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Adaptive Tow Ship Noise Cancellation Using Deep Regression Neural Network

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Abstract:

This paper investigates the problem of cancellation of noise generated by own platform in shallow water scenario. In the case of underwater acoustics, the target signal detection and tracking in the presence of tow ship noise is a challenging task. A computationally intensive technique is necessary for tow ship noise suppression. In this paper, an algorithm using deep regression neural network (DRNN) along with minimum variance distortionless response (MVDR) beamformer is presented for tow ship noise cancellation. Nine DRNN's each with different weight initialization techniques and activation functions are designed for effective tow ship noise cancellation. The designed DRNNs is tested using the simulated data and further validated using the real data collected during the trials from Arabian Sea.

Keywords:

deep regression neural network, towed sensor array, tow ship noise cancellation, weight initialization

1 Introduction

Estimating the direction-of-arrival (DOA) of propagating waves is an active research area with applications in a wide range of fields like medical imaging, seismology, acoustics, radar and sonar signal processing [1]. Localization of underwater targets is a challenging task owing to the complex nature of ocean medium. An array of sensors distributed in space which spatially and temporally samples the signal emanating from the source, is generally used for estimating the DOA.

Lower frequency spectrum of acoustic signals propagates over long distances in ocean. For detecting quiet targets like stealthy submarines from far ranges, a long

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array towed behind the warship is used [2]. The low frequency narrowband signals emitted by the potential targets are better captured by this towed array of sensors having long aperture. Also, these arrays can be lowered to varying depths to take advantage of the ocean condition. Towed arrays are widely used for long-range submarine detection, oil exploration, seismic studies and ocean bottom profiling and surveying [2, 3].

Shallow ocean is a bounded medium, characterized by propagating modes with complex amplitude functions and modal values, making up a hostile environment for wave propagation [4, 5]. Anti-submarine warfare is shifting to the littoral shallow waters and hence protecting the harbor assets and constant coastal surveillance is crucial in the emerging global scenario.

A major practical difficulty faced in towed array processing is the intense self-noise of the ship which is picked up by the sensors through direct and multi paths thereby masking the target signatures, despite being at a distance from the mother ship [2]. The tow ship noise is of high intensity and is present in a wide frequency band. In shallow ocean scenario, this problem is more severe due to multipath and bottom bounce reflections, affecting beams in many directions. This interference adversely affects the detection and tracking performance especially in the vicinity of the dominant direction of the tow ship.

In the past decades, a few methods have been developed to mitigate the effects of the own platform noise. Traditionally, adaptive spatial filtering techniques and sectoral null steered beamforming methods [6-9] are the two popular approaches employed for noise suppression of tow ship, which steers a null in the direction of the tow ship. However, this nulling reduces the interference only in a limited bearing interval. Signal- noise subspace separation-based methods by analyzing eigenvalues [10, 11], and principal component inverse (PCI) [12] based method is some of the common approaches employed for the illustrated purpose. Y. Song et al. [13] suggest a scheme based on Blind Source Separation. Another popular method is to use the principle of inverse beamforming [14], where the interference is subtracted from received signals at the hydrophone level. Later Li. et al. [15] proposed a combination of IBF and CLEAN algorithm, to improve the results of inverse beamforming, by removing sidelobes. Jia et al. [16] presents a comparison of null steered beamformer and IBF. However, IBF based schemes falters at severe multipath environment. Sullivan et al. [17] use a model-based approach employing Extended Kalman Filter. Space time adaptive processing (STAP) algorithm, which samples the signal in both time and frequency was developed for effective self-noise cancellation [18, 19]. However, in all the above mentioned eigen decomposition-based schemes, the computational complexity limits its application is real-time scenario. Later a method exploiting the eigenvector analysis of spatio-temporal covariance matrix based on STAP was proposed for suppressing tow ship interference. However, the method requires prior knowledge about the interference characteristics and is computationally complex [20].

Deep learning, a new area of machine learning research proposed by Hinton [21] in 2006, has drawn wide attention in the area of image processing and speech signal processing. Deep learning technique, due to its self-learning ability and high feature extraction capability, is used in speech signal separation [22-23], speech recognition [24], and speech denoising [25, 26]. However, in recent years, the deep learning technique has also been applied for DOA estimation [27-29]. The supervised learning approaches being data-driven, can be adapted to different acoustic conditions through training [28]. Following this, in this paper DRNN along with MVDR beamformer is investigated for effective self-noise cancellation in the towed sensor array. To the best of our knowledge, deep learning-based algorithm is employed for the first time for tow-ship noise suppression application as per literature. Effective suppression of self-noise signal helps in accurate target detection. The effectiveness of the DRNN based algorithm has been proven through extensive simulations over various conditions. The experimental results show that once trained properly, the DRNNs can be used in real-time scenario for self-noise cancellation. The main contributions of this paper can be summarized as follows:

- nine different DRNNs, each with different weight initialization techniques and activation functions were designed to extract features of the array data (using STFT) for effective tow ship noise cancellation. This does not necessitate any knowledge of signal subspace and noise subspace of the source signal,
- generated large sets of training data, considering the array geometry and various scenarios. The network learning parameters were decided iteratively and the performance of the networks was compared through extensive simulation in MATLAB 2019, over the simulated data,
- validated efficacy of the scheme using data from field experiments.

The outline of this paper is as follows. Section 2 presents the methodology used for tow ship noise cancellation. The array data modal used to simulate the signal, data generation for training and testing the neural network, the network model, and tow ship noise cancellation process using DRNN are explained in detail. The results and discussion based on the simulations and real data are given in section 3. Conclusions are presented in section 4.

2 Methodology

2.1 Array Data Model

An array of sensors provides significantly enhanced location performance as compared to a single antenna array. The development of the array model is based on the following assumptions:

- the sources are assumed to be in the far field of the array,
- the sources and sensors in the array are assumed to be in the same plane,
- the sources are also assumed to be point emitters,
- it is also assumed that sensors in the array can be modelled as linear time invariant systems.

The position of a source is defined by the azimuth angle, elevation angle, and range. To obtain a simplified array model, only one parameter is considered per source, i.e., the angle of arrival or DOA, which characterizes the source location.

We model the ocean as a horizontally stratified water layer of constant depth overlying a horizontally stratified bottom [30]. This model implies that the ocean is range independent, i.e., variation of its acoustic properties in the horizontal direction is negligible in the range of interest. Fig. 1 shows the source-receiver geometry for a uniform linear array (ULA).

Let $x(t)$ denote the value of the signal as measured at some reference point, at time t. The reference point in this regard can be one of the sensors of the array or any point near it, so that the assumption of planar wave propagation holds. The physical signals received by the array are continuous-time signals and hence 't' is a continuous variable.

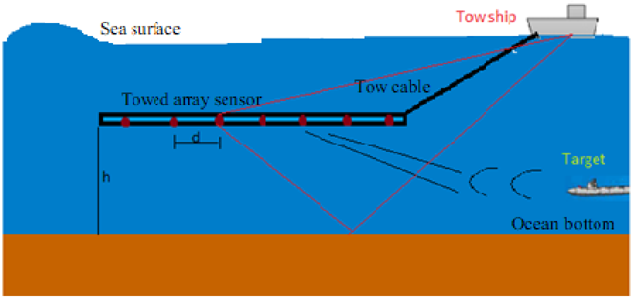


Fig. 1 ULA sensor array geometry and source locations in the ocean

Let τ_k denote the time needed for the wave to travel from reference point to sensor k, (k = 1, 2, …, M). Then the output of sensor k can be written as:

$$\boldsymbol{y}_k(t) = \boldsymbol{h}_k(t) * \boldsymbol{x}(t - \tau_k) + \boldsymbol{e}_k(t) \tag{1}$$

where $\boldsymbol{h}_k(t)$ is the impulse response of the k^{th} sensor, '$*$' denotes convolution and $\boldsymbol{e}_k(t)$ is the additive noise.

The variation of DOA i.e., θ is not only through τ_k but also with $H_k(\omega_c)$, where ω_c is the angular frequency of the source signal. If the sensors are assumed to be identical and the first sensor is chosen as a reference point, then $\boldsymbol{a}(\theta)$, the array steering vector for an M sensor array is given as:

$$\boldsymbol{a}(\theta) = \begin{bmatrix} 1 & \mathrm{e}^{-\mathrm{j}\omega_c \tau_1} & \cdots & \mathrm{e}^{-\mathrm{j}\omega_c \tau_{M-1}} \end{bmatrix}^{\mathrm{T}} \tag{2}$$

For multiple sources, a direct application of the principle of superposition leads to the following array model,

$$\begin{aligned} \boldsymbol{y}(t) &= \left[\boldsymbol{a}(\theta_1) \cdots \boldsymbol{a}(\theta_J)\right]\left[\boldsymbol{s}_1(t) \cdots \boldsymbol{s}_J(t)\right]^{\mathrm{T}} + \boldsymbol{e}(t) \\ \boldsymbol{y}(t) &= \boldsymbol{A}\boldsymbol{s}(t) + \boldsymbol{e}(t) \end{aligned} \tag{3}$$

where $\boldsymbol{y}(t)$ is the output of sensor array, $\boldsymbol{A}$ is the array manifold matrix, $\boldsymbol{s}(t)$ is the signal vector corresponding to J narrowband sources, and $\boldsymbol{e}(t)$ is the additive white Gaussian noise (AWGN).

The broadband signal is synthesized by composing uniformly spaced narrowband signals over the band of interest [31].

2.2 Data Generation

Large sets of data are simulated to train the regression neural network. Here we need predictor input and desired output to train our DRNN's. The dataset for training and validation is generated using the array data model mentioned in section 2.1. A ULA of 40 sensors is assumed. For simulating the target of interest (TOI) signal the bearing is varied from [−90°:90°] with a resolution of 5°. The tow-ship signal is fixed at a bearing of 20°. For each bearing, we considered the data collected from 40 sensors for one second. The data collected for one second has 12 800 samples. Hence to train the DRNN, we have 512 k samples of the data from 40 sensors. The datasets are generated for various scenarios and bearings. The signal received by a towed sensor array contains TOI, tow ship noise and ambient noise. The data is then converted to one dimensional (1D) data by arranging samples from each sensor, one below the other in linear fashion. We used the normalized concatenated data of the received signal as the predictor input. The normalized noise free TOI data with corresponding target bearing is considered as the desired output for the DRNN. For testing the neural network, the normalized data as received by the towed sensor array is fed to the DRNN. The simulated acoustic signal is having a frequency bandwidth from 1 000 Hz to 4 000 Hz with the center frequency of 2 500 Hz. The network is trained further by varying the signal to interference plus noise ratio (SINR) value of the TOI.

2.3 Brief Review of DRNN

Deep Learning is a sub-field of machine learning. The emergence of deep learning technique has permeated the signal processing field due to its self-learning ability and high feature extraction capability. The ability of neural networks to learn features hierarchically helps the models perform well.

A DRNN is a neural network with a certain level of complexity with more than two layers. DRNNs use sophisticated mathematical modelling to process data in complex ways, and are more powerful than two-layer neural networks. However, the efficiency of the regression models depends on the weight and bias values chosen to match the predictor input and the desired output. There are different ways to initialize the weights of neural networks. Here the self-noise cancellation is carried out using fully connected neural networks with different weight initialization techniques and activation functions. Most of the regression models will not perfectly fit the data at hand. So, to meet the performance requirements, the only solution is to design more complex models to suit the problem. The right choice of weight initialization method and activation function can speed up time to convergence considerably.

A basic DRNN structure has an input layer, multiple hidden layers, and an output layer. The number of features that the neural network uses to make its predictions is directly related to the number of input neurons. For a fully connected neural network, if the input image is of the size $m \times n$, then $m*n$ neurons are needed at its input layer. The output neurons are decided by the number of predictions that the neural network wants to make. The number of hidden layers is dependent on the problem and the architecture of the neural network. Generally, up to five hidden layers are used. The number of hidden layers in the network determines the performance efficiency. Using the same number of neurons in each hidden layer is adequate as a thumb rule. A performance boost can be obtained by adding more layers rather than adding more neurons in each layer. If the number of layers chosen is very small, then the network will not be able to learn the underlying patterns in the data. A pragmatic approach is to start with a huge number of hidden layers and then to use a dropout layer [32].

2.4 Design, Training and Testing of DRNN

In research presented in this paper we designed nine different DRNNs using a fully connected layer with different weight initialization techniques and activation functions. Initially the network DRNN0 with *zero* weight initialization technique and *tanh* activation function with 5 hidden layers were designed. Each hidden layer contains a fully connected layer, an activation layer, and a batch normalization layer. Based on the observations, the networks were modified to improve their performance with more hidden layers, different weight initializations and activation functions. Fig. 2 shows the basic structure of the designed DRNN architecture.

In deep learning, the dataset plays a crucial role in training the neural network. For proper training and performance efficiency of the neural network, large samples of data are required. The dataset for training the neural network is prepared as mentioned in section 2.2. For validation, as part of training, sensor data is randomly simulated for different bearings. For testing the neural network, the signal is generated as received by a towed sensor array for different bearings and SINR values. In the testing phase, the input to the neural network is the array data vector as received by a towed sensor array.

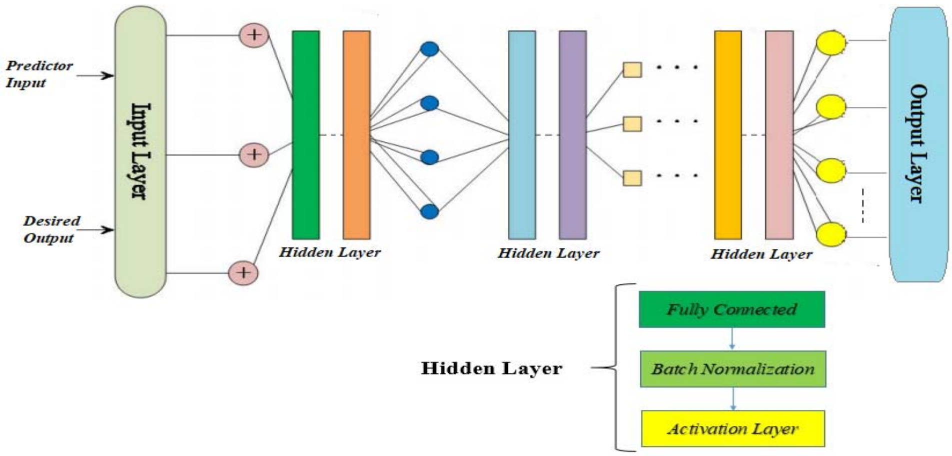


Fig. 2 The basic structure of the designed DRNN architecture

For accurate estimation of TOIs and tow ship noise suppression, the neural network should be trained with a large number of samples of signals. However, validation and testing of the trained neural network can be achieved using few samples as compared with the training dataset. To minimize the complexity of the network the training signals are normalized to the same power.

To train the neural network, the normalized predictor input signal and the desired output signal were transformed into spectrograms using the short time Fourier transform (STFT) with Hanning window of 32 samples and an overlap interval of one sample. The magnitude and phase components were separately fed to the neural network to estimate the magnitude and phase of the TOI. The designed DRNN tries to minimize the root mean square error (RMSE) between the desired output and the estimated output.

$$RMSE = \sqrt{\frac{1}{N}\Sigma\left(\boldsymbol{y}_i - \hat{\boldsymbol{y}}_i\right)^2} \tag{4}$$

N indicates the number of neurons, $\boldsymbol{y}_i$ the desired output and $\hat{\boldsymbol{y}}_i$ the estimated output. At all stages of the network, it is necessary to normalize the data to stabilize and speed up the network training process. Thus, the predictors are normalized before feeding to the network and each layer output is normalized using the batch normalization layer. Training options are then set for proper training of the neural network.

To train the neural network, adaptive moment estimation (Adam) optimizer [33] is used. The sensor data is trained for 25 epochs with mini-batch of size 128 and initial learn rate set to 0.001. However, the learning rate is lowered after 5 epochs. To monitor the network efficiency and accuracy during training, validation data and validation frequency are specified. The software trains the network using training data and calculates the accuracy of the validation data at regular intervals. For training the DRNN8 with 12 800 samples of data corresponding to 40 sensors for bearings varying from [−90°:90°] in 5° steps, for a single SINR value, we require around 8 hours of time. The network was trained using MATLAB 2020b on an Intel i7 CPU based workstation.

2.5 Processing Steps Leading to Self-Noise Cancellation

- Dataset generation: Dataset for training the DRNN is prepared as described in section 2.2,
- pre-processing stage: The simulated signal as received by the towed array is concatenated to normalized ID data and is transformed to spectrograms. Initially, a Hamming window function is applied to the signal and STFT is computed to generate the spectrogram of the signal. The phase and magnitude are separated and given to the DRNN for training and validation,
- to model the target signal characteristics: Characteristics of the TOI (Phase and magnitude) is modelled as the noise free signal,
- to train the neural network: DRNN is trained to estimate the magnitude and phase of the TOI from the received signal. The DRNN tries to minimize the RMSE between the desired output and estimated output,
- to estimate the target signal characteristics from the neural network: Estimated characteristics (magnitude and phase) of TOI are multiplied together and an inverse STFT is applied to obtain the actual estimated TOI,
- localization: The estimated target signal is subjected to beamforming for detection and bearing estimation of targets. Here MVDR beamformer is used as the response function. Fig. 3 shows the detailed block diagram of self-noise cancellation using the proposed deep learning algorithm.

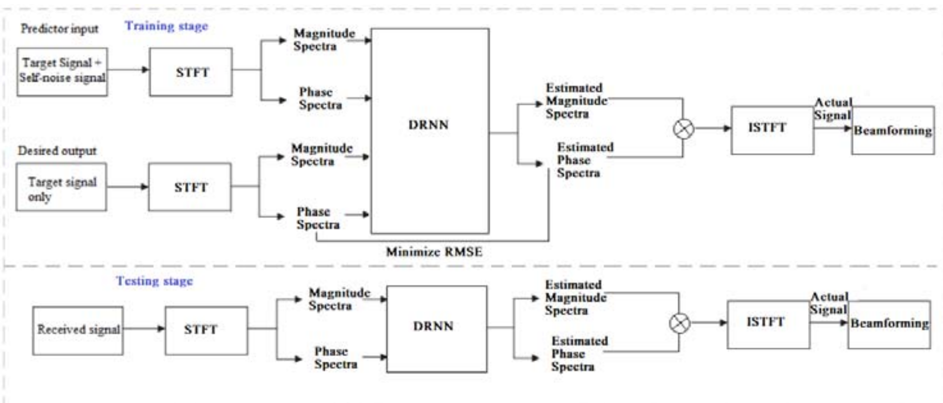


Fig. 3 Block diagram of self-noise cancellation using the proposed deep learning-based algorithm

This work shows how to use a deep learning network to separate target signal from tow ship noise. The TOI and self-noise signals are simulated and the two signals are combined to generate the signal, as received by a towed sensor array. Here we want to separate the TOI and self-noise.

The signal received by a sensor array is converted to normalized 1D data. The signal is then transformed to the frequency domain using the STFT, with a window length of 32 samples, an overlap of 31, and a Hamming window. The predictor input consists of 12 consecutive STFT vectors with sequence overlap of 8. The network is trained to estimate the phase and magnitude of the TOI. The regression neural network tries to minimize the RMSE between the desired output and estimated output.

During testing phase, the normalized 1D signal as received by the towed sensor array is transformed using STFT and is fed to the neural network. The DRNN will estimate the phase and magnitude of the TOI. The estimated phase and magnitude are multiplied and an inverse STFT is applied to obtain the actual estimated TOI. The signal is then subjected to MVDR beamforming for DOA estimation.

3 Results and Discussion

3.1 Using Simulated Data

In this section, the simulation results of DRNN based on an algorithm along with MVDR beamformer are presented in detail. We simulated acoustic signal data as received by a ULA of 40 sensors with an inter-sensor spacing of 0.175 m, which is half a wavelength corresponding to 4 kHz. The towed ship data is simulated at a bearing of 20°. Along with this, ambient sea noise as per the Wenz curve [1] is also added. A realistic scenario is simulated by adding a TOI at various bearings from [−90°:90°] at a resolution of 5° to this case.

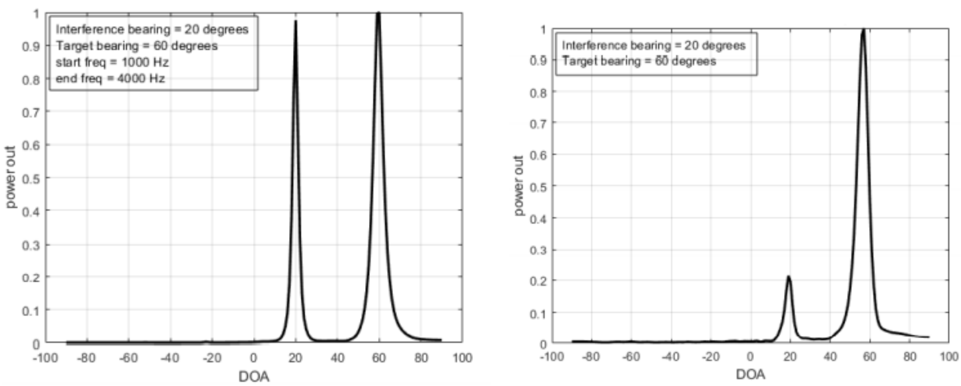
Nine different DRNNs with different weight initialization and activation functions using fully connected neural network were designed. Self-noise cancellation was tried out using these nine different DRNN. The spectrogram of the signal was taken and its magnitude and phase were separately trained in the DRNN. To train the designed DRNN, the signals as received by the towed sensor array for one second (12 800 samples) from 40 sensors of different TOIs ([−90°:5°:90°]) were converted to 1D normalized data, which is of size of 512 k × 1. Hence in total we have 512 k × 37 samples of data to train the network. In addition, the network was trained further by varying the SINR value of the TOI. To test the trained DRNN, normalized 1D signal of size 512 k × 1 data was utilized. Thus, the network is trained to estimate the magnitude and phase of the TOI. The performance efficiency of the network is determined using RMSE value and error variation. Tab. 1 summarizes the performance of different DRNN for SINR 15 dB. It may be noted that the DRNN8 using random weight initialization (Randn) and the PReLU activation function with 25 layers performs the best. Fig. 4 illustrates the designed DRNN8 network.

Effective training of DRNN enhances the suppression of self-noise signals. Simulation results obtained for DRNN8 with MVDR beamformer as response function are shown in Fig. 5. It is to be highlighted that the method is implementable in real time scenario owing to the lesser computational requirements, even though the training requires longer time and large samples. Fig. 5 illustrates the MVDR beamformer output of the received signal with and without DRNN based self-noise cancellation algorithm. TOI is at 60° while the tow ship is at around 20°. It may be observed that the tow ship noise is reduced considerably while the TOI power and hence the target detection remains unaffected.

Fig. 4 DRNN8 using Randn weight initializer with 25 layers

Tab. 1 Performance Efficiency of DRNNs

DRNN	Weight Initialization	No. of Layers	Activation function	RMSE	Error range
DRNN0	Zero	18	tanh	44.60	−6:6
DRNN1	Glorot	18	tanh	37.43	−5:5
DRNN2	Glorot	18	ReLU	37.24	−4:4
DRNN3	He	18	ReLU	33.70	−3:3
DRNN4	He	18	ReLU	27.40	−3:3
DRNN5	Randn	18	ReLU	22.70	−2:2
DRNN6	Randn	18	ELU	17.80	−2:2
DRNN7	Randn	18	PReLU	13.41	−1:1
DRNN8	Randn	25	PReLU	10.47	−1:1



(a) (b)

Fig. 5 MVDR beamformer response function. (a) without self-noise cancellation (b) with self-noise cancellation using DRNN

Though the training requires more samples and time, after proper training tow ship noise can be suppressed effectively using fewer samples within a few seconds. The designed DRNN system using random weight initializer works effectively for both positive and negative SINR values. Tab. 2 shows the RMSE value obtained for DRNN8 for different SINR values.

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Tab. 2 RMSE value obtained using DRNN8 for different SINR values

SINR [dB]	RMSE
−15	11.121
−5	10.780
5	10.670
15	10.470
25	10.288

3.2 Experimental Validation

We have also evaluated the scheme with the real field noise data collected during trials in the Arabian Sea, with a simulated target signal added to this recorded data. The data collected during the experimental trials of a passive towed array sonar system was used for validating the performance of the algorithm. The trial was conducted in the Arabian Sea, off Kochi, where the water depth is approx. 200 m.

The data collected from an under-water acoustic sensor array goes through a chain of analog signal conditioning hardware. It is first received by low noise charge amplifiers, further it is passed through a pre-whitening filter and anti-aliasing filter. Using a 24-bit sigma delta ADC, the data is digitized and then it is packetized into Ethernet frames with proper header structures, MAC addresses and payload. The frame ends with a frame check sequence, which is a 32-bit cyclic redundancy check used to detect whether any error occurs during the time of transmission of the data. This data is stored in a digital data recorder and later retrieved to run the algorithms. The collected data is then converted to a number of samples-by-number of sensors $S \times M$, the format where S is the number of samples and M is the number of sensors. Ethernet output is passed on to the DRNN and further to the beamformer module.

The recorded data from the towed sensor array of 5 seconds duration is used to prove the efficacy of the proposed method. The sensor array supports multi-octave band reception, consisting of 96 non-uniformly spaced sensors to achieve uniform beam width across the bands of operation. There are four octave bands viz. band I up to 500 Hz, band II (500 Hz-1 kHz), band III (1-2 kHz) and band IV (2-4 kHz). The 32 hydrophones in the central part of the array are positioned for band IV with an inter-element spacing of 0.1875 m. Similarly, alternate elements in band IV and 8 elements each on both sides (spaced at 0.375 m) together form 32 elements of band III and so on.

For analysis, the data from 32 hydrophones in the central part are taken. Hence for processing 64 K samples, the data from 32 sensors is used. Here the beam direction is from (0°:180°). A target signal is then synthetically simulated at a bearing of 110° and added to the real data. It may be noticed that tow ship noise is present at a bearing of 20° and a multipath reflected version of the signal is also seen at a bearing of 32°. The normalized 1D signal after STFT is fed to the trained DRNN to estimate the magnitude and phase of the TOI. The estimated magnitude and phase are combined and an inverse STFT is performed to estimate the TOI signal. Fig. 6 shows the MVDR beamformer response function with and without the DRNN based algorithm on the real experimental data. From Fig. 6, it is clear that the proposed DRNN based algorithm effectively suppresses the tow ship-noise signal and corresponding multipath signal, while the TOI detection is not hampered.

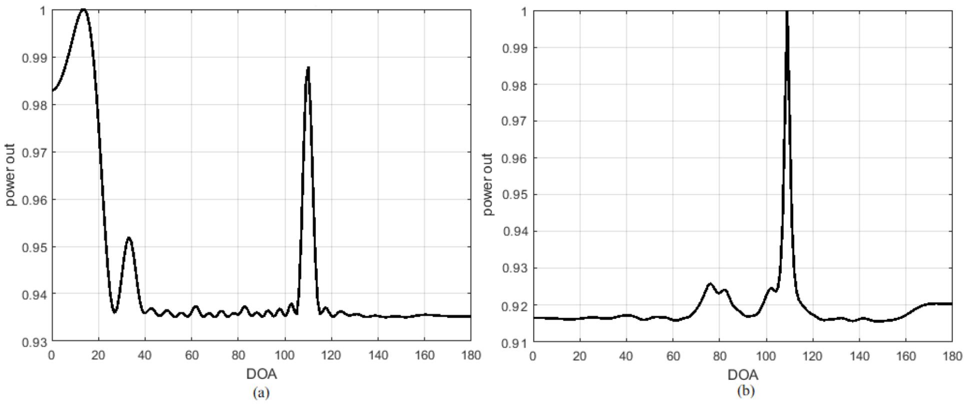

Fig. 6 MVDR response function of real experimental data for 5 second with multipath interference at bearing 32°. *(a) without applying self-noise cancellation (b) after applying DRNN based algorithm*

To understand the efficiency of the designed DRNN, error analysis is carried out using both the RMSE value and mean absolute error (MAE) value. We obtained the RMSE value of 19.48 dB during testing the DRNN with the real experimental data. Subsequently, the MAE value between the estimated output and the predictor input is also calculated. Fig. 7 shows the histogram plot of the mean absolute error using DRNN8.

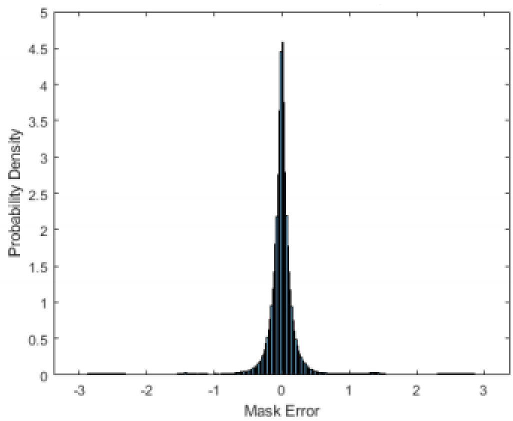

Fig. 7 Histogram plot of the MAE value between the estimated and desired output

The computational complexity, strengths and weaknesses of the proposed method are compared with the existing methods. Tab. 3 lists the comparison results. The proposed deep learning-based algorithm is computationally more efficient and is suitable for real time application. Even though the training requires time, after the training phase, the network needs only minimum time irrespective of the size of the data, when deployed. Also, the trained network does not require any prior knowledge about the signal characteristics to achieve effective self-noise suppression.

Tab. 3 Performance comparison with existing methods

Method	Reference	Performance Analysis		
		Complexity	**Strength**	**Weakness**
PCI	[12]	Low	Effective in suppressing single direction interference	Cannot remove far field interference Requires prior knowledge about signal characteristics
ECA	[10, 11]	Medium	Simple decision criterion	Difficult to fix decision threshold Requires prior knowledge about the signal
Eigen vector analysis based on STAP	[18-20]	High	Effective interference suppression	Requires prior knowledge about the interference Difficult to fix decision threshold
Proposed Method		Medium (during training) Low (during deployment)	Effective interference suppression irrespective of the size of the data No need of selecting threshold values Suitable for real-time applications	Training requires more time Large data set is needed for training

4 Conclusion

In this paper, we have presented the DRNN based technique along with MVDR beamformer for tow ship noise cancellation. The proposed scheme helps in effective suppression of tow ship noise without necessitating any prior knowledge of signal subspace and noise subspace. Deep learning technique due to its self-learning ability and high feature extraction capability leads to an effective noise cancellation. Nine DRNNs, each with different weight initialization techniques and activation functions are designed and the performance of each network is evaluated for the effectiveness of self-noise cancellation. It is observed that the DRNN8 using random weight initialization (Randn) and the PReLU activation function with 25 layers performs the best. The efficacy of the proposed scheme is demonstrated through extensive Monte-Carlo simulations, exhibiting the mitigation of self-noise. The robustness of the method is further validated with the data collected from a field experiment conducted at the Arabian Sea off Kochi, India. The less computational demands of the network during testing makes it suitable for real time implementation, hugely aiding the long-range detection and classification of stealthy targets, in passive sonar.

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