Recurrent Neural Networks for Range-based Indoor Robot Localization

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***Abstract*— Range-only SLAM is a method for localizing a mobile robot and beacons by mainly utilizing distance measurements. Unlike the traditional probability-based range-only SLAM method, we present a novel approach using a recurrent neural network architecture that directly learns the end-to-end mapping between distance data and robot position.**

I. INTRODUCTION

As deep learning age has come, various kinds of deep neural architectures have been proposed for many tasks. Especially, recurrent neural networks (RNNs) have been shown to achieve better performance in case of dealing with time variant information, such as not only speech recognition, but also pose estimation and robot localization, than traditional methods.

In this poster, we tested various kinds of RNN models for robot localization using range data. We trained 4 kinds of RNNs; LSTM [1], GRU [2], Bi-LSTM [3], stacked Bi-LSTM, which are basic architecture units of many RNNs. Using deep learning, these structures directly learn the end-to-end mapping between distance data and robot position.

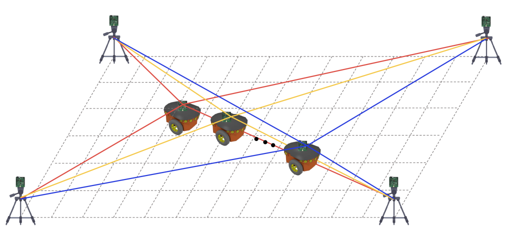


Fig. 1. System overview. A robot localizes its own pose through distance data and the derivative of distance data.

II. EXPERIMENT

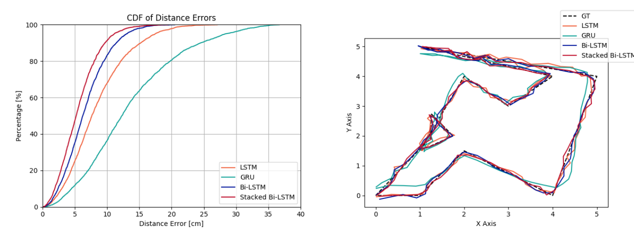
We set the experiment on the virtual situation and generate distance data set which corresponds to the position with 10% noise error and let RNN be trained using these distance data. Train data are just zigzag paths and test data is an arbitrary path, so we also check if RNN can estimate the position despite the variation of distance data as input.

Let Θ be the parameters of our RNN model, then our final goal is to find optimal parameters Θ^* for localization by minimizing Mean Square Error (MSE) of Euclidean distance between ground truth position Y_k and estimated position $\hat{Y}_k$.

$$\Theta^* = \underset{\Theta}{\operatorname{argmin}} \sum_{k=1}^{N} \parallel Y_k - \hat{Y}_k \parallel^2 \tag{1}$$

III. RESULTS

The prediction of trajectory results are shown in Fig. 2(b) and Root-Mean-Squared Error (RMSE) are shown in Table I. As a result, the stacked Bi-LSTM showed better performance than the other RNNs. Therefore, we can conclude that the performance improves as the nonlinearity of the architecture increases.



(a) (b)

Fig. 2. (a) CDF of distance errors gragh (*The trial that reaches 100% faster is better*) (b) trajectory results of RNNs. .

TABLE I: RMSE of each RNN model from the test data.

RMSE of Localization [cm]			
LSTM	GRU	Bi-LSTM	Stacked Bi-LSTM
9.6839	15.5183	7.5110	**6.3788**

IV. CONCLUSIONS

We suggested a novel approach to range-based localization using recurrent neural network models. Results show that the RNN-based localization can reduce position error. As a future work, RNNs need to be tested in the real-world

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