Planning the Circular Motion of a Mobile Robot by Using Complex-Valued Neural Network

T. Ogawa¹, Y. Kagawa², A. Okazaki³, and T. Takahashi⁴
¹Department of Electronics and Computer Systems, Takushoku University, Tokyo, Japan
²Department of Mechanical System Engineering, Takushoku University, Tokyo, Japan
³Department of Design, Takushoku University, Tokyo, Japan
⁴Department of Computer Science, Takushoku University, Tokyo, Japan

Abstract - Neural networks extended to complex numbers have been studied. Complex-valued neural networks (CVNNs) can be used for learning geometric mappings in a two-dimensional plane. CVNNs can learn geometric structures sufficiently from lower dimensional data. In this study, we consider determining the path of a mobile robot in a two-dimensional plane by learning. We introduce learning by using a CVNN for planning the circular motion of a point robot that moves in the two-dimensional plane. We demonstrate the effectiveness by simulation.

Keywords: Complex-valued neural network, mobile robot, circular motion.

1 Introduction

Neural networks extended to complex numbers have been studied previously in literature [1-2]. Various complex-valued neural network (CVNN) models have been proposed. CVNNs can naturally learn complex input/output relations. In particular, the multilayered model of the CVNN, which is a natural extension of the real-valued model, can learn the relationship between complex inputs and outputs. A number of complex-valued neuron models have been proposed [2]. Among them, the model using the sigmoid functions independently for the real and imaginary parts has a simple learning rule and is advantageous for practical use. CVNNs can be used for learning geometric mappings in a two-dimensional plane [3].

Because the motion planning or path planning of a mobile robot is important in robotics, a number of methods have been proposed for this. A vector field and potential field are factors for guiding a robot by setting a certain field. Construction of these fields is considered to be conducted by learning from several observation data. We consider making a multilayered neural network learn the field. CVNNs can learn geometric structures correctly from lower dimensional data. In this study, we propose the generation of the motion of a mobile robot by learning a field from motion data with a CVNN.

In this study, we determine the path of a robot moving in a two-dimensional plane by learning. We deal with circular motion around the object and examine the generation of a circular trajectory from the given learning data. This method can be applied to, for example, a robot for watching or protecting the object. Thus, we introduce the learning by a CVNN for the motion planning of a point robot circling in a two-dimensional plane, and we show the effectiveness by the simulation.

2 Complex-valued neural network

Various models of CVNNs exist, such as multilayered, self-organizing, associative memory type, and recurrent. In this study, we use a multilayered model for supervised learning. Further, complex neuron models include independent real/imaginary model, simple complex function model, and amplitude/phase (polar coordinate) model. In this study, we handle an independent real/imaginary model, which is convenient to handle and has no singular point.

2.1 Learning from lower dimensional data

The advantage of CVNNs is their short learning time and high learning efficiency compared to real-valued ones, because CVNNs have inherent complex-valued structures. Another advantage is learning from incomplete data. This is because of the characteristics of the CVNN, which include robustness to rotation, and the possibility of sufficient learning even from lower dimensional data.

Here, we consider the learning of rotational mapping in two-dimensional space. We prepare three types of learning data, namely, on the grid, on the line, and only two points. There are two types of networks, a real-valued neural network (RVNN) and a complex-valued one. The former has two input, ten hidden, and two output units, and it learns the coordinates. The latter has an input, five hidden, and an output unit, and it learns complex coordinates. The estimated errors are shown in Table 1. According to the results, there is no difference between the RVNN and CVNN in higher dimensional data (on the grid). However, CVNN produces better results than RVNN for lower dimensional data (on the line and two points).
3 Planning of circular motion

As the motion planning of a mobile robot is important in robotics, a number of methods have been proposed for this. As the simplest abstraction of a mobile robot, there is a method of expressing a robot as a point and handling it on the coordinates of a two-dimensional plane. In this study, we handle the motion planning of a point robot. Let the coordinates of the point robot be \((x, y)\) and the point after movement be \((x + \Delta x, y + \Delta y)\). We consider learning this rule of movement with variety of movement data. Letting the initial position of the point robot be \((x_0, y_0)\), the position after the \(N\)th movement is \((x_N, y_N) = (x_0, y_0) + \Sigma(\Delta x_i, \Delta y_i)\) in general. Here, we consider learning the above movement with RVNN and CVNN. In the case of CVNN, we consider the coordinate of the point robot on the complex plane.

CVNN can correctly learn geometric structures from lower dimensional data. In this study, we propose generating the motion of a mobile robot by learning a field from the mapping data with a CVNN. As a motion of a point robot, we consider a circular orbit around the object. We examine the learning of circular orbit from different dimensional learning data. This method can be applied to, for example, a robot for watching or protecting the object. In addition, if we assume a movement to guide the object, we can consider an elliptical orbit in addition to a circular orbit. In this study, we introduce the learning by CVNN for the motion planning of the point robot circling in a two-dimensional plane, and show the effectiveness in the simulation.

4 Simulation

RVNN and CVNN learn the circular motion. RVNN has two input, ten hidden, and two output units, whereas CVNN has an input, five hidden, and an output unit. The transfer function of the real–valued neuron is \(f(u) = \tanh(-u)\), where \(u\) is the weighted sum of the inputs. The transfer function of the complex-valued neuron is expressed by the function as \(f(u) = f_R(u) + if_I(u)\), \(f_R(u) = \tanh(\text{Re}(u))\), and \(f_I(u) = \tanh(\text{Im}(u))\), where \(u\) is the weighted sum of the complex inputs. As in the experiment in Section 2.1, we use three types of learning data, namely, on the grid, on the line, and only two points.

Figs. 1 and 2 show the results of the successive estimations of the location of a point robot by using neural networks. The trajectories are estimated by RVNN or CVNN from the initial positions of the random numbers in the range \([0.4, 0.6]\). According to the results, RVNN cannot learn with lower dimensional data, whereas CVNN can. In conclusion, it is effective to use a complex neural network for planning of circular motion.

5 Conclusions

In this study, we showed the effectiveness of using CVNNs for learning geometric mapping in a two dimensional plane. CVNN can sufficiently learn the geometric structure from lower dimensional data. Then, we introduced learning using a complex-valued neural network for planning the circular motion of a point robot in a two-dimensional plane. The effectiveness was shown by the simulation. As future work, we consider the trajectory planning of the elliptical orbit or moving center.

Table 1 Estimated errors by neural networks learned with the learning data of different dimensions

<table>
<thead>
<tr>
<th>NN type</th>
<th>Arrangement of training data</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>On grid</td>
</tr>
<tr>
<td>RVNN</td>
<td>0.0671</td>
</tr>
<tr>
<td>CVNN</td>
<td>0.0668</td>
</tr>
</tbody>
</table>

Fig. 1 Circular trajectories by RVNN learned with the data (a) on grid, and (b) as points.

Fig. 2 Circular trajectories by CVNN learned with the data (a) on grid, and (b) as points.

6 References