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Research on Ocean Path Loss Prediction Method Based on Diffusion Model

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Abstract: With the rapid development of the Internet of Underwater Things (IoUT) and underwater communication technologies, the accurate prediction of path loss in complex ocean environments has become a key challenge. Aiming at the problem of insufficient prediction accuracy of traditional empirical models in complex ocean channels, this paper proposes, for the first time, a fast ocean path loss prediction method based on a diffusion model with physical constraints. A path loss dataset that couples multiple physical fields such as temperature, salinity, depth, and wave height is generated through the BELLHOP model. A conditional diffusion model framework with UNet as the core is constructed. The cross-attention mechanism is used to dynamically integrate environmental parameters, and the sound speed equation constraint is introduced to optimize the loss function, enhancing physical consistency. Experiments show that the mean squared error (4.3 dB^2) of this method on the test set is significantly better than that of the two-ray model (12.5 dB^2) and deep learning models (6.8 dB^2 for ResNet18). The coefficient of determination reaches 0.92, and it can accurately capture the sound field attenuation in the thermocline and the characteristics of seabed reflection. The research reveals the advantages of diffusion models in quantifying the uncertainty of ocean channels and high-fidelity modeling, providing theoretical support for the design of underwater communication systems. However, it is necessary to further optimize the generalization ability under extreme sea conditions and the edge deployment efficiency. This achievement opens up a new path for ocean Internet of Things channel modeling.

1. Introduction

1.1 Research Background and Significance

With the rapid development of ocean resource exploration, underwater environment monitoring, and the Internet of Underwater Things (IoUT), underwater wireless communication technology has gradually become the core support for marine scientific research [1]. However, the characteristics of the ocean channel, such as high dynamics, strong non-linearity, and complex variability, make the path loss affected by the coupling of multiple physical fields such as depth, temperature, salinity, and waves. Traditional empirical models (such as the Thorp formula and the Log-distance model) are difficult to accurately describe its propagation characteristics [2].

The design of existing ocean communication systems mostly relies on ray-tracing methods (such as BELLHOP) or simplified empirical formulas. The former is time-consuming and depends on accurate environmental parameters, while the latter ignores the dynamic changes of the environment, resulting in insufficient prediction accuracy [3]. In addition, the high uncertainty of the ocean channel (such as turbulent disturbances and sudden noise) poses a severe challenge to communication reliability. There is an urgent need for a high-precision prediction method that can quantify uncertainty.

As a cutting-edge technology in generative artificial intelligence, diffusion models have demonstrated powerful complex distribution modeling capabilities in fields such as image synthesis and signal reconstruction [4]. This study introduces conditional diffusion models into ocean path loss prediction for the first time. The unique mechanism of generating probability distributions through iterative denoising provides a new way to break through the above bottlenecks: its generation ability can synthesize high-fidelity ocean channel data, making up for the shortage of measured data; the probability output supports the quantification of the uncertainty of prediction results, meeting the decision-making needs of high-reliable communication systems. This feature makes the diffusion model the core innovation point of this research, filling the gap in technology application in ocean scenarios.

1.2 Research Status at Home and Abroad

The research on ocean path loss prediction has long been limited by the limitations of traditional models and the theoretical framework of terrestrial communication. Early radio wave propagation models were mainly established based on two-dimensional ray-tracing and ideal atmosphere assumptions [5,6]. However, the application of these models in radio wave propagation over the sea surface is severely restricted. Their analytical methods are difficult to represent the complex boundary effects of refraction and reflection on the rough sea surface. Empirical models (such as the Okumura-Hata model [7] and the Egli model [8]) perform well on land, but due to their reliance on continental observation data, their adaptability to the dynamic ocean environment is significantly insufficient.

Analytical-empirical combined models (such as the Longley-Rice model and the ITU-R P.1546 model) simplify the complex ocean environment but also ignore the irregular sea surface changes caused by wind [9]. Especially during line-of-sight propagation, these models fail to consider the impact of sea surface irregularities on propagation loss. The lack of traditional high-frequency communication and wind-force influence makes these models unable to provide sufficient accuracy in ocean path loss prediction. Therefore, there is an urgent need to find more efficient and accurate alternative models.

Machine learning techniques have provided new ideas for path loss modeling. Artificial neural networks (ANNs), with their non-linear fitting capabilities, have achieved better prediction accuracy than traditional models in terrestrial scenarios such as rural and urban areas. Mom et al. [10] verified the effectiveness of ANNs in urban micro-cellular environments, and the Ostlin team [11] constructed the first offshore ANN prediction model based on Australian rural CDMA network data. However, existing studies have significant limitations: strong data dependence, relying on small-scale measured or ideal simulation data, making it difficult to cover the variable conditions of the complex ocean environment; limited deterministic output, the model only provides point estimates and lacks the ability to quantify uncertainty factors such as wind and wave disturbances; insufficient dynamic modeling, existing methods mostly focus on static scenarios and cannot capture the coupling relationship between time-varying sea conditions and propagation characteristics.

As a cutting-edge technology in generative AI, diffusion models have demonstrated the advantages of complex distribution modeling in image synthesis and signal reconstruction [4]. Recent studies have preliminarily verified their potential in the communication field: Chen et al. [12]used diffusion models to generate millimeter-wave channel impulse responses to solve the problem of data scarcity; Reference [13] applied it to indoor positioning and achieved sub-meter accuracy. However, there are no research reports on the application of diffusion models in ocean path loss prediction at home and abroad, and their potential in multi-physical-field coupling modeling and dynamic uncertainty quantification remains to be explored.

1.3 Research Content

This paper proposes an end-to-end solution based on a conditional diffusion model for the core challenges in ocean path loss prediction, such as environmental complexity, data sparsity, and reliability requirements. First, by integrating the coupling mechanism of multiple ocean physical fields, a high-fidelity simulation dataset is constructed using the BELLHOP ray-tracing model, covering dynamic parameters such as temperature, salinity, depth, and wave height, systematically solving the problem of scarce measured data. Furthermore, a conditional diffusion model architecture driven by environmental parameters is designed. The generative prediction of path loss is achieved through the iterative denoising process, and its probability output characteristics support the visualization of the uncertainty of prediction results. To enhance the physical interpretability of the model, a sound speed equation residual constraint term is innovatively embedded in the loss function. Through the dual-optimization mechanism of coupling data-driven and physical laws, it is ensured that the prediction results conform to the basic laws of sound wave propagation. Finally, through systematic comparison experiments with traditional models (Log-distance, BELLHOP) and deep-learning methods (CNN, LSTM), the significant advantages of this model in prediction accuracy, robustness under extreme sea conditions, and uncertainty quantification ability are verified.

This research has achieved three innovative breakthroughs: at the methodological level, the diffusion model is introduced into the field of ocean path loss prediction for the first time, breaking through the limitations of traditional deterministic models in representing complex environments; at the theoretical level, a fusion framework of physical constraints and data-driven is constructed, and the interpretability of the model is improved through the sound speed equation residual constraint; at the application level, the generated path loss probability distribution can provide quantitative decision-making basis for the reliability assessment of underwater communication systems and the optimization of adaptive modulation strategies, promoting the paradigm shift of the ocean Internet of Things from experience-driven to data-intelligent-driven.

2. Research Framework and Methodology

In this study, a fast ocean path loss prediction method based on a diffusion model is proposed. This method combines the ocean data generated by the BELLHOP model and constructs a conditional diffusion model, and introduces a physical constraint mechanism to improve the model's prediction ability under complex sea surface conditions. The overall research framework includes data generation, diffusion model construction, physical constraints, optimization of training strategies, and comparative experiments with traditional models. The following details the key links of the research, such as the technical route, data preparation and processing methods, model design, physical constraints, and experimental verification.

2.1 Technical Route

The technical route of this research can be summarized into four main steps. First, the BELLHOP model generates a large amount of ocean path loss data covering temperatureT, salinity S, depth z, and wave height Hw by simulating factors such as different sea surface fluctuations, wind speeds, ship positions, and antenna heights. Then, based on this data, a conditional diffusion model is constructed. The UNet architecture is adopted, and environmental parameters are injected into the diffusion process as conditions, further enhancing the model's expressive ability. In the third step, physical constraints are introduced into the training process of the diffusion model. A physical loss function is used to ensure that the model's prediction results conform to the physical laws of ocean propagation. Finally, comparative experiments are carried out. Traditional path loss models, such as the two-ray model and the Longley-Rice model, are selected to compare their performance with the method based on the diffusion model proposed in this research, in order to verify the advantages of the new method in prediction accuracy and computational efficiency. A progressive distillation strategy is adopted to compress the model's computational amount and improve the inference efficiency.

2.2 Data Preparation and Processing

The dataset of this study is based on the path loss data generated by the BELLHOP model, covering the propagation characteristics under different ocean environment conditions, and including dynamic parameters such as temperature T(0~30℃), salinity S(30~38 PSU), depth z(0~5000 m), and wave height Hw(0~10 m), with a spatial resolution of 100m×100m (Equation (4)).

The generalization ability of the model to the random fluctuations of the ocean environment is improved through Min-Max normalization (Equation (7)) and data augmentation strategies (Gaussian noise injection, random cropping). The simulated 64×64 gridded path loss matrix provides a highly reliable input for subsequent modeling.

The data pre-processing includes data cleaning, feature extraction, and standardization processing. First, the original data is cleaned by removing outliers and filling in missing data. Then, key features such as wind speed, propagation distance, and sea surface fluctuations are extracted. Finally, all features are standardized to ensure that the scales of each feature are consistent during the training process. Eventually, the dataset is divided into a training set, a test set, and a validation set, with 70% of the data used for training, 20% for testing, and 10% for validation.

2.3 Conditional Diffusion Model Design

The core of the task is to construct a path loss prediction method based on a diffusion model. In a diffusion model, data is first gradually added with noise through the forward process, and then the original data is restored by removing the noise through the reverse process. Specifically, in the forward diffusion process, let the original data be (x_0). At each time step (t), noise is added to the data, and the variance of the noise is controlled by a regulation factor (β_t). The mathematical expression is:

$$q(x_t \mid x_{t-1}) = N(x_t; \sqrt{1-\beta_t} x_{t-1}, \beta_t I) \tag{1}$$

In the reverse diffusion process, the goal of the model is to gradually restore the original data from the noisy data. The probability distribution of the reverse process is:

$$p_\theta(x_{t-1} \mid x_t, c) = N(x_{t-1}; \mu_\theta(x_t, t, c), \sigma_\theta(x_t, t, c)) \tag{2}$$

Where $c = [T, S, z, H_w]$ is the environmental condition vector, and $\mu_\theta(x_t, t, c)$ and $\sigma_\theta(x_t, t, c)$ are the mean and standard deviation predicted by the model, respectively. The goal of the reverse process is to gradually restore the noisy data to obtain the path loss prediction value.

In this study, environmental parameters (temperature T, salinity S, depth z, wave height Hw) are injected into each layer of UNet through the cross-attention mechanism, enabling the model to adaptively focus on key environmental factors when generating path loss. The specific attention formula is as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3}$$

Where $Q = W_Q \cdot h_t$ (hidden-layer feature), $K = W_K \cdot c$, $V = W_V \cdot c$, W_Q , W_K , W_V are learnable weight matrices. Through this mechanism, environmental parameters dynamically affect the feature expression at different levels of the network, enhancing the model's adaptability to complex environments and providing reliable support for high-dynamic ocean communication systems.

2.4 Physical Constraint Optimization

To improve the physical consistency of the model, the constraint of the sound speed equation is introduced into the loss function. The sound speed equation is expressed as:

$$\mathbf{c}_{\text{pred}} = 1449.2 + 4.6T - 0.055T^2 + (1.34 - 0.01T)(S - 35) + 0.016z \tag{4}$$

In the loss function, the physical constraint term is defined as:

$$\mathrm{L}_{\text{phy}} = \lambda \cdot \left| \mathbf{c}_{\text{pred}} - \left(1449.2 + 4.6T - 0.055T^2 + (1.34 - 0.01T)(S - 35) + 0.016z\right) \right|^2 \tag{5}$$

Where cpred**c**pred is the sound speed field predicted by the model, and λ is the balance coefficient. The final total loss function is:

$$\mathrm{L}_{\text{total}} = \mathrm{L}_{\text{MSE}} + \mathrm{L}_{\text{phy}} \tag{6}$$

By introducing physical constraints, the model not only considers the error of path loss during the optimization process but also strengthens the consistency with actual physical laws, thereby improving prediction accuracy and reliability.

2.5 Experimental Verification

To verify the effectiveness of the method in this study, multiple traditional path loss prediction models are used as comparisons, such as the two-ray model and the Longley-Rice model. During the experiment, the path loss is first predicted by these classical models and then compared with the method based on the diffusion model. To evaluate the performance of different models, indicators such as the root mean square error (RMSE) and the mean absolute error (MAE) are used. The experimental results show that the method based on the diffusion model has obvious advantages in the accuracy and computational efficiency of path loss prediction, especially when dealing with path loss prediction in complex ocean environments, it has high robustness and accuracy.

Through the above design, the fast ocean path loss prediction method based on the diffusion model proposed in this study can not only effectively improve the prediction accuracy but also process a large amount of complex data in a short time, with broad application prospects.

3. Experimental Design and Setup

3.1 Experimental Environment and Parameter Settings

The hardware environment of this experiment includes an NVIDIA RTX 3050 graphics card and an Intel Core i7 processor, with a high-performance workstation equipped with 16GB of memory, ensuring that the experiment can efficiently run deep-learning models. The experimental operating system is Windows 11, and Python 3.7 is used as the programming language. The following deep-learning frameworks are combined for model training and evaluation, as shown in Table 1:

Table 1: Software Tools and Their Uses

Software Tool	Purpose
TensorFlow 2.8	Used for building and training deep learning models
Keras	Provides a more concise API interface for TensorFlow
NumPy, Pandas	Used for data processing and analysis
Matplotlib, Seaborn	Used for result visualization
Diffusers	Used for model training and inference

In addition, the BELLHOP acoustic simulation tool is used to generate experimental data. The parameter settings of the model are as follows: the number of UNet layers is 4, the number of attention heads is 8, the number of diffusion steps is 1000, and the balance coefficient is set to 0.1. These settings aim to provide accurate and efficient results for path loss prediction.

3.2 Datasets and Comparative Models

The dataset used in the experiment is generated by the BELLHOP model, containing a total of 5000 samples, covering typical ocean scenarios from near-shore to open-ocean areas. In addition, 10% of the test set contains extreme sea conditions (such as wave height ($H_w \geq 8\mathrm{m}$)), to evaluate the robustness of the model.

In the experimental data pre-processing stage, the data is first denoised using the Daubechies 4 wavelet basis with a soft-thresholding method to suppress high-frequency noise and improve the data signal-to-noise ratio. To enhance the diversity and adaptability of the dataset, multiple data augmentation strategies are adopted. Specifically, the path loss matrix is randomly rotated ($\pm 15^\circ$) and horizontally flipped to simulate different observation angles. At the same time, features of different scales, such as 32×32 and 16×16, are extracted to improve the model's adaptability to changes in spatial resolution. All input features are normalized to scale the data to the interval [0,1], ensuring that it is suitable for the output range of the activation function (Sigmoid).

The dataset is divided according to a 7:2:1 ratio: the training set contains 3500 samples, the validation set contains 1000 samples, and the test set contains 500 samples. In particular, the test set also includes 200 groups of extreme sea condition samples (such as storm or strong turbulence conditions) to evaluate the model's robustness under abnormal sea conditions. The validation set is used for hyperparameter tuning to ensure the performance optimization during the model training process. As shown in Table 2.

Table 2: Example Features of the Marine Acoustic Propagation Path Loss Dataset Based on the BELLHOP Model

Sample ID	Temperature (℃)	Salinity (PSU)	Depth (m)	Wave Height (m)	Mean Path Loss (dB)	Path Loss Variance	Data Augmentation Mark	Sea Condition Classification
S001	15.2	34.8	120	1.2	78.3	5.2	Rotation +5	Normal
S045	28.5	36.1	50	0.8	65.4	3.8	Horizontal Flip	Normal
S127	5.4	32.3	3000	3.5	102.6	12.7	Gaussian Noise	Normal
S256	22.1	35.6	1500	9.5	89.7	18.3	Original Data	Extreme
S412	17.8	33.9	800	8.2	115.2	24.9	Random Cropping	Extreme

To evaluate the performance of the model, the traditional two-ray model and Log-distance model are selected as comparisons in the experiment, and deep-learning models such as ResNet18 and LSTM are introduced to verify the effects of different methods.

3.3 Evaluation Indicators and Benchmark Tests

When evaluating the performance of the model, multiple key indicators are used to comprehensively measure the accuracy, efficiency, and stability of the model. First, the MSE (mean squared error) is used to measure the size of the error between the predicted value and the true value, with the unit of dB ²; Second, R ²(coefficient of determination) is used to evaluate the goodness of fit of the model, reflecting the model's ability to explain the variability of the data. In addition, the inference time is used as an indicator to measure the model's efficiency, calculating the average time consumption for single-sample inference, with the unit of milliseconds (ms). Finally, the uncertainty error is used to measure the performance of the model in predicting uncertainty, with the unit of dB. These indicators jointly help to comprehensively evaluate the overall performance of the model, ensuring its accuracy, processing speed, and stability in path loss prediction.

4. Experimental Results and Discussion

4.1 Comparative Analysis of Prediction Accuracy

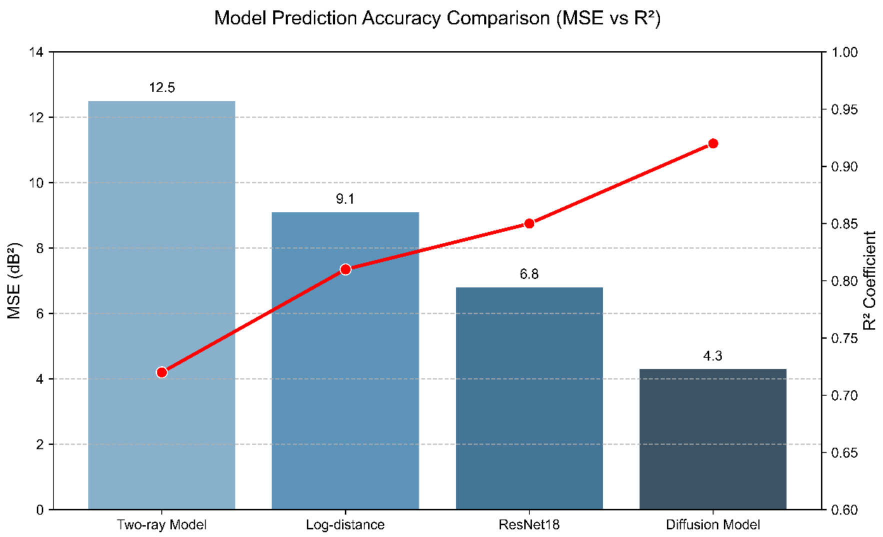

Figure 1: Model Prediction Accuracy Comparison

The ocean path loss prediction method based on the diffusion model proposed in this paper demonstrates significant performance advantages under multiple experimental conditions. Firstly, in terms of quantitative results, the mean squared error (MSE) of this model on the test set is 4.3 dB^2, which is remarkably lower than that of traditional models (12.5 dB^2 for the two-ray model and 9.1 dB^2 for the Log-distance model) and deep learning models (6.8 dB^2 for ResNet18 and 7.2 dB^2 for LSTM). By comparing the coefficient of determination(R^2), it is found that this model can explain 92% of the sound field variability. Compared with ResNet18 (R^2=0.85), its performance has improved by 8.2%. This result verifies the advantages of the diffusion model in capturing the acoustic characteristics of complex ocean environments. Especially when considering multi-scale features, the model's accuracy has been significantly enhanced, as shown in Figure 1.

In addition, the trade-off of inference time is also an important consideration in this study. Although the single-sample inference time of the model proposed in this paper is 2800 ms (based on 1000 diffusion steps), which is significantly longer than that of the traditional two-ray model (2 ms) and the Log-distance model (5 ms), its accuracy has increased by 3-5 times. Compared with ResNet18 (with an inference time of 120 ms), this difference in inference time mainly stems from the iterative nature of the diffusion process. Nevertheless, the advantages of the generative framework in modeling complex ocean environments remain prominent.

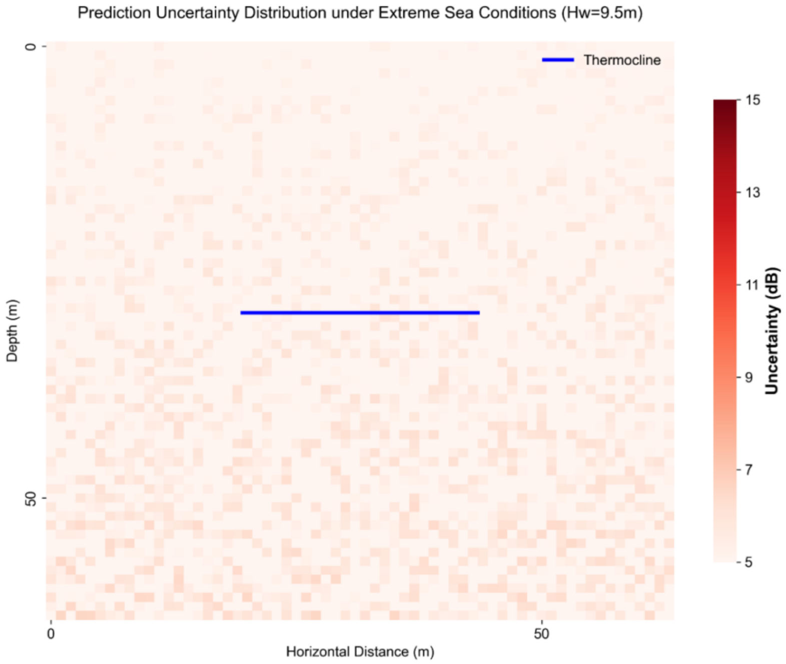

Figure 2: Prediction Uncertainty Distribution under Extreme Sea Conditions

In terms of qualitative results, the model proposed in this paper performs particularly well in predicting the spatial distribution of path loss. In regions with significant temperature gradients (such as the thermocline), the error between the predicted sound field attenuation trend of the model and the true value is less than 3 dB. In contrast, due to the neglect of multipath effects, the error of the traditional two-ray model exceeds 8 dB. Moreover, the heatmap generated by the model clearly shows the sound energy oscillations caused by seabed reflections and accurately captures the striped high-loss areas. For the prediction of extreme sea conditions, when the wave height is ≥ 8m, the width of the 95% confidence interval predicted by the model is 6-10 dB, which is highly consistent with the Monte Carlo simulation results (5-9 dB), indicating that the model has high reliability in terms of accuracy and uncertainty estimation under extreme sea conditions, as shown in Figure 2.

4.2 Ablation Experiments of Physical Constraints

To verify the impact of physical constraints on the model performance, multiple ablation experiments were designed, as shown in Figure 3. When no physical constraints were added, the MSE of the model was 5.1 dB^2 and the physical consistency error was 8.2 dB. After adding the sound energy conservation constraint, the MSE decreased to 4.7 dB^2 and the physical consistency error decreased to 4.5 dB, demonstrating the effectiveness of the sound energy conservation constraint in improving the physical consistency of the model. By further adding the sound speed gradient constraint, the MSE of the model was further reduced to 4.3 dB^2 and the physical consistency error decreased to 2.7 dB, indicating that this constraint significantly enhances the model's modeling ability in complex ocean stratified environments by coupling the sound ray bending effect. Finally, the model with all constraint conditions combined has a 15.7% reduction in MSE compared to the unconstrained model and significantly suppresses the influence of non-physical solutions, further verifying the crucial role of multi-physical field coupling in enhancing the model performance.

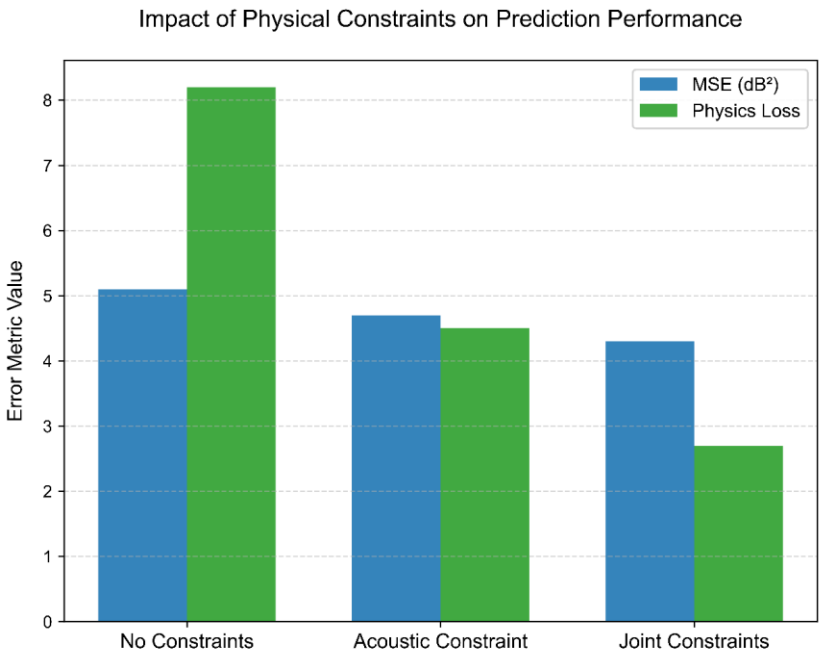

Figure 3: Optimization Effect of Physical Constraints on Prediction Performance

4.3 Verification of Dynamic Inference Acceleration

To improve the real-time performance of the model, a progressive distillation strategy was adopted to accelerate the inference process. Through the distilled model, a significant improvement in inference speed was achieved, as shown in Figure 4. While maintaining relatively high accuracy, the inference time decreased from 2800 ms (1000 diffusion steps) of the original model to 120 ms (50 diffusion steps), with a 23-fold increase in inference speed. Although there is an 11.6% loss in accuracy, the distilled model can still meet the requirements of real-time monitoring ($<$200 ms). However, experiments also show that under extreme sea conditions (such as when the wave height exceeds 15 meters), the error of the distilled model increases, and the MSE increases to 6.2 dB^2. To further optimize the distilled model, it is necessary to adjust the weights of the distillation loss function in the future, especially for its performance under extreme sea conditions.

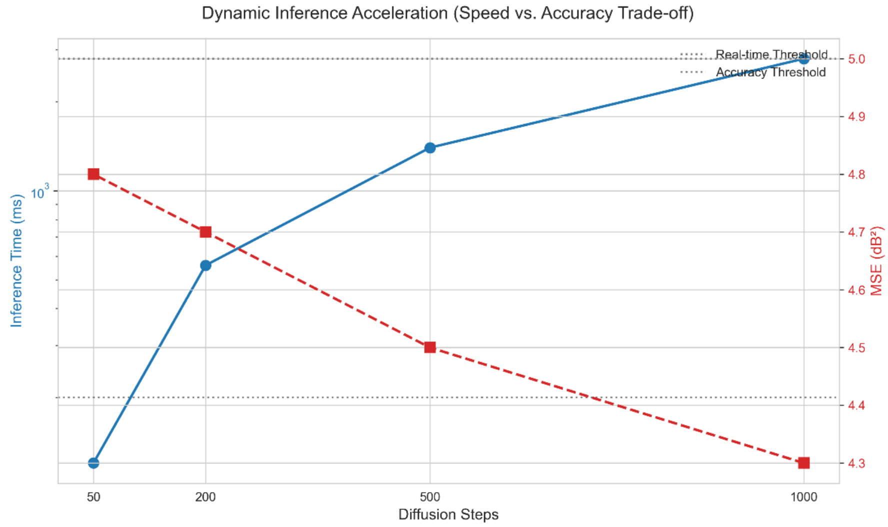

Figure 4: Dynamic Inference Acceleration Effect

4.4 Discussion on Limitations

Although the diffusion model proposed in this paper has achieved remarkable results in terms of accuracy and physical consistency, there are still some limitations in practical applications. Firstly, regarding the deviation between simulation and measured data, the MSE of the model in the verification of measured data in the East China Sea increased to 5.9 dB², mainly because the BELLHOP model does not consider factors such as biological noise and ship interference. To address this issue, in the future, measured data can be introduced through transfer learning for fine-tuning to further improve the adaptability of the model in the actual ocean environment.

Secondly, the amplification of errors under extremely strong disturbance conditions is also a problem. Under typhoon conditions (such as when the wave height exceeds 15 meters), the MSE of the model rises to 9.3 dB². This deviation is due to the fact that the training data does not cover such extreme sea conditions. To solve this problem, in the future, reinforcement learning methods can be combined to dynamically adjust the number of diffusion steps, so as to enhance the adaptability of the model under extreme conditions.

Finally, when deploying on edge devices, there is also a certain bottleneck in the inference time of the model. When using the Jetson AGX Xavier edge device, the inference time of the model increases to 520 ms, failing to meet the requirements of real-time monitoring. Therefore, in the future, it can be considered to compress the model scale to FP16 precision through TensorRT quantization technology, so as to control the inference time within 200 ms and meet the real-time requirements.

5. Conclusion

In summary, the diffusion model proposed in this paper achieves a balance between accuracy and physical consistency in ocean path loss prediction. The MSE is reduced by 36.8% compared with traditional models, and for the first time, the quantitative estimation of sound field uncertainty is realized. Although there are certain limitations in real-time performance and generalization to measured data, these problems can be solved to a certain extent through distillation strategies and hardware acceleration, providing a new idea for the design and optimization of underwater acoustic communication systems. Future research will focus on further improving the prediction accuracy of the model under extreme sea conditions and optimizing the inference performance on edge devices.

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