Image De-Noising Using Adaptive Filters

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***Abstract*—Sparse representation of images or signals is becoming significant these days. This method is used to remove noise from the received signal and obtain compact and accurate signal. Natural signals such as images, admit a sparse decomposition over a unnecessary dictionary leads to efficient algorithms for handling such sources of data. The design of well adapted dictionaries for images has been a major challenge. The K-SVD algorithm is the algorithm used for various grey-scaled images. In this project we will be implementing K-SVD algorithm for handling non- homogenous noises and getting out ways to find missing information. Our goal is to learn the analysis dictionary from a set of examples.**

***Index Terms*—image representations, sparse representation, denoising, non homogenous noises, dictionary approach, OMP(orthogonal match pursuit).**

I. Introduction

The corrupted images can be represented by sparse-land models, which is based on sparsity and redundancy of signal data. A dictionary based approach is one, which is used for learning prior information and changing adaptively, according to new denoised images and helps in image-denoising. The basic assumption of this model is that natural signals can be expressed as a sparse linear combination of atoms, chosen from a collection called a dictionary. By removing noise from patches of images through adaptive filtering methodology and using parametric learning model, Image quality could be improved. K-SVD (k-Singular value decomposition), is one such dictionary-based adaptive filtering iterative algorithm, which we are using in our project.

For a signal $y \in R^n$, this can be described by y = Dx, where $D \in R^{n \times m}(n < m)$, is a redundant dictionary that contains the atoms as its columns, and $x \in R^m$ is the representation vector. Given the signal y, finding its representation can be done in terms of the following sparse approximation problem:

$$\min \|x\|_0 \text{ subject to } \|y - Dx\|_2 \leq \epsilon$$

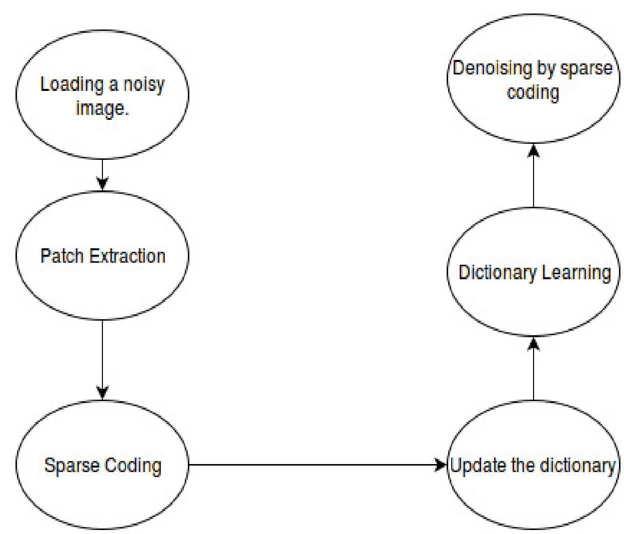
,where ϵ is a permitted deviation in the representation accuracy, and the expression $\|x\|_0$ is a count of the number of non-zeroes in the vector x. A fundamental element in this problem is the choice of the dictionary D. The dictionary learning problem can be written as:

$$argmin \quad \frac{1}{2}\|Y - DX\|_F^2 \text{ subject to } \|x_i\|_0 \leq p \forall i$$

,where $Y \in R^{n \times N}$ is a matrix containing N signal examples, and $x \in R^{m \times N}$ are the corresponding sparse vectors, both ordered column wise.

When basing the learned prior on image examples, the first junction to cross is the one which splits between parametric and nonparametric prior models. The parametric path suggests an analytical expression for the prior, and directs the learning process to tune the prior parameters based on examples.The alternative path, a nonparametric learning, uses image examples directly within the reconstruction process. Direct methods avoid the prior and target instead the posterior density, from which reconstructions easily obtained.As such, the approach we adopt is the parametric one. The learning we propose leans on both external data-set, as well as on the damaged image directly.

II. Flowchart



III. Literature Review

In paper [1], they have introduced a framework for color image restoration, and presented results for color image denoising, inpainting, and demosaicing.This algorithm uses either orthogonal matching pursuit (OMP), or basis pursuit (BP),as part of its iterative procedure for learning the dictionary. In the frameworks based on learning models for sparse color image representation, they also introduced grayscale K-SVD algorithm and it proved to be robust towards the dimensionality increase resulting from the use of color.

In paper [2], they have concentrated on an alternative, analysis-based model, where an analysis operator – hereafter referred to as the analysis dictionary – multiplies the signal, leading to a sparse outcome. The goal is to learn the analysis dictionary from a set of examples.

In paper [3] — they have presented a new approach of incorporating kernels into dictionary learning. The kernel K-SVD algorithm (KKSVD), which has been introduced in a previous paper, shows an improvement in classification performance, with relation to its linear counterpart K-SVD. However, this algorithm requires the storage and handling of a very large kernel matrix, which leads to high computational cost, while also limiting its use to setups with small number of training examples.

In paper [4] - they have showed how to efficiently handle bigger dimensions and go beyond the small patches in sparsity-based signal and image processing methods. They have builded an approach based on a new cropped Wavelet decomposition, which enables a multi-scale analysis with virtually no border effects. We then employ this as the base dictionary within a double sparsity model to enable the training of adaptive dictionaries. At the same time, they present an Online Sparse Dictionary Learning (OSDL) algorithm to train this model effectively.

In paper [5] - they have offered various ways to address the problemof de-noising , ranging from simple linear space-invariant interpolation schemes (e.g., bicubic interpolation), to spatially-adaptive and non-linear filters of various sorts. It also include a major simplification of the overall process both in terms of the computational complexity and the algorithm architecture, using a different training approach for the dictionary-pair, and introducing the ability to operate without a training-set by boot-strapping the scale-up task from the given low-resolution image.

IV. Result

The approach adapted to solve the problem of denoising is through the implementation of ksvd.The images used were corrupted by gaussian noise of varying nature. It uses dictionary learning which was implemented to learn the representation to optimize the sparsity of the dictionary . The nature of the noisy image is Gaussian of varying of varying amounts of noise.

Since the learning is computationally intensive, one can only apply it to small patches extracted from an image. Given a dictionary, we compute it's sparse approximation.The initial dictionary is computed by a random selection of patches.The sparse coding is obtained by minimizing a L1 penalized optimization.This is achieved using an iterative thresholding method (forward-backward iterations).The value of lambda controls the sparsity of the coefficients. As the number of iterations for the iterative thresholding increases, the decay of energy is minimized.Once the sparse coefficients X have been computed, one can update the dictionary.The full dictionary learning is achieved by iteratively computing the coefficients X and then updating the dictionary D.

V. Future Work

Implementation of denoising on a broader range of images. Denoising imaging exhibiting various other kinds of noises other than gaussian noise, like salt and pepper, poisson's etc. Along with that, we will also attempt to denoise images in the rgb domain.

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