GPU TECHNOLOGY CONFERENCE

A Dictionary Learning approach in GPU for Image Denoising

Lizeth Joseline Fuentes Pérez   Luciano Arnaldo Romero Calla   Anselmo Antunes Montenegro

Institute of Computing - Federal Fluminense University

Abstract

- Many image processing problems require image denoising as a preprocessing step. We address the problem of removing white Gaussian noise in images via dictionary learning, which is a technique that has been proved to better fit a signal than fixed dictionary approaches.
- Learning an overcomplete dictionary for sparse representation is a problem that involves a high computational cost. In this poster, we present an efficient parallel algorithm on GPU to reduce the whole processing time of image denoising algorithm via dictionary learning.

Introduction

Nowadays, sparse representation of signals has attracted considerable interest. Basically, sparse representation is based on the idea that a signal can be decomposed as a sparse linear combination of atoms, which are understood in a base called dictionary [1]. In image processing, dictionary learning is a successful technique with several applications such as denoising, inpainting, demosaicing and comprehensive sensing [2].

Dictionary learning is an NP-hard problem because the complexity of exhaustive search to solve the sparseness is exponential [3]. Hence, the exact computation of a sparse representation is not deemed a feasible approach. In the literature, several algorithms approximate the solution quite well; for instance greedy algorithms such as Orthogonal Matching Pursuit (OMP), gradient descent algorithms and the LASSO [4]. The K-SVD algorithm is usually used to train an overcomplete dictionary[5].

We propose a GPU Dictionary Learning algorithm based on K-SVD and OMP, to deal with the high computational complexity that implies solving large-scale optimization problems.

GPU Dictionary Learning algorithm

Formally, the dictionary learning problem can be formulated as:

$$min_{\alpha \in \mathbb{R}^m} ||x - D\alpha||_2^2 \ s.t. \ ||\alpha||_0 \leq L$$

where x is a set of training signals $x_{i=1}^{M} \in \mathbb{R}^n$, M is large, n is the dimension of each patch, $D \in \mathbb{R}^{n \times m}$, $m < M$.

K-SVD algorithm in GPU is used to train the dictionary and is composed by two main stages, K represents the number of iterations of the algorithm.

Sparse coding stage, we create an OMP kernel for the sparse representation of the dictionary. OMP solves the following optimization problem:

$$min_{\alpha \in \mathbb{R}^p} ||x - D\alpha||_2^2 \ s.t. \ ||\alpha||_0 \leq L \qquad (1)$$

K-SVD Dictionary update stage, basically update each dictionary atom.

We create the following kernels:

- Compute the residual matrix fixing one dictionary atom.
- Compute single value decomposition (SVD) to update the dictionary.

Experiments and Result

- Tests were performed on an Intel (R) Core (TM) i7-3770 CPU @ 3.40GHz processor with 24.5 GiB RAM; NVIDIA® Tesla™ K40C GPU Computing Accelerator - 12GB GDDR5 - 2880 CUDA Cores. We used Cusolver of CUDA 7.0 for computing linear algebra algorithms.
- The parameters used in the experiments are: threads number NT is 256, blocks number is $(x + NT - 1)/NT$, where x is the number of patches.

Speedup GPU Image Denoising

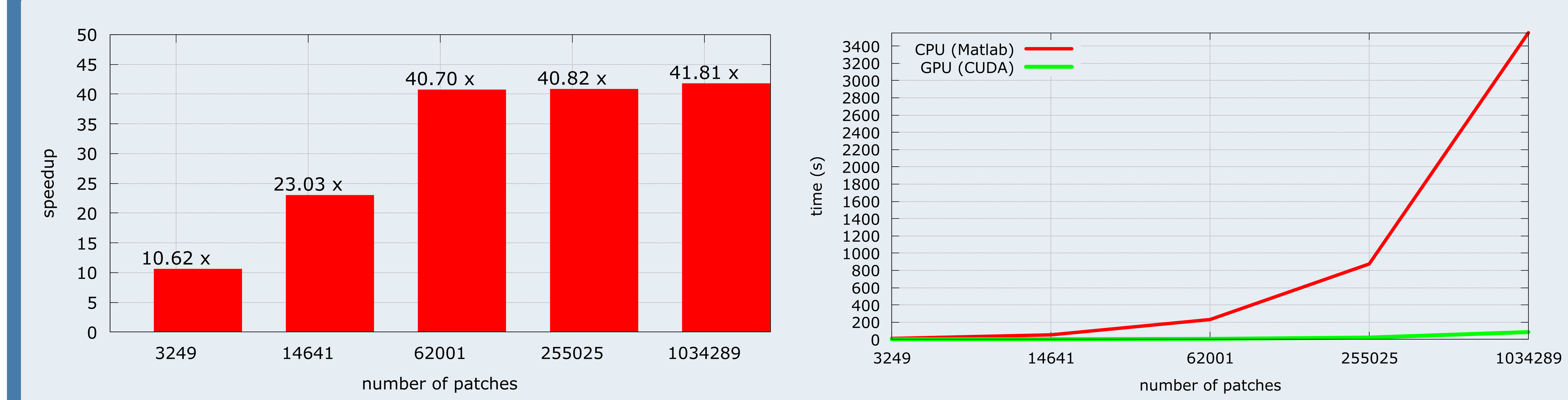

Figure 1: Speedup GPU image denoising.

Methodology

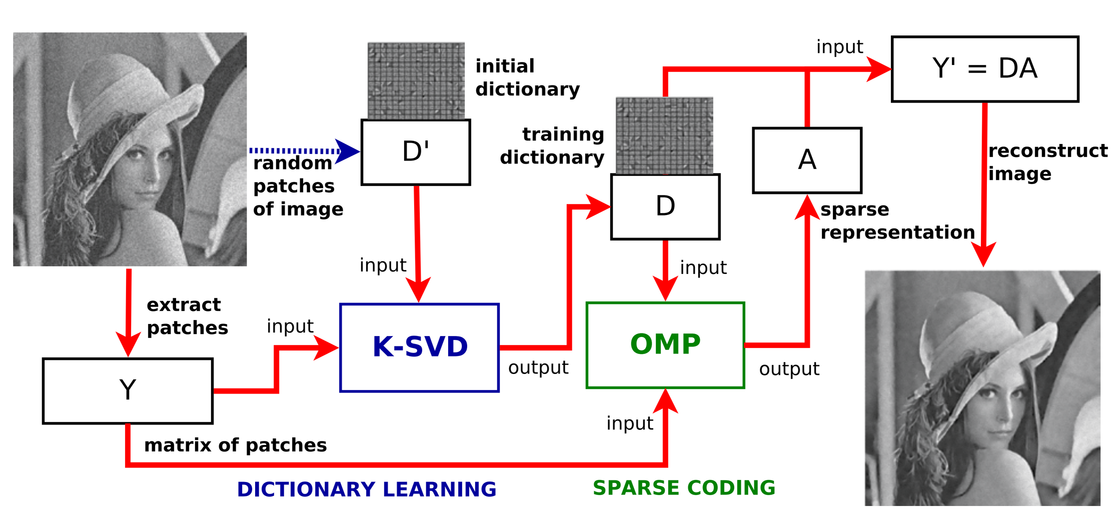

Figure 2: Methodology for image denoising process

Conclusions

In the experiments we compared our GPU implementation with a Matlab CPU implemenation with optimized linear algebra operations. The results have shown that we achieved a approximate speed up of 40×. Note that this is based on the total time of image denoising procedure, which is strongly dominated by the time of dictionary training using the K-SVD algorithm.

References

[1] R. Rubinstein, T. Faktor, and M. Elad. K-svd dictionary-learning for the analysis sparse model. In *Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on*, pages 5405–5408, March 2012.

[2] Jian Zhang, Debin Zhao, and Wen Gao. Group-based sparse representation for image restoration. *Image Processing, IEEE Transactions on*, 23(8):3336–3351, Aug 2014.

[3] Michael Elad. *Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing*. Springer Publishing Company, Incorporated, 1st edition, 2010.

[4] Joel A. Tropp, Anna C. Gilbert, and Martin J. Strauss. Algorithms for simultaneous sparse approximation: Part i: Greedy pursuit. *Signal Process.*, 86(3):572–588, March 2006.

[5] M. Aharon, M. Elad, and A. Bruckstein. Svdd: An algorithm for designing overcomplete dictionaries for sparse representation. *Trans. Sig. Proc.*, 54(11):4311–4322, November 2006.

Contact Information

- Lizeth: lfuentes@ic.uff.br
- Luciano: lromero@ic.uff.br
- Anselmo: anselmo@ic.uff.br

Instituto de Computação