

TASK SEGMENTATION IN A MOBILE ROBOT BY MNSOM AND CLUSTERING WITH SPATIO-TEMPORAL CONTIGUITY

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Received January 2008; revised June 2008

ABSTRACT. In our previous study, task segmentation was done by mnSOM, using prior information that winner modules corresponding to subsequences in the same class share the same label. Since this prior information is not available in real situation, segmentation thus obtained should be regarded as the upper bound for the performance, not as a candidate for performance comparison. Present paper proposes to do task segmentation by applying various clustering methods to the resulting mnSOM, without using the above prior information. Firstly, we use the conventional hierarchical clustering. It assumes that the distances between any pair of modules are provided with precision, but this is not the case in mnSOM. Secondly, we used a clustering method based on only the distance between spatially adjacent modules with modification by their temporal contiguity. In the robotic field 1, the segmentation performance by the hierarchical clustering is very close to the upper bound for novel data. In the robotic field 2, the segmentation performance by clustering with the spatio-temporal contiguity is very close to the upper bound for novel data. Therefore, the proposed methods demonstrated their effectiveness in segmentation.

Keywords: mnSOM, Task segmentation, Clustering, Mobile robot, Temporal contiguity, Spatio-temporal contiguity

1. Introduction. Task segmentation in navigation of a mobile robot based on sensory signals is important for realizing efficient navigation, hence attracted wide attention. Tani and Nolfi [10] proposed 2-level hierarchical mixture of recurrent experts (MRE), which is an extension of the network architecture proposed by Jacobs et al.[3]. Wolpert and Kawato [12] proposed MOSAIC architecture for motor control with a responsibility signal to each module provided by the soft-max function.

In the conventional competitive learning, only a winner module or unit is highlighted, accordingly the degree of similarity between modules or units and interpolation among them are not taken into account. There are two types of “interpolation:” one is creating an output by interpolating outputs of multiple modules, and the other is creating a module by interpolating multiple modules. Let the former be called “output interpolation” and the latter be called “module interpolation.” Our study here focuses on the latter.

The soft-max function [12] is an improvement over the conventional competitive learning in that the output interpolation is possible based on the responsibility signals. Similarity between modules, however, is not explicitly represented. Furthermore, the soft-max function and segmentation do not generally coexist; only when the soft-max function is