A Study on Acquisition of 3D Self-Localization by Fluorescent Lights

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Abstract: The authors proposed a method called "CEPHEID" in previous study. This method utilizes individual differences in power spectra obtained from illumination lights to identify individuals, allowing for self-location estimation using lighting fixtures embedded in the ceiling as landmarks. However, the information obtainable through this method is limited to a two-dimensional plane. To overcome this limitation, in this study, we introduced a regression model in addition to the deep learning model used for individual identification. The regression model aims to estimate the distance to the illumination light, enabling the acquisition of self-position information in three dimensions. This paper presents the evaluation of the accuracy of the regression model's distance estimation.

1 INTRODUCTION

In recent years, significant progress has been made in the field of robotics, particularly in areas such as autonomous driving and automation of restaurant services. These advancements have had a profound impact on society, and as a result, much research on self-location estimation, which is necessary for these purposes, has been actively conducted.

Currently, two primary methods are commonly used for self-location estimation: one that combines external and internal sensors, and another that relies solely on external sensors.

An example of the former method is Odometry. This method calculates displacements based on the rotation angles of wheels or steering in a robot (Tomonou, 2016)(Chenavier and Crowley, 1992). The robot's position is estimated using cumulative calculations. Odometry is a versatile positioning technique that is less affected by the surrounding environment. However, it is prone to a problem known as error accumulation. Therefore, the use of values from external sensors is necessary to correct these errors and improve accuracy.

On the other hand, GPS (Global Positioning System) is an example of the latter method. It relies on radio waves transmitted by satellites orbiting the Earth. GPS is widely utilized in smartphones and IoT devices due to its low cost and high accuracy, becoming an essential part of our daily lives. However, GPS has its limitations. It can experience reduced accuracy or, in some cases, fail to estimate position in areas where radio waves cannot reach, such as indoors or underground. To address this issue, various methods have been proposed, including the combination of GPS with WiFi, Bluetooth, etc. (Ban et al., 2014)(Fujihara et al., 2020). Nonetheless, these methods require additional equipment installation, posing practical challenges.

In this context, we proposed "CEPHEID (Ceiling Embedded PHoto-Echo ID)" (Yamano and Kobayashi, 2017a)(Yamano and Kobayashi, 2017b) a novel approach that leverages a deep learning model generated from the flickering patterns of lighting devices to enable self-position estimation. However, the current implementation of CEPHEID is limited to two-dimensional information. Therefore, the primary objective of this study is to achieve self-position estimation in three-dimensional space by incorporating the height of the lighting devices.

This paper is structured as follows: Section 2 provides an explanation of CEPHEID as the fundamental basis for this study. Section 3 explains the method for creating a deep learning model capable of estimating the distance to the lighting sources. Section 4 discusses the accuracy and performance evaluation of the developed deep learning model. Finally, Section 5 concludes the paper by summarizing the findings and presenting future prospects.

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2 CONCEPT

CEPHEID is named after the initials of "Ceiling Embedded PHoto-Echo ID". Unlike conventional methods (Fushimi et al., 2009) that require additional known information in the equipment, CEPHEID performs identification based on individual differences in flickering patterns of the lighting fixtures.

Figure 1 shows the power spectrum obtained from two different lighting fixtures in a room. In this image, both waveforms show a strong peak at 120Hz, and similar waveforms can be observed in other frequency bands as well. However, it can be noted that there are differences in the peaks at certain points. The exact cause of this phenomenon has not been fully revealed. We believe it is likely due to slight individual variations in electrical components. In any case, lighting devices have identifiable individual differences, and CEPHEID enables the identification of lighting sources through the use of a deep learning model.

A similar study (Zhang and Zhang, 2017) exploits individual differences observed in the MHz band. In contrast, CEPHEID utilizes individual differences in human audible frequencies, typically within the range of 20kHz. This enables the use of widely available 3.5mm audio jacks and A/D conversion circuits, which are currently prevalent.

Previous studies (Kobayashi, 2019)(Kobayashi, 2020) have shown that the model achieves an accuracy of approximately 97% in classifying 48 lighting sources. Furthermore, it has been determined that the same level of accuracy can be obtained when performing the same test again 22 days after model generation. While CEPHEID has proven to be useful indoor positioning method, one challenge is that it is inherently a classification problem and the information is limited to a two-dimensional plane.

This study aims to explore the feasibility of three-dimensional self-position estimation, considering the height of the illumination source. In this paper, we explore the introduction of a regression model that provides continuous distance values to the illumination, in addition to a classification model.

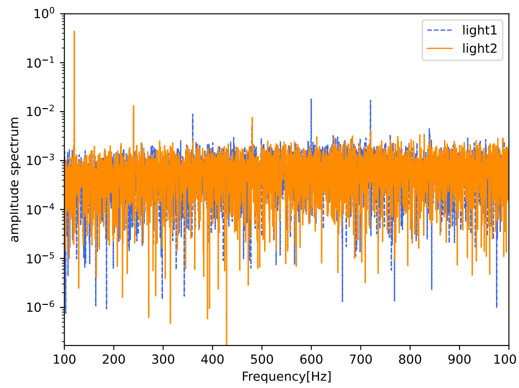

Figure 1: Power spectrum acquired from two difference lighting sources.

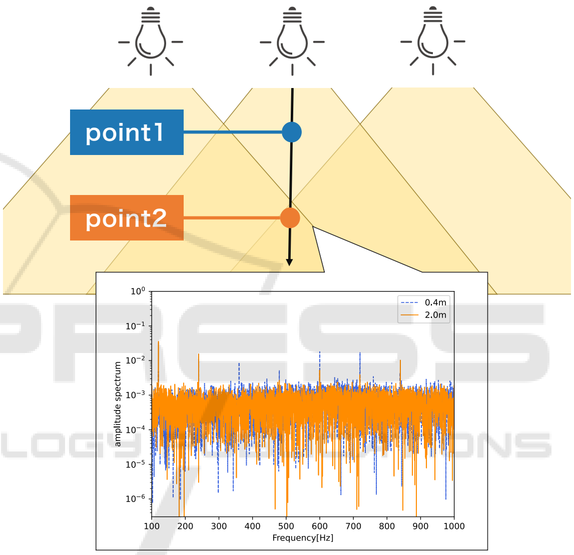

Figure 2: Power spectrum acquired at two difference distances(specifically, at 0.4m and 2.0m).

3 MODEL CREATION

3.1 Data Acquisition

Figure 3 shows the dongle utilized for data acquisition, along with its circuit diagram. This circuit consists of a 1KΩ carbon resistor and Si photodiode (Hamamatsu Photonics S2506-02). This configuration enables us to acquire data at a very low cost. In this study, the dongle is used to capture the flickering patterns of illuminations for a duration of 30 seconds. These captured patterns are subsequently used as training data for the deep learning model.

3.2 Data Padding

First, the 30 seconds of WAV data is divided into 10 segments, each separated by a 3-second interval. Then, because the division of the data may cause noise, a window function (Hanning window) is applied to weight the data, resulting in a gradual amplitude reduction at the beginning and end of the audio. Subsequently, the resulting data from these processes is subjected to the following padding methods commonly employed in speech recognition problems:

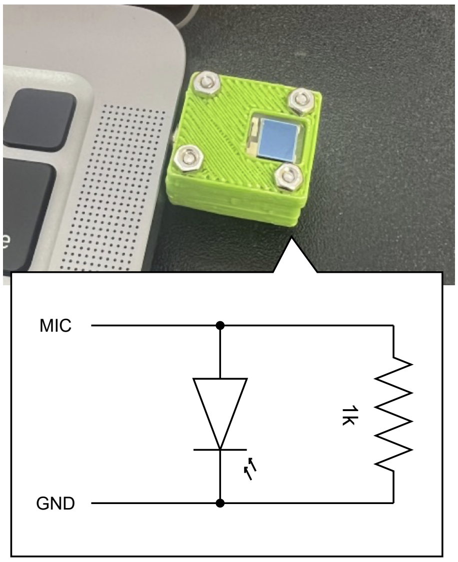

Figure 3: CEPHEID dongle.

- Pitch: Modifying the pitch of the audio.
- Shift: Shifting the starting point of the data backwards and aligning any overflowed portion to the beginning.
- Stretch: Accelerating the playback speed of the audio.

Using these methods, a total of 220 variations of data are generated from a single 30-second segment.

3.3 Data Processing

Perform a discrete Fourier transform on each of the padded data sets to obtain the following power spectrum P_{input}.

$$P_{input} = [f_0, f_1, f_2, ...] \tag{1}$$

Because P_{input} is a complex vector, its magnitude is obtained using equation (2).

$$p_i = \sqrt{(Re(f_i)^2 + Im(f_i)^2)} \tag{2}$$

Define P_{raw} as a summary of p_i. In this context, i represents the frequency corresponding to each of them.

$$P_{raw} = [p_0, p_1, p_2, ...] \tag{3}$$

The power spectrum within the audible frequency range can be obtained using this method. However, the dimensionality is too large, with several tens of thousands, so it is necessary to reduce the number of dimensions. Here, we divide P_{raw} equally along the linear axis and perform averaging within each interval. As a result, the final feature vector P becomes 1024 dimensions.

$$P = [p'_1, p'_2, p'_3, ..., p'_{1024}] \tag{4}$$

3.4 Model Structure

The structure of the model developed in this study is shown in Figure 4. The model consists of a 1D convolutional layer, a fully connected layer (Dense layer), and a dropout layer. The activation function for each layer uses the Rectified Linear Unit (ReLU) function, as shown in the following equation (5). Only the final layer was not specified.

$$\varphi(x) = max(0, x) \tag{5}$$

The loss function utilized during training is presented in equation (6).

$$Loss = \frac{1}{n}\sum_{i=0}^{n-1}(y_i - \widehat{y_i})^2 \tag{6}$$

In this equation, y_i represents predictions, $\widehat{y_i}$ represents the ground truth, and n indicates the number of data points. We have chosen Mean Square Error (MSE) as our loss function. This choice aims to ensure that the model's output represents a continuous value, reflecting the distance to the illumination light source.

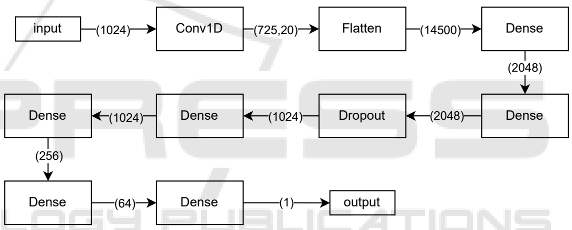

Figure 4: Model structure.

4 EXPERIMENT

4.1 Purpose

In this section, we report the experimental results. We created two deep learning models that output distances to the illumination light source as continuous values. One was trained using data collected at 0.2m intervals, while the other was trained using data collected at 0.4m intervals. Please note that both models were trained using data collected between 0.4 meters and 2.0 meters from the illumination light source, and the evaluation data was gathered one week after the training data.

To validate the effectiveness of our approach, we conducted the following three experiments:

- Experiment 1: Accuracy evaluation of deep learning models trained on data acquired every 0.2m
- Experiment 2: Accuracy evaluation of deep learning models trained on data acquired every 0.2m

Table 1: Detailed values of experiment 1.

	distance [m]								
true	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
light 1	0.395	0.593	0.766	0.931	1.121	1.353	1.662	1.809	2.058
light 2	0.410	0.591	0.816	0.996	1.157	1.398	1.582	1.755	1.898
light 3	0.396	0.618	0.830	1.024	1.154	1.408	1.635	1.715	1.939
light 4	0.389	0.594	0.809	1.041	1.185	1.377	1.609	1.795	1.980
light 5	0.378	0.603	0.748	1.037	1.172	1.401	1.555	1.766	2.025

- Experiment 3: Using the model trained in Experiment 1, we evaluated the model's performance by inferring data with randomly varying amplitudes.

In particular, Experiment 3 was conducted to confirm that the light intensity was not explicitly learned by the model. It is commonly known that light intensity is inversely proportional to the square of the distance, and by conducting this experiment, we aimed to verify that the model relied on other factors instead of explicitly learning the inverse square law.

4.2 Procedures

The experimental procedure is shown below.

1. Acquire data directly underneath the five lighting devices (Figure 5).
2. Create a deep learning model using the acquired data.
3. Evaluate the accuracy based on the inference results of the model.

Figure 5: Lighting devices to be verified.

4.3 Results

4.3.1 Experiment 1

Figure 6 shows the inference results, and Table 1 shows the detailed values. The horizontal axis represents the actual distance, while the vertical axis represents the inference results. The graph illustrates that if each dashed line closely resembles a long straight line, it indicates good accuracy. Based on Figure 6, it can be observed that the overall inferences are correct. In addition, according to Table 1 the largest error was approximately 0.1m, and the average error across all measurements was within 0.05m.

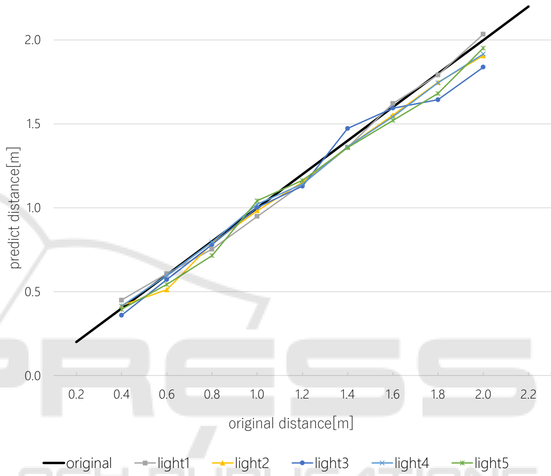

Figure 6: Inference result of experiment 1.

4.3.2 Experiment 2

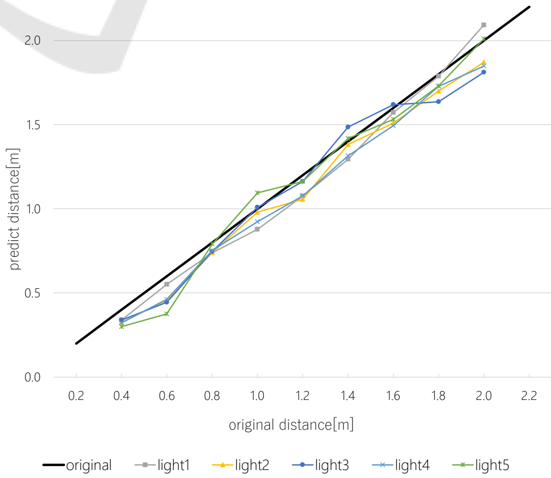

Figure 7: Inference result of experiment 2.

Figure 7 shows the inference results, and Table 2 shows the detailed values. The view of the figure 7

Table 2: Detailed values of experiment 2.

	distance [m]								
true	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
light 1	0.338	0.550	0.739	0.878	1.075	1.295	1.572	1.788	2.092
light 2	0.325	0.456	0.740	0.980	1.056	1.382	1.510	1.700	1.871
light 3	0.339	0.444	0.747	1.009	1.163	1.486	1.619	1.636	1.812
light 4	0.323	0.462	0.752	0.924	1.078	1.315	1.494	1.727	1.849
light 5	0.300	0.376	0.791	1.096	1.163	1.418	1.532	1.730	2.010

is the same as in Experiment 1. Based on Figure 7, it can be observed that the overall inferences are correct. In addition, according to Table 2 the largest error was approximately 0.22m, and the average error across all measurements was within 0.08m.

From these result, It was found that doubling the interval between data to be acquired approximately doubles the error.

4.3.3 Experiment 3

The figure and table are omitted because this experiment yielded identical results to Experiment 1. Based on the findings from this experiment, it was observed that the trained model generated this time is not reliant on light intensity.

5 CONCLUSIONS

This paper presents the results of a deep learning model for estimating the distance of multiple lighting devices. In Experiment 1, the maximum error was approximately 0.1m. This indicates the generation of a useful learning model. Experiment 2 exhibited an average error of approximately 0.2m, which was slightly larger than the error in Experiment 1 but overall distance estimation remained accurate. Experiment 3 revealed that the learning model did not capture the intensity of light.

Based on the above findings, the model demonstrated the ability to estimate distances effectively, providing practical applicability. However, because the inference results were derived from static data, the actual sensitivity of the model has yet to be verified. Therefore, we plan to verify the effectiveness of this method in real-time scenarios.

This method also presents a challenge due to the time-consuming nature of preparing training data, as it requires multiple shots for each illumination. Therefore, our goal is to develop a method that simplifies the process of preparing training data.

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