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UNDERWATER TARGET CLASSIFIER USING A MODIFIED TRANSFORM BASED FEATURE SET

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ABSTRACT

Underwater target classification has been a domain of considerable importance due to its immense applications in sonar engineering. Various classification schemes have been evolved over the time, taking into account, the aspects that can maximize the system performance. The judicious selection of source specific features in a classifier system determines its efficiency and performance in a broad perspective. Discrete sine transform (DST) possesses the essential traits suitable for the extraction of target specific features from underwater signals. The DST based features can be modified by the application of second degree Hermite polynomial functions. The Hermite polynomial modified DST feature set can be efficiently incorporated onto a suitably formulated Hidden Markov Model(HMM) which provide a robust architecture that can be utilized in the classification of underwater noise sources. The modeling and performance analysis of a 20-state HMM based classifier for underwater targets in Gaussian ambient noise and in nonlinear channel conditions have been presented in this paper. The Hidden Markov Models utilizing these modified DST based feature sets are found to perform efficiently in underwater target classification scenario. The system performance has been simulated for a variety of underwater signals and the results have also been summarized in this paper.

KEYWORDS: Discrete Sine Transform, Hermite Polynomials, K- Means Algorithm, Hidden Markov Models, State Transition Probabilities

INTRODUCTION

The class of underwater signals calls for special processing techniques because of the complex and bewildering mix of noises emanating from various sources in the ocean. The primary requirements of a target classifier include the capability of extracting and selecting the relevant feature sets by judiciously selected processing techniques, there by generating unambiguous source specific classification clues. Underwater signal classifiers require robust methods for the extraction of specific characteristic features of the targets, taking into account, the diverse nature of the noise generating mechanisms, coupled with a highly variable and reverberant environment.

A new adaptive underwater target classification system to cope with environmental changes, using a back propagation neural network has been proposed in [1]. However, the system is specifically designed for backscattered data. Another classification scheme using wavelet packets and Linear Predictive Coding, which also emphasizes on backscattered data has been described in [2]. Pezeshki *et al.* [3] has proposed a canonical correlation based feature extraction technique for underwater target classification, with a back propagation neural network model. However, the system assumes the constraint of linear dependence or coherence between two consecutive target signals. A multi-aspect HMM scheme, appropriate for underwater target classification has been proposed in [4], making use of synthesized active sonar signals, assuming simple target models and environments. The robustness and efficiency of many of the existing systems degrade in the nonlinear underwater scenario and the problem is further accentuated by the presence of Gaussian ambient noise. Existing feature extraction techniques for underwater signals, specifically do not address this problem, which cannot be overlooked in real time ocean environments. This paper presents an efficient feature extraction technique that performs well in noisy and nonlinear underwater environments.

Discrete Transforms possess many characteristics which can be suitably exploited for various signal processing applications. Of these, the Discrete sine transform (DST) operates on a specific function at a finite number of discrete data points [5] and are capable of highly efficient performance in data enhancement and other signal processing applications. The DST based features are being modified by operating with second degree Hermite polynomial to extract the feature set for the underwater target signals. An HMM based classifier, modeled using the Hermite polynomial modified DST features, for underwater target classification is presented in this paper. The performance of the system under non ideal conditions of Gaussian ambient noise with varying levels has also been studied. Appropriate compensation mechanisms based on Butterworth and Chebyshev filters have been found to yield better results in terms of increased Success Rates for the proposed system. The system performance under nonlinear channel conditions has also been analyzed and results are presented.

PRINCIPLES

The proposed underwater signal classifier system makes use of second degree Hermite polynomial modified DST based feature set. This extracted feature set of the training signals has been utilized in the design of the Hidden Markov Model.

Discrete Sine Transform

For a sequence *x(n)*, the DST and the Inverse DST can be defined [5] as

$$X_k = \sqrt{\frac{2}{N+1}}\sum_{n=1}^{N} x(n)\sin\left(\frac{nk\pi}{N+1}\right) \tag{1}$$

$$x(n) = \sqrt{\frac{2}{N+1}}\sum_{k=1}^{N} X_k \sin\left(\frac{nk\pi}{N+1}\right) \tag{2}$$

where n=1,2,…N and k=1,2,…N. Underwater signal classification technique, making use of DST based features, has been mentioned in [6]. DST based feature set for underwater signals can be modified by Hermite polynomials with the prime objective of resolving the ambiguity function and this will render itself to the algorithmic clustering technique adopted by the HMM during the training phase of the Hidden Markov Model. This feature set is found to possess specific characteristics suitable for classification, which are being exploited by the system.

Hermite Polynomial Modified Features

Hermite polynomials are classical orthogonal polynomial sequences that have applications in numerical analysis and in system theory [7]. Hermite polynomial expansions have also been utilized in the identification and analysis of system nonlinearities [8]-[9]. These can be effectively applied in underwater target classification where they operate on the DST based components to produce a modified feature set. This extracted feature set of underwater signals form a significant parameter in the design and performance of the classifier. The n^{th} degree Hermite polynomial can be defined as in (3).

$$H_n(x) = (-1)^n e^{x^2} \frac{d^n}{dx^n} e^{-x^2} \tag{3}$$

The generating function of Hermite polynomial is:

$$e^{2tx-t^2} = \sum_{n=0}^{\infty} \frac{H_n(x)t^n}{n!} \tag{4}$$

Also for distinct *m* and *n*, the Hermite polynomials form a complete orthogonal set in the interval $-\infty < x < \infty$, with respect to the weighting function as in (5).

$$\int_{-\infty}^{\infty} e^{-x^2} H_m(x) H_n(x) dx = 0 \tag{5}$$

The second degree Hermite polynomials are found to exhibit certain specific characteristics, which can be utilized in underwater signal classification. The DST based features functionally operate on the second degree Hermite polynomial to generate a modified set of features, which constitutes one of the major design parameters of the Hidden Markov Model.

DST based feature set modified by second degree Hermite polynomial function possesses improved capability for underwater signal classification by reducing the ambiguity in the decision making process. Let X denotes the DST based feature set and the variance of X be σ^2. Also let X^2=U, X^3=V and X^4=W. Using (3), when *n*=2, the variance of second degree Hermite polynomial modified DST feature set, denoted by $H_2(X)$, becomes:

$$\mathrm{var}[H_2(X)] = \mathrm{var}[4U-2] = 16\,\mathrm{var}[U] \tag{6}$$

Using the basic definition of variance, (6) becomes:

$$\mathrm{var}[H_2(X)] = 16[E[W] - 2\mu E[U] + \mu^2] \tag{7}$$

where μ denotes the mean of (X^2 =U). Again, using the basic definition of covariance between two signals X and (X^3=V),

$$E[W] = \mathrm{cov}[XV] + mE[V] \tag{8}$$

where *m* is the mean of X. Similarly, utilizing this recurrence relation to evaluate $E[V]$ and $E[U]$ for substituting in (8) gives:

$$E[W] = \mathrm{cov}[XV] + m\,\mathrm{cov}[XU] + m^2\sigma^2 + m^4 \tag{9}$$

Then the variance of second degree Hermite polynomial modified feature set becomes:

$$\mathrm{var}[H_2(X)] = 16[\mathrm{cov}[XV] + m\,\mathrm{cov}[XU] + m^2\sigma^2 + m^4 - 2\mu\sigma^2 - 2\mu m^2 + \mu^2] \tag{10}$$

With $|m| \geq 1$ and $\mu < 0$, it is obvious from (10) that var[$H_2(X)$] > var[*X*]. Further, when $\mu > 0$, an offset *C* is inserted to *U* so as to ensure $\mu < 0$, such that var[$H_2(X)$] > var[*X*].

If *m* = 0, a similar offset insertion can be made in order to satisfy the condition $|m| \geq 1$.

Increased variance for a particular feature set implies reduced ambiguity in the classification process. As a result, the classification capability of second degree Hermite polynomial modified DST features for underwater signals is found to be greater than that of DST based features.

Hidden Markov Models

According to Rabiner [10], a Hidden Markov Model (HMM) is a doubly stochastic process that is hidden but can only be observed through another set of stochastic process that produces the sequence of observed symbols. HMM can be regarded as the simplest dynamic Bayesian network. In a dynamic Bayesian network, the hidden state is represented in terms of a set of discrete random variables. The observation can be represented in terms of another set of random variables. In a Hidden Markov model, the state is not directly visible, but the variables influencing the state are visible. Each state has a probability distribution over the possible output tokens. Hence the sequence of tokens generated by a Hidden Markov Model is capable of giving information related to the sequence of states. The HMM consists of a finite set of states, and each state is associated with a probability distribution. The transitions among the different states are governed by the parameter called State Transition Probabilities. In any state, an outcome is generated depending on the corresponding probability distribution. The states are hidden externally, while the outcomes are visible unlike a regular Markov process in which the state is directly visible to the observer. An HMM can be completely described in terms of the number of states, the initial state distribution, the state transition probabilities and the emission probabilities.

APPROACH

The different functional stages in the proposed underwater target classifier are depicted in Figure 1. These include the extraction of the right features to generate the training set, design and modeling of an HMM with twenty states, for the purpose of unambiguous classification of target signals.

Feature Extraction

For underwater targets, spectral analysis is performed to extract the required features from a sequence of samples. The sampled underwater signal is partitioned into frames for extracting the source specific features. Hamming window function, which is characterized by reduced side lobes has been applied to each frame in order to minimize the signal discontinuities. The spectral magnitudes are estimated using Fast Fourier Transform (FFT) and the power spectrum thus obtained is passed through a bank of filters to achieve nonlinear resolution. This technique imparts good discrimination properties and makes the feature set amenable to many analytical manipulations. The Discrete sine transform of the logarithm of filtered spectrum is computed and functionally operated with the second degree Hermite polynomial to obtain the desired feature set.

HMM Based Classifier System

Classification is a decision making process of identifying the unknown signal based on previously learned information. Modeling of the HMM classifier is carried out using the training set comprising the extracted features. In the matching process, a stochastic matching parameter, which is a measure of the correspondence between the features extracted from the unknown signal and the system trained data, is estimated. The various phases of operation for the Hidden Markov Model classifier can be explained as follows:

Training Phase of HMM

The HMM training procedure requires the estimation of the State Transition Probability Matrix [11], denoted by $A_{ij} = \{a_{ij}\}$, where the probability $a_{ij} = \Pr\{q_{t+1} = j | q_t = i\}$, $1 \le \{i, j\} \le N_s$, where q_t denotes the current state and N_s denotes the number of states of the model.

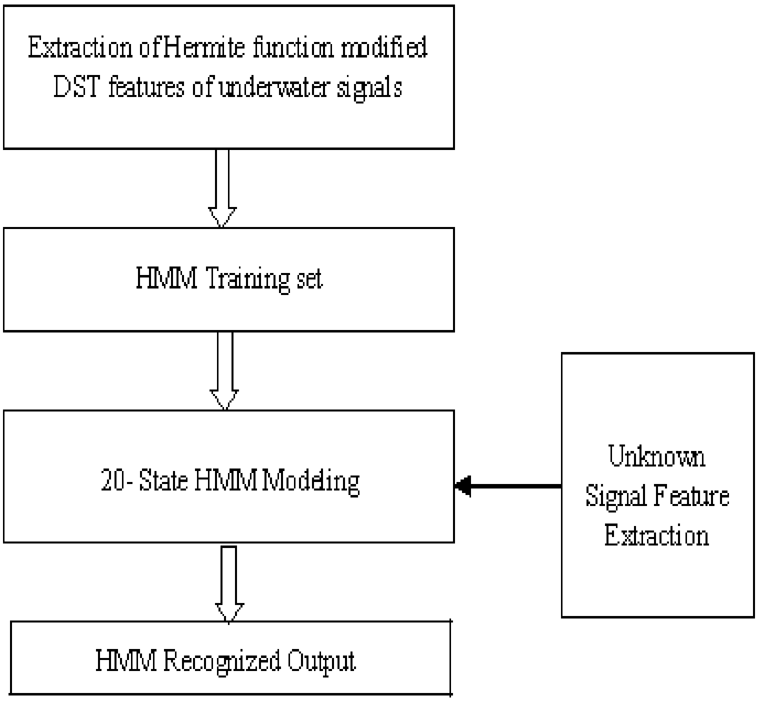

Figure 1: The Proposed Underwater Target Classifier

In the proposed system, a 20- state HMM is designed. Transition probabilities should satisfy the normal stochastic constraints, $a_{ij} \geq 0$, $1 \leq \{i, j\} \leq N_s$ and $\sum_{j=1}^{N_s} a_{ij} = 1$ with $1 \leq i \leq N_s$. There should also be an emission or observation probability distribution in each of the states, denoted by $B_{jO_t} = \{b_j(k)\}$, $b_j(k) = \Pr\{o_t = v_k \mid q_t = j\}$, $1 \leq j \leq N_s$, $1 \leq k \leq M_s$ where M_s denotes the number of observation symbols, v_k, the k^{th} observation symbol and o_t, the current parameter vector. There should be an initial state distribution $\Pi = \{ \Pi_i \}$, where the probability $\Pi_i = \Pr\{q_1 = i\}$, $1 \leq i \leq N_s$. Consequently, an HMM can be completely described using the parameters A_{ij}, B_jo_t and Π.

The K-means algorithm can be used for setting the centroids of a cluster model [12]. From the clustered or quantized result, unique clusters are identified for designing the Hidden Markov Model. The Forward-Backward re-estimation algorithm, used in the statistical analysis of Markov chains, can be applied for computing the probability of a particular observation sequence in the Hidden Markov Model. This can be achieved by computing the Forward probability, which is a joint probability and the Backward probability, which is a conditional probability, using algorithmic recursions [13].

The estimate of maximum likelihood state transitions corresponds to the probability of transition from one state to another and is given by (11).

$$\Lambda_{st} = \frac{\sum_{t=1}^{T} \alpha_i(t) A_{ij} B_{jO_t} \beta_j(t+1)}{\sum_{j=1}^{N_s} \sum_{t=1}^{T} \alpha_i(t) A_{ij} B_{jO_t} \beta_j(t+1)} \qquad (11)$$

The estimate of maximum likelihood emission probabilities which corresponds to an output being observed or emitted, is given by

$$\Lambda_{ep} = \frac{\sum_{i=1}^{N_s}\sum_{t=1}^{T} 1\{o_t = v_k\}\alpha_i(t)A_{ij}B_{jO_t}\beta_j(t+1)}{\sum_{i=1}^{N_s}\sum_{t=1}^{T}\alpha_i(t)A_{ij}B_{jO_t}\beta_j(t+1)} \tag{12}$$

The indicator function in the numerator implies a value of one when the condition holds and zero otherwise.

Recognition Phase

In this phase, the set of features derived from the unknown signal is applied to the previously trained HMM. The set of maximum likelihood emission probabilities corresponding to the unknown target signal is computed and the normalized values with respect to the maximum value are estimated. For HMM classifier, this normalized maximum likelihood emission probability, denoted by Λ_{epn}, is a parameter of significance and can be termed as the Discriminant factor. The maximum of Λ_{epn} will correspond to the trained signal, with which a close match has been established for the unknown target signal.

For the underwater HMM classifier, the Ambiguity Score, which is a quantitative measure of its capability for unambiguous classification can be defined as

$$AmbiguityScore = \frac{\dfrac{\sum_{i=1}^{n}\sum_{j=1}^{n}|y_i - y_j|}{n^2}}{\dfrac{\mu_y}{\sigma_y}}$$

where, y and μ_y represent the Discriminant factors and their mean respectively. σ_y denotes the standard deviation and n, the total number of trained targets. Thus, Ambiguity Score can be considered to be the mean difference of Discriminant factors, normalized with respect to the Reciprocal Variation Coefficient, measuring the spread of the Discriminant factors, which influences the classification performance of the system. While comparing different classifier systems, higher values of Ambiguity Score indicate reduced ambiguity in the classification process for the corresponding classifier.

Improved Performance under Nonlinear Conditions

Hermite polynomials have got applications in nonlinear system analysis and identification [9] [14]. The second degree Hermite polynomial modified features are capable of enhanced performance under nonlinear conditions, in underwater target classification. Let the signal Y be modified to Z, in the presence of strong second order nonlinearity. Assuming the scaling coefficient to be unity, this can be represented as:

$$Z = f(Y) = Y^2 \tag{13}$$

Also let $Y^6 = R$. For second degree Hermite polynomials, the variance under nonlinear conditions and under normal conditions can be shown by

$$\mathrm{var}[H_2(Y^2)] = [256\ \mathrm{var}[R] + 144\ \mathrm{var}[Z] - 192\ \mathrm{cov}[RZ]] \tag{14}$$

$$\mathrm{var}[H_2(Y)] = 16\,\mathrm{var}[Z] \tag{15}$$

Assuming that any nonlinearity above second order is negligible, the difference in variance between nonlinear and normal conditions of operations, denoted by D_1 , is

$$D_1 = 128\ \mathrm{var}[Z] \tag{16}$$

In the absence of Hermite polynomial modified operation, let $\mathrm{var}[Y] = \sigma_s^{\ 2}$. Under nonlinear conditions, this variance is altered to a value, var[Z], where $Z = Y^2$. Then the corresponding difference in variance, D_2 , is given by

$$D_2 = \mathrm{var}[Z] - \sigma_s^{\ 2} \tag{17}$$

From (16) and (17), it is obvious that D1 >> D2, indicating the enhanced difference in variance, with Hermite polynomial modified operation. Thus, under nonlinear channel conditions, like that for underwater signals, reduced ambiguity and increased classification capability is achieved for second degree Hermite polynomial based systems, compared to normal classifier systems.

Compensation for Gaussian Ambient Noise

The effect of Gaussian ambient noise on underwater signals has been compensated in the system by the introduction of Butterworth or Chebyshev lowpass filters. The frequency response of Butterworth filter is maximally flat in the passband and rolls off towards zero in the stop band [15]. On the other hand, Chebyshev type 1 filters have steeper roll-off but more passband ripple compared to Butterworth filters. Also, Chebyshev filters require lesser order than Butterworth filters to implement the same stopband specification. The proposed system uses a tenth order Butterworth filter for obtaining optimum performance by compensating the effects of Gaussian ambient noise. A comparative study of the system behavior for underwater signals, with a fifth order Chebyshev type 1 lowpass filter has also been conducted under varying levels of Gaussian ambient noise.

RESULTS AND DISCUSSIONS

Simulation studies have been carried out for validating the classification performance of the proposed system for underwater signals and encouraging results have been obtained. The noise data waveforms emanating from the targets of interest have been sampled and recorded as wave files and used as the input to the HMM classifier. The proposed Hermite function modified DST feature set is one of the important parameters used in the design and training of the HMM classifier.

This feature set is found to be well suited in the context of underwater signals, considering their unique characteristics and properties. The source specific features thus extracted are being utilized in training the 20-state Hidden Markov Model and acceptable Success Rates have been achieved for various noise sources in the ocean.

Figure 2 depicts the extracted DST features for the underwater signal of Ship klaxon while Figure 3 and Figure 4 represent the the second degree Hermite polynomial modified DST features for Ship klaxon and Seatrout noise sources respectively. From these, it is clear that, the particular source specific feature variations can characterize the individual noise sources, which helps in developing a class specific model. The unknown target signal to be identified is processed for the extraction of the desired feature set and used in the recognition phase of the proposed HMM classifier.

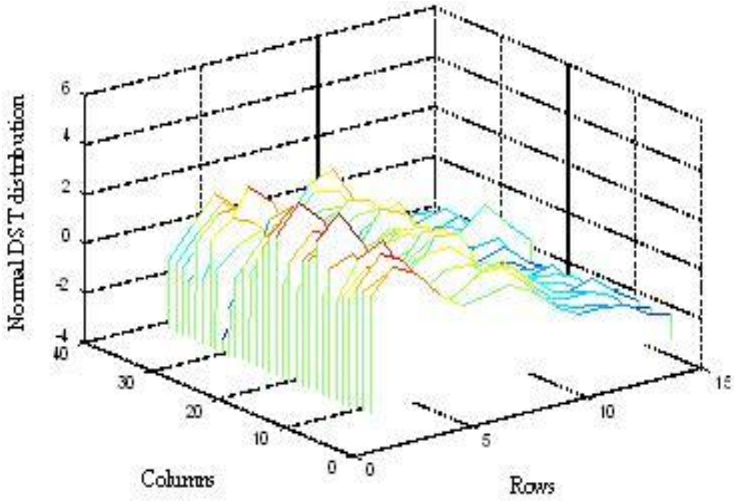

Figure 2: Extracted DST Features for the Ship Klaxon Noise

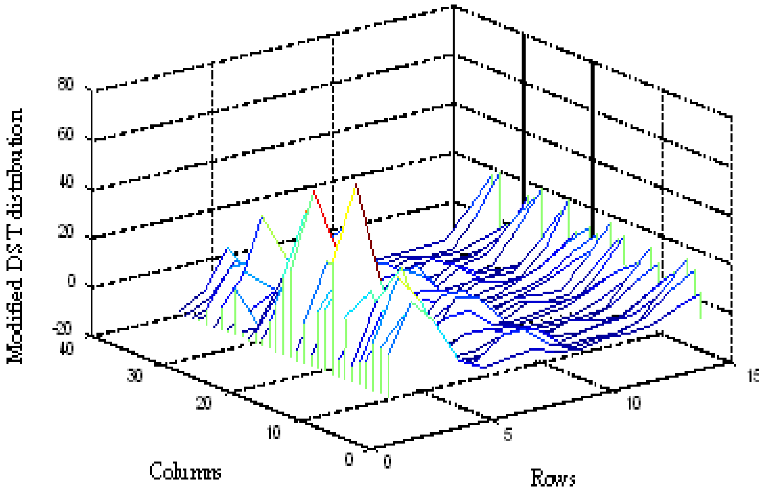

Figure 3: Extracted Hermite Function Modified DST Features for the Ship Klaxon Noise

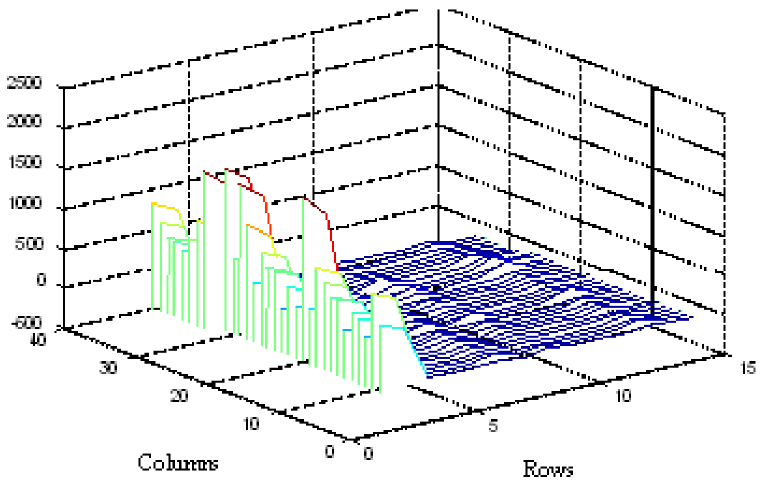

Figure 4: Extracted Hermite Function Modified DST Features for Seatrout Noise

The state transition probability distribution forms another significant parameter, which determines the classification capability of the model. As an illustration, the estimated state transition probability distribution for the Ship klaxon and Seatrout noise are depicted in Figure 5 and Figure 6 respectively. The state transition probability matrix of 400 elements corresponding to the 20- state HMM, is utilized in the recognition phase of the underwater target classifier and unambiguous classification results have been obtained by the system for different underwater noise sources.

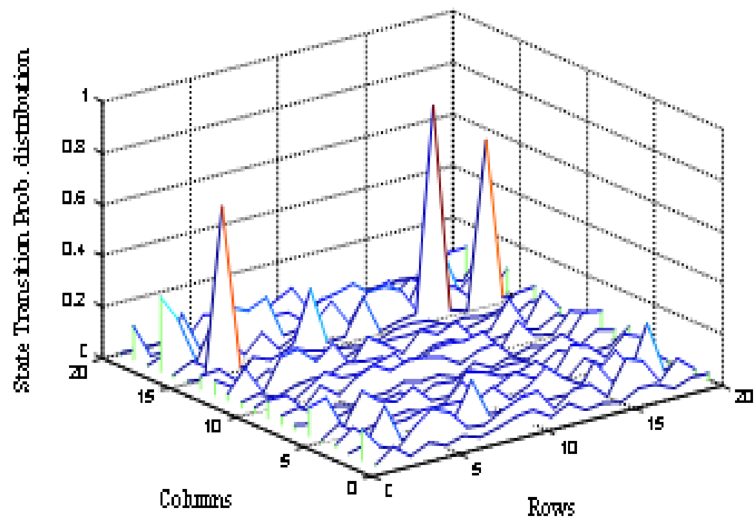

Figure 5: Estimated State Transition Probabilities for Ship Klaxon Noise

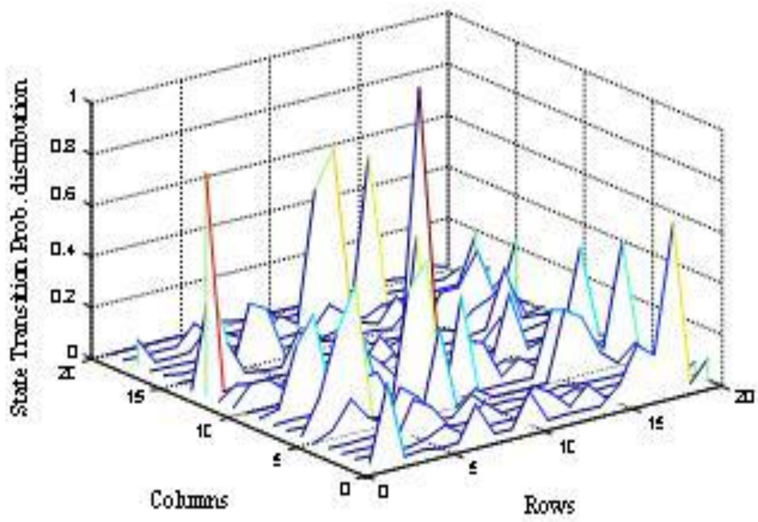

Figure 6: Estimated State Transition Probabilities for Seatrout Noise

The Ambiguity Scores for different underwater targets have been estimated for the proposed classifier and the results have been compared with cepstral coefficient based systems as well as DST based systems and are summarized in Table I. The DST based systems are found to have high values of Ambiguity Scores, which imply an enhanced classification capability for such classifiers compared to normal cepstral based ones. Also, second degree Hermite polynomial modified DST based systems perform better when compared to normal DST based systems, as indicated by their higher Ambiguity Scores.

The system behavior under Gaussian ambient noise conditions has also been analyzed using simulation studies. Table II shows the classifier performance under different conditions of operation. For the trained HMM, the Success Rate is found to be 89% under ideal noise free environment, whereas with Gaussian ambient noise, the Success Rate of the classifier is seen to be 87% when the SNR is 20 dB, by compensating with a tenth order lowpass Butterworth filter. For the same conditions of operation, with a fifth order Chebyshev type 1 filter compensation, the Success Rate has been found to be 86%. For increased Gaussian ambient noise levels, with SNR of 14 dB, the Butterworth filter based compensation gives a Success Rate of 84% while the same for the Chebyshev type 1 filter based system was found to be 82%. For further increased Gaussian ambient noise levels, with SNR of 10 dB, the Butterworth filter based compensation gives a

Success Rate of 80% and the same for the Chebyshev type 1 filter based system was found to be 79%.

Table 1: Ambiguity Scores for Different Underwater Target Classifiers

Input Underwater Signal	Cepstral Coefficient Based	DST Based	Hermite Polynomial Modified DST Based
Boat	1006	1123	1256
Submarine	796.10	845.49	897.06
Engine	844.20	1639	1897
Dolphin	865.91	887.65	952.12
Hump	1560	1665	1777
Beluga	847	1386	1398
3Blade	841.21	845.23	855
Torpedo	848.12	860.76	885
Bagre	710.63	755.67	886.5
Bad gear	844.73	855.57	865.47

Table 2: Success Rates for the Hermite Polynomial Modified DST Based Underwater Target Classifier

<table>
<tr><th colspan="3">Conditions of Operations</th><th>Success Rates</th></tr>
<tr><td colspan="3">Without Ambient Noise</td><td>89%</td></tr>
<tr><td rowspan="6">With Gaussian Ambient noise (SNR dB)</td><td rowspan="2">20 dB</td><td>With Butterworth filter compensation</td><td>87%</td></tr>
<tr><td>With Chebyshev type 1 filter compensation</td><td>86%</td></tr>
<tr><td rowspan="2">14 dB</td><td>With Butterworth filter compensation</td><td>84%</td></tr>
<tr><td>With Chebyshev type 1 filter compensation</td><td>82%</td></tr>
<tr><td rowspan="2">10 dB</td><td>With Butterworth filter compensation</td><td>80%</td></tr>
<tr><td>With Chebyshev type 1 filter compensation</td><td>79%</td></tr>
<tr><td colspan="3">Under nonlinear conditions of second order, without ambient noise</td><td>87%</td></tr>
</table>

The classifier performance under nonlinear channel conditions, with a nonlinearity of second order, has also been studied. The system yielded an acceptable Success Rate of 87% as shown in Table II. The feature set for underwater signals under non linear conditions of operation has seen to be capable of efficient performance. The proposed Hermite polynomial function modified DST feature set along with the compensation techniques, is found suitable for the HMM decision making, as indicated by the acceptable Success Rates obtained for the assumed set of noise waveforms in non ideal and nonlinear underwater environments.

CONCLUSIONS

The system proposed in this paper makes use of a twenty state HMM for the detection and classification of underwater target signals. Hermite polynomial modified Discrete sine transform based features possess unique properties suitable for the classification of underwater signal sources. The Hidden Markov Model classifier utilizing the extracted features has to be trained using a set of underwater signals and good Success Rates have been obtained for the assumed source signals. The process of underwater target classification using this approach involves second degree Hermite polynomial modified DST based feature extraction, HMM modeling and training, as well as validating the classifier performance. The system performance under Gaussian ambient noise conditions and typical nonlinear conditions have also been analyzed in the simulation phase. A tenth order Butterworth lowpass filter and a fifth order Chebyshev type 1 filter based schemes have been used for providing the required compensations under Gaussian noise conditions. In the presence of Gaussian ambient noise, the proposed system gives low error rates, with acceptable classifications for targets.

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