyp}$  which is Gaussian pattern for the deep sea as mathematically defined below:

$$F(x)_{hyp} = \frac{1}{\sigma_{emp}\sqrt{2\pi}} e^{\left[-\frac{1}{2}\left(\frac{x-\mu_{emp}}{\sigma_{emp}}\right)^2\right]} \quad \dots (2)$$

$x \in (-\infty, \infty)$  (Gaussian)

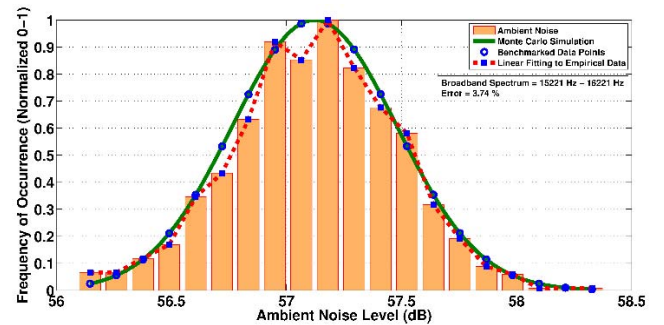


Figure 2: Comparison of Experimental / Empirical Noise Pattern and Hypothesized Gaussian Noise Pattern

Having  $n$  ordered data points,  $x_1 < x_2 < x_3 < \dots < x_n$ , the computational design calculates the maximum vertical axis difference between  $F(x)_{hyp}$  and  $F(x)_{emp}$  as given

$$T_{max} = \sup_x |F(x)_{hyp} - F_n(x)_{emp}| \quad \dots (3)$$

The computational design compares  $T_{max}$  with  $1 - \alpha$ . If  $T_{max}$  is exceeded from  $1 - \alpha$  quantile as shown in the quantile table for KS test statistics, then it rejects the hypothesis regarding a hypothesized Probability Density Function (PDF). Otherwise, it accepts the hypothesis and indicates or recognizes that the statistical pattern of data values allocated in variable  $\varphi$  belong to one of the possible pattern found in the deep sea.

## V. RESULTS

For the testing and verification of the results obtained by the proposed computational design, we referenced the time domain maps or statistics of acoustic noise (dB) from a detailed version of referenced paper mentioned at [1]. Occurrence or Frequency of data values have been mapped on the scale of 0 to 1. Some different empirical data distributions have been chosen based on their different mean and standard deviation which give them slightly a unique shape or pattern as depicted in figure. 3 to figure. 5.

Utilizing mean and standard deviation of empirical data distribution, we hypothesized the corresponding Gaussian data curve. The comparison of empirical data distribution against its corresponding Gaussian data curve was performed by using KS test statistic. In all cases, empirical data distribution is closely found to be matched with the corresponding hypothesized Gaussian data curve. These results clearly indicate that the proposed computational design is fully capable of recognizing a diversity of noise patterns found in the deep sea.

## VI. SIGNIFICANCE AND IMPLICATION

Dynamic sampling acquired in aquatic environment is one of the most important tasks of the aquatic surveying and undersea exploration. Such sort of surveying and exploration is so much crucially important and is often needed by a diverse range of applications [12]. One of the most recent application is the deployment of Wireless Sensor Networks in aquatic environment. Underwater Wireless Sensor Networks (UWSN) use acoustic communication channels which spatiotemporally face considerable impediments in smooth communication due to the involvement of background ambient noise. In this paper, the proposed computational design performs noise pattern recognition which is so helpful for simulation scenario in designing and pre-deployment phase of WSN. It also opens avenue to suggest such a suitable aquatic regions which offer minimum ambient noise hindrances in acoustic communication.

## VII. CONCLUSION

Ubiquitous observational evidences of noise taken at different widespread geographical regions of the deep sea have been found to follow the Gaussian noise pattern. In this paper, a computational design has been proposed and tested to compare the empirical noise data pattern with that of hypothesized Gaussian noise data pattern based on Kolmogorov-Smirnov (KS) test statistic. The verification of this comparison is in agreement. This computational design recognizes the noise pattern keeping the Gaussian noise pattern in consideration. Additionally, it analyzes the changeability in the pattern of background ambient noise which is so conducive to simulate the oceanic environment for the oceanographic monitoring.

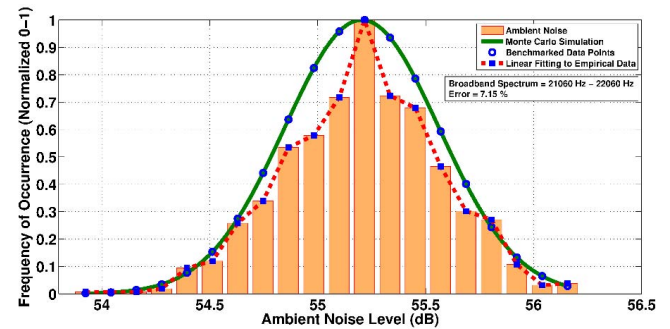


Figure 3: Data Agreement of Experimental / Empirical Noise Pattern and Hypothesized Gaussian Noise Pattern with 7.15 % Error.

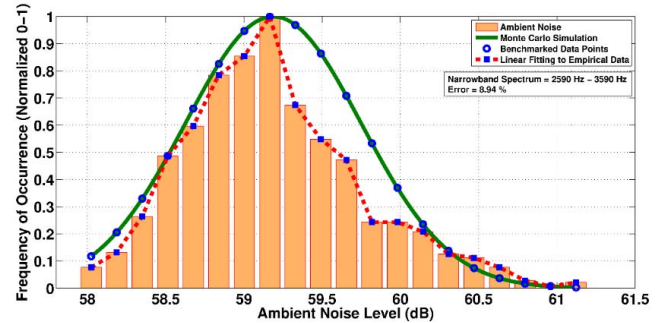


Figure 4: Data Agreement of Experimental / Empirical Noise Pattern and Hypothesized Gaussian Noise Pattern with 8.94 % Error.

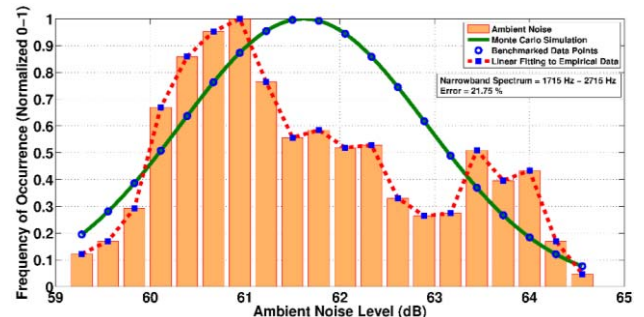


Figure 5: Data Agreement of Experimental / Empirical Noise Pattern and Hypothesized Gaussian Noise Pattern with 21.75 % Error.

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