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Loss Recomputed-Least Mean Square-Ten Split Feature Extraction and Statistical Range Comparison (LORE-LMS-TESFESRACO) Algorithm

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Abstract: The SOund NAvigation and Ranging (SONAR) is an underwater sound propagation technique used for navigation, communication or detection of objects on or under the surface of the water. The objects may be submarines, vessels etc. It involves the use of frequencies from very low or infrasonic range to extremely high or ultrasonic range. Proper design of a SONAR system requires accurate detection of the signals. Here, tonal features of the received signal are analyzed based on the signal detection theory. Using filtering and several comparison techniques, the targets can be detected and this can be simulated via variables using MATLAB. This paper attempts to design an algorithm for range estimation and target classification using Passive SONAR. The hardware implementation has a wide arena of applications mainly in the defence sector.

Keywords: Acoustic Propagation Loss, Least Mean Square Adaptive Filter, Energy Entropy, Short Time Energy, Zero Crossing Rate, Spectral RollOff, Spectral Centroid, Spectral Flux, Mean, Standard Deviation.

I. INTRODUCTION

A sound is a wave that travels through air, water or any other medium without which it cannot exist and is a compressional or longitudinal wave in which the particles move parallel to the direction in which the wave is travelling. Intensity, Frequency and Wavelength are important characteristics of sound. Sound travels at a speed of about 1500 meters per second in seawater. Sound spreading and Sound absorption are the reasons why a sound wave becomes smaller and smaller as it propagates. Reflection, Refraction and Scattering make the transmission of sound through the ocean complicated. Hydrophones are used to convert sound in water in to electrical signals that can be amplified, recorded, played back over loudspeakers and hence to measure the characteristics of sound. Sounds may be displayed as an animated frequency spectrum, a waveform or a spectrogram.

SONAR originally was designed and developed during World War II for the purpose of tracking enemy submarines. Currently, SONAR systems are used for many purposes as follows;

- Detection, identification and location of submarines
- In acoustic homing torpedoes
- In acoustic explosive mines and mine detection
- In finding fish schools
- In depth sounding applications
- Mapping of seabed
- Navigation
- Location of submerged wrecks
- For echo detection to maximize the range at which submarines can be detected and tracked

Signal Detection Theory (SDT) was originated as a model of perceptual judgement where the performance of the people in tasks to detect a certain type of stimulus were described and analyzed. Tanner and Swets in 1954 proposed for the first time, a decision-making theory of visual detection, showing the importance of both sensory and decision making processes in perceptual tasks. When there are uncertainties, judgements are made of signifying something that is perceived rather than the other.

When signal detection theory is applied to the data obtained from the SONAR, it becomes SONAR detection theory. For an efficient SONAR system with minimized cost of false alarms and to avoid accidents, the raw data obtained from the SONAR has to be analyzed accurately.

In order to detect and identify the obstacles, the designed detection system must be effective and with a significant detection threshold which is well enough to distinguish between a true signal and a false alarm.

Many of the obstacles and/or accidents that may occur in the course of travel may be avoided by proper detection and identification of the received signal. Minimized false alarms can also reduce losses that may be incurred due to incorrect detections.

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II. LOSS RECOMPUTED-LEAST MEAN SQUARE-TEN SPLIT FEATURE EXTRACTION AND STATISTICAL RANGE COMPARISON (LORE-LMS-TESFESRACO)

Even when the signals are obtained from the same source, there will be large variability in both the temporal and spectral characteristics and this makes the automatic classification of the underwater signals obtained from the passive SONAR a bit complicated. The signals may consist of passive SONAR signals radiated by various vessels, underwater transients such as sperm whale clicks, porpoise whistles, ice crackles etc., each of which has its own characteristics and which were identified conventionally by human experts either by listening to or by looking at the spectrograms of the processed SONAR signals. To reduce the operator's load, it is necessary that the underwater signals be classified automatically. As the neural networks have adaptive and parallel processing ability, it is applied to fields such as speech recognition [2, 22], SONAR signal processing [8, 13, 14], automatic target recognition [27] etc.

Passive SONAR systems are actually underwater acoustic receiving systems used for receiving underwater signals radiated by various ships, marine biology etc. Thus the characteristics of the radiated signals from ships are of great importance in the identification of the ships. Based on the previous works [32] about the models of underwater signals radiated by ships, it can be concluded that the signal sources can be divided into three categories as follows;

- Machinery signals: They are the signals originated as a result of mechanical vibration of the diverse parts of a moving ship such as shafts, motor armature, gear teeth, turbine blades etc. which produce a line component spectrum dominated by tonal components at the fundamental frequency and harmonics of the vibration-producing process and pumps, pipes and valves which produce a continuous spectrum with superimposed line components
- Propeller signals: They are the signals originated outside the hull as a result of the propeller action and are principally the signals of cavitations induced by the rotating propellers, which create tonal components also in addition to the continuous spectrum of cavitation signals
- Hydrodynamic signals: They are originated as a result of the irregular and fluctuating flow of fluid past the moving vessel and consist of hull generated Gaussian signal and flow signals which are very similar to the ambient signals in the ocean

Tonal content of the radiated signals of a ship are characteristic of that ship. Although some of the frequency components and harmonics vary with speed of the engine, tonal caused by power generator and similar ones stay fixed. The performance of four neural network classifiers are investigated to check their feasibility in the recognization or classification of the passive tonal signals radiated by the ships at various speeds that have propagated through an ocean environment.

The power spectral density of the radiated signals of a ship changes slowly with time and hence non-overlapping spectrogram is a suitable time-frequency distribution. The spectral envelope can be then obtained by averaging over each spectrum in the spectrogram. The Average Power Spectral Density (APSD) of a typical time-domain passive SONAR signal can be calculated from the Fast Fourier Transform (FFT) using a 1024 point window and only positive half spectrum needs to be plotted as the Fourier transform of a real signal is symmetric. From the analysis of the spectrum, it is evident that the radiated signal consists of mainly two different spectral types as follows;

- Broad-band type with a continuous spectrum
- Narrow-band type with a discontinuous spectrum having line components occuring at discrete frequencies

These two types of signals are found as a mixture in the radiated signals of the ships and hence the key task is to effectively extract tonal features from this mixed spectra.

Tonal features are buried in the position and the magnitude of the tonal in the spectrum. First, the continuous spectrum is estimated by re-computing the acoustic propagation loss and then tonal components are extracted and their statistical parameters are compared with the database of different ranges of the statistical parameters to classify the audio signal and to re-compute the range or distance to the target. An algorithm that can be used for this purpose is the LOss REcomputed-Least Mean Square-TEn Split Feature Extraction and Statistical RAnge Comparison (LORE-LMS-TESFESRACO) algorithm.

III. ACOUSTIC PROPAGATION LOSS

In underwater acoustic cellular systems, both distance-dependent path loss and frequency-dependent absorption are present. For a signal frequency of f, the attenuation or path loss in an acoustic channel at a distance r is given by,

$$A(r, f) = r^{k} * a(f)^{r}$$

where k is the spreading factor (assumed to be 1.5 practically) and a(f) is the absorption coefficient. In dB,

$$10\log[A(r, f)] = k * 10\log[r] + r * 10\log[a(f)]$$
$$= \text{spreading loss} + \text{absorption loss}$$

where according to Thorp, the absorption loss in dB/km is,

$$10\log[a(f)] = \frac{0.11*f^2}{1+f^2} + \frac{44*f^2}{4100+f} + 2.75 * 10^{-4} * f^2 + 0.003$$

(f is in kHz)

IV. LEAST MEAN SQUARE (LMS) ADAPTIVE FILTER

The continuous spectrum of the original signal is estimated from the received signal by using a Least Mean Square (LMS) adaptive filter. Least Mean Square algorithm is an adaptive algorithm which can be used to find out the filter coefficients of an adaptive filter such that these coefficients produce least mean squares of the

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error signal. Here, the filter is adapted based on the current error. LMS algorithm can be described by the following equations;

$$y(n) = w^T(n-1)\,u(n)$$
$$e(n) = d(n) - y(n)$$
$$w(n) = w(n-1) + f(u(n), e(n), \mu)$$
$$f(u(n), e(n), \mu) = \mu\, e(n)\, u^*(n)$$

where y(n) is the filtered output at step n, w(n) is the vector of estimates of filter weights at step n, u(n) is the vector of buffered input samples at step n, e(n) is the estimation error at step n, d(n) is the desired response at step n, μ is the adaptation size and u* (n) is the complex conjugate of u(n) at step n.

V. FEATURES OF AN AUDIO SIGNAL

The features or characteristics that are unique to each of the audio signals are;

- Energy Entropy
- Short Time Energy
- Zero Crossing Rate
- Spectral RollOff
- Spectral Centroid
- Spectral Flux

A. Energy Entropy

German physicist Rudolf Clausius introduced Entropy as a thermodynamic state variable as;

$$dS = \frac{\delta Q}{T}$$

where dS is an elementary change of entropy, δQ is a reversibly received elementary heat and T is an absolute temperature. The first postulate of thermodynamics, which states that "Any macroscopic system which is in time t_0 in given time-invariant outer conditions will reach after a relaxation time the so-called thermodynamic equilibrium. It is a state in which no macroscopic processes proceed and the state variables of the system gains constant time-invariant values", gave a definition for the entropy as a measure of system disorganisation. Entropy is maximal at thermodynamic equilibrium.

Entropy can be statistically defined as;

$$H(x) = -\,_{t=1}\sum^{N} p(x_i)\log_{10} p(x_i)$$

and in bits;

$$H(x) = -\,_{t=1}\sum^{N} p(x_i)\log_{2} p(x_i)$$

where $x = \{x_1, x_2, \ldots, x_N\}$ is a set of random phenomena and $p(x_i)$ is a probability of a random phenomenon x_i.

The hypothesis that a noise is a projection of a system in thermodynamic equilibrium into a signal is the basis for the relationship between entropy and signal processing. Noise is supposed to have highest entropy value.

B. Short Time Energy

It provides a convenient representation to reflect the amplitude variations in an audio signal. Short Time Energy is given by;

$$E_n = \,_m\sum[s(m)\,w(n-m)]^2$$

where s(m) is the short time audio segment obtained by passing the audio signal x(n) through window w(n). As Short Time Energy is a square function, it is very sensitive to the large signal amplitude levels.

C. Zero Crossing Rate

It is the number of zero crossings or the number of times the sequence changes the sign per second. If discrete time signals are considered, successive samples of different algebraic signs correspond to a zero-crossing.

$$Z = \frac{2F_0}{F_S}\ \text{crossings/sample}$$

where F_0 is the frequency of a sinusoid and F_S is the sampling frequency. Thus Zero Crossing Rate can be stated as a measure of the frequency content of the audio signal. Mathematically;

$$Z_n = \,_m\sum|\mathrm{sgn}[s(m)] - \mathrm{sgn}[s(m-1)]|\, w(n-m)$$

where s(m) is the audio signal and w(m) is the window.

D. Spectral RollOff

It is defined as the frequency below which 85 percentage of the magnitude distribution of the spectrum is concentrated. Spectral RollOff is a measure of the spectral shape. Higher the frequency, higher is the Spectral RollOff. It can be represented mathematically as;

$$_{k=1}\sum^{M}|X_r[k]| = 0.85\,_{k=1}\sum^{N/2}|X_r[k]|$$

M is the RollOff if it is the largest value of k that satisfies this equation.

E. Spectral Centroid

German It is defined as the center of gravity of the spectrum and is given by;

$$C_r = \frac{_{k=1}\sum^{N/2} f[k]|X_r[k]|}{_{k=1}\sum^{N/2}|X_r[k]|}$$

where f[k] is the frequency at bin k.

It is a measure of the spectral shape and models the sharpness of sound. When the centroid values are higher, textures are brighter and with more high frequencies.

F. Spectral Flux

German The Spectral Flux is defined as the squared difference between the normalized magnitudes of successive spectral distributions that correspond to successive signal frames. It is given by;

$$F_r = \,_{k=1}\sum^{N/2}(|X_r[k]| - |X_{r-1}[k]|)^2$$

VI. STATISTICS

Statistics is an area of Mathematics that pertains to data analysis. Statistical methods and equations can be used to analyze and interpret results, explain data variations or predict future data. Out of the many statistical parameters, two most useful parameters are;

- Mean or Average
- Standard Deviation

A. Mean

Mean or Average can be obtained by dividing the sum of the observed values or samples by the number of observations or samples. It is a good estimate for predicting the subsequent data points. Mean is given by;

$$\text{Mean} = \frac{_{i=1}\sum^{i=n} x_i}{n}$$

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where X_i is the i^{th} observed value or i^{th} sample and n is the number of observations or samples.

B. Standard Deviation

The Standard Deviation indicates how close the entire data set is to the Mean value. Small Standard Deviation corresponds to tightly grouped precise data whereas large Standard Deviation corresponds to data spread out over a wide range of values. It can be computed as;

$$\text{Standard Deviation} = \sqrt{\frac{1}{n} i = 1 \sum^{i=n} (X_i - \text{Mean})^2}$$

VII. STATISTICAL PARAMETERS OF THE AUDIO SIGNAL FEATURES FOR AUDIO SIGNAL CLASSIFICATION

In order to classify the audio signal, we compute the statistical parameters or their combination of the audio signal features as follows;

- Energy Entropy - Standard Deviation
- Short Time Energy - Standard Deviation by Mean Ratio
- Zero Crossing Rate - Standard Deviation
- Spectral RollOff - Standard Deviation
- Spectral Centroid - Standard Deviation
- Spectral Flux - Standard Deviation by Mean Ratio

VIII. LOSS RECOMPUTED-LEAST MEAN SQUARE-TEN SPLIT FEATURE EXTRACTION AND STATISTICAL RANGE COMPARISON (LORE-LMS-TESFESRACO) ALGORITHM

The LOss REcomputed-Least Mean Square-TEn Split Feature Extraction and Statistical RAnge COmparison (LORE-LMS-TESFESRACO) algorithm that can be used to recompute the range or distance to the target and to classify the audio signal is as follows;

- Step 01: Check whether the amplitude of the received signal is greater than at least one threshold value in the database
- Step 02: If Step 01 results in "YES" then store the possible frequencies of sounds and go to Step 04
- Step 03: Display "Out-of-range target. Please try again." and stop
- Step 04: Estimate the original signal from the received signal using Least Mean Square Adaptive filter
- Step 05: Split the estimate of the original signal into 10 equal parts
- Step 06: Extract the audio signal features such as Energy Entropy, Short Time Energy, Zero Crossing Rate, Spectral RollOff, Spectral Centroid and Spectral Flux for each of the 10 parts
- Step 07: Compute the statistical parameters for the audio signal features
- Step 08: Estimate the original signal frequency and arrange the possible frequencies in the database in the increasing order of their difference with the estimate of the original frequency
- Step 09: Re-compute the acoustic propagation loss and modify the received signal by adding this recomputed acoustic propagation loss to it so as to compensate the original acoustic propagation loss using the arranged possible frequencies and distance values following a try-determine-fix method
- Step 10: Repeat Steps 04 to 07 with the modified received signal and compare the obtained statistical parameter values with the database of the range of statistical parameters of different sounds or targets
- Step 11: Once a match is found, display the name of the target and range or distance to the target and stop
- Step 12: If no match is found after trying out all the arranged possible frequencies and distance values, then go to Step 03

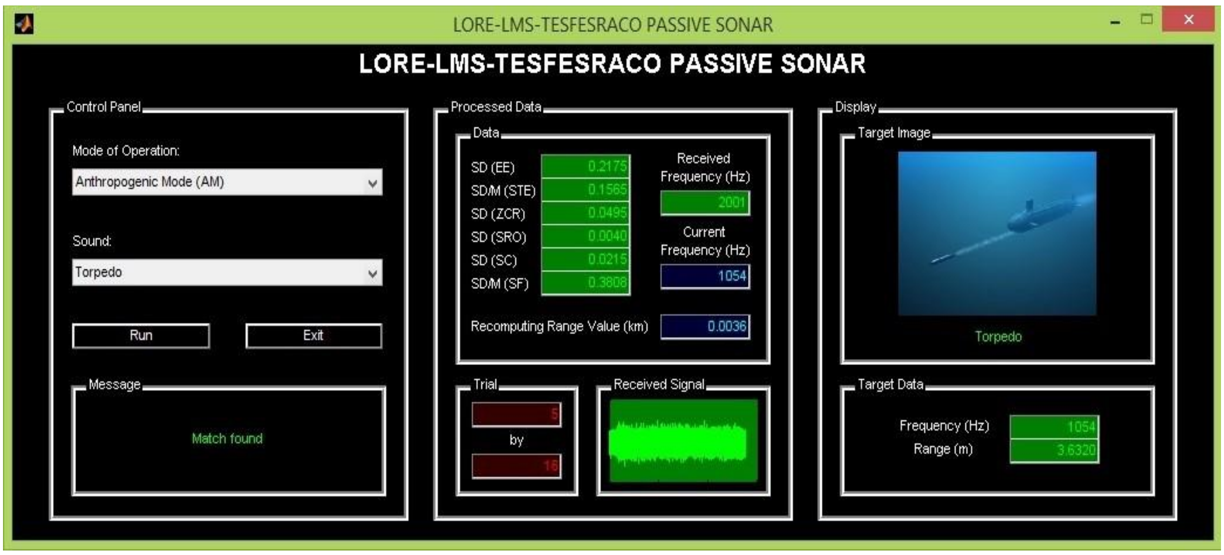

Figure I: MATLAB simulated GUI of the Passive SONAR that employs the proposed LORE-LMS-TESFESRACO algorithm

IX. SAMPLE OUTPUT

The LORE-LMS-TESFESRACO algorithm can be implemented in a Passive SONAR for estimation of the range or distance to a target and to classify the target. MATLAB simulated GUI of the Passive SONAR that employs the proposed LORE-LMS-TESFESRACO algorithm is as shown in figure I.

X. CONCLUSION

The performance of the SONAR system is heavily dependent on the accuracy of signal detection. Efficient monitoring and detection of the received signals can be done in SONARs with the help of the Signal Detection Theory (SDT). Different SONAR systems (based on the purpose for which they are designed) have different Detection Thresholds (DTs) and the effectiveness of each of the systems lie in the accuracy of detection of incoming signals. The designed LOss Recomputed-Least Mean Square-TEn Split Feature Extraction and Statistical RAnge COmparison (LORE-LMS-TESFESRACO) algorithm works accurately in most cases. The algorithm successfully computes the range to the target and classifies the target correctly.

SONARs are used in almost all parts of the world and is a technology that is being tested and experimented frequently. Considerable changes can be made in many fields such as fishing industry, salvage and robotics if the technological advancements enable us to view a wider range of the surroundings. It might become easier for the fishermen to track the fishes and the people involved in salvage to spot shipwrecks and to make a detailed map of the seabed. If the degree of view is enhanced to 360 degree, better service can be provided by the robots as they can get signals from all directions. Higher resolution SONAR systems enables identification of exact objects and with the help of computers, a three dimensional view of the object can be produced. The proposed LORE-LMS-TESFESRACO algorithm could serve as a strong backbone in such systems.

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BIOGRAPHIES

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