Exploiting Compressed Eigencomponent Transformation in DNN Framework for Passive SONAR Self-noise Cancellation

Pawan Kumar, Karan Nathwani
Department of Electrical Engineering, Indian Institute of Technology Jammu, India

***Abstract*—Self-noise is a barrier to detecting hidden targets by passive SONAR systems. Earlier work uses a DNN to map a high-dimensional noisy/clean pair to perform denoising. The significant problem with the approach is its high memory requirement and computational time. To address this issue, this work proposes two approaches. The first approach, DNN-based Compressed Eigencomponent Transformation (DNN-CET-Supervised), utilises the diagonal matrices of compressed noisy and clean data to learn the mapping between them. Since obtaining original clean target data is challenging in real-world scenarios, a second approach, namely the DNN-CET Semi-supervised framework, is also proposed. In this technique, the diagonal matrix of the estimated compressed target data is computed using "compressed sensing singular value decomposition (CSSVD)" in place of the original clean data for mapping. During the prediction, compressive sampling matching pursuit (COSAMP) is utilized to recover the signal in the original domain. The proposed approach requires less memory and time during transmission from encoder to decoder. The experimental results are demonstrated through beampattern plots (BP), waterfall displays(WD), and output signal-to-interference-noise ratio (SINR) versus input SINR.**

***Index Terms*—Self-Noise Cancellation, Compressed Sensing, Deep-Learning, Eigenvector, Passive SONAR.**

I. Introduction

Self-noise is a challenge in passive SONAR systems, which hinders the precise detection of hidden targets. Therefore, self-noise cancellation (SNC) is necessary for accurate target detection. Researchers have recently investigated numerous strategies for SNC. Traditional underwater noise cancellation techniques are adaptive filtering [1] and spectral subtraction [2]. While these methods have been demonstrated to be effective against white noise, they fail to eliminate self-noise.

Mode decomposition strategies handle various noises in addition to white noise, decomposing noisy signals into distinct frequency components. Empirical Mode Decomposition (EMD) has gained widespread recognition for its effectiveness in data and feature extraction [3], [4]. Nonetheless, when the Signal-to-Interference Ratio (SINR) is low, EMD modes might overlap and cause interference. In contrast to EMD, Variational Mode Decomposition (VMD) [5] approximates the center frequencies of the noisy signal into intrinsic mode functions (IMFs) and permits the simultaneous extraction of all modes. Nevertheless, high degrees of non-stationarity, such as abrupt signal onset, cannot be handled by VMD [6].

This problem can be solved in [7], which breaks a signal into its orthogonal component. The approach determines singular values corresponding to the self-noise by evaluating the correlation coefficient between the noisy signal and the self-noise. Subsequently, the corresponding singular values are nullified to suppress the self-noise. The authors in [8] employ an adaptive eigencomponent decomposition approach to address non-stationary interference distributed across multiple eigenvectors. Both methods mentioned above depend on a threshold to select an eigenvector corresponding to self-noise, which might produce sub-optimal outcomes and miss essential signal characteristics.

To address these issues, the authors in [9] establish a subspace orthogonal to the self-noise, and the noisy data is projected onto this subspace for SNC. However, these approaches encounter substantial obstacles in a dynamic oceanic environment where noise characteristics change continuously.

DNN has recently been used to address various forms of intricate and evolving noise challenges in different fields [10]–[12]. A DNN approach is better than a traditional approach in its ability to accurately model complex relationships between sources and labels, which helps it handle such noises. An autoencoder is a DNN that learns and reconstructs clean data from noisy data [13]. Regarding SNC, authors in [14] employ a direct approach to SNC, mapping noisy/clean pairs in the time-frequency domain. In [13], a method DNN-based eigencomponent transformation (DNN-ET) maps a diagonal matrix of noisy data to a diagonal matrix of an updated matrix derived from the original target data. The approach transforms the eigencomponent of the noisy data to obtain clean data. The above-mentioned conventional and DNN-based approaches are employed in higher-dimensional space, require significant time and memory, and encounter significant challenges.

In [7], eigenvectors corresponding to self-noise are nullified with the help of the correlation coefficient in the compressive domain. Although the computational complexity during transmission of this approach is relatively low compared to high-dimensional approaches, this approach depends on a threshold. In [15], authors utilized null-space projection to perform compressive SNC. This adjustment addresses the computational demands of high-dimensional data independent of the threshold, providing more efficient and practical solutions in such scenarios. However, the performance of these approaches deteriorates in complex noise environments.

Therefore, we uses a hybrid model comprising CS [15]–[17], SVD [18], and DNN [13] to overcome these chal-

lenges and named as DNN-based Compressed Eigencomponent Transformation (DNN-CET). We have proposed two approaches: DNN-CET supervised (DNN-CET-S) and DNN-CET semi-supervised (DNN-CET-SS). The DNN-CET-S involves training compressed pairs of diagonal matrices of noisy and estimated clean data during training. The diagonal matrices are obtained by Singular Value Decomposition (SVD). The DNN-CET-SS maps the diagonal matrix of compressed noisy data to estimated compressed clean data obtained using CSSVD [15]. During testing, distinct compressed noisy data from training data is used to predict compressed clean data. Once compressed clean data is obtained, a matching pursuit algorithm, Compressive Sampling Matching Pursuit (COSAMP) [19], is used to recover the data in the high-dimensional domain. The contribution of this work is illustrated as follows:

1) The approach uses a compressed noisy/clean pair for training, significantly reducing training time and memory requirements.
2) The approach doesn't depend on any threshold. Thus, it maintains consistent performance without requiring frequent adjustments to any threshold, making it more reliable in dynamic and unpredictable environments.
3) We map a diagonal matrix, which transforms the eigencomponent of noisy data to provide clean data. The approach can effectively isolate and cancel out self-noise without needing complicated computations.

The paper is structured as follows: The proposed method is discussed in section II followed by results and simulation in section III with a brief conclusion in section IV.

II. Proposed Approach: SNC using DNN-based Compressed Eigencomponent Transformation (DNN-CET)

The DNN-ET [13] approach encounters challenges such as high computational complexity and substantial memory requirements due to directly mapping of noisy/clean pairs in high-dimensional domain. To counter this concern, this paper introduces novel supervised and semi-supervised versions of the DNN-CET approach. The approach needs less memory and computational time during transmission. The algorithm of the proposed approach is discussed in subsection II-A. The retrieved data in the original high-dimension is obtained by solving a reconstruction problem, discussed in subsection II-B. An autoencoder trains noisy/clean pairs to get the optimum weight, explained in subsection II-C.

A. Algorithm of proposed Approach

The pseudo-codes of the training phase of proposed approach is illustrated in Algorithms 1. It comprises three parts: A. Source Generation, B. Label Generation, and C. Autoencoder Training.

For source generation, we initially compress the noisy data. Subsequently, we calculate the SVD of the $\mathbf{Y_{CS}}$ as given in (5). The source to the autoencoder is $\mathbf{D_{CS_y}}$. Thereafter, we have to generate the label for DNN-CET-S and DNN-CET-SS. DNN-CET-S aims to identify eigenvectors corresponding to compressed clean data. Suppose in (5) we multiply $\mathbf{D_{CS_y}}$ with the appropriate weight vector so that it provides an assessment of compressed clean data [13].

$$\begin{aligned} &\mathbf{S_{CS}} = \mathbf{U_{CS_y}} \mathbf{W} \mathbf{D_{CS_y}} \mathbf{V_{CS_y}}^{\mathcal{T}}, \\ &\mathbf{U}_{\mathbf{CS_y}}^{\mathcal{T}} \mathbf{S_{CS}} \mathbf{V_{CS_y}} (\text{say } \mathbf{D_{CS_u}}) = \mathbf{W} \mathbf{D_{CS_y}}, \end{aligned} \tag{1}$$

Therefore, $\mathbf{D_{CS_u}}$ is considered the label for the DNN-CET-S approach. For the DNN-CET-SS, label $\mathbf{D_{CSSVD}}$ is given as

$$\mathbf{D_{CSSVD}} = \mathbf{U}_{\mathbf{CS_y}}^{\mathcal{T}} \mathbf{S_{CSSVD}} \mathbf{V_{CS_y}} \tag{2}$$

Our goal is to obtain the weight matrix $\mathbf{W}$ in (1) using an autoencoder with source $\mathbf{D_{CS_y}}$ and label $\mathbf{D_{CS_u}}$ or $\mathbf{D_{CSSVD}}$. The autoencoder aims to learn a representation of the compressed clean data ($\mathbf{D_{CS_u}}$) that accurately captures the essential features. The learned weight matrix $\mathbf{W}$ is an outcome of this training process.

The testing phase in Algorithm 2 includes two parts: A. Compressed clean data prediction, and B. Signal Recovery to High-Dimensional Domain. Once we determine the weight matrix $\mathbf{W}$ through training, we can obtain the predicted diagonal matrix $\mathbf{D_{CS_{Pred}}}$, and the compressed version of the clean data.

$$\mathbf{S_{DNN-CET}} = \mathbf{U_{CS_y}} \mathbf{D_{CS_{pred}}} \mathbf{V_{CS_y}}^{\mathcal{T}} \tag{3}$$

B. Signal Recovery to High-Dimensional Domain

We have to reconstruct the estimate of the clean signal back in the original high-dimensional domain. It has been proven that achieving a reliable recovery of $\mathbf{S}$ based on its sparse representation $\mathbf{A}$ is feasible when the sensing matrix $\mathbf{\Phi}$ adheres to the Restricted Isometry Property (RIP) and exhibits incoherence with the basis $\mathbf{\Psi}$ [16], [17]. The process of estimating the signal matrix involves addressing N independent inverse problems, each characterized by the following form:

$$\begin{aligned} &\text{argmin} \|\hat{\mathbf{S}}_{\mathbf{CS}} - \mathbf{\Phi}\mathbf{\Psi}\mathbf{A}\|_F^2 \ \text{ s.t. } \ \|\mathbf{a}_i\|_0 \leq k, \\ &\mathbf{A} = [\mathbf{a}_1 \ \mathbf{a}_2 \ \mathbf{a}_3 \ldots]; \quad \hat{\mathbf{S}} = \mathbf{\Psi}\mathbf{A}, \end{aligned} \tag{4}$$

Here, $\hat{\mathbf{S}}_{\mathbf{CS}}$ can be retrieved from compressed versions of proposed DNN-CET ($\hat{\mathbf{S}}_{\mathbf{DNN-CET}}$) or other baseline approaches. In (4) $\|.\|_0$ refers to the ℓ_0-norm. Solving the optimization problem (4) involves utilizing matching pursuit-based greedy algorithms or relaxing the sparsity constraints and employing ℓ_1-norm-based solvers [16]. In this analysis, we have chosen the discrete-time cosine transform (DCT) as the sparsifying basis and a random-ortho Gaussian matrix as the measurement matrix. This selection is inspired because it fulfills incoherence or Restricted Isometry Property (RIP) requirements with high probability [17]. We employ greedy sparse recovery algorithms to recover the signal from projected CS samples, such as compressive sampling matching pursuit (COSAMP) [20]. Following signal recovery, the recovered signal is passed through a delay-and-sum beamformer to obtain a beamformed output.

Algorithm 1: DNN-CET Training: Source Label Mapping

Input: Noisy data $\mathbf{Y}$, Clean data $\mathbf{S}$ (for DNN-CET-S), Estimated Clean data $\mathbf{S_{CSSVD}}$ (for DNN-CET-SS), measurement matrix $\mathbf{\Phi}$, sparsifying basis $\mathbf{\Psi}$

Output: Diagonal matrices: $\mathbf{D_{CS_y}}$, $\mathbf{D_{CS_u}}$, $\mathbf{D_{CSSVD}}$

A. Source Generation

Obtain the compressed version of noisy data: $\mathbf{Y_{CS}} \leftarrow \mathbf{\Phi Y}$

Calculate the SVD of $\mathbf{Y_{CS}}$:

$$\mathbf{Y_{CS}} \rightarrow \mathbf{U_{CS_y}} \mathbf{D_{CS_y}} \mathbf{V}^{\mathcal{T}}_{\mathbf{CS_y}} \tag{5}$$

Take $\mathbf{D_{CS_y}}$ as source to the autoencoder

B. Label Generation:

if *DNN-CET-Supervised (DNN-CET-S)* **then**

Obtain the compressed version of clean data: $\mathbf{S_{CS}} \leftarrow \mathbf{\Phi S}$

Compute labels: $\mathbf{D_{CS_u}} \leftarrow \mathbf{U}^{\mathcal{T}}_{\mathbf{CS_y}} \mathbf{S_{CS}} \mathbf{V_{CS_y}}$, $\mathbf{U_{CS_y}}$ and $\mathbf{V_{CS_y}}$ are orthogonal vectors of $\mathbf{Y_{CS}}$

else if *DNN-CET-Semi-supervised (DNN-CET-SS)* **then**

Compute labels: $\mathbf{D_{CSSVD}} \leftarrow \mathbf{U}^{\mathcal{T}}_{\mathbf{CS_y}} \mathbf{S_{CSSVD}} \mathbf{V_{CS_y}}$

C. Autoencoder Training:

Source $\leftarrow \mathbf{D_{CS_y}}$, Label $\leftarrow \mathbf{D_{CS_u}}$ or $\mathbf{D_{CSSVD}}$, learn weight matrix $\mathbf{W}$ (refer subsection II-C)

Algorithm 2: DNN-CET Testing: Clean Data Recovery

Input: $\mathbf{D_{CS_y}}$, $\mathbf{U_{CS_y}}$,$\mathbf{V_{CS_y}}$ (from $\mathbf{Y_{CS}}$), $\mathbf{W}$ (from training)

Output: $\hat{\mathbf{S}}$

A. Compressed clean data prediction:

Obtain the predicted diagonal matrix: $\mathbf{D_{CS_{Pred}}} \leftarrow \mathbf{W D_{CS_y}}$

Compute the compressed version of clean data: $\mathbf{S_{DNN-CET}} \leftarrow \mathbf{U_{CS_y}} \mathbf{D_{CS_{Pred}}} \mathbf{V}^{\mathcal{T}}_{\mathbf{CS_y}}$

B. Signal Recovery to High-Dimensional Domain:

Solve the optimization problem using (4) to recover $\hat{\mathbf{S}}$ in high-dimensional domain

C. Architecture of DNN-CET Autoencoder

Autoencoders find widespread applications in noise reduction for both image and audio processing [13]. Autoencoders are particularly effective in reducing unwanted noise in data. In underwater acoustics, an autoencoder is a valuable SNC tool and enhances the clarity of target signals in noisy environments. The autoencoder depends on several hyperparameters to optimize its weights properly. Many experiments have been conducted to find the most suitable hyperparameters to get the best output SINR. These include the type of pooling, kernel size, learning rate, and activation functions.

The source to the encoder is $\mathbf{D_{CS_y}} \in \mathbb{R}^{M \times N \times 1}$. The encoder section employs 2D convolutional layers for feature extraction and dimension reduction. Each convolutional layer is followed by a Rectified Linear Unit (ReLU) layer, and the number of filters doubles with each subsequent layer, maintaining the same padding. To further reduce dimensionality, average-pooling layers are utilized, as illustrated in Fig. 1.

Conversely, the decoder utilizes 2D transpose convolutional layers with a stride of two and the same padding for upsampling. Similar to the encoder, ReLU layers follow each 2D transpose convolutional layer. A dropout layer is incorporated

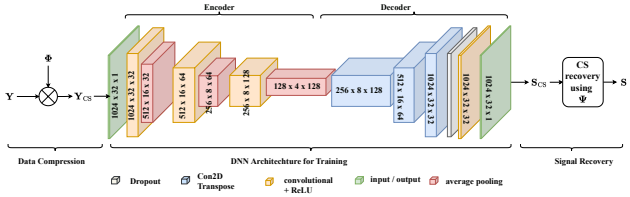

Fig. 1. Network Architecture of SNC using autoencoder

to mitigate overfitting. A 2D convolutional layer with a "tanh" activation function generates the output.

The network is optimized using gradient descent with back-propagation to minimize the mean square error. DNN-CET-S (DNN-CET-SS) minimizes the difference between $\mathbf{D_{CS_u}}$ and $\mathbf{D_{CS_{Pred}}}$ ($\mathbf{D_{CSSVD}}$ and $\mathbf{D_{Pred}}$). The autoencoder utilizes the Adam optimizer with an initial learning rate of 0.0001, which decreases by a factor of 0.5 every ten epochs. Parameter updates are performed for 200 epochs, employing a batch size of 32 and a kernel size of 3×3. Additionally, early stopping is implemented to halt training if the validation loss does not decrease for three consecutive epochs.

III. Results and Simulation

A. Experimental Setup

To train the autoencoder, the input SINR ranges from -30 dB to 0 dB with a step size of $\Delta = 1$ dB and Target Bearing (TB) varies from 30° to 150° with a step size of $\Delta = 2^\circ$. We have selected ambient noise as Gaussian with unity standard deviation. We employed distinct input data from the training set for testing. The self-noise bearing is fixed at 15°, and the Uniform Linear Array (ULA) comprises 32 sensors. The sampling frequency is set to 4096. The compression ratio (CR), M/T, is 0.25, where M and T are the numbers of time samples in the compressed and original domain. To train the DNN, we have considered 1 second of data. Post-training, testing, and prediction are conducted for 40 seconds. Results are visualized using a beampattern (BP) and waterfall display (WD) with a delay-sum beamformer, where powers are normalized with their maximum values.

In a real-world scenario, the speed of sound in water (c) is approximately 1500 m/s. The self-noise and target signal frequencies are fixed at 1200 Hz and 1300 Hz, respectively, with the upper frequency (f) for designing the ULA set to 4000 Hz. The distance between sensors is maintained at half the wavelength ($\lambda/2 = c/2f$), i.e., 18.75 cm.

The evaluation metric for our proposed approach is the output Signal-to-Interference-plus-Noise Ratio (SINR), representing the difference between power at the TB and the mean of power at all other bearings except TB in dB after SNC. Our proposed DNN-CET-S and DNN-CET-SS results are compared with CSSVD [15], ECACS [7], DNN-ET-S and DNN-ET-SS [13] and DNN-DCS-S and DNN-DCS-SS [21].

We evaluated the results of the matched and mismatched conditions to underscore the advantages of our proposed methods. In matched conditions, the standard deviation of

TABLE I
TRANSMISSION TIME AND MEMORY REQUIREMENT

	Dataset Memory	Average Training Time per epoch	Average Prediction Time
DNN-ET-S	1.4 GB	7 sec	1.80 sec
DNN-DCS-S	831 MB	**3 sec**	**0.57 sec**
DNN-CET-S	**467 MB**	**3 sec**	0.69 sec

ambient noise remains the same for training and testing data. In mismatched conditions, the standard deviation of ambient noise is doubled during testing. During training, we did not change the standard deviation. Our approaches are compared with signal processing based methods, namely CSSVD [15] and ECACS [7]. The performance is also compared with DNN-based approaches, including the supervised and semi-supervised versions of the eigen transformation-based method in high-dimensional domain [13], referred to as DNN-ET-S and DNN-ET-SS, respectively, as well as direct mapping of compressed noisy pairs in supervised and semi-supervised settings, referred to as DNN-DCS-S and DNN-DCS-SS, respectively [22].

B. Comparison of Transmission Time and Memory Requirement

Table I compares the transmission time and memory requirement of three DNN methods: DNN-ET-S, DNN-DCS-S, and DNN-CET-S. Our training datasets exhibit similar variations in target bearings and SINRs across all approaches. We observe that the suggested DNN-CET method uses significantly less memory than the other two. Consequently, the proposed approach has shorter training and prediction times than DNN-ET and is comparable to DNN-DCS. Therefore, the DNN-CET approach is a promising solution, suggesting both computational time efficiency during transmission and reduced memory needs, especially for naval personnel handling high-dimensional data in real-world situations.

C. Results for Stationary Target

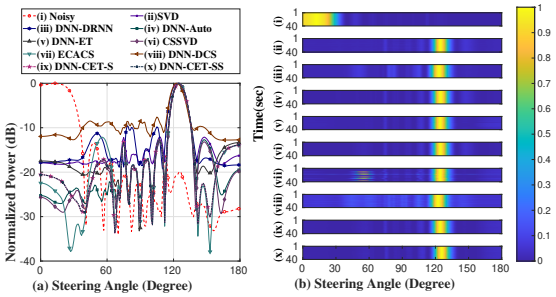

Fig. 2. (a)BP and (b) for a Stationary Target at 125° with SINR=-20.5 dB in Matched Conditions

Fig. 2 represents experimental results for the stationary target at 125° with SINR=-20.5 dB in matched conditions. The figure demonstrates that the proposed approach outperforms all except CSSVD in matched conditions. However, considering Fig. 3 in mismatched conditions, we observe that the proposed

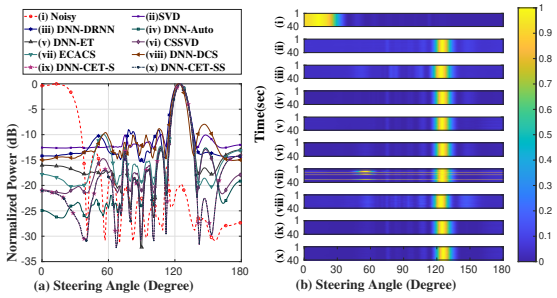

Fig. 3. (a)BP and (b)WD for a Stationary Target at 125° with SINR=-20.5 dB in Mismatched Conditions

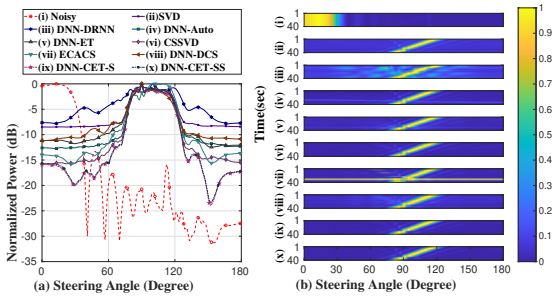

Fig. 4. (a) BP and (b) WD for Moving Target Initially at 80° and Moving with 1° per Second at SINR -20.5 dB

method significantly outperforms all other methods, including CSSVD. In both figures, ECACS has higher energy at 55° along with 125°, while the proposed approach shows higher energy only at 125°. The results demonstrate that the proposed approaches perform the SNC effectively.

Table II represents the variation of output SINR with input SINR when the TB is 121° in matched and mismatched conditions. Considering matched conditions, output SINR in the case of CSSVD is better at −20.5 dB. However, as SINR is lowered to -25.5 and -30.5 dB, the proposed DNN-CET-SS and DNN-CET-S surpass all other methods. In mismatched conditions for each SINR, including −20.5 dB, the DNN-CET-S approach overwhelmed the CSSVD and other approaches. Interestingly, DNN-CET-SS almost matches DNN-CET-S in terms of performance. These findings demonstrate the significance of the semi-supervised method in the absence of clean data.

Table III represents the variation of output SINR with TB when input SINR is -30.5 dB in matched and mismatched conditions. We observed that CSSVD at 31° and ECACS at 91° provide the highest output SINR in matched and/or mismatched conditions. The poor result of the proposed approach at 31° due to the lower sensitivity of received signals near the end-fire direction. However, as we move to the broadside direction, the proposed approaches perform better than all other approaches, especially in mismatched conditions.

D. Results for Moving Target

Fig. 4 represents experimental results for a moving target at SINR -20.5 dB when the target is initially at 80° and moving

TABLE II
VARIATION OF OUTPUT SINR (IN DB) WITH INPUT SINR WHEN TB IS 121° WITH MATCHED [MISMATCHED] CONDITIONS

SINR (dB)	CSSVD	ECACS	DNN-ET-S	DNN-ET-SS	DNN-DCS-S	DNN-DCS-SS	DNN-CET-S	DNN-CET-SS
-30.5	13.92[8.36]	15.69[7.3]	11.05[9.1]	10.89[8.98]	3.33[2.59]	4.69[2.8]	17.03[14.65]	**17.05**[**14.69**]
-25.5	17.11[12.93]	18.5[11.9]	14.22[12.5]	13.96[12.31]	6.33[7.23]	6.73[7.66]	**18.56**[**17.95**]	**18.56**[17.94]
-20.5	**19.45**[16.55]	18.85[15.3]	16.69[15.36]	16.26[15.04]	10.12[10.43]	10.77[10.6]	19.11[**19.03**]	19.13[18.98]

TABLE III
VARIATION OF OUTPUT SINR (IN DB) WITH TB WHEN INPUT SINR IS -30.5 DB WITH MATCHED [MISMATCHED] CONDITIONS

TB (degree)	CSSVD	ECACS	DNN-ET-S	DNN-ET-SS	DNN-DCS-S	DNN-DCS-SS	DNN-CET-S	DNN-CET-SS
31	**12.25**[**7.40**]	0.22[-0.00]	1.43[0.44]	1.52[0.57]	-1.01[-0.97]	-0.91[-0.81]	-0.34[0.11]	-0.32[0.05]
61	13.51[8.34]	15.21[7.03]	10.71[8.71]	10.59[8.61]	4.50[4.21]	5.09[4.71]	**16.93**[14.74]	16.92[**14.76**]
91	15.74[9.91]	**21.36**[9.48]	11.24[10.98]	10.63[10.54]	4.99[4.82]	6.74[6.49]	17.59[**16.42**]	17.57[16.38]

with 1° per second for 40 seconds in mismatched conditions. We observe that both DNN-CET-S and DNN-CET-SS perform SNC and detect the moving target. Furthermore, the proposed methods work better than all other methods. The outcomes demonstrate the proposed approaches' ability to identify the target at any position, even when it is moving.

IV. CONCLUSIONS

This work delivers a compressed eigencomponent transformation (DNN-CET)-based self-noise cancellation (SNC) approach for passive SONAR. The proposed approach conducts SNC and provides output SINRs of 18.56 dB for the proposed supervised and 17.95 dB for the proposed semi-supervised approaches, even at a low SINR of -25.5 dB when the target is at 121°. The proposed method achieves SNC for multiple stationary targets and a moving target. Our future work will focus on including real ocean noise in the model and using an appropriate neural network architecture to enhance SNC performance further.

ACKNOWLEDGEMENT

This work is financially supported by TIH IIT Guwahati under Project No. TIH/TD/0425.

REFERENCES

[1] C. Yuan, M. R. Azimi-Sadjadi, J. Wilbur, and G. J. Dobeck, "Underwater target detection using multichannel subband adaptive filtering and high-order correlation schemes," *IEEE Journal of Oceanic Engineering*, vol. 25, no. 1, pp. 192–205, 2000.

[2] Y. Deqiang and G. Haiyan, "Weak target detection based on fractional spectral subtraction in sea clutter," in *2011 International Conference on Electric Information and Control Engineering*, pp. 6355–6358, IEEE, 2011.

[3] P. Li, H.-A. Qiu, C. Wang, Y. Wu, and F. Miao, "Research on reverberation cancellation algorithm based on empirical mode decomposition," in *2020 IEEE International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA)*, vol. 1, pp. 941–945, IEEE, 2020.

[4] Y.-x. Li and L. Wang, "A novel noise reduction technique for underwater acoustic signals based on complete ensemble empirical mode decomposition with adaptive noise, minimum mean square variance criterion and least mean square adaptive filter," *Defence Technology*, vol. 16, no. 3, pp. 543–554, 2020.

[5] K. Dragomiretskiy and D. Zosso, "Variational mode decomposition," *IEEE transactions on signal processing*, vol. 62, no. 3, pp. 531–544, 2013.

[6] H. Ashraf, U. Shafiq, Q. Sajjad, A. Waris, O. Gilani, M. Boutaayamou, and O. Brüls, "Variational mode decomposition for surface and intramuscular emg signal denoising," *Biomedical Signal Processing and Control*, vol. 82, p. 104560, 2023.

[7] P. Kumar, K. Nathwani, V. Abrol, and S. K. Natarajan, "Eigen vector association method in compressed domain for self-noise cancellation in underwater acoustics," in *OCEANS*, pp. 1–6, IEEE, 2023.

[8] B. F. Harrison, "The eigencomponent association method for adaptive interference suppression," *The Journal of the Acoustical Society of America*, vol. 115, no. 5, pp. 2122–2128, 2004.

[9] M. Remadevi, N. Sureshkumar, R. Rajesh, and T. Santhanakrishnan, "Cancellation of towing ship interference in passive sonar in a shallow ocean environment," *Defence Science Journal*, vol. 72, no. 1, pp. 122–132, 2022.

[10] K. Wang, T. Hu, B. Zhao, and S. Wang, "Random noise attenuation using an unsupervised deep neural network method based on local orthogonalization and ensemble learning," *IEEE Transactions on Geoscience and Remote Sensing*, 2023.

[11] L. Yang, W. Chen, H. Wang, and Y. Chen, "Deep learning seismic random noise attenuation via improved residual convolutional neural network," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 59, no. 9, pp. 7968–7981, 2021.

[12] M. Mao, H. Wang, P. Nie, S. Xiao, and R. Wu, "Denoisenet: Deep generator and discriminator learning network with self-attention applied to ocean data," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–12, 2022.

[13] P. Kumar and K. Nathwani, "Self-noise cancellation in underwater acoustics using deep neural network-based eigencomponent transformation," *IEEE Sensors Letters*, vol. 7, no. 11, pp. 1–4, 2023.

[14] P. Kumar, M. Ali, and K. Nathwani, "Self-noise cancellation in underwater acoustics using deep neural network frameworks," in *OCEANS*, pp. 1–6, IEEE, 2023.

[15] P. Kumar, K. Nathwani, V. Abrol, and S. Kumar, "Compressive self-noise cancellation in underwater acoustics," in *SSPD*, pp. 1–5, IEEE, 2022.

[16] R. G. Baraniuk, "Compressive sensing," *IEEE Signal Processing Magazine*, vol. 24, no. 4, pp. 118 – 121, 2007.

[17] E. J. Candes, M. B. Wakin, and S. P. Boyd, "Enhancing sparsity by reweighted $\ell 1$ minimization," *Journal of Fourier Analysis and Applications*, vol. 14, no. 5, pp. 877–905, 2008.

[18] D. Kalman, "A singularly valuable decomposition: the svd of a matrix," *The college mathematics journal*, vol. 27, no. 1, pp. 2–23, 1996.

[19] D. Needell and J. A. Tropp, "Cosamp: Iterative signal recovery from incomplete and inaccurate samples," *Applied and computational harmonic analysis*, vol. 26, no. 3, pp. 301–321, 2009.

[20] D. Needell and J. A. Tropp, "CoSaMP: iterative signal recovery from incomplete and inaccurate samples," *Applied and computational harmonic analysis*, vol. 26, no. 3, pp. 301–321, 2009.

[21] X. Lu, Y. Tsao, S. Matsuda, and C. Hori, "Speech enhancement based on deep denoising autoencoder.," in *Interspeech*, vol. 2013, pp. 436–440, 2013.

[22] Y. Xu, J. Du, L.-R. Dai, and C.-H. Lee, "A regression approach to speech enhancement based on deep neural networks," *IEEE/ACM transactions on audio, speech, and language processing*, vol. 23, no. 1, pp. 7–19, 2014.