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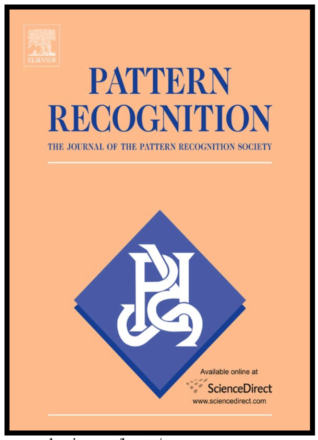

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Sequential Dimensionality Reduction for Extracting Localized Features

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Abstract

Linear dimensionality reduction techniques are powerful tools for image analysis as they allow the identification of important features in a data set. In particular, nonnegative matrix factorization (NMF) has become very popular as it is able to extract sparse, localized and easily interpretable features by imposing an additive combination of nonnegative basis elements. Nonnegative matrix underapproximation (NMU) is a closely related technique that has the advantage to identify features sequentially. In this paper, we propose a variant of NMU that is particularly well suited for image analysis as it incorporates the spatial information, that is, it takes into account the fact that neighboring pixels are more likely to be contained in the same features, and favors the extraction of localized features by looking for sparse basis elements. We show that our new approach competes favorably with comparable state-of-the-art techniques on synthetic, facial and hyperspectral image data sets.

Key words: nonnegative matrix factorization, underapproximation, sparsity, hyperspectral imaging, dimensionality reduction, spatial information

1. Introduction

Linear dimensionality reduction (LDR) techniques are powerful tools for the representation and analysis of high dimensional data. The most well-known and widely used LDR is principal component analysis (PCA) [14]. When dealing with nonnegative data, it is sometimes crucial to take into account the nonnegativity in the decomposition to be able to interpret the LDR meaningfully. For this reason, nonnegative matrix factorization (NMF) was introduced and has been shown to be very useful in several applications such as document classification, air emission control and microarray data analysis; see, e.g., [7] and the references therein. Given a nonnegative input data matrix $M \in \mathbb{R}^{n \times m}_{+}$ and a factorization rank r, NMF looks for two matrices $U \in \mathbb{R}^{n \times r}_{+}$ and $V \in \mathbb{R}^{r \times m}_{+}$ such that $M \approx UV$. Hence each row $M(i,:)$ of the input matrix M is approximated via a linear combination of the rows of V: for $1 \leq i \leq n$,

$$M(i,:) \quad \approx \quad \sum_{k=1}^{r} U_{ik} \, V(k,:).$$

In other words, the rows of V form an approximate basis for the rows of M, and the weights needed to reconstruct each row of M are given by the entries of the corresponding row of U. The advantage

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