A Non Parametric Estimation Based Underwater Target Classifier

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Abstract

Underwater noise sources constitute a prominent class of input signal in most underwater signal processing systems. The problem of identification of noise sources in the ocean is of great importance because of its numerous practical applications. In this paper, a methodology is presented for the detection and identification of underwater targets and noise sources based on non parametric indicators. The proposed system utilizes Cepstral coefficient analysis and the Kruskal-Wallis H statistic along with other statistical indicators like F-test statistic for the effective detection and classification of noise sources in the ocean. Simulation results for typical underwater noise data and the set of identified underwater targets are also presented in this paper.

Keywords: Cepstral Coefficients, Linear Prediction Coefficients, Forward Backward Algorithm, Kruskal-Wallis H Statistic, F-test Statistic, Median, Sum of Ranks.

1. INTRODUCTION

Underwater acoustic propagation depends on a variety of factors associated with the channel in addition to the characteristic properties of the generating source. Studies on noise data waveforms generated by man made underwater targets and marine species are significant as they will unveil the general characteristics of the noise generating mechanisms. The composite ambient noise containing the noise waveforms from the targets, received by the hydrophone array systems are processed for extracting the target specific features. Though quite a large number of techniques have been evolved for the extraction of source specific features for the task of identification and classification, none of them are capable of providing the complete set of functional clues. Of these, many of the techniques are complex and some of them lead to ambiguities in the decision making process. Since classification of noise sources using certain traditional techniques yields low accuracy rates, many improved approaches based on non-parametric and parametric modeling have been mentioned in open literature [1]. Some of the modern approaches for the extraction of spectral profiles give more emphasis to spectral resolutions and increased signal detection capabilities while others rely on the extraction and utilization of acceptable features of underwater signal sources .The proper identification and classification of underwater man-made and biological noise sources can utilize the cepstral feature extraction and non parametric statistical approaches which do not rely on any assumption that the data are drawn from a given probability distribution and includes non parametric statistical models, inference and statistical tests. The Kruskal-Wallis H test is a non parametric test and the H statistic can be efficiently employed in different statistical situations[2]. The underwater noise signal is sampled, processed and cepstral features are extracted and hence the sample set of transition probability values of the system model is estimated. The H statistic, F-test statistic, Median value and Sum of Ranks are estimated for the sample sets of various underwater signals, the transition probability values and a reference signal, which were found to be occupying non overlapping value ranges and can be utilized in the system design for the identification of underwater signal sources.

2. PRINCIPLES

Cepstral coefficients are widely used as features for a variety of recognition and classification applications. In a cepstral transformation, the convolution of two signals $x_1[n]$ and $x_2[n]$ becomes equivalent to X_c, which is the sum of the cepstra of the two signals.

$$X_c = \hat{x}_1[n] + \hat{x}_2[n] \tag{1}$$

Defined otherwise, P discrete cepstrum coefficients[3], c_p where $p = 0,\ldots..P-1$ define an amplitude envelope $|H(\omega)|$ equals $\exp(c_0 + 2\sum_p c_p\cos(p\omega))$ with p varying from 1 to P-1.
The Inverse Fourier Transform of the log amplitude gives the cepstral coefficients. The discrete cepstrum coefficients can be described by a set , at frequencies ω_k with amplitudes X_k with k= 1,….P. This can be expressed mathematically:

$$X(\omega) = \sum_{k=1}^{P} (X_k \partial(\omega - \omega_k)) \tag{2}$$

where $\partial(\omega)$ denotes the Dirac delta distribution. The calculation of c_p can be done by minimizing the square difference of $|H(\omega)|$ and $|X(\omega)|$.

Non parametrical analysis provides effective methods for target detection and classification of underwater targets. Such a strategy may also be incorporated into a hierarchical classification framework, where a target is first assigned to a class and later with additional information, it may be identified as a particular target within that class. In order to train a statistical model for each class, many methods can be used, which may consist of several training states. The system can be trained on the target data associated with their respective classes. Statistical non parametric tests can be considered as an alternative for comparisons of data of which the distribution is not Gaussian[4]. The exact distribution of H-statistic in the Kruskal-Wallis test is conventionally fitted to a Chi-squared approximation. In state based models, the sequence of tokens generated by it may give some information about the sequence of states. Even though the states possess different attributes, for many practical applications there will be often some physical significance associated to the set of states and their transition probabilities. The proposed procedure can utilize a codebook to estimate the required parameters. In a codebook, a large number of observational vectors of the training data is clustered into a certain number of observational vector clusters using K- means iterative procedure. Based on this clustered observational vectors, estimates of the parameters are generated during system modulation.

2.1 LPC Analysis

Linear Prediction Coefficients(LPC) Analysis is used to calculate the Cepstral coefficients. LPC is a powerful modeling technique used for signal analysis. LPC encodes a signal by finding a set of weights on earlier signal values that can predict the next signal value. Linear prediction coefficients can be transformed to cepstral coefficients which is a more robust set of parameters. In matrix form,

$$\mathbf{Ra} = \mathbf{r} \tag{3}$$

Where **r** is the autocorrelation vector, **a** is the LPC vector and **R** is the Toeplitz matrix of **r**.
The solution is:

$$\mathbf{a} = \mathbf{R}^{-1}\mathbf{r} \tag{4}$$

2.2 Cepstral Coefficients and Clustering

The p Cepstral coefficients c_m, for m=0,1…p-1 derived from the set of LPC coefficients using the LPC to Cepstral coefficient recursion[5].

K-means is one of the learning algorithms that solve the clustering problem . It is an algorithm to cluster *n* objects based on attributes into *K* partitions, where $K < n$. It attempts to find the centers of natural clusters in the data. It assumes that the object attributes form a vector space. The main idea is to define *K* centroids, one for each cluster. The result it tries to achieve is to minimize the total intra-cluster variance, or, the squared error function [6]

$$V = \sum_{i=1}^{K} (x_j - \mu_i)^2 \tag{5}$$

where there are *K* clusters S_i, $i = 1, 2, \ldots K$, and μ_i is the centroid or mean point of all the points x_j which will form the elements of S_i and considered in the above computation.

2.3 Forward-Backward Algorithm

The Forward-Backward Algorithm is an algorithm for computing the probability of a particular observation sequence. Let the forward probability $\alpha_j(t)$ for some model M with N states be defined as $\alpha_j(t)=P(o_1,\ldots,o_t),x(t)=j|M)$. That is, $\alpha_j(t)$ is the joint probability of observing the first t vectors and being in state j at time t.

This recursion is based on the fact that the probability of being in state *j* at time *t* and having observation o_t can be found by adding the forward probabilities for all possible previous states *i* weighted by the transition probability a_{ij} . Also,

$$\alpha_N(T) = \sum_{i=2}^{N-1} (\alpha_i(T) a_{iN}) \tag{6}$$

and $P(O|M)$ equals $\alpha_N(T)$.

The backward probability $\beta_j(t)$ is defined as:

$$\beta_j(t) = P(o_{t+1},\ldots,o_T \mid x(t) = j, M) \tag{7}$$

The forward probability is a joint probability and the backward probability is a conditional probability. Also, $\alpha_j(t)\ \beta_j(t)= P(O,x(t)=j|M)$. Hence the probability of state occupation becomes $S_j(t)= P(x(t)=j|O,M)$ which in turn equals P(O, x(t)=j|M) ÷P(O|M). Let P(O|M)be denoted by P_o. Then

$$S_j(t) = \frac{1}{P_o} \alpha_j(t) \beta_j(t) \tag{8}$$

2.4 H-Statistic

Statistical indicators measure the significance of the difference between the performance of different systems and can be used to grade the systems if the performance difference is significant. Kruskal-wallis H-test is a non parametric test[7] of hypothesis whose test statistic can be effectively utilized in underwater signal classification. The H-statistic is given by:

$$H = \frac{12}{N(N+1)} \sum_{j=1}^{G} \frac{R_j^2}{N_j} - 3(N+1) \tag{9}$$

where G is the total number of samples, N_j , $j= 1,\dots G$, is the size of sample j , R_j , $j = 1,\dots G,$ is the rank of the sample j . Let (R_j^2/N_j) of the different sample sets be termed as C which forms an intermediate parameter in H estimation and

$$N = \sum_{j=1}^{G} N_j \quad (10)$$

2.5 F-Statistic

A F-test is a statistical test which is usually applied when comparing statistical models and is used to assess if the expected values of a quantitative variable within several pre-defined groups have difference among each other. The test statistic in an F-test is the ratio of two scaled sums of squares following Chi-squared distribution, indicating different sources of variability. The F-test statistic is given as the ratio of 'Between-Group variability'(BG) to 'Within-Group variability'(WG). The two terms can be defined mathematically as follows:

$$BG = \sum_i n_i (y_{iav} - Y_{av}) / (N_g - 1) \quad (11)$$

where y_{iav} denotes the sample mean in the i^{th} sample group, n_i is the number of observations in the i^{th} group and Y_{av} denotes the overall mean of the data. Also

$$WG = \sum_{ij} (Y_{ij} - y_{iav})^2 / (N_0 - N_g) \quad (12)$$

where Y_{ij} is the j^{th} observation in the i^{th} out of N_g groups and N_0 is the overall sample size.

2.6 Median (M) and Sum of Ranks (R)

The statistical estimate Median (M) is an important characteristic of signals from any underwater source. It is a measure of the skewness of the sampled signal distribution and also an indicator of the amplitude variations in the sample set of the particular signal. The Median of the signal can be estimated as that amplitude value in the sample set from which there occurs equal numbers of positive and negative amplitude deviations. The M parameter, along with H and F values helps in the classification of a particular signal. The other statistical estimate used along side H, F and M parameters in the proposed system is the Sum of Ranks (R). It gives a measure of the relative gradation of signal amplitude variations of the signal, taking into consideration, the sample location indices in the sample set of the underwater signal. The R parameter can be estimated for a sample set of by reordering the samples in the increasing order of amplitudes and replacing the original samples with their respective ranks, in the distribution. A minimum rank of unity can be assigned to a sample. For equal valued samples, average of the corresponding rank can be assigned. The sum of all the individual sample ranks will give the parameter R, which forms an important property, when utilized along with other parameters of the system. For the underwater signals with closely related H and F parameters, the R parameter can be helpful for identification in association with the M parameter.

3. METHODOLOGY

The methodology consists of various stages and the different steps involved in the extraction of feature vectors are furnished below.

3.1 Cepstral Coefficient Extraction

3.1.1 Sampling and Frame Conversion

The noise data waveforms emanating from the underwater target of interest have been sampled and recorded as a wave file data, which is sampled to be converted to frames of N_s samples, with adjacent frames being separated by m_d samples[5]. Denoting the sampled signal by s[n], the l^{th} frame of data by $x_l[n]$, and there are L frames, then

$$x_l[n] = s[m_d l + n] \quad (13)$$

Where $n = 0, 1, \dots, N_s - 1$, and $l = 0, 1, \dots L-1$.

3.1.2 Windowing

Each individual frame is windowed to minimize the signal discontinuities at the boundaries of each frame. If the window is defined as *w[n]*, then the windowed signal x_w is

$$x_w = x_l[n]w[n] \qquad (14)$$

where $0 < n < N_s-1$.

Hamming window is used as a typical window for the autocorrelation method of LPC.

A frame based analysis of the noise data waveform has been performed to generate the sample vector, which can be used to estimate the statistics needed for target classification. The sampled signal is partitioned into frames of N_s samples, and consecutive frames are spaced m_d samples apart. Each frame is multiplied by a N_s-sample Hamming window, and LP analysis is performed[8]. The Linear Prediction Coefficients are then converted to the required number of Cepstral coefficients, which are weighted by a raised sine window.

3.2 Vector Quantization

The next step in the system is a clustering process which can be used to generate a code book which in turn is utilized in the estimation of transition probability vector. The K-means algorithm has been used to fix the centroids of a cluster model. The extracted cepstral coefficients of the underwater signal source are being utilized as the data in this vector quantization process of unique cluster identification. A matrix is defined, which represents the data which is being clustered, in a concatenation of K clusters, with each row corresponding to a vector. The cluster centroids are generated as a vector with the cluster identity. The sum of square error function is used in the algorithm, and a log of the error values after each iteration can be returned in a variable. The maximum number of iterations can also be specified.

3.3 Transition Probability Vector Generation

A Vector of transition probabilities can be generated from the vector quantized output, for the estimation of the Decision Statistics. The algorithm for the generation of the transition probability vector is as follows:

```
START:
   Segregate the data into Frames.
   Windowing the Frames using Hamming Window.
   Generation of Linear Prediction Coefficients.
   LPC to Cepstral Coefficient conversion.
   Vector Quantization and code book generation.
   Set N_it = maximum iterations

 LABEL 1:
    While (count <= N_it)
   {
      Compute the forward probability αj(t) for all states j at times t.
      Compute the backward probability βj(t).
      If (P(O|M)<= value of previous iteration)
       {
         go to LABEL 2
       }
     Estimate Transition Probability Sj(t).
     count = count + 1.
    }
```

LABEL 2:
Generate a single column vector by concatenating individual columns of the estimated transition probability matrix.
END

3.4 Decision Statistics Estimation

The H and F statistics are estimated as illustrated in Fig 1 with the three sample set consisting of the previously generated transition probability vector, a down sampled version of the original underwater signal and a predefined reference sample vector. A correction for ties can be made by dividing the H-statistic value by a Correction Factor(CF) defined as follows:

$$CF = 1 - \frac{1}{(N^3 - N)} \sum_{i=1}^{g} (t_i^3 - t_i) \quad (15)$$

where g is the number of groupings of different tied ranks, and t_i is the number of tied values within group *i* that are tied at a particular value. This correction usually makes only negligibly small change in the value of test statistic unless there are large numbers of ties. Additional statistical parameters like Median and Sum of Ranks can also be estimated along with, for the underwater signal being processed.

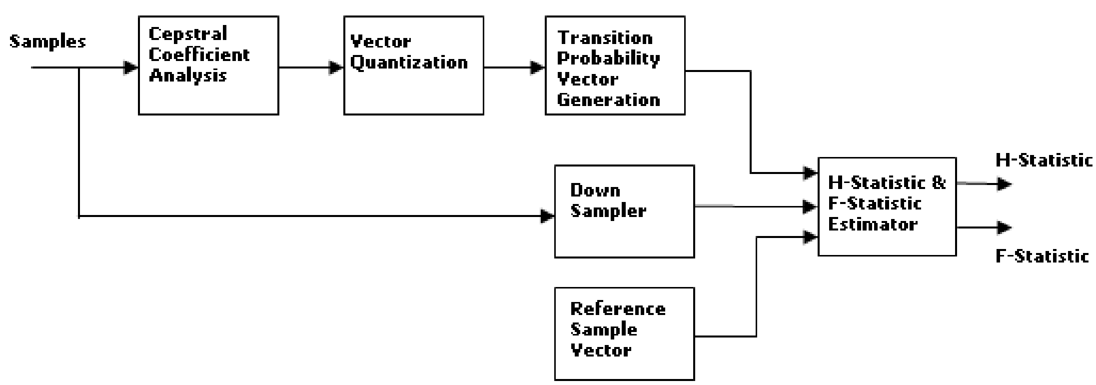


FIGURE 1: Estimation of Decision Statistics

4. IMPLEMENTATION

The sampled underwater noise source is divided into frames of 400 samples (N_s). Consecutive frames are spaced 19 samples apart. Each frame is multiplied by an N_s-sample Hamming window. Because of lower side lobe levels, Hamming window is a good choice for comparatively accurate signal processing systems. Each windowed set of samples is auto correlated to give a set of coefficients. Then linear prediction coefficient analysis is done on the autocorrelation vector to estimate the LP coefficients and using recursion method, linear prediction coefficients are converted to cepstral coefficients. They are then weighted by a raised sine window function. By applying K-means algorithm, K centroids are defined, one for each cluster. Random selection of K vectors is done. K=16 is selected in the algorithm. The next step is to take each vector and associate it to the nearest centroid. At this point, readjusting the centroids is done based on the new assignment. The algorithm minimizes the squared error function mentioned earlier. Thus, vector quantization is carried out and unique clusters are defined for the particular underwater noise waveform.

4.1 Sample Sets Under Consideration

Using Forward-Backward re-estimation algorithm, the transition probabilities for the twenty states of the system model are estimated leading to the generation of the transition probability vector which is considered as the first sample set. A vector of down sampled values of the underwater noise source with a down sampling factor of 0.5 forms the second sample set while a reference sample set of 1000 samples with sample values of 0.5 for the first 500 samples and 0.25 for the next 500 samples as depicted in Fig 2, forms the third sample set.

The Kruskal-Wallis H-statistic is estimated with the correction factor to obtain the Chi-squared statistic approximation. The F-statistic approximation is also estimated for the system. The Median(M) of the underwater signal and Sum of Ranks(R), taking into consideration, the three vectors, of the same underwater signal are also evaluated. The estimated values for the four parameters of different underwater noise sources possess divergent statistical properties which can be utilized in the effective identification and classification of the unknown underwater signal source under consideration.

5. RESULTS AND DISCUSSIONS

The system has been validated using simulation studies and the estimated H-statistic as well as F-statistic approximations, median values(M) and sum of ranks(R) of different underwater signal sources have been tabulated in Table 1.

Underwater signal source	Estimated H-Statistic Approximation value	Estimated F-Statistic Approximation value	Estimated Median value(M)	Estimated Sum of Ranks value(R)
Shors	2090	3465	-0.0025	833927
Toadfish	1798	2322	0.001975	1002781
Beluga	2044	3242	-0.00158	908441
Bagre	2420	5706	0.03316	1445904
Outboard	1951	2791	0.00355	971748
Damsel	2115	3616	0.0012571	827679
Sculpin	1172	933	0.21805	1414338
Atlantic croaker	1987	3023	-0.0004	862176
Spiny	2450	6076	-0.005633	631137
BlueGrunt	2097	3570	0.0003167	860600
Dolphin	2146	3455	-0.00108	863228
01m	1172	940	0.0772	1313128
Barjack	2021	3050	0.00228	892434
Bow1	2168	3939	-0.0049167	782094
Boat	1494	1451	0.0024	1136117
Chord	2160	3783	0.000625	778549
3Blade	1837	2372	-0.004733	988073
Torpedo	2563	9757	-0.007817	540386
Rockhind	2075	3394	0.0013125	864103
Snap1	2117	3632	-0.000483	823856
Scad	1990	2893	0.0006667	869278
Finwhale	2134	3875	-0.000453	793392
Seal1	2051	3187	0.0241	1040226
Garib	1896	2635	-0.049514	969721
Grunt	1955	3259	0.00235	888618
Ocean Wave	2054	3558	-0.006425	844440
Minke	2130	3476	0.0001	823722
Hump	2156	3838	-0.010267	786830
Seatrout	2051	3251	0.01018	934365
Silverperch	2064	3193	0.0031	855612
Cavitate	1877	2559	-0.007275	1004192
Sklaxon	2141	3744	-0.00995	807558
Submarine	1644	1843	-0.040775	1012841
Badgear	2060	3453	-0.000217	852301
Seacat	1731	2580	-0.003825	985634
Searobin	1844	2394	-0.002425	962476

TABLE 1: Underwater signal sources and their estimated values of H-statistic, F-statistic, Median and Sum of Ranks.

The Reference Sample Set of the type depicted in Fig 2, having a statistical variance of 0.0156 has been considered in the proposed technique. Also, the Coefficient of Variation (CV) which is defined as the ratio of the Standard Deviation to modulus of Mean, for this reference sample set is seen to be 0.124.

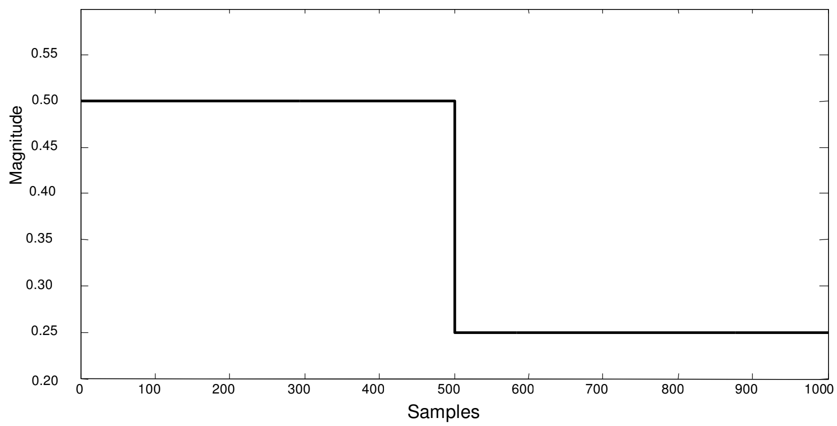
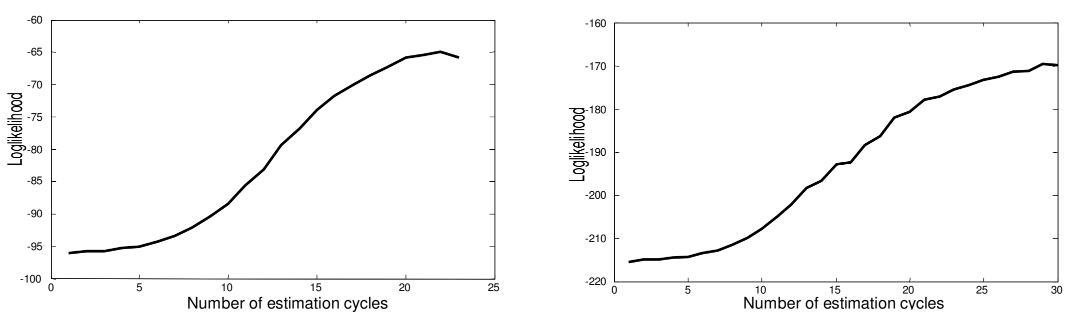


FIGURE 2: Plot of Reference Sample Set values used in the system.

The (H, F, M, R) components form the recognition parameter for a given underwater signal source. The plots of the loglikelihood in transition probability estimation for the underwater noises of Toad Fish and Submarine are depicted in Fig 3 (a) and (b). The unknown underwater signal is processed and the extracted H,F,M,R components are assigned to known underwater signal categories by judiciously matching the component parameters. The signals listed out in Table 1 have been tested with the system, utilizing the (H,F,M,R) components and correct recognition has been obtained except for the Searobin and 3Blade underwater signals. The system possesses a tolerance specification of ±1% for the parameters used in this technique.



(a) (b)

FIGURE 3: Plots of loglikelihood in Transition probability estimation for (a) Toad Fish (b) Submarine.

The proposed system is optimized for the classification of underwater noise sources in the ocean. Non-parametric estimators and the featured statistical indicators possess increased robustness essential for the efficient classification capability of a system. State Transition Probability estimation has been utilized in the design of Hidden Markov Model based speech recognition systems [1][9]. In this underwater target classifying system, the transition probabilities form a significant sample set in the estimation of recognition parameters of a particular signal. The simulated results, using the four components, show high recognition capability of the system for underwater signals. The increased computational complexity of the system is offset by the improved classification efficiency, while upholding the inherent advantages of non-parametric classifiers.

6. CONCLUSIONS

The proposed system makes use of statistical indicators along with non-parametric estimations like the cepstral coefficients for the identification and classification of underwater targets utilizing the target emanations. Using simulation studies, the H-statistic as well as F-statistic approximations along with the Median and Sum of Ranks parameters for different underwater signal sources have been estimated and are utilized for the identification of the unknown noise sources in the ocean. The system can also be augmented with other features and can be effectively used for the identification and classification of noise sources in the ocean, with improved success rates.

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8. REFERENCES

[1] Lawrence R. Rabiner, *"A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition"*, Proceedings of the IEEE, 77(2):257-273, 1989

[2] W. H. Kruskal and W. A. Wallis, "*Use of ranks in one-criterion variance analysis*," Journal of American Statistics Association, 47 : 583-621, Dec.1952

[3] Schwarz and X. Rodet *"Spectral Envelope estimation and representation for sound analysis- synthesis"*, In Proceedings of International Computer Music Conference, ICMC 99, Beijing, 1999

[4] Dirk K. de vries and Yves Chandon, *"On the false positive rate of Statistical equipment comparisons based on the Kruskal-Wallis H-statistice"*, IEEE Transactions on Semi conductor manufacturing, 20(3), 2007

[5] Lawrence Rabiner and Biing-Hwang Juang , "*Fundamentals of Speech Recognition"*, NJ: PTR Prentice Hall, pp. 112-117 (1993)

[6] Donghu Li, Azimi Sadjadi, M. R and Robinson, M, *"Comparison of different Classification Algorithms for underwater target discrimination"*, IEEE Transactions on Neural Networks, 15(1), 2004

[7] M. Hollander & D.A. Wolfe, "*Non parametric Statistical methods"*, New York, Wiley, (1973).

[8] J. R Deller, J. G. Proakis and F. H. L Hansen, *"Discrete time processing of speech signals"*, IEEE Press, p. 71, (2000)

[9] L. R. Rabiner and B. H. Juang, "*An Introduction to Hidden Markov Models"*, IEEE ASSP Magazine, 3(1): pp. 4-16, 1986