Journal of Research in Science and Engineering (JRSE)
ISSN: 1656-1996 Volume-7, Issue-1, January 2025
DOI: 10.53469/jrse.2025.07(01).15

Source Depth Estimation Based on Random Forest Approach Using Ocean Waveguide Data

Linglin Shen*, Xiangbo Sun

Hangzhou Applied Acoustics Research Institute, Hangzhou 310023, China
**Correspondence Author*

Abstract: ***In practice, the estimation of source localization based on matched field processing is significantly affected by environmental parameters, leading to the so-called mismatch problem. This paper models the sound source depth estimation problem as a classification issue in machine learning and discusses how the random forest method can be used to solve the depth estimation problem of sound sources. The paper uses the SWELLEX-96 sea trial environmental parameters and the Kraken model to generate ocean waveguide data received by a vertical line array at different depths of the sound source. After normalizing and extracting features from the generated ocean waveguide data, the random forest (RF) method is applied to estimate the depth of the sound source. The results indicate that the RF method is feasible for estimating the depth of sound sources.***

Keywords: Passive localization, Normal mode, Random forest, Match field processing**.**

1. Introduction

Source depth localization is a challenging issue in underwater acoustics, as the complex marine waveguide environment significantly impacts the depth localization of sound sources. Matched field processing (MFP) is a mainstream method for addressing underwater sound source localization, which involves correlating the replicated field signals obtained from sound propagation models with array reception data to estimate the position of underwater sound sources [1-2]. However, due to the complexity and variability of the marine environment, it is difficult to completely and accurately obtain all the parameters of sound field models. When the model used is mismatched with the actual environment, the accuracy of the sound source location estimation significantly decreases. To reduce the mismatch sensitivity of the MFP method, scholars represented by Frichter [3] have begun to consider incorporating both array reception data and source position information into the estimation metrics to enhance the robustness of the MFP method. In recent years, an increasing number of scholars have been studying how to extract more valuable information from data [4-6].

Therefore, we aim to find a method for estimating the depth of sound sources that does not overly rely on acoustic field models. Considering the relationship between the data received by arrays and the position of sound sources, a specific implementation involves effectively extracting features from the array data and then using the relationship between this data and the depth information of sound sources to construct a classifier model, thereby transforming the problem of estimating sound source depth into a classification problem [7-11]. The random forest algorithm, known for its ability to handle high-dimensional data and its robustness against noise and outliers, remains highly applicable in the processing of underwater acoustic data. The following discussion focuses on the application of the random forest method in estimating the depth of sound sources.

2. The Problem of Source Depth Estimation

2.1 Data Preprocessing

In the marine waveguide propagation model, the sound pressure formula is:

$$p(f) = S(f)g(f,r) + \varepsilon \tag{1}$$

In the formula, $p(f)$ obtained by processing the array element reception data through a discrete Fourier transform, $S(f)$ represents the spectral data of the sound source, $g(f,r)$ is the Green's function containing information about the distance between the sound source and the receiving array element, and ε is the noise interference term.

For a vertical array with N elements, the received complex sound pressure is given by: $(f) = [p_1(f), p_2(f), \cdots, p_N(f)]^T$. The formula for normalization is as follows,

$$\bar{P}(f) = \frac{p(f)}{\sqrt{\sum_{i=1}^{N} |p_i(f)|^2}} \tag{2}$$

Solve for the covariance matrix (SCM) from the normalized sound pressure data, and calculate the average for L snapshots as follows:

$$SCM(f) = \frac{1}{L}\sum_{j=1}^{L} \overline{P_J}(f)\overline{P_J}^H(f) \tag{3}$$

To improve computational efficiency, take the eigenvectors of the covariance matrix as features, concatenated into a $1 \times (N \times N)$ size data input into RF. Assuming the depth range of the sound source is (R_{min} to R_{max}), the depth is divided equidistantly into Q categories, with the depth division interval is:

$$R = \frac{R_{max} - R_{min}}{Q} \tag{4}$$

The label for the k-th sample is:

$$label_k = \frac{R_k - R_{min}}{\Delta R} \tag{5}$$

Thus, a dataset consisting of feature data and labels under different sound source depths can be obtained. The complete preprocessing workflow is shown in Figure 1.

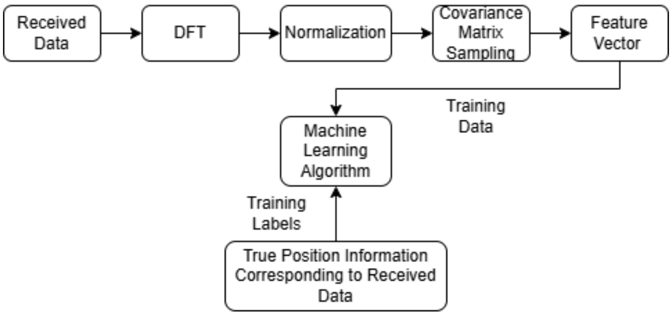


Figure 1: The complete preprocessing workflow

2.2 Random Forest Model Training

The essence of the training process for a random forest model involves the iterative calling of decision trees, with array-received data and sound source depth, after feature extraction, serving as inputs to the random forest model, as shown in Figure 2. This paper obtains a new dataset through random sampling of the original dataset, and the label with the highest proportion in the decision tree voting results is selected as the final prediction outcome. The trained model can predict the depth of sound sources from the array-received data in the test set.

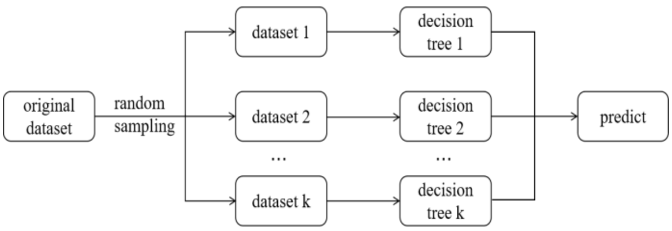


Figure 2: Random Forest training model.

2.3 Evaluation Metrics

Using the trained random forest model to predict test set data, this paper evaluates the model's predictions using three metrics: Accuracy, Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE).

Accuracy

$$Accuracy = \frac{n}{m} \cdot 100 \tag{6}$$

In this formula, mmm is the total number of samples in the test set, and nnn is the number of samples where the model's predictions match the actual values. This metric measures the accuracy of the model's predictions; the higher the value, the more accurate the model's predictions.

Mean Squared Error (MSE)

$$MSE = \frac{1}{m} \sum_{i=1}^{m} \left(R_i - \hat{R}_i\right)^2 \tag{7}$$

In this formula, R_i represents the true depth of the sound source, and $\hat{R}_i$ represents the predicted depth by the model. This metric intuitively describes the difference between the model's predictions and the actual values on a magnitude scale.

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{m} \sum_{i=1}^{m} \left|\frac{\hat{R}_i - R_i}{R_i}\right| \cdot 100 \tag{8}$$

3. Simulation-test Results

This paper uses environmental condition parameters from the SwellEx-96 sea trial experiment to simulate acoustic data using the Kraken model. As shown in Figure 3, the sea surface is modeled as an absolute soft boundary, and the seabed is modeled as a three-layer structure consisting of a sediment layer, a mudstone layer, and a half-space. The sediment layer has a thickness of 23.5 m and a density of 1.76 g/cm³, with sound speeds at the top and bottom of the layer being 1572 m/s and 1593 m/s, respectively. The mudstone layer has a thickness of 800 m and a density of 2.06 g/cm³, with sound speeds at the top and bottom of the layer being 1881 m/s and 3245 m/s, respectively. In the third layer half-space, the density is 2.66 g/cm³ and the sound speed is 5200 m/s. In the three-layer space modeled at the seabed, the compressional attenuations are 0.2, 0.06, and 0.02 dB/kmHz, respectively.

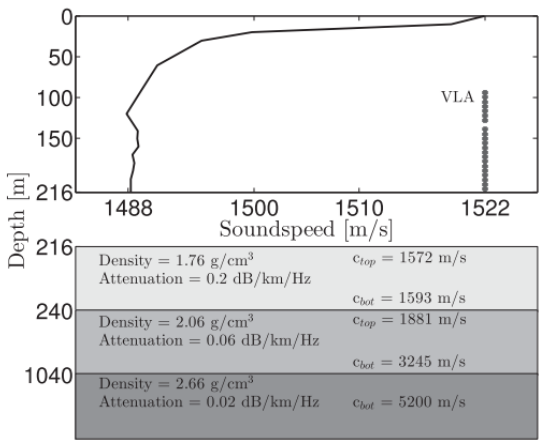
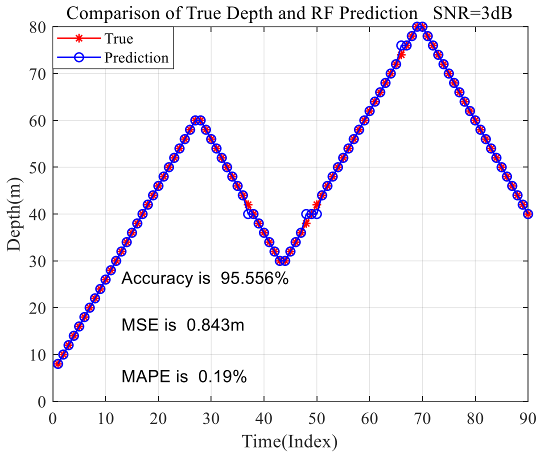


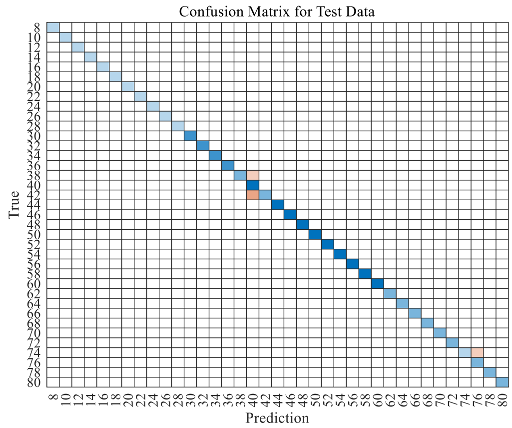
Figure 3: Basic experimental environment.

The receiving array is a 21-element uniform vertical line array, deployed at depths ranging from 94m to 212m, with an element spacing of 5.6m. In the simulation, the transmitting sound source is set at a frequency of 150Hz, with a horizontal distance of 3Km from the receiving array. During the 90s observation period, the horizontal distance between the sound source and the receiving array remains constant, with the sound source moving vertically up and down at a constant speed of 2m/s. The sound source's trajectory is as follows: initially, the sound source starts at a depth of 8m and moves downward at a constant speed, descending to 60m at 27s. Then, from 28s to 44s, it ascends from 60m to 30m at a constant speed. Next, from 45s to 71s, it descends from 30m to 80m. Finally, from 72s to 90s, it ascends from 80m to 40m.

To construct the training data for the random forest model, the vertical distance range of the sound source is from 6m to 100m, divided into 48 categories, with each category spaced 2m apart. Based on the above marine environmental parameters and transmission and reception settings, the Kraken model is used to simulate ocean waveguide data at different depths of the sound source. The simulated array-received data is preprocessed and concatenated into a 1×441 vector, which is then input into the random forest model for training. Afterwards, the trained model is used to estimate the depth of the sound source from the array-received data in the test set.



(a) Depth predictions by RF on test data with SNR of 3dB



(b) Confusion matrix for test data

Figure 4: Simulation -test results

The specific results are shown in Figure 4. Figure 4(a) compares the predicted depths from the random forest model with the actual depths in the test data at a 3dB signal-to-noise ratio, and Figure 4(b) shows the confusion matrix of the classification results for the test data at a 3dB signal-to-noise ratio. At a 3dB signal-to-noise ratio, the accuracy of the random forest model's predictions reached 95.556%, with a mean squared error of 0.843m, and a mean absolute percentage error of 0.19%. From the confusion matrix of the classification results, it is evident that the predictions generally align with the actual values, and even in cases of misclassification, the predicted results are close to the true values, demonstrating the feasibility of the random forest model in the problem of sound source depth localization.

Table 1. presents the prediction results of the random forest model at different signal-to-noise ratios. The random forest model provides accurate depth estimations of the sound source at higher signal-to-noise ratios, with its estimation capability improving as the signal-to-noise ratio increases. This is because at low signal-to-noise ratios, the strong interference from noise makes it difficult for the model to establish a connection between array data and sound source depth, leading to biases in the model's depth estimations of the sound source.

Table 1: Prediction results by RF on test data with different SNR

Model	SNR(dB)	Accuracy(%)	MSE(m)
RF	5	100	0
RF	3	95.556	0.843
RF	0	82.222	1.838
RF	-5	51.111	3.211

4. Conclusion

In applying the random forest model to the problem of estimating the depth of sound sources, this study uses machine learning methods to correlate ocean waveguide data received by arrays with the depth of the sound sources, transforming the matching issue into a classification problem and resolving the mismatch issues that arise with matched field models when environmental parameters are unknown. This paper uses ocean waveguide data generated with reference to the SWELLEX-96 sea trial environmental parameters to train the random forest model, which is then employed for estimating the depth of sound sources. Experimental results show that the random forest model's capability to estimate the depth of sound sources improves with increasing signal-to-noise ratio, providing accurate depth estimations at higher signal-to-noise ratios, confirming the feasibility of the random forest model for estimating the depth of sound sources.

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