Training Expert Modules for a Mobile Robot using mnSOM

M. Aziz Muslim[a,*], Masumi Ishikawa[a], Tetsuo Furukawa[a]

[a] *Dept. of Brain Science and Engineering,*
Kyushu Institute of Technology, Japan

Abstract. A promising approach to perform a complex task for mobile robot navigation is to decompose it into simpler subtasks by task segmentation. Proposed is a new method for task segmentation in navigation of mobile robots by a modular network SOM (mnSOM). mnSOM has the ability of both segmentation and interpolation. In a standard mnSOM algorithm, data classes need to be known in advance. In a mobile robot application, however, data classes are unknown. Hence, we propose to decompose sequence data into many subsequences, supposing that a class does not change within a subsequence. During learning, modules in mnSOM compete with each other, generating a winner in each subsequence called an expert. The resulting mnSOM demonstrates good segmentation performance of 94.05% for a novel dataset.

Keywords: mobile robot, navigation, task segmentation, modular network SOM (mnSOM)

1. Introduction

Task segmentation in navigation of mobile robots has attracted wide attention. Tani and Nolfi [1] proposed a 2-level hierarchical mixture of recurrent experts (MRE). Another hierarchical structure, using 2-level prediction networks, was also proposed in [2]. In the above studies, modules are in isolation. Accordingly, interpolation among modules or units is not possible as it is. We propose to use a modular network SOM (mnSOM) [3][4] to simultaneously realize segmentation and interpolation in mobile robot navigation.

In a standard mnSOM algorithm, data classes need to be known in advance. In a mobile robot application, however, data classes are unknown. Hence, we propose to decompose sequence data into many subsequences, supposing that a class label does not change within a subsequence. Accordingly, training of mnSOM is done for each subsequence in contrast to that for each class in the standard mnSOM.

2. Task Segmentation in Navigation of a Mobile robot

Experiments are carried out using a Khepera II mobile robot. The robot movement is controlled by a PC via serial connection. The robot moves from the start position to the end position by wall following on the robot field in Fig.1. During the movement, robot

* Corresponding author. Tel: +81-695-6116. Fax: +81-695-6106.
E-mail address: aziz-muslim@edu.brain.kyutech.ac.jp.
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turns left twice and turns right twice. For later evaluation of training and test results, the whole datasets are manually segmented into 9 sequences based on motor commands as in Fig.1. Sequences, 1, 3, 5, 7 and 9, correspond to the class of forward movement, sequences, 2 and 4, correspond to the class of left turn, and sequences, 6 and 8, correspond to the class of right turn.

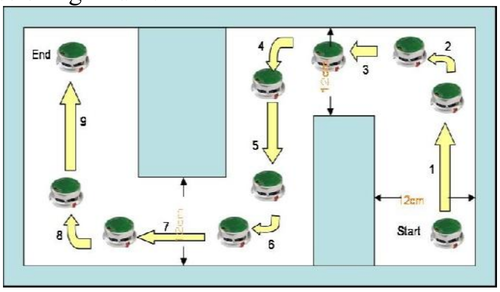

Fig. 1. The field for the mobile robot.

The whole dataset with 843 samples is split into many subsequences with the fixed length. In case of the length 20, it is decomposed into 42 subsequences, the last 3 subsequences being the length 21. Table 1 shows the division, where labels “F”, “L”, “R”, “L/F”, and “R/F” stand for forward, left turn, right turn, transition between forward movement and left turn, and transition between forward movement and right turn, respectively.

Table 1.
Division of dataset into subsequences of the length 20

Sequence	Data Numbers	Subsequence Numbers	Labels
1	1-131	1,2,3,4,5,6,7	F,F,F,F,F,F,L/F
2	132-187	7,8,9,10	L/F,L,L,L/F
3	188-312	10,11,12,13,14,15,16	L/F,F,F,F,F,F,L/F
4	313-368	16,17,18,19	L/F,L,L,L/F
5	369-496	19,20,21,22,23,24,25	L/F,F,F,F,F,F,R/F
6	497-549	25,26,27,28	R/F,R,R,R/F
7	550-666	28,29,30,31,32,33,34	R/F,F,F,F,F,F,R/F
8	667-719	34,35,36	R/F,R,R/F
9	720-843	36,37,38,39,40,41,42	R/F,F,F,F,F,F,F

Because of the uniform division in Table 1, several subsequences stretch over two consecutive sequences (i.e., a forward movement sequence and a left turn sequence). They are called “transition” subsequences, and constitute virtual classes.

3. Experiments

An mnSOM is composed of modules, each being a fully connected recurrent neural network (FRNN) with 10 external inputs (composed of 8 IR sensor values and 2 motor commands), 10 outputs (i.e. prediction of IR sensor values and motor commands at the next time step), 27 hidden nodes, and sigmoidal activation functions. It is trained to generate an expert module in each subsequence. Fig.2 illustrates the architecture of mnSOM and the function module as its element.

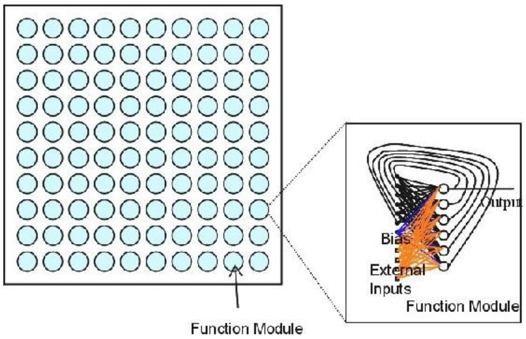

Fig.2. Array of modules in mnSOM and the function module as its element. The function module is a fully connected RNN.

Fig. 3 illustrates the resulting map and its labels given by manual segmentation. The green color stands for a forward movement, while the red and blue stand for left turn and right turn, respectively. The light brown and light blue colors stand for the transition between forward movement and left turn, and that between forward movement and right turn, respectively.

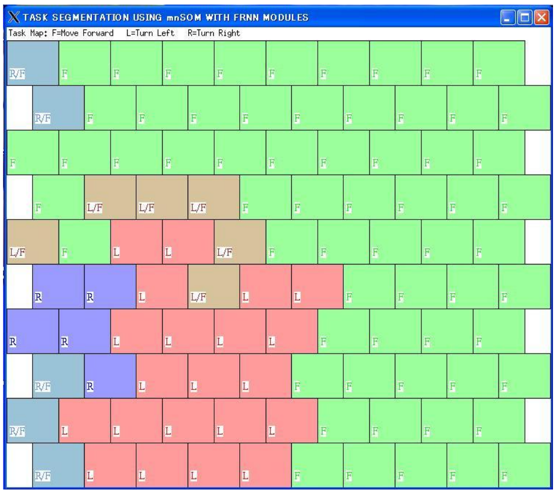

Fig.3. The resulting task map

We evaluate the resulting task map using a novel dataset based on the mismatch between the color of a subsequence and that of a module. Table 2 summarizes the overall performance for training datasets and a novel dataset for test. Table 2 indicates that subsequence with the length of 20 is the best.

Table 2.
Classification and segmentation performance of the resulting task map

The number of samples in each subsequence	The number of misclassifications					Correct segmentation rate (%)	
	Datasets					training datasets	novel dataset
	1	2	3	4	novel		
10	6	6	5	8	15	92.56	82.14
15	4.5	1.5	3.5	2	5	94.87	91.07
20	1.5	1.5	2.5	0	2.5	96.73	94.05
25	3	1.5	1	2	4.5	94.32	86.36
30	2	1.5	1	2	3.5	94.30	87.50

3. Conclusions

We have proposed to use a modular network SOM (mnSOM) for task segmentation of a mobile robot with slight modification of the standard mnSOM. The resulting mnSOM using subsequences with the length of 20 produces the best segmentation performance of 96.73% for training datasets and 94.05% for a novel dataset [6]. We also proposed a similar method taking temporal continuity of winner modules into account [5], but the present proposal is simpler and superior to the previous one [6].

In the current study sensory-motor signals are obtained from a real mobile robot and task segmentation is done successfully based on them. The original purpose of using mnSOM, however, was to provide desirable control to a mobile robot based on the resulting segmentation. This is left for further study.

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