NON-NEGATIVE MATRIX FACTORIZATION FOR BLIND IMAGE SEPARATION

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A dissertation submitted in partial fulfilment of the
requirements for the award of the degree of
Master of Science (Computer Science)

Faculty of Computing
Universiti Teknologi Malaysia

May 2014

Dedicated with love to those I care,,,

ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious, the Most Merciful. Praise be to Allah, Lord of the universe for making me able to undertake this research work until the end. I would like to present my sincere gratitude to my supervisor Dr. Andri Mirzal for his invaluable guidance, dedication, time and earnest encouragement in working toward the development this research.

In preparing this dissertation, I was in contact with many people, researchers, academicians and practitioners. They have contributed towards my understanding and thoughts.

Special gratitude to all my fellow colleagues and friend from Computer Science and Indonesia Student Society whom which I cannot write all of them here for their encouragement, discussion and friendship, in which I considered as my family. My gratitude also to the lecturers and staffs for their knowledge and support during the duration of the study as the students in University Teknologi Malaysia

Finally, I deliver my deepest and endless gratitude towards my dearest mother and father : Hj Anniyati and Prof. H Eddy Sumarno Siradj, my little sister Puri Bestari Mardani, for their continuous encouragement, patience and support to pursue my study and the same time to be close at hand to render love, comfort and support. May Allah return all your good deeds and provide His blessing and guidance to all of us.

ABSTRACT

Hyperspectral unmixing is a process to identify the constituent materials and estimate the corresponding fractions from the mixture, nonnegative matrix factions (NMF) is suitable as a candidate for the linear spectral mixture mode, has been applied to the unmixing hyperspectral data. Unfortunately, the local minima is cause by the nonconvexity of the objective function makes the solution nonunique, thus only the nonnegativity constraint is not sufficient enough to lead to a well define problems. Therefore, two inherent characteristic of hyperspectal data, piecewise smoothness (both temporal and spatial) of spectral data and sparseness of abundance fraction of every material, are introduce to the NMF. The adaptive potential function from discontinuity adaptive Markov random field model is used to describe the smoothness constraint while preserving discontinuities is spectral data. At the same time two NMF algorithms, non smooth NMS and NMF with sparseness constraint, are used to quantify the degree of sparseness of material abundances. Experiment using the synthetic and real data demonstrate the proposed algorithms provides an effective unsupervised technique for hyperspectial unmixing.

ABSTRAK

Hyperspectral unmixing merupakan proses untuk mengidentifikasi konstituen sebuah bahan dan memperkirakan fraksi dari sebuah mixture (campuran), nonnegative matrik factorization (NMF) merupakan pasangan yang tepat untuk linear spectral pada bagian mixture, dimana telah di usulkan sebagai unmixing hyperspectral data. Sayangnya local minima terjadi karena penyebab adanya nonnegativity constraint yang tidak mencukupi untuk menyelesaikan masalah. Oleh karena itu, dua karakteristik yang melekat pada data hyperspectal, lapisan dan kelancaran (baik temporal dan spasial) data spektral dan kekurangan fraksi kelimpahan setiap materi, yang memperkenalkan kepada NMF. Fungsi potensi adaptif dari discontinuity adaptive Markov random field model digunakan untuk menggambarkan kendala kelancaran sambil menjaga diskontinuitas data spektral. Pada saat yang samakedua algoritma tersebut baik NMF dan NNMF dan NMF dgan sparseness constraint, digunakan untuk mengukur tingkat kekurangan material abundances. dua algoritma NMF, non halus NMS dan NMF dengan kendala kekurangan, digunakan untuk dari kelimpahan materi. Percobaan menggunakan simulasi dan data real menunjukkan algoritma yang diusulkan memberikan teknik yang efektif untuk unmixing hyperspectial.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ABBREVIATION	MEANING
UTM	University Teknologi Malaysia
NMF	Non-negative Matrix Factorization
BSS	Blind Source Separation
BIS	Blind Image Separation
ENMF	Extended Non-negative Matrix Factorization
NMFLS	Non-negative Matrix Factorization Lee and Seung
SNR	Signal Noise Ratio
ICA	Independent Component Analysis

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Nonnegative Matrix Factorization (NMF) (Lee and Seung, 1999; Pattero and Tapper, 1994) has attracted many attentions for the past decade as a dimension reduction method in machine learning and data mining. NMF are considered as one of the highest dimensional data where each element has a nonnegative value, and provide a lower rank approximation that formed by factors whose elements are also nonnegative.

Due to the nonnegativity, the factors of lower rank approximation given a natural interpretation: for each object is explained by an additive linear it combines of intrinsic ‘parts’ of the data (Lee and Seung, 1999). Numerous successes were reported in application areas including text mining (Pauca et all, 2004), text clustering (xu et all, 2003), computer vision (Li et all, 2001), and cancer class discovery (Brunett et all, 2004; Kim and Park, 2007).

NMF can be traced back to 1970's (Notes from G. Golub) and it studies extensively by Paatero (Pattero and Tapper, 1994). Suggested that NMF factors contain coherent parts of the original images. They confirm that the difference between NMF and vector quantization (which is essentially the K-means clustering).

However, later experiments (Hoyer,2004; Pattero and Tapper, 1994) do not support the coherent part interpretation of NMF. Moreover, most applications make use of the clustering aspect of NMF, which is de-emphasized by Lee and Seung (Lee and Seung, 1999). A recent theoretical analysis (Ding et all, 2005) shows the equivalence between NMF and K-means / spectral clustering.

In these days, automatic organization of documents becomes crucial since the number of documents to be handled increases rapidly. Document clustering is an important task in organizing documents automatically, which simplifies many subsequent tasks such as retrieval, summarization, and recommendation.

Document is represented as an unordered collection of words, which leads to a term-document matrix for a set of documents to be processed. Term-document of matrix is nothing but co-occurrence table which is a simple case of dyadic data. Dyadic data refers to a domain with two finite sets of objects in which observations are made for dyads, i.e., pairs with one element from either set (Hofmann, Puzicha, & Jordan, 1999).

Matrix factorization-based methods have established as a powerful techniques in dyadic data analysis where a fundamental problem, for example, is to perform document clustering or co-clustering words and documents given a term document matrix. Nonnegative matrix factorization (NMF) (Lee & Seung, 1999, 2001) was successfully applied to a task of document clustering (Shahnaz et all, 2006; Xu, Liu, & Gong, 2003), where a term-document matrix is taint into a product of two factor matrices, one of them is corresponds to a cluster canters (prototypes) and the other one which is associated with cluster indicator vectors. Orthogonal NMF, where an orthogonally constraint is imposed on a factor matrix in the decomposition, was shown to provide more clear interpretation on a link between clustering and matrix decomposition (Ding, Li, Peng, & Park, 2006).

New Extended algorithms for Non-negative Matrix Factorization (NMF). The proposed of the algorithms are to characterized by improving the efficiency and convergence rate, it can also be applied for various distributions of data and additive noise. Information theory and information geometry play an important roles in the derivation of new algorithms. Several loss or functions are used in information theory which allow us to obtain generalized forms of multiplicative NMF learning adaptive algorithms. Flexible and relaxed are also forms of the NMF algorithms to raise convergence speed and impose an additional constraint of sparsity.

The scope of these results is vast since discussed generalized divergence functions include a large number of useful loss functions such as the Amari α–divergence, Relative entropy, Bose-Einstein divergence, Jensen-Shannon divergence, J-divergence, Arithmetic-Geometric (AG) Taneja divergence, etc. Applied the developed algorithms successfully to Blind (or semi blind) Source Separation (BSS) where sources may be generally statistically dependent, however are subject to additional constraints such as nonnegativity and sparsity. Moreover, we applied a novel multilayer NMF strategy which improves performance of the most proposed algorithms (Cichocki et all, 2006).

1.2 Problem background

Many problems in signal and image processing can be expressed in terms of matrix factorizations. Different cost functions and imposed constraints may lead to different types of matrix factorization. The Nonnegativity constraints and other constraints such as sparseness and smoothness. Non-negative matrix factorization (NMF) decomposes the data matrix, having only non-negative elements.

The NMF (Non-negative Matrix Factorization) sometimes called also PMF (Positive Matrix Factorization) does not assume explicitly or implicitly sparseness or mutual statistical independence of components, however usually provides sparse decomposition (Lee and Seung, 1999).

The most existing NMF algorithms perform blind source separation rather very poorly due to non-uniqueness of solution and/or lack of additional constraints which should be satisfied. The main objective of this contribution is to propose a flexible NMF approach and generalize or combine several different criteria in order to extract physically meaningful sources from their linear mixtures and noise. Whereas most applications of NMF focused on grouping elements of images into parts (using the matrix A), the dual viewpoint by focusing primarily on grouping samples into components representing by the matrix X of source signals.

1.3 Problem statement

Nonnegative matrix factorization (NMF) is a technique to cluster and mixing image, but there are issues occurred to NMF for Blind source separation (BSS). Based on observation on techniques and methods of NMF, there is an opportunity for improvement in the technique. Therefore, the main research question that intended in this research is:

"How to enhance existing techniques in Nonnegative Matrix Factorization for Blind Image separation?" And with the sub research questions of:

1. How to compare the existing with the extended Nonnegative matrix factorization?
2. How to reduce the noise from clustered image?
3. How to use image as a source for Blind Image separation?

Enhancement of this technique will open a greater chance for a fully integrated Nonnegative Matrix Factorization.

1.4 Objective

1. To Study the use of Nonnegative Matrix Factorization NMF for blind image separation (BIS).
2. To recover reduce noise from clustering image.
3. To compare extended Nonnegative matrix factorization with Nonnegative matrix factorization.

1.5 Scope

1. The technique of blind image separation will be enhanced to increase tolerance of real data image recovery to signal form.
2. The enhanced algorithms will be implemented and simulated with Nonnegative Matrix Factorization for Blind image separation.
3. The mixture set of image will use a certain number of mixtures (4, 6, 8, 10, 12).
4. The data set sample is a greyscale image of with pixel size 300 X 400.

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