A Novel Regression Learning Algorithm for Optical Indoor Localization

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광신호 기반의 실내 측위를 위한 새로운 회귀 학습 알고리즘

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Abstract

Indoor localization systems have gained much interest recently, while visible light positioning attracts appreciable attention with its advantages. In this paper, we present a novel supervised machine learning (ML) approach for indoor localization using a regression learning algorithm. The algorithm identifies the user's location in an indoor optical transmission environment quickly. The paper also presents the optimal ML parameters which minimize the cost function, when quantifying the prediction error. It is anticipated that this ML algorithm will be helpful for the successful deployment of future optical indoor localization applications.

Ⅰ. Introduction

Recently, numerous examples of indoor localization, such as Bluetooth and Wi-Fi technology, were presented to the public with optimized near-range transference. However, these techniques have limitations as they result in deci-meter to meter accuracy with large infrastructures [1] and are likely to cause electromagnetic interference during positioning [2]. As opposed to these conventional methods, visible light positioning (VLP) systems have become attractive along with low cost and long service life [3] with the visible light communication which is envisioned for 6G transmission [4]. Nevertheless, in most methods of indoor optical localization, outcomes are deduced from enormous iterations to train the algorithm, making the computation complexity very high [5]. We propose a novel regression learning algorithm for indoor optical positioning to compute the user position swiftly.

Ⅱ. System Model

1. Overall simulation settings

In overall simulation settings, we use the same ideal room setting as the one in [6], which introduced the indoor positioning method with a densely connected neural network (DNN), in Figure 1. This setting considers both line-of-sight (LoS) and non-line-of-sight (NLoS) characteristics. We also note that the only transmitter (Tx) is placed on the ceiling, while the receivers are moving in the room.

2. Regression Learning Algorithm

The proposed machine learning approach for the indoor localization is illustrated in Figure 2. The algorithm input data originates from the simulation results. The input is made from the total received power

Figure 1. Simulation setting.

Room size	5m × 5m × 5m
Power of LED (P_{LED})	20mW
Field of view(FOV) at the receiver (ψ_C)	70 °
Semi-angle at half power ($\phi_{1/2}$)	50 °
Physical detection area of the photodiode (PD) (A_R)	1(cm^2)
Transmission coefficient of the optical filter ($T_S(\psi)$)	1.0
Floor reflection index	0.5
Wall reflection index	0.7

and x, y, and z user coordinates, and the output as the actual position. We can make a cost function of the algorithm from the mean squared error using the target user position and the estimated user position. Mean-squared error formula can be represented as:

$$J(w,b) = \frac{1}{2m}\sum_{i=1}^{m}(x_i w_i + b - y_i)^2 \tag{1}$$

where x_i is the ith input data, w_i is the ith weight, y_i is the target data and m is the shape of the feature. Among those variables, the weights and model bias are the model para- meters that determine the consequence of (1).

However, with the absolute value of total received power given by the position of the mobile user, the weight is minimal and the weight of the coordinates in very large, since the feature-weight relationship is at a reciprocal proportion. The instability of the weights can make the weight-to-weight graph elliptical, and takes a great deal of time if we find the optimal value of the weights. As a result, the system will be impractical for real-time implementation.

Therefore, it is very important to scale the feature; thus, we regulate the feature with Z-score normalization. The Z score normalization can be expressed as:

$$Z = \frac{x-\mu}{\sigma} \tag{2}$$

where μ is the mean of the feature data and σ is the standard deviation of the input.

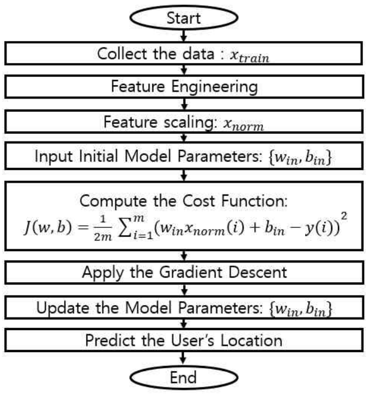

Figure 2. Simulation setting.

After calibrating the range, we initialize the model parameters w_i and b, then compute the cost function as described in (1). Then, we apply the GD algorithm to find the global minimum and eventually seek the required values of the model parameters. Since it is vital to find the position where the result is zero when the differentiation is made with each model parameter, an precise algorithm is needed. This algorithm is explained in Algorithm 1. As a result, the scope calibration is made before the algorithm operation and then we can successfully find the knee of the cost function curve and calculate the user position quickly with a knee of the curve made in 100 iteration steps.

Algorithm 1: Regression Learning Steps.

Initialization : $w_{in} = [0, 0, ..., 0]$, $b_{in} = 0$
Inputs : Learning rate α, Number of iterations I
from i = 1 **to** I **do**

$$\frac{dJ}{dw} = \frac{1}{m}\sum_{i=1}^{m}(f_{w,b}(x(i) - y(i)))x(i)$$

$$\frac{dJ}{db} = \frac{1}{m}\sum_{i=1}^{m}(f_{w,b}(x(i) - y(i)))$$

Update: $w = w - \alpha\frac{dJ}{dw}$

Update: $b = b - \alpha\frac{dJ}{db}$

Return w, b

3. Feature scaling with mean-squared error

The coordinate location of the user and the total received power have different value scales which were figured in [6]. With feature inputs which are not scaled, we cannot attain the balanced result against the model. Therefore, we standardize the data with Z-score normalization, then calculate the distribution of pre-normalization and the post-normalization features. We found that the results are quite identical to the initial features.

4.. Gradient descent and obtaining discrete values

With the distribution graphs, we can derive a gradient descent on each position with the cost function manifested in (1). Since every cost function has its local minimum and global minimum, the graph's gradient will be zero by at least one point. Additionally, on the global minimum, we can find the optimal value of the weight and bias, making the algorithm very fast and well-optimized with the concurrent position of the user with the estimated value.

5. Results

We performed with thousand iterations at a learning rate of 0.1 with hundred input-and-output values, which help to obtain more accurate location of the user than any other algorithms. The results show very low error rate in comparison with the mapping system we have illustrated. Comparing the resulting data created by the algorithm with the total target data, we have found an error rate by less than 9 percent.

Ⅲ. Conclusions

We have proposed a new regression algorithm for indoor optical localization with feature scaling. With this proposed method, we have successfully made the input normalized and the model parameters more adequate with optimized values. By doing so, the model parameters are more balanced and proper in most general environments. Consequently, the outcome shows that the algorithm is more accurate than other traditional algorithms in general environment settings.

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