類神經法與雙線性內外插法預測機器人聲納感應值之誤差量化比較研究

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摘 要

本研究嘗試以類神經網路法及雙線性內外插法，來預測移動式機器人在眞實環境中之聲納模型。聲納取樣值是經由一具移動式自主機器人在眞實的環境中收集而得。在預測機器人於眞實環境中聲納感測值之準確性比較上，本實驗之四次驗證結果顯示，類神經法都比雙線性內外插法之預測結果較好，尤其是在取樣密度較低之區域中更爲明顯。本研究之結論指出，在資料模擬或資料預測之使用目的下，使用類神經網路法可以比使用傳統內外插法有更好之結果。不僅如此，使用類神經網路法在收集取樣資料之工作上也會更爲便利。

關鍵字：類神經網路、多層感知器、機器人、電腦模擬、內外插法

Quantitative Comparison between Artificial Neural Networks and Bilinear Interpolation to Predict a Real Robot's Sonar Sensor Readings

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Abstract

This paper presents examples using bilinear interpolation and Artificial Neural Networks (ANNs) to approximate the underlying sonar model of a mobile robot in a real environment. Sonar samples were collected by a mobile robot from a real environment. The comparison between results of approximation by ANNs and interpolation show that ANNs has a better performance than bilinear interpolation for four different trials, especially for those low density sampling areas. This outcome indicates that the method of using ANNs to predict unknown data for simulation or prediction purposes is more useful than using interpolation not only for the accuracy but also for the convenience of collecting samples.

Key words: Artificial Neural Networks (ANNs), Multilayer Perceptron (MLP), Robot, Simulation, Interpolation.

Ⅰ.Introduction

An approach to using an acquired ANN model to predict the robot's exteroceptive [1] sensor readings for a high-fidelity mobile robot simulation was presented by Lee[2] [3] [4] [5] and T. Kyriacou et al. [6]. This approach used a real mobile robot to collect its physical positions and those corresponding sensory readings, while it traveled along an arbitrary path in a real environment. Those acquired samples were then used as training data to teach an ANNs to learn the relationship between the robot's positions and their corresponding sensory readings. After training, the ANNs then can be used to predict the sonar readings of the real robot in that specific environment.

However, besides ANNs other techniques can also be used to approximate intermediate data between samples. Among them linear interpolation is a fast and easily implemented technique to generate the data between samples. Therefore, in this paper a real robot experiment was performed to present the comparison between ANNs and interpolation for approximating the underlying sonar model of a mobile robot in a real environment. Their results of predictions for those intermediate positions between training samples are compared with the actual sonar readings. Among four different trials, ANNs presents better perform-

[1] Exteroceptive sensors are those sensors that detect the robot's external world, e.g. sonar sensors, infrared sensors, laser range finders, etc.

ance than interpolation, especially in those low density sampling areas. This indicates that ANNs approximates the unknown data using whole training data while interpolation uses neighbouring samples only. Therefore, ANN method can be more useful not only for its higher performance of prediction but also for the convenience of data collections.

Ⅱ.Experimental setup

A.The mobile robot

In the experiments reported here a Nomad 200 autonomous mobile robot, designed by Nomadic Technologies, was used. The robot is a three-wheel driven mobile robot, 56 cm in diameter and 100 cm in height. The robot is equipped with 16 sonar sensors, 16 infrared sensors, 20 tactile sensors and odometry sensors. In all experiments, the turret was kept at a constant orientation (due to a three-wheel chassis design, the turret can be faced to any direction while the robot is moving) and only one sonar sensor and odometry sensors were used. Exploration was carried out using the separate translational and rotational motors located in the base of the robot.

Figure1　An autonomous mobile robot manufactured by Nomadic Technologies.

B.A real environment

In this experiment, an autonomous mobile robot, manufactured by Nomadic Technologies, collected sonar responses to brick walls and a plywood door from one of its sonar sensors (the one with a 45 degree incident angle to the walls and the door) as it travelled along a path. The environmental setup is illustrated in Figure 2. The robot paths for collecting training data and testing data are shown in Figure 3.

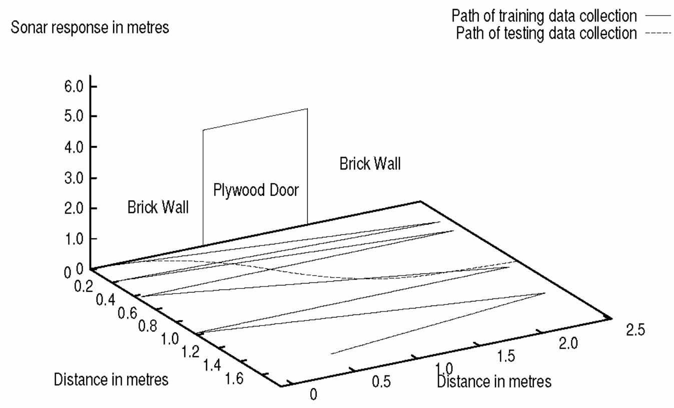


Figure2 the experimental setup for collecting sonar readings in a single wall environment.

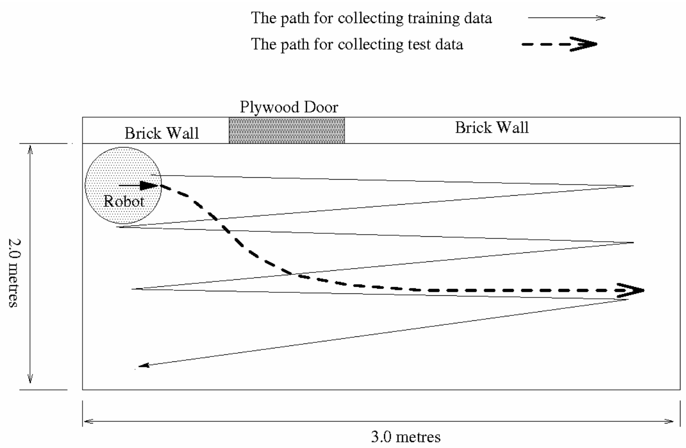


Figure3 The robot paths of collecting training data and testing data.

C.Samples collected

The robot's sonar sensor responses recorded along the training path are presented in the top picture of Figure 4, and the sonar sensor responses recorded along test paths are presented in the bottom picture of Figure 4. In all experiments, a sonar reading was recorded per one inch of robot travelling distance.

Due to the difference of surface texture between the brick walls and the plywood door, in the top picture of Figure 4, the values of the real sonar readings abruptly increase in some positions because of the specula effects caused by the surface of the plywood door (a plywood door has a smoother surface than the brick walls). As can be seen, the sonar responses collected along the testing paths also exhibit the abruptly raised values, shown in the bottom picture of Figure 4.

As it is impossible to have a robot to collect its sonar responses for all positions in a real environment, for positions other than those on the training path (such as positions along testing paths), a method of approximation has to be used to generate the data for intermediate positions between samples. However, can an ANN have better performance than that of interpolation in predicting the corresponding sonar responses for those unvisited positions?

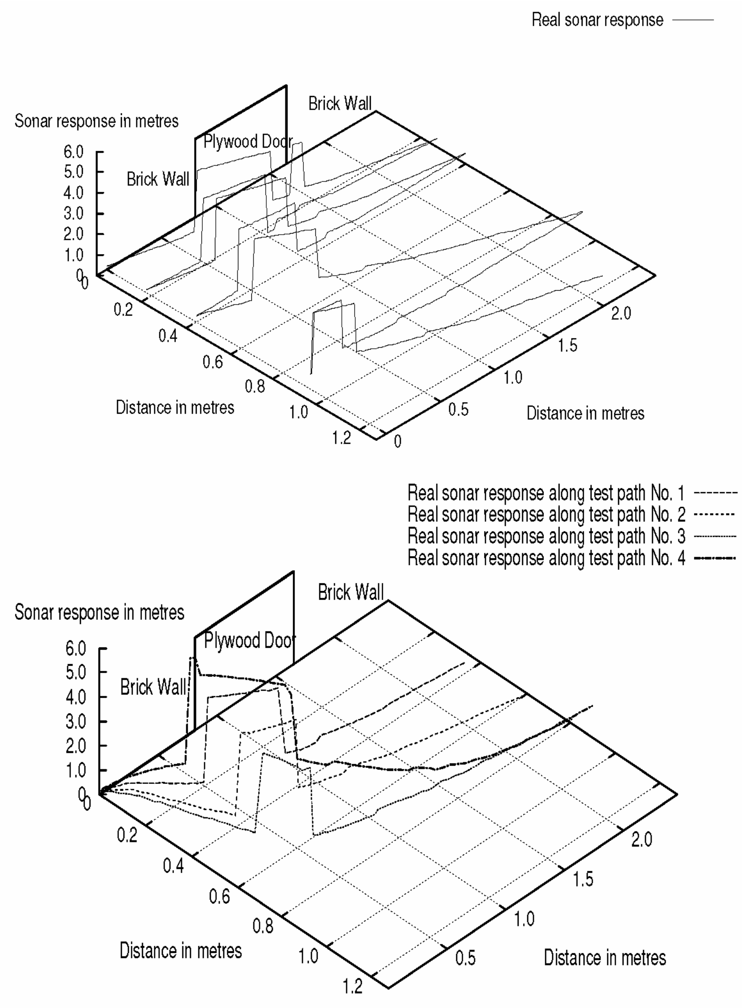


Figure4　The robot paths of collecting data (Top：The real sonar response along the training path in Figure3) (Bottom：Real sonar responses along four different testing paths in Figure 3)

The following section shows that both methods of bilinear interpolation and ANNs were used to predict the sonar responses along four testing paths by using training data only.

Ⅲ.Sonar model approximation

A two-dimensional (X and Y coordinates) linear interpolation was applied to generate the predicted sonar responses on the test path. The details of this bilinear interpolation are described in [7].

A.Bilinear interpolation

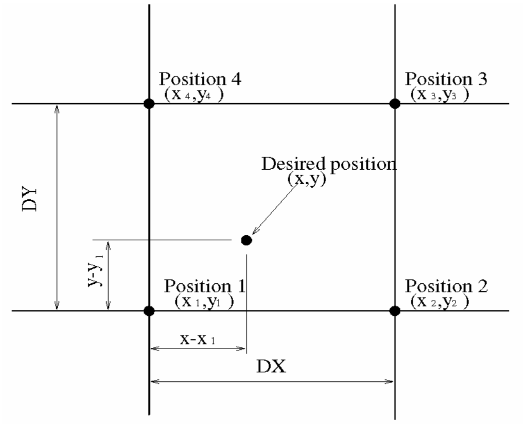


Figure5 Bilinear interpolation. (The sonar reading associated with the intermediate position can be bilinear interpolated by using four nearest neighbours)

For each position on the testing path, four adjacent positions from the training path (the two nearest positions in the X direction and the two nearest ones in the Y direction) and their corresponding sonar responses are used to bilinear interpolate the sonar reading of that position. Figure 5 illustrates how the sonar reading associated with the intermediate position is approximated. The output of sonar reading by bilinear interpolation for intermediate position is calculated from equation 1.

$$f(x,y) = (1-t)(1-u)s(x_1,y_1) + t(1-u)s(x_2,y_2) + tus(x_3,y_3) + (1-t)us(x_4,y_4) \text{-------} (1)$$

With

$$t = (x - x_1) / \mathrm{DX}$$
$$u = (y - y_1) / \mathrm{DY}$$

Where t and u lies between 0 and 1.

$s(x, y)$ is the sonar reading at position (x, y).

B.Learning the relationship between robot position and sonar reading by ANNs method

The ANNs is also used to learn the relationship between the robot's position and the corresponding sonar readings. A two-hidden-layer Multi-Layer Perceptron (MLP) was used in this experiment. This MLP has two inputs for encoding the robot's x and y coordinates, one output for the corresponding sonar readings and twenty seven hidden units in each hidden-layers. The detailed training procedures and the method of selecting high performance network architecture (2-27-27-1) were described in [4]. Our experiments showed that more hidden notes will get more accurate result with the payment of a longer learning time. Our results also indicate that 10 to 27 hidden notes for each hidden layer will get similar sonar predictions.

Figure 6 illustrates the idea of associating robot position with its corresponding sonar value. The MLP was trained with the training data only (as shown in the top picture of Figure 4). The four different sets of test data (as shown in the bottom picture of Figure 4) were used merely for testing the performance of this trained ANNs model. The learning algorithm used is a standard error back-propagation with a sigmoid function [1].

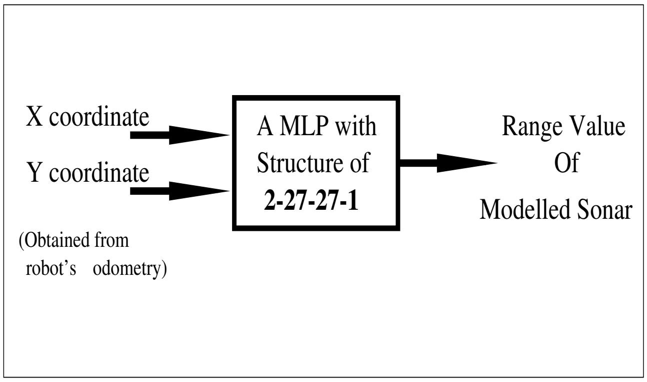
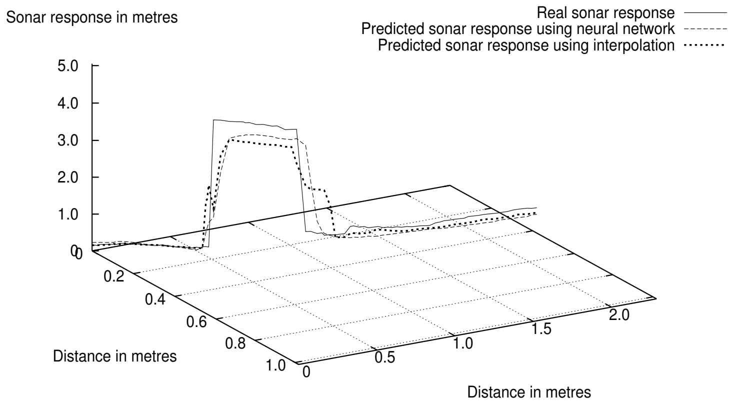


Figure6 Association of robot's position with sonar range value by means of an artificial neural network.

Ⅵ.Experimental results

A.Qualitative comparisons

Predicted sonar curves along four test paths using bilinear interpolation and ANN were compared with the curves of real sonar data. Figures 7 and 8 present the results. It can be seen that for test paths *No.1* and *No.2* (Figure 7), interpolation and ANN model both predict abruptly raised values while the robot's positions are in the speculating region of sonar signals caused by the smooth surface of a plywood door.



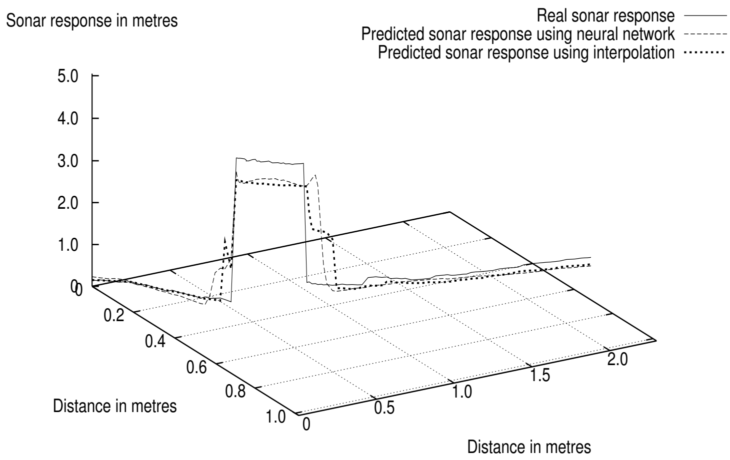
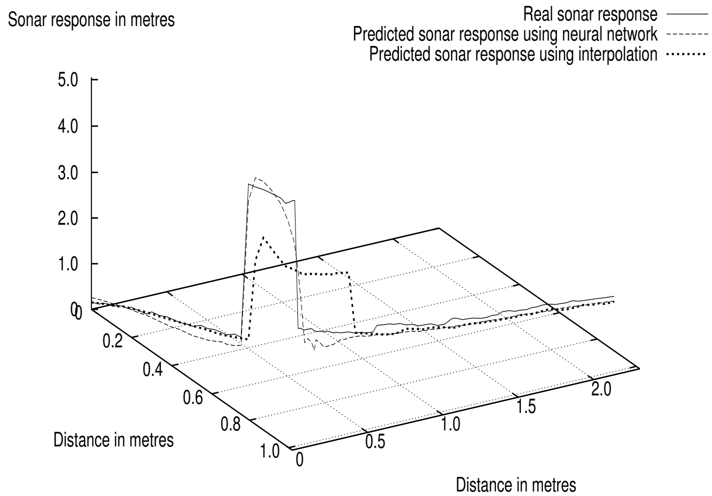


Figure7 The predictions of using bilinear interpolation and using ANN compared with the real data. (Top: Predictions on test path No.1. Bottom: Predictions on test path *No.2.*)

However, the difference between predictions made by interpolation and ANN model is not very distinct in these two trials. For trials along test paths No.3 and No.4 (Figure 8), the difference of predictions between interpolation and ANN model is very clear. The pictures of Figures 8 show that the sonar curves generated by ANN model are more resembled to the real ones than those from bilinear interpolation, especially for the predictions along the test path *No.3*.

This can be explained that in the sonar speculating region, the distances between samples along test path *No.3* are the biggest among the four test paths. As interpolation uses the nearest neighbours only to approximate intermediate data between those far distance samples, ANN model uses all training samples to adapt associated weights in the MLP. Therefore, ANN can perform better than interpolation especially in the low density sampling area. Quantified values for each test comparison between predicted and the real ones are given in the next section.



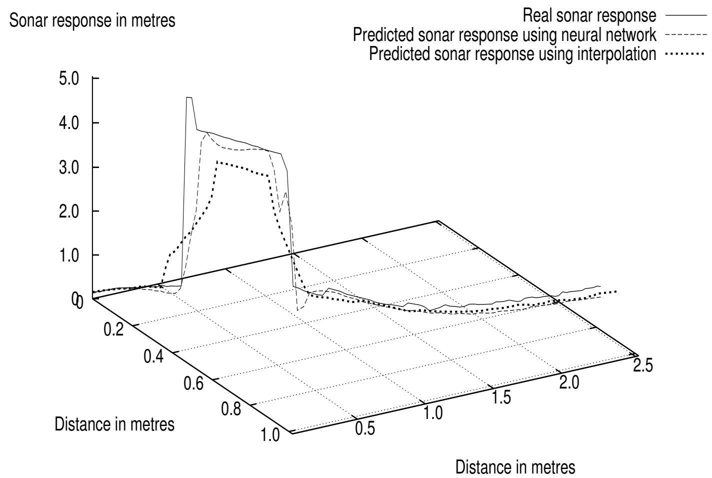


Figure8 The predictions of using bilinear interpolation and using ANN compared with the real data. (Top: Predictions on test path No.3. Bottom: Predictions on test path *No.4.*)

B.Quantitative Comparisons

The mean error between predicted sonar values and the real ones is calculated for both ANN model and bilinear interpolation. We calculated the average of absolute difference between predicted sonar ranges and the real ones. The values of mean error along four different test paths are presented in Table 1. The results indicate that ANN model has lower mean errors than those of interpolation for all four trials. The difference is obvious especially for test paths *No.3*.

Table 1　Mean error of predictions

Methods	Mean error between predicted and real data			
	Path			
	No.1	No.2	No.3	No.4
Neural Networks	0.25 *m*	0.33 *m*	0.19 *m*	0.27 *m*
Interpolation	0.30 *m*	0.35 *m*	0.51 *m*	0.36 *m*

Ⅴ.Conclusions

This paper presents examples of modelling robot's sonar readings by interpolation and ANN. Although, theoretically an ANN model with a sigmoid transfer function can have better performance in approximating a smooth curve than interpolation, e.g. approximating a polynomial curve, the quantified values in *Table1* do not show that the mean error between the real sonar readings and the predictions from ANN are always obviously smaller than those from interpolation. This can be explained that the underlying sonar curves is more like step functions rather than polynomial curves. Therefore, the higher accuracy of prediction is not contribute by a smooth mapping but that the ANN uses all training samples to change its weights instead of using nearest neighbours only. The prediction results from test path *No.3* describe the reason why interpolation gets a much bigger error than ANN in a *low density* sampling area.

Therefore, in the case of modelling a mobile robot's exteroceptive sensors, an ANN model can be more useful than interpolation. This is not only for its higher accuracy of prediction but also for its constant accuracy over uneven density of sampling area. As an arbitrary path can be used for an ANN model and the interpolation needs equally-spaced samples to maintain accuracy, an ANN model can therefore make data collection much easier than interpolation because it will be convenient to have robot collect data randomly in an arbitrary path than from a pre-programmed formatted path.

It can be noted that the experimental environment is only 2x3 meter square. Therefore, the position error caused by odometry will not be significant. However, we do suggest that for applications of large real environments a better positioning system will be required.

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