IDENTIFICATION OF AQUATIC PLANTS IN SHALLOW WATERS BASED ON THE SOUND ABSORPTION MODEL COMBINED WITH THE DEEP LEARNING METHOD

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Due to the eutrophication phenomena in shallow waters, e.g. lakes and rivers, aquatic plants may grow rapidly and cause serious ecological problems. Therefore, the measurement and evaluation of the underwater plants are important for the environmental protection and ecological restoration of shallow waters. Ultrasonic sensors are widely used to detect underwater objects due to the advantages of low cost and real-time monitoring. This paper develops an echo-location measurement system which includes the acoustic source, the propagation model of the water media and the sound absorption model of the aquatic plants and sediments. The proposed sound absorption model shows the relationship between sound absorption coefficients and the amount of plant. Experiments are then carried out to measure and identify the sound absorption coefficients of the plant samples. Considering variations of different kind of plants, a deep learning method is employed to identify different plants and eliminate the differences in experiments. By using the model of plants, the identification and quantity estimation of aquatic plants with conventional ultrasonic sensors are realized.

Keywords: aquatic plants identification, sound absorption model, deep learning

1. Introduction

Aquatic plants play an important role in underwater ecosystems and have impacts on biodiversity [1]. In case of eutrophication, the uncontrollable growth of some aquatic plants may cause serious reduction of other species [2-3]. Therefore, monitoring quantities of different aquatic plants is important for protection of underwater ecosystems.

Many underwater target detections focused on the detection and classification of rigid targets or fishes using imaging sonar or sensor array [4-6]. Aquatic plants image detection and classification can be realized using the high-resolution imaging sonar [7]. However, the application of this method is largely limited by the complex operation. Acoustic characters of plants are also ignored in this work.

Recently, high classification accuracy is achieved by combining sonar signals and deep learning method image processing technic with the help of image sonar [8] or side-scan sonar [9]. Among these imaging sonars or sonar systems, the pulse echo of ultrasonic sensor includes less information for classification. As a result, we propose a hybrid approach using both deep learning and acoustic characters to identify spices and quantities with high accuracy. Deep learning method is used to identify the distinguish features which can hardly be captured manually or by traditional method. Acoustic characteristics of
different species of aquatic plants were measured in laboratory environment and provided for the prediction of plant quantity.

2. Preliminaries

2.1 Target Plants for Analyzation

Two spices of plant targets with distinctive features are analyzed, which have different range of leaf morphologies, areas, and orientations. Figure 1 shows the photographs of herb of spiral wildcelery (denoted as Plant A) and ceratophyllum demersum (denoted as Plant B). Table 1 presents the porosity $\varphi$ and the leaf area per unit volume $\sigma$ for further model analysis. The measurement method refers to the method introduced in [11]. We assume that the porosity of plants is constant under natural growth.

![Figure 1: Photograph of two spices of plants, (a) Plant A: herb of spiral wildcelery, (b) Plant B: ceratophyllum demersum. (c) Photograph of two spices of plants](image)

<table>
<thead>
<tr>
<th>Spice</th>
<th>$\varphi$</th>
<th>$\sigma (m^{-1})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plant A</td>
<td>0.68</td>
<td>8.15</td>
</tr>
<tr>
<td>Plant B</td>
<td>0.87</td>
<td>10.23</td>
</tr>
</tbody>
</table>

2.2 Experiment setup

In order to measure the acoustical characters of plants, a sonar measurement system was set up. The detection target is held in a cylindrical container with diameter of 600 mm and height of 1500 mm. The ultrasonic sensor, which is immersed in water, emits acoustic waves and receive the reflected ones, as shown in Figure 2(a). The distance between the sensor and the target is denoted as $H$. The experiment was carried out at the room temperature (15 °C, sound speed in water 1466 m/s). Figure 2(b) shows the calibration of the attenuation of sound in water. Figure 2(c) shows the measurement of plants, where $d$ is the thickness of the plants. Figure 2(d) shows the piezoelectric probe. The waveform and spectrogram of the pulse signal emitted from the ultrasonic sensor are shown in Figure 3, and the center frequencies of the pulse energy can be chosen as 200 kHz and 300 kHz.
Figure 2: Demonstration of the sonar measurement system

Figure 3: Waveform and spectrogram of the pulse signals

2.3 Sound attenuation in water

The water attenuation of this system is measured at first before absorption coefficient calculation in chapter 3.2. The intensity attenuation of sound propagates in water from $x_0$ to $x_0$ can be described as:

$$p(x) = p(x_0) e^{-\beta (x-x_0)}$$  \hfill (1)

For ultrasonic sensors, the emitted or received acoustic sound pressures are directly proportional to the voltage amplitude $u$. Therefore, the incident and reflected sound pressures of the object (placed at distance $H$) can be represented by the emitted and received sensor voltage.

$$p_i(H) = p_i e^{-\beta H} = u_i k_1 e^{-\beta H}$$  \hfill (2)

$$p_r(H) = p_r e^{\beta H} = u_r k_2 e^{\beta H}$$  \hfill (3)
During the system calibration, the target is replaced by a steel plate as a full-reflective test object, as shown in Figure 2(b). Since \( p(H) = p_r(H) \), the attenuation factor can be calculated according to the emitted and received voltage amplitude:

\[
\beta = \frac{1}{H - (-H)} \ln \left( \frac{\sum p_{l0}}{\sum p_r} \right) = \frac{1}{2H} \ln \left( k \frac{\sum u_l}{\sum u_r} \right)
\]

(4)

where \( k = k_1/k_2 \). In order to calibrate the attenuation of sound in water, measurements were carried out in terms of distance \( H \), from 40 cm to 100 cm, with 5 cm space interval. Figure 4 shows the received signals for different target distance in full-reflective test object measurements. The calculated attenuation factor \( \beta \) and sensor efficiency \( k \) for the system are shown in Table 2.

### Table 2. Measured attenuation and sensor electrical-acoustical converting factors of system.

<table>
<thead>
<tr>
<th>f(kHz)</th>
<th>( \beta )</th>
<th>( k(= k_2/k_1) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>0.73</td>
<td>15.36</td>
</tr>
<tr>
<td>300</td>
<td>0.83</td>
<td>8.96</td>
</tr>
</tbody>
</table>

After calibration, when sound waves are incident on the surface of the material with a hard back wall, a portion of the incident acoustic energy \( (E_i) \) is reflected \( (E_r) \), and the left is absorbed by the material. The ratio of the absorbed portion over the incident energy is defined as the sound absorption coefficient, which is represented by

\[
\alpha_r = 1 - \frac{E_r}{E_i} = 1 - \frac{\sum p_r^2}{\sum p_i^2} = 1 - \frac{\sum u_r^2}{\sum u_i^2} k^2 e^{-2\beta H}
\]

(5)

### 3. Theory

#### 3.1 Plant classification by CNN

Convolutional neural networks (CNN) is a widely used and effective approach in signal processing and classifications [13]. CNN is able to extract potential features of signals after learning. Compared with traditional model-based methods, CNN omits the complex transformation and filtering process.

In order to build a dataset of received signals for classification, each kind of aquatic plants was tested under 5 different distances, and each distance contains 5 groups of data measured at both 200 kHz and 300 kHz, totally 100 sets of data. A pre-process is applied to intercept the received signals from the whole process. Figure 5 shows the signals in the dataset. The combination of 200 kHz and 300 kHz signals for each data is applied to classification to contain enough information for CNN and guarantee the classification accuracy. The adopted CNN model contains 3 hidden layers, as shown in Figure 6, which is trained
by a training set including 70% of the whole data, while the other 30% of the whole data are allocated into the validation and test set. The results show that CNN can achieve 97% accuracy for plants classification, regardless of distance.

Figure 5. Typical signals in dataset.

![Figure 6: Structure of the CNN for classification.](image)

### 3.2 Absorption model of plants

The neural networks are proved capable to classify plants with raw data collected by sensors and achieves high accuracy, which is hard for traditional signal processing ways. Since then, the determination of thickness is therefore much more simplified based on the classification results. The relationship between sound absorption coefficient and thickness could be obtained by our acoustical model.

<table>
<thead>
<tr>
<th>f (kHz)</th>
<th>Species</th>
<th>5 cm</th>
<th>10 cm</th>
<th>15 cm</th>
<th>20 cm</th>
<th>25 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>Plant A</td>
<td>0.8683</td>
<td>0.9091</td>
<td>0.9391</td>
<td>0.9651</td>
<td>0.9892</td>
</tr>
<tr>
<td></td>
<td>Plant B</td>
<td>0.8528</td>
<td>0.8750</td>
<td>0.9201</td>
<td>0.9466</td>
<td>0.9750</td>
</tr>
<tr>
<td>300</td>
<td>Plant A</td>
<td>0.9496</td>
<td>0.9680</td>
<td>0.9767</td>
<td>0.9843</td>
<td>0.9962</td>
</tr>
<tr>
<td></td>
<td>Plant B</td>
<td>0.9365</td>
<td>0.9476</td>
<td>0.9699</td>
<td>0.9801</td>
<td>0.9952</td>
</tr>
</tbody>
</table>

In order to study the acoustic properties of plants, Kirill V. firstly establish an equivalent model for plants [11]. They assume plants have acoustical behaves as an equivalent fluid in a rigid frame porous medium, and studied systematically the effect of leaf morphology and area on the acoustic absorption coefficient of a series of low growing plants. However, the empirical model in air is not available for
aquatic plants. Based on the previous study, the leaf surface area and porosity are the main factors affecting the absorption coefficient. We fit the semi-empirical formula equation

$$\alpha = 1.087 \frac{d}{f} + 0.000735f + 0.588\sigma - 4.584\varphi - 0.935$$

which represents the relationship between absorption efficiency and acoustic characters for a certain type of plant, where $f$ is the frequency (kHz), $d$ is the thickness of plants (cm), $\varphi$ is the porosity, $\sigma$ is the leaf area per unit volume ($m^{-1}$). Table 3 shows the measured absorption coefficients by our system as described in chapter 3.1.

In order to estimate the amount of plant, we focus the relationship between the sound absorption coefficients and the thickness of plants. The fitting results are shown in Figure 7.

![Figure 7. Proposed absorption absorption-thickness model.](image)

The model is verified by the dataset, while the thickness of each data is calculated according to the equation and compared to the actual values. The results show that our model could achieve 90% possibility of high accurate quantity estimation (relative error less than 20%).

<table>
<thead>
<tr>
<th>Error%</th>
<th>0~5%</th>
<th>6~10%</th>
<th>11~15%</th>
<th>16~20%</th>
<th>21~25%</th>
<th>&gt;25%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
<td>12</td>
<td>29</td>
<td>27</td>
<td>22</td>
<td>7</td>
<td>3</td>
</tr>
</tbody>
</table>

4. Conclusion

A hybrid recognition system for water plants based on the equivalent sound absorption model and deep learning method was developed to realize recognition and estimation of the amount of plants. An acoustic measurement system was designed for laboratory experiments and accurate measurement. Experiments were carried out to measure the acoustic absorption characters of plants. Experiment results show that the neural network can recognize the plants with 97% accuracy, and the probability for quantity estimation relative error within 20% is 90%.

REFERENCES


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