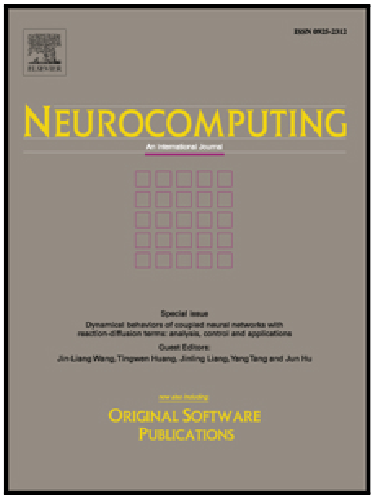

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DCT based Weighted Adaptive Multi-linear Data Completion and Denoising

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Abstract

This paper emphasises on formulating a weighted adaptive transform based solution for multi-linear signal completion and denoising problems based on the fact that the real-valued DCT based tensor algebra provides better low-rank representation compared with the existing Fourier transform based framework. Using an m-mode DCT based tensor SVD, complementary information existing in all modes of the tensor is effectively employed to achieve better performance. Further improvement in the tensor recovery is accomplished by adaptive low-rank regularization via measuring the degree of the low-rank structure existing in each mode. The proposed method follows adaptive low rank regularization strategy which provides more gravitas to the better low-rank representation. The proposed algorithm built by combining the three aspects of tensor processing such as, DCT based tensor SVD, utilization of complementary information from all the modes of the tensor and adaptive low-rank regularization to attain greater signal recovery. The performance of the proposed method is evaluated by applying to video completion and denoising problems.

Keywords: Low rank recovery, Tensor completion, Tensor decomposition, Data completion, Denoising

1. Introduction

The information conveyed by multi-linear signal highly depends on many factors during capturing or transmission processes, such as the quality of the capturing mechanism, ambient conditions, nature of the communication system and many more. In most of the cases, re-capturing or re-transmission of data is expensive or impracticable. Signal corruption by gross errors is one of the significant barriers in this field. The noise causes signal samples to receive improper values and affects the performance of further processing stages. The enormous size of the signal makes the denoising process very challenging. Partial loss of information while transmission or capturing is another major hurdle in this field. Few reasons for the signal loss are the occlusion by obstacles during capturing, errors during transmission of data conversion/transmission, segmentation or removal of objects from the signal, etc.. The partially observed signal may become useless without the estimation of missing data. High-dimensionality of multi-linear data makes the filling of missing samples very hard.

Natural signals like video or images possess low-rank structure[8, 9, 14, 16, 26, 48, 52]. Even though signal lies in a high dimensional space, it can be approximated to be live in a relatively low dimensional space by exploiting low-rank property. The low-rank approximation is one of the approaches used to build the low-dimensional estimate of multi-linear data with least error. Rank will be enhanced when the signal is affected by noise. Denoising can be effectively done by decomposing the data into low-rank and sparse components and choosing the low-rank part. Usually, sparse noise can be removed in this manner. When the partial observation is only available for a signal, the appropriate samples can be filled in the missing portion by utilising the low-rank prior. The missing samples of a signal are furnished in such a way that the neighbouring samples preserve the low-rank structure as a whole.

Singular Value Decomposition (SVD) is the strong mathematical tool to construct the low rank approximation and is defined as [15, 17, 29],

$$\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^T$$

where, $\mathbf{U} \in \mathbb{R}^{m\times m}$ and $\mathbf{V} \in \mathbb{R}^{n\times n}$ are unitary matrices and $\mathbf{S} \in \mathbb{R}^{m\times n}$ is the diagonal matrix contains singular values of $\mathbf{X}$. The low-rank approximation of a two-dimensional signal is closely related to the sum of its singular values. The singular values of a matrix $\mathbf{X} \in \mathbb{R}^{m\times n}, n < m$ is defined as follows,

$$\sigma(\mathbf{X}) = \{\sigma_1 \dots \sigma_n\} = diag(\mathbf{S}), \quad \mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^T$$

The rank of the matrix is non-convex and its closest convex approximation is the sum of the singular values termed as nuclear norm. Then nuclear norm is defined as [15, 17, 29],

$$\|\mathbf{X}\|_* = \sum_{i=1}^{r} \sigma_i, \qquad rank(\mathbf{X}) = r \tag{1}$$

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