Spectrally Normalized Memory Neuron Network based Navigation for Autonomous Underwater Vehicles in DVL-denied Environment

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***Abstract*—In this paper, we address the challenge of velocity estimation for Autonomous Underwater Vehicles (AUV) navigating in complex underwater environments without access to Doppler Velocity Log (DVL) information. The proposed solution adopts a learning-based approach taking inputs such as Inertial Measurement Unit (IMU) data, available DVL information, and past predicted velocities. It employs a novel spectrally normalized Memory Neuron network (SNMNN) to predict AUV velocity, ensuring stable and reliable performance through spectral normalization. The model is trained using the SNAPIR AUV dataset, incorporating IMU and DVL beams. The estimated velocity from the SNMNN is compared with the actual DVL velocity. The proposed method outperforms existing DVL-denied algorithms in terms of velocity estimation. It achieves lower root mean square error (RMSE) and higher variance accounted for (VAF) values. The results indicate a 7.41% reduction in RMSE and a 1.2% improvement in VAF values.**

I. Introduction

The domain of underwater vehicles is rapidly evolving, with the quest for enhanced navigation systems taking center stage. AUVs have the advantage of not being physically tethered, enabling them to conduct missions across larger areas. Consequently, they demand more sophisticated navigation technologies to achieve precise position estimates during deployment, operation, and recovery. Nevertheless, AUV navigation poses a significant challenge due to the absence of Global Navigation Satellite Systems (GNSS). These receivers are renowned for their high positioning accuracy in many navigation applications. However, in the underwater realm, GNSS encounters limitations as it cannot receive satellite signals, rendering it unusable in the complex, unstructured nature of the underwater environment [1].

Underwater navigation heavily relies on crucial sensors, specifically Inertial Navigation Systems (INS) and Doppler Velocity Logs (DVL), providing essential data on position, velocity, and orientation of the vehicle. However, INS can be susceptible to misalignment, noise, and bias accumulation over time [2]. Conversely, DVL offers precise velocity measurements, accurate to 0.2% of the current value [3]. To enhance the accuracy of INS and DVL integration, nonlinear estimators like Kalman filter (KF), Extended Kalman Filter (EKF), Unscented Kalman Filters (UKF), ensemble Kalman filter (EnKF), and fuzzy Kalman filter (FKF) are commonly employed ([4] and [5]).

The field of AUV navigation has witnessed significant advancements to address the challenges of underwater environments [1]. Traditional techniques like Dead Reckoning and Simultaneous Localization and Mapping (SLAM) have laid the foundation [6]. More recently, Deep Neural Networks (DNNs) have gained prominence, especially when ample datasets from extended missions are available. In [7], the fault-tolerant deep learning model "NavNet" is introduced, combining Attitude and Heading Reference System (AHRS) with DVL for accurate estimates. The integration is extended with a recurrent neural network (RNN) in [8]. Additionally, an integrated dead reckoning and long short-term memory (LSTM) approach is proposed [9]. The article [10] examines a gated RNN that effectively deals with model errors, whereas [11] investigates the use of radial basis functions to compensate for current in INS and DVL. Data-driven deep learning strategies, such as the Beamsnet approach [12], and methodologies for calibrating DVLs to enhance AUV navigation accuracy with particle swarm optimization are presented in [13]. These strategies predominantly focus on predicting the AUV's state.

In environments characterized by uneven seabeds, strong sea currents, or sensor obstructions, DVLs, despite offering high accuracy in velocity estimation, encounter operational challenges and may experience missing beams or complete outages [14]. AUVs frequently confront scenarios where traditional methods become insufficient due to sensor limitations, especially when DVL data is unavailable or unreliable [15]. In the tightly coupled INS/DVL approach, the navigation filter is updated exclusively with available beam measurements using a sequential measurement update method [16]. Additionally, [17] contributes to refining navigation precision by correcting errors in DVL caused by uneven seafloor conditions. A comparative study involving multi-layer perception (MLP), convolutional neural network (CNN), and LSTM-CNN is presented in [18], specifically when direct DVL measurements are unavailable. An LSTM is proposed to compensate for scenarios with one missing DVL beam in [19], and this approach is further extended with support vector machines in [20]. Complete DVL outages are addressed by Set-Transformer BeamsNet [21], designed to bridge the gap in scenarios where DVL data are scarce or nonexistent.

In this paper, a data-driven learning model incorporating IMU, DVL, and past predicted values for training. The novel Spectrally Normalized Memory Neuron Network is used to predict the AUV velocity under two scenarios based on the availability of DVL beams. This network is similar to the

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architecture proposed in [22]. Additionally, weighted spectral normalization is applied to adapt the weights of regular and memory neurons, ensuring stable and reliable performance. A comparative study is presented to demonstrate the performance improvement compared to state-of-the-art DVL denial algorithms. The primary goal is to significantly reduce RMSE and mean absolute error (MAE).

The paper is organized as follows: Section II offers a detailed exploration of the SNMNN architecture, specifically tailored for precision navigation in AUVs. Section III delves into the intricacies of data processing, collection, and presents extensive experimental results, including comparisons. The paper concludes with final remarks on the proposed SNMNN architecture in Section IV.

II. Methodology

The idea of incorporating memory for time series forecasting and system identification has been explored in existing literature. Sastry et al. [23] introduced the MNN architecture, which was applied to identify helicopter dynamics [24]. Moreover, a Neuro-Fuzzy Inference System with Dynamic Neurons has been utilized for both system identification and time-series forecasting [25]. Another approach, the Adaptive Temporal Neural Network (ATNN), features an elastic memory capable of automatically selecting the number of previous samples to be used [26].The SNMNN method, which has previously been verified for unmanned aerial vehicles in GPS-denied environments [22], aims to greatly improve error measurements in AUV navigation. This encourages the adoption of the SNMNN model, known for its unique architecture designed to improve accuracy and reliability in scenarios that lack traditional DVL data.

A. *DVL Velocity Calculation*

The input to SNMNN includes the DVL beam data (b_1, b_2, b_3, b_4) with intentionally added noise to replicate challenging underwater scenarios. DVL beams are calculated depending on their geometrical placement on AUVs [27],

$$b_j = \begin{bmatrix} \sin \Psi_i \sin \alpha \\ \cos \Psi_i \sin \alpha \\ -\sin \alpha \end{bmatrix} j \in [1\ 4] \tag{1}$$

where the beam number is given by j and α is the angle between the beams and the transverse plane of the AUV. The angles Ψ_j are calculated as [19]:

$$\Psi_j = (j-1)\frac{\pi}{2} + \frac{\pi}{4} \tag{2}$$

Thus the transformation between body fixed frame velocity v_B to beam velocity measurements v_b is given by,

$$v_b = B v_B, \; B = \begin{bmatrix} b_1 \\ b_2 \\ b_2 \\ b_4 \end{bmatrix} \tag{3}$$

Further, it is necessary to introduce a beam error model that models the measured beam velocities $\hat{v}_b$. In this regard, a bias b_{DVL}, scale factor s_{DVL}, and zero-mean Gaussian noise N_G are incorporated into the beam velocity measurements v_b. This addition of components accounts for potential errors and uncertainties in the measured beam velocities, enhancing the accuracy of the overall velocity modelling.

$$\hat{v}_b = B v_b (1 + s_{DVL}) + b_{DVL} + N_G \tag{4}$$

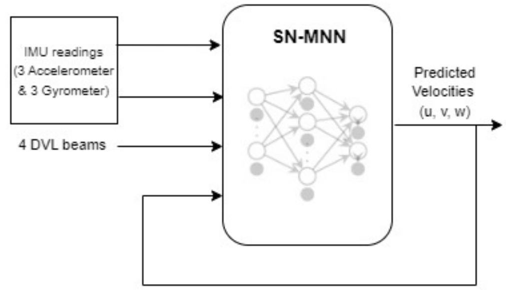

Fig. 1. Block diagram of SM-MNN

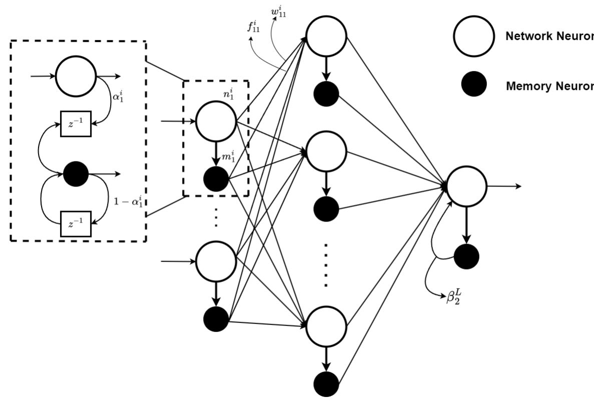

Fig. 2. MNN Architecture [23]

B. *Spectrally Normalized Memory Neuron Network*

The SNMNN architecture is shown in Fig. 1. It consists of three layers input, one hidden and The output layer. The output layer gives the estimate of the AUV's velocity vector across three axes $(x,\ y,\ z)$ represented as $(u,\ v,\ w)$ respectively. The inputs are three-dimensional accelerometer and gyroscope data, DVL beams and the outputs are fed back to improve the prediction accuracy.

The proposed SNMNN architecture is unique in its combination of fully connected network neurons with memory neurons [23]. Fig. 2 illustrates the MNN architecture, where each network neuron, except for the output layer neuron, is paired with an attached memory neuron. This special feature of SNMNN involves incorporating memory elements with each neuron, allowing efficient storage and retrieval of temporal information. The structure follows a feed-forward network for network neurons. The weights of both regular and memory neurons are dynamically updated during backpropagation, enhancing the model's ability to utilize historical data and significantly improving predictive accuracy.

The core strength of SNMNNs lies in their ability to maintain predictive stability across a variety of environments. To ensure stable reliable prediction performance spectral weight normalization is employed for both the network neurons weight W and the memory neurons weight F [22]:

$$\overline{W} = \left(\frac{W}{\rho(W)}\right)\gamma^{\frac{1}{L}} \quad (5)$$

$$\overline{F} = \left(\frac{F}{\rho(F)}\right)\gamma^{\frac{1}{L}} \quad (6)$$

where γ is the Lipschitz constant of the network, $\rho(.)$ denotes the spectral normal of the matrix, and L is the layer number. This adaptation underscores the versatility of SNMNNs and their applicability in DVL-denied navigation.

III. Experimental Results

Our study explores two distinct scenarios: one where the DVL sensor operates seamlessly and another where a simulated DVL outage occurs. The training and validation datasets are meticulously curated from nine diverse AUV missions, spanning a total duration of 13,886 seconds, resulting in 1,388,600 IMU measurements and an equivalent number of DVL measurements. Detailed information about this dataset can be found in [12].

Each mission exhibits unique characteristics, such as mission length, objectives, AUV speed, depth, and specific maneuvers. Further, we supplement our dataset with additional collection from a separate mission undertaken by Snapir in May 2022 [12], incorporating varying sea conditions. This supplementary dataset serves as our test set, comprising 2001 DVL measurements and 200,100 IMU measurements. Simulating the scenario where DVL data is denied involves introducing a DVL outage every 4 seconds, similar to the conditions presented in [21]. This intentional disruption allows us to assess the robustness and performance of our SNMNN network in scenarios with intermittent DVL sensor functionality.

To assess the effectiveness of our proposed approach, we employ four performance metrics [21]

1) Root Mean Squared Error (RMSE)

$$RMSE(y,\hat{y}) = \sqrt{\frac{\sum_{i=0}^{N-1}(y_i - \hat{y}_i)^2}{N}} \quad (7)$$

2) Mean Absolute Error (MAE)

$$MAE(y,\hat{y}) = \frac{\sum_{i=0}^{N-1}|y_i - \hat{y}_i|}{N} \quad (8)$$

3) The coefficient of determination R^2

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (9)$$

4) Variance Accounted For (VAF)

$$VAF(y,\hat{y}) = 100 \times \left[1 - \frac{var(y_i - \hat{y}_i)}{var(y_i)}\right] \quad (10)$$

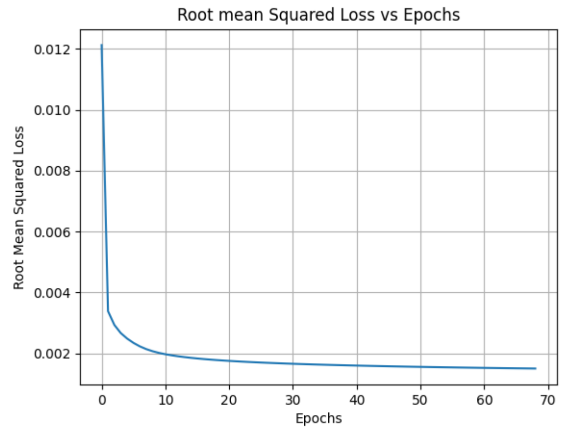

Fig. 3. RMSE Loss function vs Epoch with SM-MNN

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) serve as metrics to quantify velocity errors, measured in units of [m/s], while R^2 (R-squared) and VAF (Variance Accounted For) are dimensionless. In an ideal scenario, optimal performance would be represented by a VAF of 100, an R^2 of 1, and both RMSE and MAE values of 0, indicating perfect agreement between predicted and actual velocities.

The SNMNN architecture consists of 13 input neurons, one layer of 50 hidden neurons, and 3 output neurons. The network is trained for 70 epochs, maintaining a consistent learning rate of η set at 0.001 for regular learning and a memory coefficient learning rate η' set at 0.0005. Fig. 3 illustrates the training loss as a function of epochs. The RMSE loss consistently diminishes with each epoch, eventually reaching an impressively low value of 0.0018. This trend underscores the effective learning and convergence throughout the training process.

Fig. 4 through Fig. 6 illustrate the test results when the DVL information is available. These figures compare the predicted velocities in the x, y, and z directions with the desired velocities. It is evident that there are no visible changes in the graphs. The consistent matching between the predicted and target velocities is observable which indicates the robust performance of the SNMNN model. Further, through qualitative analysis, it becomes apparent that the SNMNN exhibits outstanding performance by consistently yielding low RMSE values in certain directions. The model shows good performance, with RMSE values of 0.01480 m / s for the x direction, 0.00777 m / s for the y direction and 0.00284 m / s for the z direction. The overall RMSE is impressively low at 0.00847, accompanied by a MAE of 0.00563. The predictive accuracy is remarkable, as indicated by an R^2 value of 0.9998 and an exceptionally high variance (VAF) of 99. 99%.

Fig. 7 through Fig. 9 illustrate the predicted and actual velocity under DVL-denied scenarios. Despite the denial, the model's predictions closely align with the actual AUV velocities, showcasing the model's effectiveness in capturing velocity dynamics even in the absence of DVL data. The model

TABLE I
METRICS COMPARISON IN DVL DENIED SCENARIO: SNMNN AND ST-BEAMSNET

Evaluation Metrics	SNMNN	ST-Beamsnet
RMSE [m/s]	0.091	0.098
MAE [m/s]	0.0411	0.064
VAF	98.16	96.971
R^2	0.9796	0.968

continues to exhibit competence. The RMSE values of the estimated velocity for the x, y, and z directions are 0.13377, 0.06559, and 0.07383 m/s, respectively. The overall RMSE under DVL denial is 0.09106, with a corresponding MAE of 0.04111. While these errors are higher compared to normal conditions, the model still maintains substantial predictive power, reflected in an R^2 value of 0.9797 and a VAF of 98.17%. These outcomes demonstrate the robust performance of SNMNN network, even in scenarios where DVL data is unavailable, indicating the model's capability to handle such challenging conditions effectively.

Comparing the performance metrics between the ST-Beams net [21] method and the SNMNN method under DVL denied conditions reveals notable improvements across various criteria as shown in Table I. The SNMNN method exhibits a 7.14% reduction in overall RMSE, showcasing enhanced accuracy in predicting velocity dynamics compared to the ST-Beams net method. Moreover, the SNMNN method demonstrates a substantial 35.93% improvement in mean absolute error (MAE), indicating a more precise estimation of the AUV's velocity in the absence of DVL data. The variance accounted for (VAF) metric sees a significant 1.24% enhancement, highlighting the SNMNN method's superior capability in capturing the underlying dynamics of the underwater vehicle. Additionally, the R^2 metric shows a noteworthy improvement of 1.15%, emphasizing the increased predictive power of the SNMNN method over the ST-Beams net method in scenarios where DVL information is denied. These results collectively underscore the superior performance and improved predictive accuracy of the SNMNN method in comparison to the ST-Beams net method under challenging DVL-denied conditions.

The metrics reflect the model's ability to capture and predict linear velocities with high precision, a crucial factor in the navigational efficacy of AUVs. These values show the robust performance of SNMNN in the context of DVL-denied underwater navigation. Further, these are much lower compared to values shown in [21].

IV. CONCLUSION

In this paper, we have demonstrated that the SNMNN predicts velocities accurately. To the best of our knowledge, the proposed neural model is computationally efficient with a simple architecture. This simplicity makes it an alternative to deep learning models that heavily rely on LSTM methods for time-series forecasting. Due to its integration of temporal

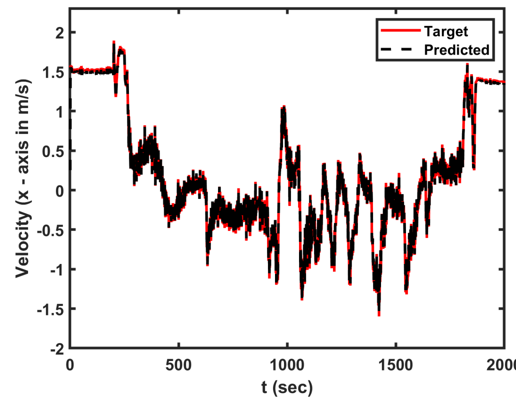

Fig. 4. Actual vs Predicted Velocity with DVL - x direction with SM-MNN

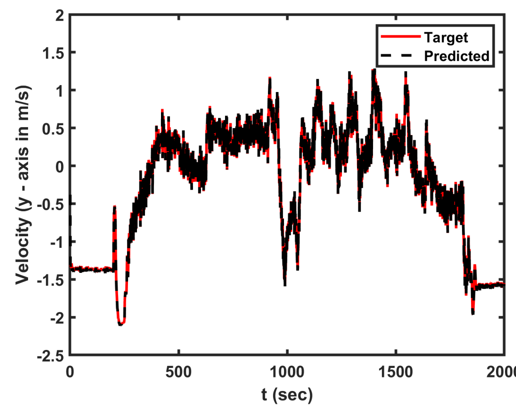

Fig. 5. Actual vs Predicted Velocity with DVL - y direction with SM-MNN

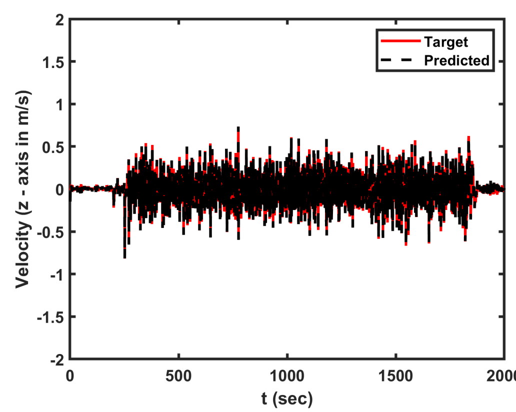

Fig. 6. Actual vs Predicted Velocity with DVL - z direction with SM-MNN

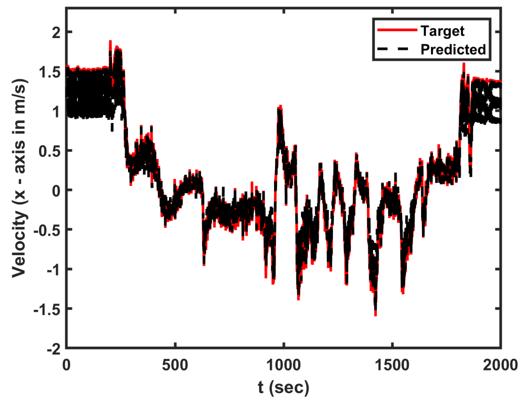

Fig. 7. Actual vs Predicted Velocity under DVL denied scenario - x direction with SM-MNN

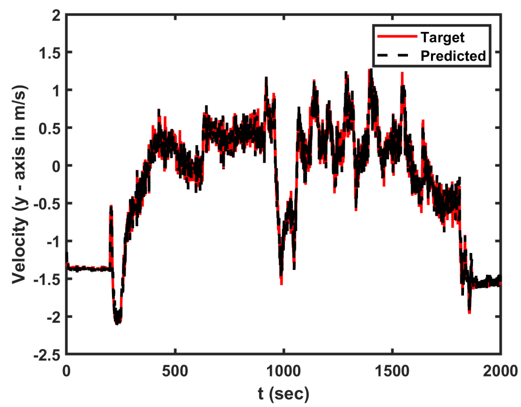

Fig. 8. Actual vs Predicted Velocity under DVL denied scenario - y direction with SM-MNN

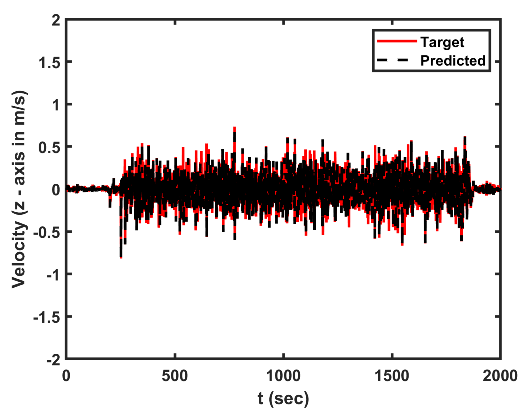

Fig. 9. Actual vs Predicted Velocity under DVL denied scenario - z direction with SM-MNN

memory, a crucial feature that renders it particularly well suited for navigation tasks. When DVL beams are available, the SNMNN achieves impressively low RMSE and MAE values across all directions. Even under DVL-denied conditions, the model maintained substantial prediction accuracy. This performance significantly exceeds that of the ST-Beams net method with a 7.14% reduction in overall RMSE and a 35.93% improvement in MAE. This demonstrates the capability of SNMNN in predicting the velocity of AUV under challenging conditions. Thus the proposed method enhances the precision of AUV navigation in DVL-denied underwater environments.

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