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An efficient MDS-based topographic mapping algorithm

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Abstract

Here, an multidimensional scaling-based (MDS-based) topographic mapping algorithm is proposed, named the stochastic MDS network. Because this network utilizes not local but global information over all the units, it can find more optimal results than previous models. In addition, by using a stochastic gradient algorithm, the mapping formation in this network is carried out as efficiently as in SOM-like models based on only the local information. Some simple numerical experiments verified the validity and efficiency of this network. It was also applied to the formation of large-scale topographic mappings, and could form various interesting mappings.
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Keywords: Multidimensional scaling; Stochastic gradient algorithm; Topographic mapping; The self-organizing map

1. Introduction

Many artificial neural network models have been proposed for forming topographic mappings (see [2,3,16] as the reviews). It is also well-known that some of these models (such as the self-organizing map (SOM) [6,7] and the neural-gas

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network [11]) are useful in dimension-reduction problems. For practical use, the most significant advantage of these neural network models is their efficiency. They can form a global topographic mapping by using just the local interactions among units (e.g. the neighborhood function in the SOM), while other dimension-reduction methods such as multidimensional scaling (MDS) [10,1] require high computational costs of square order because they have to manage all the interactions including the global ones. However, if global interactions are crucial, the local-interaction-based models often fail to find a solution. In such a case, the global-interaction-based methods using all the interactions have to be employed. But, existing methods are not applicable to large-scale problems because they require heavy computation.

In this paper, a new topographic mapping algorithm is proposed based on MDS, named "the stochastic MDS network." Our stochastic MDS network avoids the above computational cost problem by a stochastic gradient algorithm. Since this network can utilize global interactions over all the units without calculating the interactions for each pair of units, it can find out *good* topographic mappings *efficiently* for large-scale problems.

This paper is organized as follows. The stochastic MDS network is defined in Section 2. In Section 3, the results of numerical experiments confirm that the stochastic MDS network is more efficient than a usual (non-stochastic) MDS model and it finds better (namely, nearer to the optimum) results more efficiently than local-interaction-based models (the SOM and the neural-gas network). In Section 4, this network is applied to forming large-scale topographic mappings, and show that it forms various interesting mappings such as twofold ones from both eyes and independent ones from different input systems. This paper is concluded in Section 5.

2. Stochastic MDS network

2.1. Brief introduction to MDS

Our algorithm is based on multidimensional scaling (MDS). Here, a brief introduction of MDS is given in order to describe our algorithm simply in the following.

MDS is a widely used dimension-reduction method for multivariate data analysis. It finds a mapping of units in a low-dimensional space, which preserves "the intrinsic similarities" (or disparities) among all the units as "faithfully" as possible [10,1]. MDS finds a dimension-reduction mapping by minimizing a criterion, which is often called a *stress*. For example, ALSCAL [18] (one of the most famous MDS methods) uses the following criterion named SSTRESS:

$$\mathrm{SSTRESS} = \sum_{i,j} (d_{ij}^{\mathrm{int}} - d_{ij}^{\mathrm{low}})^2, \tag{1}$$

where i and j denote units, d_{ij}^{int} is the square Euclidean distance between i and j in the intrinsic space, and d_{ij}^{low} is that in the low-dimensional space where the mapping is embedded. Each d_{ij}^{int} is given in advance. By minimizing SSTRESS, ALSCAL finds a

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