Higher Order Feature Set For Underwater Noise Classification

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Abstract

The development of intelligent systems for classification of underwater noise sources has been a field of research interest for decades. Such systems include the extraction of features from the received signals, followed by the application of suitable classification algorithms. Most of the existing feature extraction methods rely on the classical power spectral methods, which may fail to provide information pertaining to the deviations from linearity and Gaussianity of stochastic processes. Hence, many recent research efforts focus on higher order spectral methods in order to prevail over such limitations. This paper makes use of bispectrum, which is a higher order spectrum of order three, in order to extract a set of robust features for the classification of underwater noise sources. An SVM classifier is used for evaluating the performance of the feature set.

Keywords: Bispectrum, Bicoherence, SVM, HOS, Target Classification.

1. INTRODUCTION

The development of intelligent systems for classifying underwater noise sources, based on their acoustic signatures has gained a considerable attention due to its strategic as well as commercial importance. Traditionally, power spectral analysis and its variants have been used as the feature extraction technique for such systems. However, being a linear method, and most of the complex signals like underwater noise are nonlinear, the use of power spectral analysis may turnout to be inadequate. Nonlinear methods may be used in such cases, in order to gain a more complete understanding of the underlying signal dynamics.

The bispectrum, which is based on the third order cumulant sequence of a signal, can play a key role in characterizing the nonlinearities of the underlying signal generating mechanisms, especially those containing quadratic nonlinearities [1]. Also, as bispectrum and all higher order spectra for Gaussian process are identically zero, it suppress the effect of additive white Gaussian noise while preserving the magnitude and phase information of the original signal. Bispectrum has been used in many signal processing applications, such as robust signal reconstruction [2], pattern recognition [3], [4] as well as detection of nonlinearities and quadratic phase couplings [1]. However, the direct use of bispectral or bicoherence matrix as a feature vector can pose the problem of high dimensionality. For example, when the direct method is used, with an N point FFT, the resulting matrix will have a dimension of N^2 that is exponential in nature, which for $N = 128$ will account for 16384 data points, which obviously demands higher computational costs and even leads to over-fitting in certain cases.

Recent research efforts show a significant surge of interest in various types of integrated bispectra, due to its attractive properties of low dimensionality, scaling and translation invariance among others [3], [5]. The use of bispectrum estimate in detecting non-Gaussianity, nonlinearity, and harmonic coupling of underwater acoustic data has been demonstrated in [6]. Target classification attempts with bispectral features has been carried out in [7], [8] with a very limited number of targets. As it is obvious, a robust feature vector should capture the most invariant characteristics of the underlying signal, even in the presence of noise as well as in situations where the signal undergoes arbitrary scaling and translations that are quite common in underwater acoustic channels. This paper examines the feasibility of Integrated Bispectra, along with some other higher order features for deriving a robust feature set for underwater target detection and classification. The proposed algorithm has been evaluated using a database of 20 underwater targets in different levels of additive Gaussian noise.

The organization of the paper is as follows. Section 2 gives an overview of the higher order features. Feature selection is covered in section 3, and section 5 gives an overview of the SVM classifier. The details of the simulations conducted are presented in section 4. Finally, the results and discussions are given in sections 6 followed by the conclusions in section 7.

2. HIGHER ORDER FEATURE SET FOR CLASSIFICATION

Most of the existing feature extraction methods rely on the conventional power spectral estimation methods, which may fail to provide information pertaining to the deviations from linearity and Gaussianity of stochastic processes, as in the case of ocean acoustic signals. Such limitations motivate the use of higher order spectral methods instead of the conventional power spectral methods. Along with this, Bispectrum, being a higher order spectra of order three, is identically zero for many noise processes, especially the Gaussian process, it can be used to suppress the effect of additive white Gaussian noise while preserving the magnitude and phase information of the original signal [2]. The following sections describe the higher order features used in this paper.

2.1 Bicoherence

The third order spectrum or the bispectrum $B(f_1, f_2)$ is defined as the Fourier transform of the third order cumulant.

$$B(f_1,f_2)=\sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty}C_{xx}(k,l)\exp(-j2\pi f_1 k)\ \exp(-j2\pi f_2 l)$$

$$=E\{X(f_1)X(f_2)X^*(f_1+f_2)\} \tag{1}$$

It is found that, at the bifrequency (f_1, f_2), the complex variance of the bispectrum is proportional to the product of the power of the signals [9] at the frequencies f_1, f_2 and $(f_1 + f_2)$. That is,

$$\mathrm{var}[B(f_1,f_2)] \quad \alpha \quad P(f_1)P(f_2)P(f_1+f_2) \tag{2}$$

Thus, in order to make the bispectrum independent of the energy content at the bifrequencies, another parameter called bicoherence is used. Bicoherence, which is a normalized form of the bispectrum, can be defined as [1],

$$bic(f_1,f_2)=\frac{\left|B(f_1,f_2)\right|}{\left[P(f_1)P(f_2)P(f_1+f_2)\right]^{1/2}} \tag{3}$$

Since the bicoherence is independent of the energy or amplitude of the signal, it can be used as a convenient test statistic for the detection of non-Gaussian, non-linear and coupled processes. Here, the diagonal and anti-diagonal slices of the bicoherence matrix have been used as the feature vector.

2.2 Radially Integrated Bispectrum (RIB)

Chandran and Elgar [3], first proposed the use of radially integrated bispectra in pattern recognition and demonstrated its applicability. The RIB is obtained by integrating the bispectrum along radial lines passing through the origin in bifrequency space, as shown in Figure 1. The integrated bispectra can be defined as:

$$RB(a) = \int_{0+}^{1/(1+a)} B(f_1, af_1)df_1 \tag{4}$$

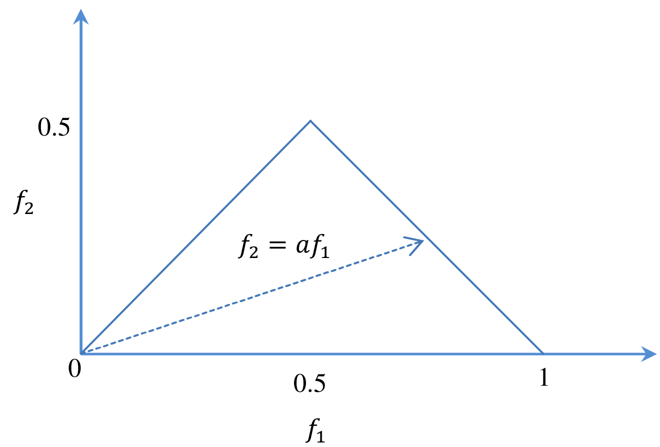

FIGURE 1: RIB Computation - Integrating the bispectrum along the dashed line with slope=a.

In the discrete domain, the integration can be approximated by

$$RIB(a) = \sum_{k=1}^{\left\lfloor (\frac{N}{2}-1)/(1+a) \right\rfloor} B(f_1, af_1) \tag{5}$$

2.3 Circularly Integrated Bispectrum (CIB)

As the name suggests, for the Circularly Integrated Bispectrum, the integral paths are a set of concentric circles with the origin as the center. The CIB can be defined as [10]:

$$\mathrm{CIB(a)} = \int \mathrm{B_P(a, \theta)d\theta} \tag{6}$$

where $B_P(a,\theta)$ is the polar representation of $B(\omega_1,\omega_2)$

2.4 Axially Integrated Bispectrum (AIB)

The Axially Integrated Bispectrum (AIB) is obtained by integrating the bispectra along paths parallel to the ω_1 or ω_2 axes in bifrequency plane and retains the scale characteristics of the signal [11].

$$AIB(\omega) = \frac{1}{2\pi}\int_{-\infty}^{\infty} B(\omega_1,\omega_2)d\omega_2 = \frac{1}{2\pi}\int_{-\infty}^{\infty} B(\omega_1,\omega_2)d\omega_1 \tag{7}$$

Though the AIB contains less phase information when compared to the bispectra, the estimation variance of the AIB is much less, equivalent to that of power spectrum.

2.5 Bispectral-MFCC (BMFCC)

The Mel Frequency Cepstral Coefficients (MFCC) has been widely used in various feature extraction scenarios due to its low computational complexity and good performance under clean matched conditions. However, the performance of MFCC is directly proportional to the Signal to Noise Ratio (SNR), hence the performance generally degrades rapidly in the presence of noise [12].

Since the bispectrum suppress the additive white Gaussian noise while preserving the magnitude and phase information of the original signal, it can be used to compute a clean estimate of the magnitude spectrum of the noisy signal. The estimated spectral magnitude |X(ω)| is obtained as:

$$|X(\omega)| = e^{[DFT(g(n))]} \tag{8}$$

where,

$$g(n) = F_1^{-1}\left[\frac{1}{2\pi}\int_{-\pi}^{\pi} \log\left(\left|B(\omega_1,\omega_{2)}\right|\right) d\omega_2\right] \tag{9}$$

The final BMFCC features has been computed from the estimated spectrum |X(ω)| by adopting the usual MFCC feature extraction method. The block diagram illustrating the steps of the BMFCC extraction is given in Figure 2.

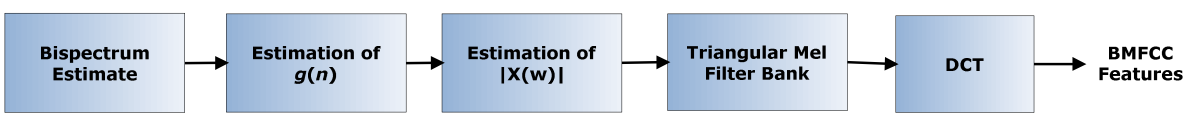

FIGURE 2: BMFCC Feature Extraction.

3. FEATURE SELECTION

High dimensional feature space can pose problems like over-fitting to trivial aspects of the signal and high computational burdens. Therefore it would be desirable to identify a salient subspace of the original feature space based on some decision criteria, that would effectively remove the irrelevant or redundant features while leaving out the most discriminant ones intact, and the process is generally termed as feature selection.

3.1 Fisher Ratio for Class Separability Measure

The Fisher Ratio depends on the interclass difference and the intraclass spread or variance, and is defined as the ratio of the interclass difference to the intraclass spread [13]. Let the mean and variance of the l^{th} feature of the classes C_i and C_j are denoted by $m_{i,l}$, $m_{j,l}$, $\sigma^2_{i.l}$ and $\sigma^2_{j.l}$ respectively.

The Fisher Ratio of the l^{th} feature is then defined as

$$\lambda_{i,j,l} = \frac{(m_{i,l} - m_{j,l})^2}{(\sigma^2_{i,l} + \sigma^2_{j,l})} \tag{10}$$

The definition given in equation (10) can be further extended to multiclass problems, where there are C classes, in order to find the average class separability measure λ_l of the l^{th} feature,

$$\lambda_l = \frac{\sum_{i=1}^{C} \sum_{j=1}^{C} \lambda_{i,j,l}}{C(C-1)}, \qquad i \neq j \tag{11}$$

A high value of λ indicates less intraclass spread and more interclass difference, hence represents a strong discriminative feature. Feature selection has been accomplished by retaining all features having a λ value above a predetermined threshold.

4. SVM CLASSIFIER

The theory behind SVM relies on the fact that it is possible to transform the data into a space where the classes are linearly separable with dimensionality at least equal to the data's Vapnik-Chervonenkis (VC) dimension [14]. That is, some nonlinear operator $\Phi(\circ)$ is used to map the input pattern x into a higher dimensional space H so that the transformed data is linear in H. In general a kernel function $K(\circ,\circ)$ which implicitly defines the nonlinear mapping function $\Phi(\circ)$ can be used to map the nonlinear space into a linear one. There are a wide variety of possible Kernel functions, including linear, polynomials and RBFs. In this paper, an RBF Kernel has been used, which is defined as:

$$k(\mathrm{x}_i, \mathrm{x}) = e^{-\|x - x_i\|^2/(2\sigma^2)} \tag{12}$$

For any kernel, there will be some parameters that would determine the properties and efficiency of the classifier involved. For instance, there are two parameters for an RBF kernel, namely C and γ. The optimal values for these parameters are not known beforehand and consequently some kind of model selection (parameter search) must be carried out in order to ensure the best possible performance of the classifier. Cross-validation and Grid-search is an efficient and simple strategy for identifying such optimal values for the kernel parameters [15]. Once the data has been transformed to the higher dimensional space H, there may exist many hyperplanes that separate the classes as shown in Figure 3.

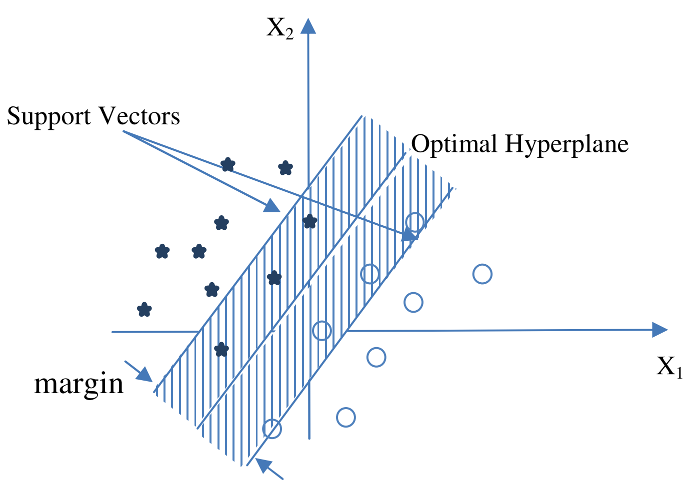

FIGURE 3: Hyper plane and support vectors.

The SVM classifier will try to find the hyperplane that maximizes the separating margin between two classes and this can be further extended to multiclass scenarios [16].

5. DETAILS OF EVALUATIONS CONDUCTED

A set of acoustic waveforms collected from 20 underwater noise sources has been used for evaluation of the system. Each of these noise waveforms is sliced in to 20 frames of 10240 elements, with a finite overlapping. The bispectrum and bicoherence matrix of each record is computed using equation (1) and equation (3). The following features were extracted from the target waveforms

a) Axially Integrated Bispectra (AIB)
b) Radially Integrated Bispectra (RIB)
c) Circularly Integrated Bispectra (CIB)
d) Bispectral-MFCC (BMFCC)
e) Diagonal and anti-diagonal slice of the bicoherence matrix (DiagBic)

No.	Feature	Properties	Ref.
(a)	Axially Integrated Bispectra (AIB)	Translation invariance	[11]
(b)	Radially Integrated Bispectra (RIB)	Scale invariance	[3]
(c)	Circularly Integrated Bispectra (CIB)	Translation invariance	[10]
(d)	Bispectral-MFCC (BMFCC)	Noise resistance, as it is derived from Bispectrum	[12]
(e)	Diagonal and anti-diagonal slice of the bicoherence matrix (DiagBic)	Self coupling Frequencies	[1]

A subset of the original feature set containing only relevant features that would potentially contribute to the classification process has been computed using equation (11), considering all targets. Simulations were conducted with different limits for the fisher's score, for each feature. From these simulations, an optimal threshold for each feature was identified. Table 1 summarises the thresholds and the percentage of the features selected during feature selection.

Feature Vector	Threshold	%of Features Used
RIB	600.00	58.24
CIB	2500.00	51.56
AIB	1000.00	60.94
BMFCC	1000.00	46.00
DiagBic	250.00	30.86
Overall		**45.16**

TABLE 1: Result of feature selection using Fisher's Criterion.

The reduced feature sets has been combined to train an SVM classifier. The whole procedure is illustrated in the Figure 4. A Matlab based framework has been developed in order to evaluate the performance of the proposed classifier system under realistic scenarios. Since the underwater acoustic signals are generally corrupted by the ambient noise which is Gaussian in nature, the framework provides options for adding white Gaussian noise to the signals to ensure the robustness of the classifier in the presence of noise. Simulations were also carried out to study the performance of SVMs trained with different noise levels.

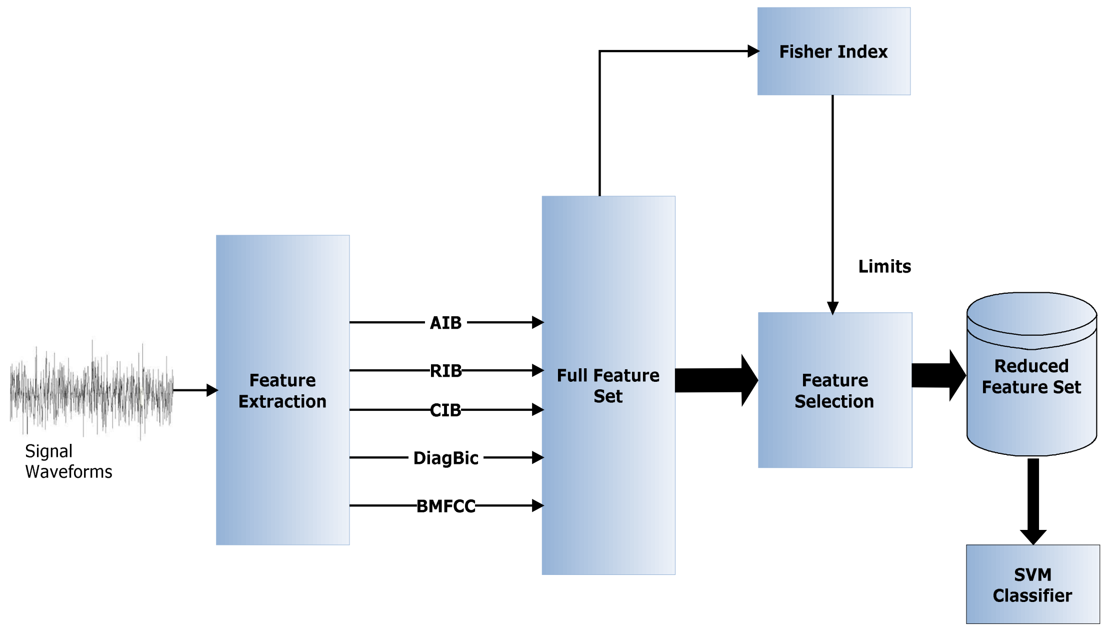

FIGURE 4: Block diagram of the complete training Process.

6. RESULTS AND DISCUSSIONS

The noise data used for evaluating the performance of the classifier mainly comprises of anthropogenic noises as well as biological noises. Some of the data sets used in developing the database were collected during scheduled cruises off Cochin and Mangalore, India. For the purpose of validating the performance of the classifiers, 400 records from 20 different targets were considered. White Gaussian noise were added to the waveforms to synthesize signals with different SNRs of 10, 15, 20, 25 and 30 db, and corresponding feature sets were extracted.

A total of 6 SVMs, each trained with different noise levels (10, 15, 20, 25,30 db and the original signal) were used for the analysis. The performance of each SVM was evaluated with all feature sets corresponding to different noise levels. In each case, an SVM classifier was trained with a training set comprising 200 randomly selected records and the success rate of the classification was evaluated. The analysis was performed 5 times, with randomly selected training set and the average performance was computed in order to get statistically reliable results.

The results of the analysis has been summarized in Table 2. Here, Classifier*N* represents a classifier trained with the features extracted from signals with white Gaussian nose added, so that the SNR is N db. For example, a success rate of 92.50% has been obtained when the SVM trained on a feature set extracted from signals having SNR of 20db, evaluated with features corresponding to 15db SNR. Classifier*Orig* denotes the classifier trained with the original signal, without adding any noise. A plot of the success rates of different classifiers is illustrated in Figure 5.

	SNR (db) of the evaluation set						Average
	10	15	20	25	30	Original Signal	
Classifier10	93.00	89.00	90.00	87.50	83.50	79.50	87.08
Classifier15	87.50	91.50	89.50	88.00	84.00	83.00	87.25
Classifier20	84.50	92.50	92.50	92.00	91.00	84.50	89.50
Classifier25	80.50	90.00	90.00	93.50	90.50	85.50	88.33
Classifier30	78.50	85.50	91.00	92.00	93.50	86.50	87.83
ClassifierOrig	73.50	82.00	85.50	85.50	85.50	94.00	84.33

TABLE 2: Success rate of SVM classifiers.

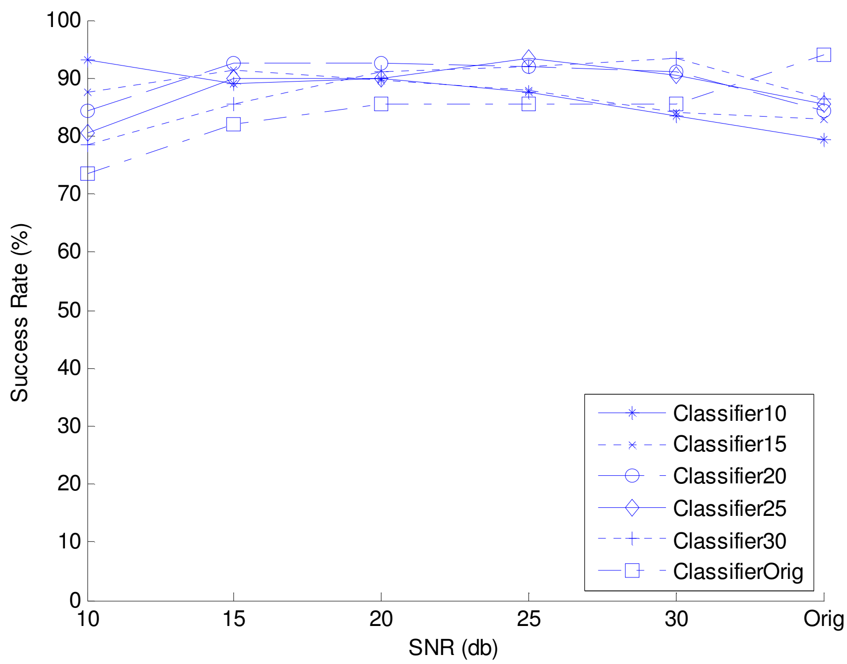

FIGURE 5: Plot showing the success rate of different classifiers.

From the simulations carried out, it was concluded that classifiers trained with signals of 20db SNR perform reasonably well for other situations of noises as well. So finally, the training sets of all individual classifiers were expanded to include features corresponding to 20db SNR and the simulation results are summarized in Table 3. Clearly, there is an improvement in success rate, which can be easily verified from the improvements in the average success rate of each classifier. The results are also illustrated graphically in Figure 6.

	SNR (db) of the evaluation set						Average
	10	15	20	25	30	Original Signal	
Classifier10	93.00	92.50	92.00	92.50	88.00	85.00	90.50
Classifier15	89.00	92.50	92.00	91.50	89.00	85.00	89.83
Classifier20	84.50	92.50	92.50	92.00	91.00	84.50	89.50
Classifier25	83.50	92.50	92.00	93.00	93.00	86.00	90.00
Classifier30	85.00	93.00	92.50	93.50	93.00	86.00	90.50
ClassifierOrig	84.50	91.50	92.00	93.50	92.50	93.50	91.25

TABLE 3: Success rate of classifiers with expanded training set.

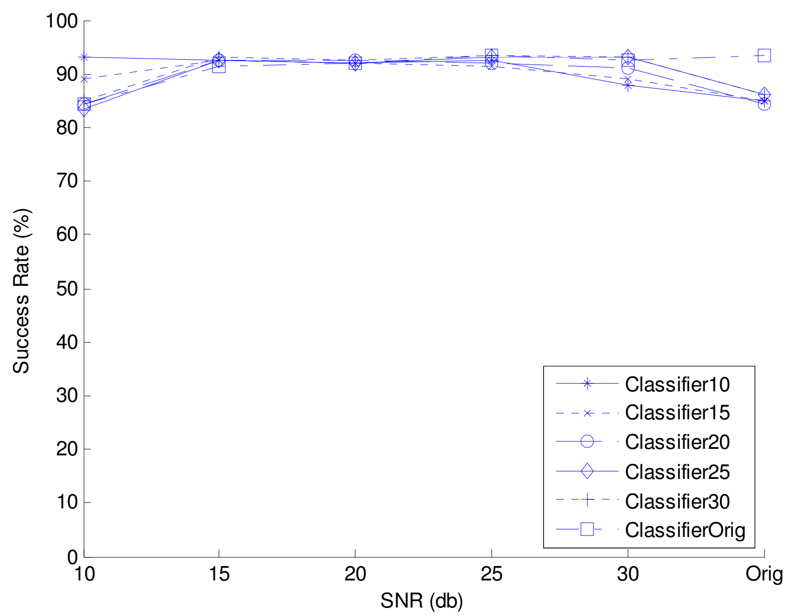

FIGURE 6: Plot showing the improved success rate.

7. CONCLUSIONS

A set of robust features derived from bispectral analysis has been proposed for underwater noise classification. The features include three types of integrated bispectras along with bispectral MFCC coefficients and self-coupling frequencies. A feature selection algorithm is used to select a robust subset of the features and an SVM classifier has been used to evaluate the classification performance. From the simulations conducted, it has been observed that the proposed higher order feature set could potentially improve the overall success rate of the classification of underwater noise sources even in the presence of different levels of ambient noise. The future work may include the incorporation of higher dimensional feature sets like trispectrum along with more robust feature selection algorithms.

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